1. MEASURING THE GREEN EFFICIENCY OF OCEAN ECONOMY IN CHINA: AN IMPROVED THREE-STAGE DEA MODEL

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Abstract

This paper aims to explore the true green efficiency of ocean economy in 11 coastal regions of China over 2004–2014. An extended three-stage DEA is proposed to improve the efficiency assessment of ocean economy. Malmquist–Luenberger productivity indexes are introduced into three-stage DEA model, which can simultaneously account for the impacts of undesirable outputs, environmental variables, and statistical noise. The results show that the environmental variables have significant impacts on regional ocean efficiency. Comparing with Malmquist productivity indexes, the average Malmquist–Luenberger productivity indexes of ocean economy have deteriorated over the past ten years. After eliminating the influences of environmental variables and statistical noise, the efficiency change and technical change of regional ocean economy are lower than the unadjusted case and technology inefficiency is the major cause of the inefficiency in China. Finally, a clustering matrix of the green efficiency of the regional ocean economy is presented to illustrate spatial refraction among 11coastal regions.

Keywords: ocean economy, three-stage DEA model, Malmquist-Luenberger index
JEL Classification: O47, C67

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1. Introduction

China's ocean economy has sustained its rapid development. However, according to the 2014 Ocean Statistical Bulletin, negative growth has been observed in the marine salt industry. While high-pollution and/or high-emission industries, such as marine mining, oil and gas, chemicals, and shipbuilding, continue to exhibit a high growth rate, marine resources and environmental issues could become bottleneck factors. This restricts the development of China's ocean economy in the future. These facts also raise important questions. What developmental pattern would the efficiency of the ocean economy demonstrate under the constraints of resource and environmental factors? How can we achieve a reasonable consumption of resources and minimal environmental impact while increasing the ocean economic efficiency? Thus, the scientific study of the green efficiency of the ocean economy and the investigation of the factors that influence that efficiency are of substantial significance to the health of the ocean economy in China.

The data envelopment analysis (DEA) is a broadly used technique to measure the efficiency of decision-making units (DMUs). The greatest advantage of this method is that it can be applied for the efficiency evaluation of any DMUs that utilize inputs in order to produce outputs. The reason is it does not depend on prior function assumptions about inputs and outputs. There are many different DEA models used in surveys of economic, social and environmental evaluation achieving good reputation (Emrouznejad and Yang, 2016). Among the related literature about extended DEA models, the Malmquist productivity index (MPI) originally proposed by Malmquist (1953) has become an important concept. This method has been developed in the non-parametric framework by several authors (e.g. Färe and Grosskopf, 1992; Thrall, 2000). Studies show that MPI has been widely recognized as an indirect measure of economic prosperity, standard of living and the competitiveness of an economy (Lall *et al*., 2002). MPI can utilize the directional distance function (DDF) to easily accommodate multiple inputs and multiple outputs cases when panel data are available. Meanwhile, changes in the MPI can be further decomposed into the components of efficiency change and technical change and offer more insights into the multiple sources of productivity growth (Lee et al., 2016). Essentially, it is an index denoted by MPI which represents total factor productivity (TFP) growth of DMUs in a multi-inputs-outputs framework (Yu et al., 2016). Furthermore, the TFP growth can reflect a kind of progress or regress inefficiency along with progress or regress of the frontier technology between two periods of time. Hence, MPI method has become very popular to evaluate efficiency of economic, energy and environmental productivity growth, which is a typical multi-inputs-outputs problem.

The sustainable economy has become an important forum for questions and concerns. From the view of sustainable growth, there are more and more attempts to develop measures of productivity growth incorporating both desirable and undesirable factors in some production processes. Chung et al. (1997) modified the MPI and gave an integrated concept about MPI and DDF. A Malmquist-Luenberger productivity index was presented, which was denoted by MLPI. Since then, the research based on the MLPI become flourishing in various domains. As the first remarkable effort employing MLPI in manufacturing industries efficiency assessment is the paper of Färe *et al*. (2001). Afterwards, a number of studies relied on the concept of MLPI to evaluate the economic energy environmental efficiency. For example, He *et al*. (2013) measured the energy efficiency and productivity change of China's iron and steel industry over the period 2001-2008. Munisamy and Arabi (2015) deployed MLPI to evaluate 48 Iranian thermal power plants productivity change in three different categories, e.g., steam, gas, and combined cycle over an eight year period of restructuring in the power industry. Emrouznejad and Yang (2016) introduced MLPI based on DDF to address the issue of productivity evolution of CO2 emissions reduction in China. In recent years, the improved DEA methods are applied to energy environmental efficiency of the ocean economy, which indicates producing more economic values with less resource and less environmental influence (Sueyoshi and Yuan, 2015; Yu *et al*., 2016; Chen, 2010). For example, Huang and Fu (2013) used the extended DEA model to measure the energy environmental efficiency of low carbon ocean economy. Ding *et al*. (2015) employed MLPI to evaluate energy environmental efficiency in the 11 coastal regions. They incorporated resource and environmental factors into the system of efficient evaluation and concluded that ignoring the changes in undesirable outputs underestimated true productivity growth accounting for pollution and irrational use of resources.

However, previous studies on the energy environmental efficiency of ocean economy have not considered the diversity of regional economy, e.g., territory, external trade and educational level. They assume that the difference in regional economy mainly comes from microcosmic management decisions, rather than specific environmental conditions. Ignoring the types of circumstances may result in biased efficiency estimation and misleading policy applications (Avkiran & Rowlands, 2008). The existence and widening of regional economic differences must receive due attention as they would inflict negative influences upon ocean economy (Chen *et al*., 2007). Hence, the main contribution of this study is the provision of more valuable suggestions for regional ocean economy, based on the true green efficiency obtained by the three-stage DEA model with consideration of environmental variables and statistical noise[4]. This method is originally proposed Fried *et al*. (2002) to purge the impacts of exogenous environmental features and statistical noise. In this study, we adopt the spirit of the three-stage methodology of Fried *et al*. and extend the conventional MPI to an adjusted MLPI that includes a comprehensive index of environmental pollution as an undesirable output. In the first stage, we choose a comprehensive index of resource consumption as the resource input, and treat a comprehensive index of environmental pollution as an undesirable output produced together with desirable outputs. Instead of using the hyperbolic output measures proposed in Chang (1999), we use the directional distance function developed in Chung *et al*. (1997) to calculate the output slack (or surplus) for each output where the regional ocean economic activities to reduce its bad outputs and increase its good outputs are described. In the second stage, we use stochastic frontier analysis (SFA) to regress the estimated output slacks against the observed environmental variables and use the regression results to adjust the observed output values while purging the influences of the environment and statistical noise. In the third stage, we re-run the DEA model based on the DDF and MLPI using the adjusted output

[4] *In order to distinguish the word of "environmental" between "energy and environmental efficiency" and "external environmental influences", we use green efficiency to denote energy and environmental efficiency.*

and input data. Panel data for 11 coastal regions in China covering the years 2004-2014 are used to analyze the green efficiency of ocean economy. The findings can help 11 coastal regions understand the real causes of poor green efficiency and make improvements accordingly. At the same time, the MLPI can also provide explanations for the reasons why some coastal regions underperform and a way by which to improve productivity at different time periods.

The remainder of this paper is structured as follows. Section 2 presents the methodology, i.e., DDF and the improved three-stage DEA method. In Section 3 the data and description are given. Section 4 reports and discusses the results of our empirical analysis. Section 5 concludes this paper.

2. Methodology

2.1 Directional Distance Function

To construct the best-practices boundaries for the production of China's ocean economy in each period, this study regards each coastal region as a decision-making unit. Resources are viewed as investment resources, and based on social preferences for output and output's ability to improve social welfare, we consider environment damage as undesired output and the gross ocean production (GOP) as desired output. The possible set of all production that contains the two output types is termed the green technology of marine production, which reflects the input-output relationship that can be achieved using technology during each decision-making unit's production process under the constraints of resources and the environment.

Based on output-oriented production, we assume that $k = 1, \ldots, K$ production units use N factor inputs $x = (x_1, \ldots, x_n) \in R_+^N$ and obtain M desired outputs $y = (y_1, \ldots, y_M) \in R_+^M$ and I undesired outputs $b = (b_1, \ldots, b_I) \in R_+^I$. This paper uses DDF to conduct optimized adjustment of desired output and undesired output in different directions to optimize marine output growth and reduce pollution (Chung *et al.*, 1997). Thus, the DDF is defined as follows:

$$\vec{D}_0(x, y, b; g_y, -g_b) = sup\{\beta: (y + \beta g_y, b - \beta g_b) \epsilon\, p(x)\} \qquad (1)$$

where: β is the distance function value, which indicates the maximum extent of increase in desired output and decrease in undesired output when the output combination (y, b) moves to the production frontier according to the directional vector. β can be obtained by solving the following linear programming:

$$\overrightarrow{D_0^t}(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t) = \max\beta$$
$$s.t. \sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t \quad , \quad m = 1, L \quad, M$$
$$\sum_{k=1}^{K} z_k^t b_{ki}^t \geq (1-\beta) b_{k'i}^t \quad , \quad i = 1, L \quad, I \qquad (2)$$
$$\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t \quad , \quad n = 1, L \quad, N$$
$$z_k^t \geq 0 \quad , \quad k = 1, L \quad, K$$

where: k' represents the kth region, z_k^t represents the weight of the kth sample observation value, and a non-negative weight indicates an unchanged scale of production technology. $\beta y_{k'}^t$ represents the expansion ratio of the desired output y, and $\beta b_{k'}^t$ represents the reduction ratio of undesired output. β = 0 indicates that production decision-making units are at the frontier. A larger β value indicates that the efficiency of production decision-making units is lower when they are farther from the frontier.

2.2 Improved Three Stage DEA

In the first stage, we use DEA to analyze input and output and measure the green TFP of the ocean economy when each DMU is considering resource and environmental factors, which is the measurement result of the second part.

In the second stage, we use an analysis similar to SFA and first obtain the value of output difference variance during the first stage. Then, during the second stage, we combine this value with external environment variables to construct an SFA model to examine the respective impacts of external environmental factors, random errors, and inefficient management on the slack variables of desired output and undesired output. Firstly, the SFA model with slack variables of desired output, slack variables of undesired output, and environmental variables is defined as follows:

$$S_{mk} = f^m(\lambda_k; \delta^m) + v_{mk} + u_{mk}; \; S_{ik} = f^i(\lambda_k; \delta^i) + v_{ik} + u_{ik} \qquad (3)$$

In Equation (3), S_{mk} is the balance value when the kth DMU produces the mth desired output, S_{ik} is the balance value when the kth DMU produces the ith undesired output, $\lambda_k = [\lambda_{1k}, L \;, \lambda_{pk}]$ represents the pth observable exogenous environmental variable, δ is the parameter of the environmental variables to be estimated, and $f(\lambda_k; \delta)$ indicates how environment variables affect the balance value, which is represented by a linear form. $v_{m,ik} + u_{m,ik}$ is a mixed error term, and $v_{m,ik}$ represents a random disturbance term that is subject to a normal distribution with a mean of zero and the same variance $v_{m,ik} \sim N(0, \sigma^2_{vm,i})$. $u_{m,ik}$ indicates management inefficiency and is presumably subject to a truncated normal distribution $u_{m,ik} \sim N^+(u, \sigma^2_{um,i})$. The two are independent and unrelated. We make $\gamma^{m,i} = \sigma^2_{um,i} / \sigma^2_{um,i} + \sigma^2_{vm,i}$. γ close to 1 indicates that the effect of management factors is dominant. γ close to 0 indicates that the effect of random errors is dominant.

Next, we use the regression results ($\hat{\delta}, \hat{u}, \hat{\sigma}^2_{uk}, \hat{\sigma}^2_{vk}$) from Equation (3) and the estimate of management inefficiency $\hat{E}\left[u_k / \left(v_k + u_k\right)\right]$ to separate random errors from management inefficiency items. Thus, we obtain the estimate of random error v_{nk}:

$$\begin{aligned} &\hat{E}\left[v_{mk} \ v_{mk} + u_{mk}\right] = S_{mk} - \lambda_k \hat{\delta}^m - \hat{E}\left[u_{mk} \ v_{mk} + u_{mk}\right] \\ &i = 1,\ldots,K; \quad m = 1,\ldots,M \end{aligned} \tag{4}$$

We use the same method to obtain the estimated value of random error v_{ik}.

Finally, we adjust the two types of output to remove the effects of different external environmental factors and random errors so that decision-making units from different external environments can be placed in the same environment (Fried *et al.*, 2002). Specifically, we place all decision-making units in a good external environment. When experiencing good luck, we adjust the desired output upward by a small amount and the undesired output downward by a small amount. The adjustment formula is as follows:

$$y^*_{mk} = y_{mk} + \left\{ f^m\left(\lambda_k; \hat{\delta}^m\right) - \min\left[f^m\left(\lambda_k; \hat{\delta}^m\right)\right]\right\} + \left\{\hat{v}_{mk} - \min\left[\hat{v}_{mk}\right]\right\}] \tag{5}$$

$$b^*_{ik} = b_{ik} - \left\{ f^i\left(\lambda_k; \hat{\delta}^i\right) - \min\left[f^i\left(\lambda_k; \hat{\delta}^i\right)\right]\right\} - \left\{\hat{v}_{ik} - \min\left[\hat{v}_{ik}\right]\right\} \tag{6}$$

where: y^*_{nk}, y_{nk} are adjusted and original desired output values, respectively, and b^*_{ik}, b_{ik} are adjusted and original undesired output values, respectively. In Equations (5)-(6), the first brace to the right represents placing all DMUs in the same external environment, and the second brace represents all DMUs having the same luck after adjustment.

In the third stage, with the desired and undesired output data after adjustment replacing the original output data, we reapply the DDF and re-calculate the MLPI of various DMUs. This paper defines the MLPI denoted by ML that is incorporated into resource and environmental factors from the t session to the $t+1$ session as follows:

$$ML_t^{t+1} = \left[\frac{1+\overrightarrow{D_0^t}(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D_0^t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \times \frac{1+\overrightarrow{D_0^{t+1}}(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}\right]^{1/2} \tag{7}$$

The ML represents the change in the productivity rate from the t session to the $t+1$ session (Chung *et al.*, 1997). If the ML is greater (less) than 1, the productivity rate of the DMUs is increasing (decreasing). The ML can be further decomposed into an index that calculates efficiency changes (MLEC) and an index that measures technological change (MLTC). The expressions are as follows:

$$ML_t^{t+1} = MLEC_t^{t+1} \times MLTC_t^{t+1} \quad (8)$$

$$MLEC_t^{t+1} = \frac{1+\overrightarrow{D_0^t}(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \quad (9)$$

$$MLTC_t^{t+1} = \left[\frac{1+\overrightarrow{D_0^{t+1}}(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D_0^t}(x^t, y^t, b^t; y^t, -b^t)} \times \frac{1+\overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{1+\overrightarrow{D_0^t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}\right]^{1/2} \quad (10)$$

MLEC measures the degree of approximation between each DMU and the unit's production frontier. The greater (less) value than 1 indicates improvement (deterioration) in the technical efficiency of production units. MLTC estimates frontier changes of production possibility from the t session to the $t+1$ session. The greater (less) value than 1 indicates technological progress (regression) of production units.

3.Data and Variable Specification

To keep the sample data comparable, available, and scientific, we select three input and two output indicators to measure the green efficiency of the ocean industry. The data are from the *China Marine Statistical Yearbook* (2004-2014), the *China Energy Statistical Yearbook* and the *China Environment Statistical Yearbook* (2004-2014).

3.1 Input Indicators

In our sample, each coastal region has three inputs, which are marine capital stock, marine labor force and energy consumption. Firstly, the calculation of capital investment is the key to measuring the green efficiency of the marine industry and an important part of the research reported here. Currently, there are no statistical data on ocean capital stock or marine investment in fixed assets. These data can only be obtained based on capital formation in coastal areas and annual fixed capital investment. First, we adopt the latest estimates on marine capital stock in coastal areas by Li *et al*. (2015) and then refer to the estimation method for capital stock of the three industries by Chen *et al*. (2010) to calculate the weight of the marine industry in the cumulative total of new fixed assets of the marine society in coastal areas (which represents the proportion of the marine industry in the total marine assets in the entire society). Furthermore, we multiply this weight by the marine capital stock to ultimately obtain the capital stock of the marine industry. With respect to the labor force, we consider the number of employees in the marine industry in various regions as the labor input. For the resource consumption, this study adopts a "comprehensive index of resource consumption" as the resource input of the marine industry. According to the availability of statistical data, we use "marine catches", "sea salt production" and "shipbuilding (tons)" to reflect resource consumption in the development of fisheries, the marine salt industry and the marine shipbuilding industry, respectively. The literature does not consider the consumption of marine oil and gas as well as marine mining (Yu *et al*., 2007; Cheng, 2012). Because the consumption of these resources resembles their production, this study uses “energy consumption of the marine industry” to replace the consumption of such resources to measure the depletion degree of oil, gas, and mining in the process of creating GOP. Because the DEA method limits the number of input and output indicators and to avoid magnitude difference due to different statistical units of each index, we integrate the four resource input indicators (i.e., “marine catches”, “sea salt production”, “shipbuilding capacity (tons)” and “energy consumption of the marine industry”) into a comprehensive resource consumption index with the improved entropy method.

3.2 Output Indicators

There are two outputs in our sample. For the desired output, we adopt GOP in coastal areas as the desired output. To maintain consistency with the capital stock prices of the marine industry, we conduct the conversion in alignment with the 2001 constant prices. Different from the original studies (Yu *et al*., 2007; Cheng, 2012; Huang *et al*., 2013), we adopt the “comprehensive index of environmental pollution” as the indicator of undesired output, specifically including “industrial wastewater emission from marine output of every 10,000 RMB Yuan”, “emission of chemical oxygen demand (COD) in industrial wastewater from marine output of every 100,000,000 RMB Yuan”, and “industrial solid waste emission from marine output of every 10,000 RMB Yuan”. As before, we integrate the three environmental pollution indicators into a comprehensive index of environmental pollution with the improved entropy method.

3.3 Environmental Variables

This paper chooses external environmental variables based on their definition (see details in Fried *et al*., 2002). These external environmental factors have an important influence on the green efficiency of the ocean economy in coastal regions. However, unlike the various types of environmental pollution emission, they are not in the subjective manageable range of the regions. In addition, by considering the marine industry’s characteristics, we select the following external environmental variables: marine industrial structure, regional economic development, marine professional skill level, and investment in environmental pollution control. Marine industrial structure is measured with the proportion of output value of the tertiary marine industry accounting for GOP. The reason to include it as one of the variables is that the tertiary marine industry’s low-consumption and low-pollution characteristics have a positive meaning for the development of marine green industry. Regional economic development is measured with the GOP of each coastal region. Because the ocean economy is a subsystem of the national economy, it is inevitably affected by economic development. Marine professional skill level is measured by the number of technical personnel per 10,000 employees. The reason to include it as a variable is that marine science and technology personnel are the factor that most directly advances technology. Investment in environmental pollution control is represented by the marine industry’s total investment in environmental pollution control. This variable examines the intensity of financial support from each regional government for the green development of the ocean economy.

4. Results and Discussion

4.1The Results before the Inputs Are Adjusted

This paper calculates the annual productivity index of the ocean economy in 11 coastal regions and its decomposition value in two cases. First, we do not introduce the marine resource and environmental factors into the TFP analytical framework, which uses the MPI to calculate the traditional TFP of the marine industry (MTFP), the traditional efficiency change denoted by MEFFCH, and the traditional technological change denoted by MTECH after decomposition. Then, we introduce the marine resource and environmental factors into the TFP analysis framework using the ML index based on the directional distance function to calculate the green TFP of the marine industry, denoted by MLTFP, the green efficiency change denoted by MLEFFCH, and green technological change denoted by MLTECH.

Table 1

Comparison of MPI and MLPI together with Their Decompositions (2004-2014)

Regions	MPI				MLPI			
	MEFFCH	MTECH	MTFP	Ranking	MLEFFCH	MLTECH	MLTFP	Ranking
Tianjin	0.936	1.141	1.058	9	0.980	1.165	1.138	4
Hebei	1.094	1.221	1.374	1	1.002	1.071	1.078	7
Liaoning	0.927	1.173	1.068	8	0.982	1.043	1.024	10
Shanghai	1.001	1.213	1.217	3	1.000	1.260	1.260	1
Jiangsu	1.069	1.221	1.278	2	1.029	1.127	1.149	3
Zhejiang	0.939	1.181	1.080	6	0.963	1.132	1.086	6
Fujian	0.919	1.089	0.984	11	0.962	1.124	1.077	8
Shandong	0.929	1.199	1.081	5	0.975	1.061	1.033	9
Guangdong	0.958	1.133	1.074	7	1.000	1.227	1.227	2
Guangxi	1.006	1.188	1.192	4	1.001	1.016	1.017	11
Hainan	0.973	1.086	1.048	10	0.995	1.136	1.130	5
Coastal Regions	0.964	1.163	1.109		0.987	1.118	1.103	

Table 1 shows the following results. When resource and environmental factors are not considered, the MTFP of the ocean economy in all coastal areas is increased by 10.9% in 2004-2014. This derives from MTECH's positive effects (16.3%> 3.6%). After consideration of resource and environmental factors, MLTFP's average growth rate was lower than the MTFP index, and its average annual growth rate decreased to 10.3%. In addition to MLEFFCH's negative effects, other reasons include the declining trend of MLTHCH (11.8%<16.3%). As a result, the traditional efficiency of ocean economy is overestimated. Thus, to a certain extent, policy proposals based on it are biased and misleading. According to the MTFP and MLTFP rankings of the marine industry in various coastal areas, all regions exhibited a large difference in ranks, including a decrease in the MLTFP ranks of Hebei, Liaoning, Jiangsu, Shandong, and Guangxi. It is safe to conclude that these regions did not demonstrate adequate technical efficiency in resource consumption or sufficient intensity with respect to pollution control. In contrast, Tianjin, Shanghai, Fujian, Guangdong, and Hainan rose in the rankings. For example, the MLEFFCHs of Shanghai and Guangdong were 1, which indicates that these regions were at the efficiency frontier with high capability to utilize resources and control pollution. The high change rate of green technology of Tianjin, Fujian and Hainan revealed that the growth of the marine industry in these provinces did not rely on excessive resource consumption or environmental destruction as costs. The preceding analysis reveals that compared with MTFP, MLTFP can more reasonably reflect the index of the actual efficiency of the marine industry in various coastal regions.

The preceding measurement results may be subject to the combined effects of external environmental, random, and internal management factors. The effects of external environmental factors on the green efficiency of the ocean economy must be eliminated. If not, all ineffective decision-making would be attributed to internal mismanagement, which is not an objective assessment of each DMU.

4.2 The Results of Stochastic Frontier Analysis

Based on the analysis of the MLPI of China's ocean economy in the first stage and with the slack variables of desired output and undesired output from the first stage, we use the slack variables of each output as the dependent variables and the four previously described environmental variables as explanatory variables to perform a SFA regression using the STATA13.1 software program. The results are shown in Table 2.

Table 2

SFA Estimation Results

Independent Variable / Dependent Variable	Constant Term	Marine Industrial Structure	Level of Economic Development	Level of Marine Professional Skills	Intensity of Environmental Pollution Control	δ_n^2	γ	Log Likelihood Function	LR
Slack Variables of Desired Output	288.46 *** (0.73)	-0.0599 *** (-2.58)	-0.0220 ** (-2.27)	-0.0004 *** (-2.77)	2.4777 (0.61)	35476.58 *** (4.69)	0.9694 *** (3.46)	-814.56	21.54 ***
Slack Variables of Undesired Output	0.1070 *** (17.39)	-6.99E-07 * (-1.85)	4.09 ** (2.34)	-5.13E-10 (-0.17)	-0.0006 *** (-4.61)	0.0060 *** (3.99)	0.9835 *** (4.08)	-271.16	36.08 ***

*Note: *, **, and *** represent "significant" at significance levels of 10%, 5% and 1%, respectively; the t-statistics of the corresponding estimations are provided in parentheses.*

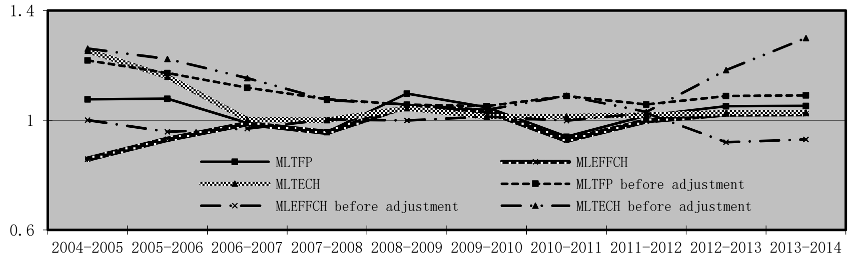
Table 2 shows two phenomena. The test statistic likelihood ratio (LR) values of the SFA model and the unilateral relaxation LR values that correspond to the slack variables of two types of output pass the 1% significance test. This outcome indicates that there is technical inefficiency in mixed errors and that the selected external environmental variables have a significant impact on efficiency, which requires SFA analysis. In both regression equations, γ is close to 1, and the significance level reaches 1%, which indicates that management inefficiency has a substantial influence on the creation of slack variables and that random factors have relatively small effects. In the regression of the external environmental variables onto the output's slack variables, the negative coefficient indicates that increased external environmental variables can help reduce slack output variables. That is, an increased number of such variables are conducive to increasing the green efficiency of the marine industry and vice versa. First, the regression coefficients of the marine industrial structure's variables in both equations are negative, and the variables pass the significance test, which indicates that the optimization and upgrading of the marine industrial structure is an important way to achieve green development of the ocean economy. Second, of the regression coefficients of the economic development variables in the two equations, one is positive and one is negative. This outcome indicates that during the pursuit of economic development in coastal regions, the regions over-emphasize the goal of development speed but ignore damage to the marine environment. Third, the regression coefficients of the variable of marine professional skill level in the two equations are both negative and the coefficient of the slack variables of undesired output does not pass the significance test. This outcome indicates that the efficiency increase of the ocean economy must rely on marine technological progress. Differently, marine professional skill level does not share a significant necessary link with undesired output. Thus, we could choose not to consider it while adjusting undesired output. Fourth, the regression coefficient of the variable of environmental pollution control with respect to the slack variables of desired output is not significant. That is, it could be excluded when desired output is adjusted. The regression coefficient of the variable of environmental pollution control with respect to the slack variables of undesired output is negative, which indicates that the government may enhance the green efficiency of the marine industry by measures such as increasing environmental protection and improving pollution control facilities.

4.3 The Results after the Inputs Are Adjusted

As can be concluded from the preceding analysis, external environmental factors generate different degrees of impact on the two types of output, resulting in the coastal regions being placed in different environments. Therefore, it is necessary to eliminate these environmental factors, adjust the desired output and undesired output according to Equations (10) and (11), and then introduce the adjusted output values and the initial investment into the directional distance function to re-calculate the marine industry MLTFP index. Figure 1 shows the decomposition and trend changes of the ocean economy's MLTFP index before and after adjustment under the condition of a time series. Table 3 displays the estimation results and the before-and-after-adjustment comparison.

Figure 1

Decomposition and Evolution Trend of the Green Efficiency of the Ocean Economy before and after Adjustment over 2004-2014Page: 16



The trend change curves in Figure 1 indicate that from the time-series perspective, MLTFP and MLTECH appeared to decrease over time based on a before-and-after-adjustment comparison. That is, the influence of good external environment and luck during the studied period was overestimated. However, in fact, mismanagement occurred. In 2006-2007, 2008-2010, and 2012-2014, MLEFFCH increased after adjustment, which indicates that the low MLTECH in these years could be attributed to poor external environment or luck but that of the other years could be partially attributed to mismanagement. By specifically analyzing the annual difference after adjustment, we obtain the following four results. Since the 2003 promulgation and implementation of the *Outline of China's Marine Economy Development Plan*, the ocean economy in China has exhibited rapid development. During 2005-2007, the MLTFP of the industry started to decrease, falling from 1.078 in 2005 to 0.957 in early 2007. The decrease was mainly due to the decrease in MLTECH, which began to reveal the substantial environmental costs of ocean economic development. The introduction of the *"Eleventh Five-year" Development Plan for National Marine Environmental Monitoring System* in 2007 indicated that China had started to pay increasingly more attention to environmental pollution and to increase the intensity of pollution control in the development of the marine industry. During 2007-2009, the MLTFP of the marine industry exhibited relatively stable growth. To recover from the effect of the US subprime mortgage crisis in 2008 on the growth of China's marine industry, China enhanced resource exploitation. After 2009, marine output exhibited a rapid upward trend. However, the MLTFP of the ocean economy decreased and again exhibited negative growth, which did not revert to positive growth until 2012. The trend of MLEFFCH over 2011-2014 indicated a decline in the marine industry's economic growth rate. Coastal areas accelerated the optimization of the marine industrial structure, implemented the strategy for sustainable marine development, and achieved a good start to the "twelfth five-year" period.

The discussion about MLTFP of the ocean economy in 11 coastal regions after adjustment is provided as follows. To compare the differences among the dynamic changes of the MLTFP index in the coastal regions, we provide the average level of MLTFP index for the different coastal regions during the sample periods and conduct comparative analysis using the MLTFP index before adjustment in the first stage (Table 3).

Table 3

Green Efficiencies in China's 11 Coastal Regions before and after Adjustment and a Comparison of Their Decomposition (2004-2014)

Regions	MLEFFCH		MLTECH		MLTFP			
	Before Adjustment	After Adjustment	Before Adjustment	After Adjustment	Before Adjustment	Ranking	After Adjustment	Ranking
Tianjin	0.980	0.944	1.165	1.038	1.138	4	0.966	11
Hebei	1.002	1.002	1.071	1.158	1.078	7	1.161	4
Liaoning	0.982	0.972	1.043	1.047	1.024	10	1.020	8
Shanghai	1.000	1.009	1.260	1.003	1.260	1	1.012	9
Jiangsu	1.029	1.036	1.127	1.021	1.149	3	1.058	6
Zhejiang	0.963	1.021	1.132	1.033	1.086	6	1.050	7
Fujian	0.962	1.063	1.124	1.090	1.077	8	1.166	3
Shandong	0.975	1.050	1.061	1.012	1.033	9	1.063	5
Guangdong	1.000	0.953	1.227	1.033	1.227	2	0.976	10
Guangxi	1.001	1.045	1.016	1.127	1.017	11	1.183	2
Hainan	0.995	1.043	1.136	1.185	1.130	5	1.231	1
Coastal Regions	0.988	0.974	1.119	1.059	1.103		1.028	

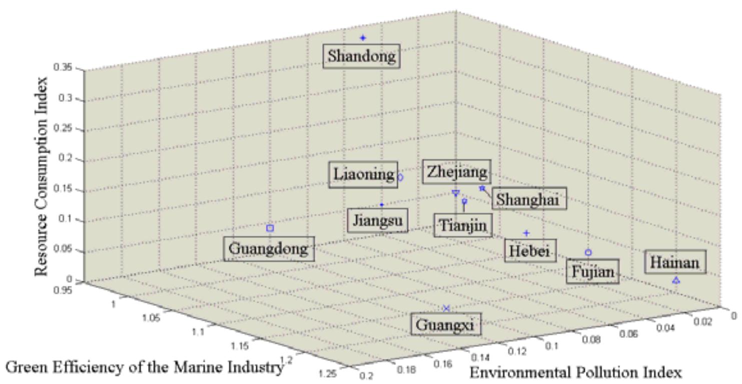
Table 3 demonstrates the following phenomena. After the impacts of external environmental variables and random factors were removed, the MLTFP of the entire coastal regions decreased from 1.103 to 1.028 because green efficiency and technological change decreased. Overall, the MLTFP of China's ocean economy was less desirable after external environmental factors and random factors were removed. Regionally, the following regions saw a lower marine industry MLTFP rank after adjustment: Tianjin (-7), Shanghai (-8), Jiangsu (-3), Zhejiang (-1), and Guangdong (-8). These changes reveal that the previous good marine industry MLTFP index of these regions was closely related to a favorable external environment and good luck. Certain provinces, such as Tianjin, Shanghai, and Guangdong, benefited from early capital accumulation and favorable geographical conditions before adjustment, resulting in their leading marine industry MLTFP levels. However, the study results for the third stage indicate that after the external environmental factors were removed, the MLTFP in these regions decreased significantly. Tianjin and Guangdong even experienced negative growth. This development was attributed to the lowering role played by the deterioration of green efficiency (i.e., MLEFFCH less than 1), which indicates that with the rapid development of the marine industry in Tianjin and Guangdong problems, such as low resource utilization and environmental mismanagement, emerged. Compared with the first-stage MLTFP, Hebei, Liaoning, Fujian, Shandong, Guangxi and Hainan exhibited an increase in the MLTFP in the third stage, which indicates that the previous low MLTFP of these regions was partly attributable to a poor external environment or bad luck and not fully attributable to mismanagement. Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong exhibited a decrease in MLTECH after adjustment, which indicates that their technological change rate was overrated because of the impact of the local external environment or luck. A low technological change rate after adjustment can more accurately reveal that strong dependence on resources and heavy pollution forced producers to focus more on resource exploitation and pollution control rather than increasing the level of production technology. Therefore, environmental pollution control temporarily lowered the level of technology progress.

4.4 A Clustering Matrix of Green Efficiency of the Coastal Regions after Adjustment

To further analyze the composition of the green efficiency of the coastal ocean economy, we considered the MLTFP index, the resource consumption index, and the environmental pollution emission index after the removal of external environmental factors to construct a three-dimensional clustering matrix of the ocean economy's green efficiency. In this approach, the green efficiency of the ocean economy in different coastal regions is divided into four categories, and a comprehensive analysis of the green efficiency structure of the marine industry in the different areas is conducted. The spatial refraction is shown in Figure 2.

Figure 2

Spatial Refraction Graph of the Green Efficiency Model of China's Ocean Economy



The first category is "low consumption—low pollution—high green", that is, the regions that perform well in marine resource consumption, marine environmental protection, and green efficiency. Only Hainan and Fujian appear in this category. The second category is "high consumption—low pollution—medium green". This category's prominent feature is that development of ocean economy primarily depends on the consumption of large quantities of marine resources. Liaoning, Shanghai, Zhejiang, and Shandong belong to this category. The green efficiency of the ocean economy in these regions is distinctly average, and the intensity of environmental emissions is relatively low compared with the intensity of resource consumption. Liaoning has a relatively large proportion of marine fisheries and shipbuilding. However, its marine industry is in the low tier and exhibits resource waste. Zhejiang enjoys rich resources with respect to its marine fisheries and sea salt industry. Its marine industry includes more resource-dependent sub-industries. This secondary marine industry exhibits excessive consumption of resources due to technology constraints. Shanghai possesses a developed shipbuilding industry, and Shandong possesses an increasing proportion of the offshore oil and gas industry. The marine resources consumed by these marine sub-industries that generate continuous stimuli for ocean economic development do not demonstrate significant impacts on the marine environment in the short term. However, in the long term, the excessive consumption of resources is bound to cause a decrease in green efficiency. The third category is “low consumption—high pollution—medium green”. This category’s prominent feature is that ocean economic development occurs at the expense of environmental pollution and high emissions. The category primarily includes Hebei, Jiangsu, and Guangxi. Hebei and Jiangsu exhibit average marine industry green efficiency. These regions do not possess rich marine resources, which results in a lower intensity of resource consumption and a high proportion of secondary marine industry. Because Hebei borders on Beijing, it performs many polluting sub-industrial tasks for Beijing, which increases Hebei’s environmental pollution. It should be noted that in Guangxi, high pollution emissions and high green efficiency coexist. This phenomenon reveals that the poor environmental emission level in Guangxi is caused by its poor external environment, such as a low level of regional economic development, lagging marine scientific research, and inadequate investment in environmental pollution control, rather than by poor management. The fourth category is “high consumption—high pollution—low green”. The regions in this category perform poorly in marine resource consumption, marine environmental protection, and the ocean economic green efficiency. Only Tianjin and Guangdong belong to this category, which should encourage those two regions not only to rely on a favorable external environment but also to focus on improving green technology management while developing the ocean economy in the future and thus to make green efficiency the engine for marine output growth.

5 Conclusions and Policy Implications

This paper first estimates the MLPI of the marine industry in 2004-2014 for 11 coastal regions. Then, it performs a comparative analysis with the traditional MPI. Finally, it revises the overestimation of marine industry efficiency due to the neglect of resource and environmental factors. To further study the impact of external environmental factors on the marine industry’s green efficiency after adjustment, we use a three-stage DEA method to comparatively analyze the differences between the initial ocean economic green efficiency and the green efficiency obtained after the removal of the impacts of external environmental factors and statistical noise. The conclusions and implications are as follows.

Marine industrial structure, level of economic development, and level of marine professional skills have a significant negative impact on the slack variables of desired output. Marine industrial structure and environmental pollution control efforts have a significant negative impact on the slack variables of undesired output. In addition, the level of economic development has a significant positive impact on the slack variables of undesired output. The green efficiency of the ocean economy relies on the optimization of the marine industrial structure and government support for the marine industry's green development. Our results also reveal that the economic development in coastal areas affects the resources and the environment of coastal waters. Therefore, China should transform its traditional marine industry, cultivate a new marine industry, plan its future marine industry, further optimize the structure of marine personnel, and enhance the ability of marine scientific support while focusing on reducing land-based pollutant emissions and stabilizing the support role of the marine environment.

After the removal of the influence of external environmental factors and random errors, the green TFP of China's ocean economy, including decomposition efficiency and technological progress rate, decreases. Technical efficiency remains the primary factor restricting the improvement of the green efficiency of China's ocean economy. This result suggests that ignoring external environmental factors and random errors result in overestimation of the green efficiency of China's ocean economy. In addition, it implies that China must balance technical efficiency and technological progress under the dual restriction of resources and the environment while developing the marine industry. On the one hand, we must foster new elements of the ocean economic development while emphasizing the use of high technology and improving the technological level and capability of industrial development. On the other hand, during the process of introducing advanced technology for ocean economic development, we must focus on the improvement of technical efficiency, which represents an important element of the comprehensive improvement of ocean economic green efficiency.

When we placed the coastal regions in the same external operating environment, their ranks for marine industry green efficiency underwent substantial changes. Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong exhibited a decrease in their marine industry green TFP, which indicated that the previous high marine industry green efficiency of these regions was caused by a favorable external environment and good opportunities for development. In fact, a degree of mismanagement of green technologies occurred. We should not fully attribute the low green efficiency of the ocean economy in the remaining six regions to the lagging green technology management of these regions. The impact of a poor external environment resulted in the underestimation of their green efficiency.

Based on the green efficiency of the ocean economy in different coastal regions, regional marine resource consumption, and environmental pollution, this study divides the green development structure of the ocean economy in the different regions into four categories: "low consumption—low pollution—high green", "high consumption—low pollution—medium green", "low consumption—high pollution—medium green", and "high consumption—high pollution—low green". Each region can examine its marine industry development model and accordingly adjust and optimize its marine industrial structure to comprehensively enhance the industry's green efficiency.

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