Journal of
Marine Science and Engineering

MDPI

Article

Analysis of Operational Efficiency Considering Safety Factors as an Undesirable Output for Coastal Ferry Operators in Korea

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Received: 14 April 2020; Accepted: 18 May 2020; Published: 22 May 2020

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Abstract: In the maritime transportation services industry, marine accidents may lead to fatalities, injuries, and property losses. Coastal ferry operators experience marine accidents and must pay attention to safety to guarantee the sustainability of their business. This study is aimed at analyzing the operational efficiency of coastal ferry operators in Korea from a safety perspective. We designed two slack-based measure of efficiency (SBM) models. One is a normal SBM, which includes only the total passenger volume as the desirable output. The other is a safety-constrained SBM, which includes marine accident records as an undesirable output with the desirable output of passenger transportation performance. We selected 44 coastal ferry operators in Korea that have been continuously operating for five years (2013–2017) as decision-making units (DMUs) and compared their operational efficiency scores. The results showed that the impact of marine accidents on business is greater in DMUs with lower transportation sales than in those with higher sales. This suggests that, while it is important for the government to strengthen safety regulations, a combination of policies that also help small ferry operators to stay in business in the long term is necessary to reduce marine accidents effectively while improving efficiency.

Keywords: coastal ferry operator; marine accident; operational efficiency; slack-based measure of efficiency (SBM); safety-constrained SBM; undesirable output

1. Introduction

Coastal ferries are an important mode of transportation that connects land and islands. They serve the function of transporting island inhabitants and tourists, and shipping necessary goods. Within Korea, there are a total of 100 ferry sea routes with 169 ships operating on these routes [1]. Having increased every year since 2015, the total number of ferry passengers in 2017 was approximately 16.9 million people [1]. Notably, with the mandatory 52-h work week having recently been enforced in Korea, the increased leisure time of citizens is expected to result in a greater number of coastal ferry passengers.

As more people use coastal ferries, the government is implementing stricter enforcement of safety regulations. With the revision of the Maritime Safety Act [2], the government created a maritime safety supervisor position in 2015 to provide regular guidance and supervise the safe operation of coastal ferries. For example, pursuant to the revised Act, the maritime safety supervisor can, if deemed necessary as a result of guidance and supervision, or in consideration of the frequency and seriousness of marine accidents, order ferry operators to take immediate remedial measures, and even order the suspension of sailing until the improvement is completed. Furthermore, with the amendment of the Marine Transportation Act [3] in January 2015, coastal ferry operators are now obligated to employ a safety manager who assumes full responsibility for the safety of ferries. The safety managers are required to meet the statutory qualification standards; the number of safety managers may be not less than the minimum number of personnel required by the amended Act in proportion to the number of operating ferries. The criteria of ships and safety facilities of coastal ferries were also reinforced through the revision of the Ship Safety Act [4]. Starting in July 2015, the ship age limit of coastal ferries was reduced from 30 years to 25 years. Also, the obligation to install a voyage data recorder (VCR), which is a black box for ships, was expanded to coastal ferries in September 2014, and the requirements for the installation of life jackets and escape aids were enhanced in December 2014. However, despite such tightening of safety regulations, the possibility of marine accidents cannot be ruled out. There are numerous sources of potential danger when operating near the coast, such as dense ship traffic, narrow channels, seaborne waste and aging crew members [5–7]. Over the past five years (2013–2017), there have been more than 40 marine accidents every year involving coastal ferries on the coast of Korea [8]. To provide safe transportation services for their patrons, a high level of safety-oriented management by coastal ferry operators is required. Company policies should be established based upon safety, and adequate resources and qualified personnel must be provided to allow ship managers to carry out their functions in a timely manner. However, a good balance is important, as such safety management activities require an investment of capital, which can restrict the productivity of the company by incurring higher transportation costs [9]. Therefore, in terms of operational efficiency, it would be preferable to use the available resources to maximize passenger transportation performance and minimize marine accidents during ferry operation.

However, most studies analyzing the efficiency of maritime logistics do not explicitly consider safety, but only desirable outputs such as sales, operating profit, and transportation performance. In particular, changes of passenger traffic volume as a result of marine accidents are not considered. As observed in the Sewol ferry disaster (April 2014), safety management has become a crucial factor for company management, as the occurrence of an accident can determine the success or failure of coastal ferry operators. Therefore, the measurement of operational efficiency with safety factor considerations is important in the field of maritime transportation. Against this background, this study aims to analyze operational efficiency by defining the marine accidents caused by coastal ferry operators as an undesirable output that constrains the production of their transportation services. For analyzing efficiency, a data envelopment analysis (DEA) was applied to this study. DEA is a nonparametric technique for measuring the relative efficiency of a set of comparable entities called decision-making units (DMUs) with multiple inputs and outputs [10,11]; it is useful for benchmarking the performance of manufacturing or service operations where no specific functional form of the production process is provided. Since the initial study by Charnes et al. [12], various DEA theoretical models that can be applied to the unique production characteristics of DMUs have been developed [13]. Among DEA models, this study used the slack-based measure of efficiency (SBM) introduced by Tone [14,15]. The SBM model is applicable to DMUs that produce undesirable outputs during the production of desirable outputs, because it is nonradial and utilizes input and output slacks directly to measure efficiency [15].

The rest of this paper is organized as follows. Section 2 reviews DEA and DEA application studies in maritime logistics such as ports and shipping operators. In particular, it explores the differences between this study and preceding studies that have analyzed similar subjects such as efficiency in the field of coastal ferry operations. Section 3 designs two SBM models for measuring the operational efficiency of coastal ferry operators. One is the normal SBM model, which includes only the desirable output, and the other is a safety-constrained SBM model, which includes both desirable and undesirable outputs (marine accident records). Section 4 measures the operational efficiency by collecting basic data from Korean coastal ferry operators and compares the efficiency scores measured via the two

SBM models. Section 5 discusses the results of the operational efficiency analysis considering safety factor and provides implications. Section 6 concludes the paper.

2. Literature Review

2.1. Data Envelopment Analysis (DEA)

DEA, the theoretical basis of this study, uses linear programming problems to measure the relative efficiencies and inefficiencies of decision-making units (DMUs). It does not assume the shape of a specific production function that is needed in traditional regression approaches. Instead, it estimates the production possibility set between input and output via nonparametric estimation [10]. Moreover, DEA has a unique method of measuring efficiency without requiring a preset weighting of multiple input and output values [16]. Once each DMU is represented as a point in a multidimensional space, DEA formulates an efficient frontier to DMUs in the form of a piecewise linear envelope [17]. All the points within the region enclosed by the frontier line can be enveloped. Because the frontier indicates the outermost boundary of the production possibility set, DMUs located at the frontier are optimally adjusted. DMUs not on the frontier are suboptimally adjusted [10,17].

There are generally two types of efficiency measures in DEA: radial and nonradial [18]. Radial DEA, which assumes proportional changes in inputs/outputs, provides only uniform input/output factor efficiency. It is mainly expressed by CCR [12] and BCC [19], each named using the initials of the surname of the researchers who first proposed the model. The CCR model belongs to the category of constant returns to scale (CRS) model, whereas the BCC model is a kind of variable returns to scale (VRS) model [17]. The nonradial DEA is represented by the slack-based measure of efficiency (SBM) [14,15]. Unlike CCR [12] and BCC [19], SBM type models do not assume specific proportional changes of inputs or outputs. They measure efficiency directly with input excess (and/or undesirable input shortfall) and output shortfall (and/or undesirable output excess) individually and independently, known as slacks [20]. Therefore, if there is an undesirable input/output involved in production activities, SBM type models would be more compatible as an efficiency measurement tool than radial DEA models.

2.2. DEA Application Studies in Maritime Logistics

DEA is widely used to evaluate performance in road, rail, and air transportation fields (e.g., Hjalmarsson and Odeck [21], Merkert et al. [22], Andrejić et al. [23], Sameni et al. [24], and Cowie [25]). In addition, it has been in continuous use in the field of maritime logistics for analyzing the operational efficiency of ports and the shipping industry [26].

In the case of seaports, most studies analyzed static and dynamic efficiencies based on the panel data of container terminals. Wilmsmeier et al. [27] used DEA to measure the efficiency of 20 container terminals in 10 countries in Latin America, the Caribbean and Spain for the period between 2005 and 2011. Through this, the effects of rapid external economic environment changes, such as financial crisis, on port productivity were analyzed. To analyze port management performance, Bergantino et al. [28] constructed a three-stage model. The first and third stages used DEA, whereas the second stage used stochastic frontier analysis (SFA) to control external environment effects on input variables. Then, using the data of 30 ports between 1995 and 2009, the operational efficiency of ports was measured. Schøyen et al. [29] observed port efficiency changes according to logistics service delivery performance outcomes from six European ports between 2010 and 2014. In addition, Schøyen and Odeck [30] addressed the efficiency of ports using the DEA methodology [31]. They studied the technical and scale efficiency of Norwegian container ports relative to a frontier composed of the best performing ones among themselves and other comparable Nordic and UK ports.

Most studies in the field of maritime transportation involve the use of DEA for analyzing the relative efficiency between major global shipping companies. Lun and Marlow [32] employed DEA to evaluate the operational efficiency of major global container shipping companies. With a combination of both nonfinancial and financial data (i.e., shipping capacity, operating cost, profit and revenue), they found that nonmega operators, i.e., with a market share of 5% or less, can operate efficiently based on the empirical data collected in 2008. Panayides et al. [17] examined the relative efficiency of 26 major international maritime firms in three key sectors: container shipping, dry bulk and tanker shipping. They applied both DEA and stochastic frontier analyses (SFA) and compared the efficiency scores obtained from the two models in view of market and operating performance. Bang et al. [33] measured the financial and operational efficiencies of 14 liner shipping companies with a two-stage approach combining radial DEA and Tobit regression. The results showed that the formation of alliances makes a positive contribution to the financial performance of liner shipping companies. Gutiérrez et al. [34] also measured the efficiency of global liner shipping companies with bootstrap DEA. In contrast to the findings of Bang et al. [33], their results showed that strategic alliance membership is not a guarantee for efficient practices in operations. Huang et al. [35] measured the efficiency of 17 major global container liners using DEA. They utilized strategic variables to evaulate efficiency, e.g., fleet capacity, asset/debt ratio, owned/chartered-in fleet ratio, noncontainer revenue ratio, and revenue. Chang et al. [36] analyzed the operational efficiency of international cruise liners by applying a slack-based network DEA model [37]. In addition to the efficiency analysis, by utilizing the bootstrapped-truncated regression method proposed by Simar and Wilson [38], influential factors that determine the operational efficiency of these cruise liners were identified. Chao [39] established a network DEA (NDEA) to evaluate the efficiency of global container companies based on the two-stage model proposed by Kao and Hwang [40]. In the study, he proposed the algorithm combining a fuzzy analytic hierarchy process (AHP) with NDEA to maximize not only the overall efficiency of DMUs, but also the subefficiency of each stage according to the priority of each stage. With the dynamic network SBM model [41], Chao et al. [42] measured and examined the division efficiency of the top 20 global container liner shipping companies in the area of shipping service production and intertemporal efficiency specifically. Meanwhile, Gong et al. [43] measured economic efficiency and cargo transport efficiency among the 26 leading international shipping companies. Unlike other studies, they further considered air pollutants as undesirable outputs, namely, CO2, NOx, and SOx, which are side-effects of production processes. Using SBM for different input/output combinations, they analyzed the efficiencies of shipping companies, both with and without consideration of the negative impact of emissions, and compared this with their environmental efficiencies.

Although efficiency studies have been undertaken since the 1990s, the number of studies associated with the coastal ferry services is very limited. Førsund [44] analyzed the operational efficiency of 23 Norwegian ferries via DEA for reforming government subsidies for coastal ferries. This was the first study of operational efficiency using DEA in the field of shipping [42]. For efficiency measurement, the author selected wages, maintenance and repair, fuel, and capital as the input variables and, selected car-nautical miles as the output variable. In a study similar to that of Førsund [44], Yu et al. [45] used a DEA model as a performance analysis method for efficiently allocating coastal ferry subsidies. Yu et al. [45] constructed a DEA-based subsidy allocation model that simultaneously considers the concepts of cross-efficiency [46] and structural efficiency [47]. This model was used for the allocation of subsidies to seven coastal ferry operators in the Taiwan strait. To measure efficiency, the operating cost was selected as an input variable, whereas the total revenue and ship-miles were selected as the output variables. Park et al. [48] analyzed the changes in passenger transportation productivity over time based on the statistics between 2007 and 2016, from 10 regions with established coastal passenger routes in Korea. Through this, it was observed that the operational efficiency worsened during the years with major marine accidents such as the Sewol disaster (2014). For the efficiency measurement, the number of ferries, the number of actual operating ships, and the number of licensed routes were set as the input variables, while the passenger transportation volume was set as the output variable.

Table 1 summarizes input and output variables, as well as the DEA methodology used in the aforementioned studies. This study has the following differences from previous studies. First, previous studies did not consider safety factors such as maritime accidents when analyzing operational efficiency. Only profitability indicators with positive characteristics, such as sales, net profit, and factors that directly affect sales, such as passenger traffic, were selected as the outputs. This contrasts with the fact that numerous efficiency analysis studies with safety factor considerations, such as traffic accidents, have been conducted in other transportation fields such as rail, road, and aviation (e.g., Weber and Weber [49], Yu and Fan [50], Chen et al. [51], Egilmez and McAvoyc [52], Pal and Mitra [53], Barak and Dahooei [54], Roets et al. [55], Djordjević et al. [56] and Stolzer et al. [57]). In contrast, in the efficiency analysis of this study, consideration was given to both the recorded passenger traffic, which is an indicator of profitability, and recorded marine accidents, which have a negative effect on efficiency. Second, the radial DEA model used in many previous studies, such as by Wilmsmeier et al. [27], Bergantino et al. [28], Schøyen et al. [29], Schøyen and Odeck [30], Lun and Marlow [32], Panayides et al. [17], Bang et al. [33], Huang et al. [35] and Førsund [44] is poorly suited to directly assign undesirable outputs with inversely proportional characteristics which increase efficiency through their reduction. This is because this model only considers desirable outputs for production optimization [56]. Therefore, Seiford and Zhu [58] and Korhonon and Luptacik [59] proposed a method to convert undesirable outputs to input variables for use in the DEA model. However, numerous studies proposed a nonradial model that allows direct representation to be made of undesirable outputs in the model without data translation (e.g., Färe et al. [60], Chung et al. [61], Tyteca [62], Boyd and MacClelland [63], Hernandez-Sancho et al. [64], Zaim [65], Färe et al. [66], Färe and Grosskopf [67], and Zhou et al. [68]). The SBM model used in this study allows the direct assignment of both undesirable and desirable outputs during efficiency analysis [43,69–72]. Third, previous studies on ferry transportation efficiency selected ship routes or ferry service areas as the decision-making units (DMUs), except for that by Førsund [44]. Existing studies that directly dealt with coastal ferry operators as DMUs are rare, even if they are entities responsible for providing transportation services and the safety management of ferries. In contrast, this study selected only coastal ferry operators that have been continuously operating for the last five years (2013–2017) as its DMU. Given the research gap and scarcity of efficiency studies in coastal ferry transportation, implications will be provided for governments to assist in improving maritime safety policies, as well as in devising management strategies for coastal ferry operators.

Table 1. Input and output variables and DEA methodology of previous studies.

Sector	Author	DMUs	Inputs	Outputs	Methodology
Seaport	Wilmsmeier et al. [27]	20 container terminals in Latin America, the Caribbean and Spain	• Terminal area (sqm) • No. of labor • Ship-to-shore crane capacity	• Container throughput (TEU)	• CCR (Charnes et al. [12]) and BCC (Banker et al. [19]) • Malmquist Productivity Index (Caves et al. [73])
Seaport	Bergantino et al. [28]	30 ports	• Dimension of quay (sqm) • No. of terminals • Port area for handling (sqm) • Handling equipment (units)	• Total movements (tons)	• Combination of DEA and SFA (Fried et al. [74])
	Schøyen et al. [29]	26 European ports	• Terminal area (sqm) • Quay length (m) • No. of yard • Machines (units)	• Container throughput (TEUs) • Price (5 Likert scale) • Tracking & tracing (5 Likert scale) • Timeliness (5 Likert scale)	• CCR (Charnes et al. [12]) and BCC (Banker et al. [19])
	Schøyen and Odeck [30]	24 Nordic and UK container ports	• Berth length (m) • Terminal area (sqm) • Yard gantry cranes • Straddle carrier	• Container handling trucks • Container throughput (TEU)	• CCR (Charnes et al. [12]) and BCC (Banker et al. [19])

Table 1. *Cont.*

Sector	Author	DMUs	Inputs	Outputs	Methodology
Maritime transportation	Lun and Marlow [32]	20 global container liners	• Shipping capacity • Operating cost	• Profit • Revenue	• CCR (Charnes et al. [12])
	Panayides et al. [17]	26 major international maritime firms	• Total assets • No. of employees • Capital expenditure	• Sales	• SFA (Aigner et al. [75]) • CCR (Charnes et al. [12]) and BCC (Banker et al. [19])
	Bang et al. [33]	14 global container liners	(For financial efficiency) • Total assets and Capex (For operational efficiency) • No. of ships and Fleet capacity	(For financial efficiency) • Revenue • Operating profits (For operational efficiency) • Cargo carried (TEUs)	• CCR (Charnes et al. [12]) and BCC (Banker et al. [19]) • Tobit regression analysis
	Gutiérrez et al. [34]	18 major international container lines	• Fleet (TEU, No. of ships) • No. of employees	• Container throughput (TEU) • Turnover (USD)	• Bootstrap DEA (Simar and Wilson [76])
Maritime transportation	Huang et al. [35]	17 global container liners	• Fleet capacity • Noncontainer revenue ratio • Asset/debt ratio • Owned/chartered-in fleet ratio	• Revenue	• BCC (Banker et al. [19]) • DEA-window (Charnes et al. [77])

Table 1. *Cont.*

Sector	Author	DMUs	Inputs	Outputs	Methodology
	Chang et al. [36]	Top 3 cruise lines	(Stage 1) • Payroll and related • Total operating expenses • Marketing, selling and administrative • Depreciation and amortization (Stage 2) • Nonoperating expenses	(Stage 1) • Passenger ticket revenue • Onboard and other revenue (Stage 2) • Net income	• Slacks-based network DEA (Tone and Tsutsui [37])
	Chao [39]	15 global container liners	• Owned fleet capacity • Chartered-in fleet capacity • Operating expense	(Intermediate output) • No. of port calls • Container lifting (Final output) • Revenue	• Network DEA (Tone and Tsutsui [37]; Kao and Hwang [40])
	Chao et al. [42]	13 global container liners	• Chartered-in fleet capacity • Expense • Employees • Owned fleet capacity	(Intermediate output) • Lifting (Final output) • Revenue	• Dynamic network SBM (Tone and Tsutsui [41])
	Gong et al. [43]	26 global shipping firms	• Ship input (capacity or no. of ships) • Employees • Fuel cost • Total assets • Capital expenditure	(For economic efficiency) • Revenue (For cargo efficiency) • Cargo carried • (For environmental efficiency) • Air pollutants (CO_2, SOx, NOx)	• SBM (Tone [14]; Tone [15])

Table 1. *Cont.*

Sector	Author	DMUs	Inputs	Outputs	Methodology
Coastal ferry transportation	Førsund [44]	Coastal ferries in Norway	• Total wage • Maintenance and repair cost • Fuel consumption • Ferry capacity	• Car-nautical miles	• Nonparametric Farrell efficiency (Farrell [77]; Charnes et al. [12]) • Parametric efficiency with deterministic frontier formalized by Cobb-Douglas kernel function
	Park et al. [48]	10 ferry service provinces in Korea	• No. of vessels • No. of actual vessels sailing • No. of routes	• No. of passengers	• SBM (Tone [14]) • DEA-window (Charnes et al. [78])
	Yu et al. [45]	7 Off-shore ferry routes in Taiwan	• Operating cost	• Total revenue • Ship-miles	• Combination of cross-efficiency (Du et al. [46]) and structural efficiency (Försund and Hjalmarsson [47])

3. Methodology

3.1. Design of SBM Model

Consider that there are n coastal ferry operators in existence, which are the DMUs defined as $\mathrm{DMU_j}$ ($\mathrm{j} = 1, 2, \cdots, \mathrm{j}$). $\mathrm{DMU_j}$ provides transportation services by inputting i type inputs (X) to produce r type desirable outputs (Y^g). However, during the passenger transportation process, unavoidable damage/casualties from marine accidents occur, yielding an undesirable output (Y^b). Accordingly, the variable marine accident records, Y^b, indicates the safety factor of coastal ferry operators in this study. Organizing these into input and output variable vectors while assuming $X > 0$, $Y^g > 0$, and $Y^b > 0$ results in the following:

$$X = [x_1,\ x_2,\ x_3,\ \cdots,\ x_i]\ \in R^{i\times n}$$

$$Y^g = \left[y_1^g, y_2^g,\ y_3^g, \cdots, y_r^g\right]\ \in R^{r\times n}$$

$$Y^b = \left[y^b\right] \in R^{1\times n}$$

The production possibility set is defined as follows:

$$\mathrm{P} = \left\{\left(x,\ y^g, y^b\right)\ \ x \geq X\lambda,\ y^g \leq Y^g\lambda,\ y^b \geq Y^b\lambda,\ \lambda \geq 0\right\} \tag{1}$$

where $\lambda \in R^n$ is the intensity vector, using the condition $\lambda \geq 0$ to assume constant return to scale (CRS) for the production possibility set. If the production possibility set is assumed via variable return to scale (VRS), then the condition $e\lambda = 0$, $e = (1, \cdots, 1) \in R^n$ may be additionally applied [15].

All the given input and output variables assume strong disposability. Particularly marine accidents, which is the selected undesirable output, is a variable that may change according to the level of safety management activities by coastal ferry operators, assuming strong disposability better reflects reality. If marine accidents are assumed to be a natural consequence of the transportation process, then the vector y^b of the production possibility set would show strict equality with the bad output. These weak disposability assumptions can be observed in environmental efficiency analyses, where environmental pollutants such as CO_2 are set as undesirable outputs that are produced alongside desirable outputs during the production process [60,66–69,79].

The two SBM models were designed in this study because they should be applied to measure the operational efficiency of coastal ferry operators either with or without considering the negative effect of marine accidents. One is a normal SBM which considers desirable output only, i.e., the number of transported passengers, and is the same as the model proposed by Tone [14]. The other is a safety-constrained SBM in which ferry service production is constrained by marine accident records as an undesirable output. The overall SBM model for further explanation can be written as:

$$[\mathrm{SBM}]\ \rho_k = \min\left(1 - \frac{1}{I}\sum_{i=1}^{I}\frac{s_i}{x_{ik}}\right) \Big/ \left(1 + \frac{1}{R}\sum_{r=1}^{R}\frac{s_r^g}{y_{rk}}\right) \tag{2a}$$

subject to

$$x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i \tag{2b}$$

$$y_{rk}^g = \sum_{j=1}^{n} y_{rj}^g\lambda_j - s_r^g \tag{2c}$$

$$y_k^b = \sum_{j=1}^{n} y_j^b\lambda_j + s^b \tag{2d}$$

$$s_i \geq 0,\ s_r^g\ \geq 0,\ s^b\ \geq 0, \lambda_j \geq 0 \tag{2e}$$

where ρ_k represents the operational efficiency score of coastal ferry operator k;

n is the coastal ferry operator $(n = 1, 2, \cdots, N)$;
i represents inputs $(i = 1, 2, \cdots, I)$;
r represents desirable outputs (r=1,2,$\cdots$,R);
x_{ik} represents the specific observation value of the i^{th} input of coastal ferry operator k;
x_{ij} is the observed amount of the i^{th} input of j^{th} coastal ferry operator;
y^g_{rk} represents the observed amount of the r^{th} desirable output of coastal ferry operator k;
y^g_{rj} is the observed amount of r^{th} desirable output of the j^{th} coastal ferry operator;
y^b_k represents the specific observation value of undesirable output of coastal ferry operator k;
y^b_j is the observed amount of undesirable output of the j^{th} coastal ferry operator;
s_i indicates the value of the i^{th} input slack;
s^g_r is the value of the r^{th} desirable output slack; and
s^b is the value of undesirable output slack.

First, the normal SBM can be formalized by deleting the constraint Equation (2d) in the overall SBM model. In the model, the objective function, i.e., Equation (2a), is designed to reflect the mean reduction rate of inputs (or input inefficiency) and mean expansion rate of desirable outputs (or desirable output inefficiency) by setting them as the numerator and denominator, respectively. The vectors $s_i \in R^i$, $s^g_r \in R^r$ indicate the input excess and output shortfall, respectively, and are known as slacks. The reduction rate of inputs is the ratio of the decrease in input x_i for all i by input slack s_i for all i to the original value. The expansion rate of desirable outputs is the ratio of increase in the desirable output value y^g_r for all r by the desirable output slack s^g_r for all r to the original value. Accordingly, the objective function value ρ_k decreases strictly monotonically with respect to s_i for all i, s^g_r for all r of coastal ferry operator k. If the output-oriented SBM focuses on changes in output, it can be defined by excluding the average input efficiency improvement ratio in the objective function [14].

Second, the safety-constrained SBM model includes marine accident records as an undesirable output. The model follows the general concept of undesirable-output-inclusive SBM proposed by Tone [15]. However, the objective function of the safety-constrained SBM is distinct from that of Tone [15], who directly includes undesirable output excess in the objective function. Specifically, the objective function is strictly decreasing with respect to the vectors s_i, s^g_r, s^b. In contrast, the objective function of the safety-constrained SBM is set up in the same way as that of the normal SBM. Instead of the constraints determining the production possibility set, strong disposability was assumed for marine accident records only, which is an undesirable output, in Equation (2d). Thus, it is possible to compare the effect of marine accidents on the operational efficiency of coastal ferry operators.

Note that the SBM model (2) is a fractional programming problem that could lead to some calculation difficulties. Using the Charnes-Cooper transition as described by Tone [14,15], the SBM model (2) can be transformed into an equivalent linear programming problem like model (3) by introducing $\Lambda_j = t\lambda_j$, $S_i = ts_i$, $S^g_r = ts^g_r$ and $S^b = ts^b$:

$$[\mathrm{SBM-LP}]\ \rho_k = \min\left\{t - \frac{1}{I}\sum_{i=1}^{I}\frac{S_i}{x_{ik}}\right\} \tag{3a}$$

subject to

$$tx_{ik} = \sum_{j=1}^{n} x_{ij}\Lambda_j + S_i \tag{3b}$$

$$ty^g_{rk} = \sum_{j=1}^{n} y^g_{rj}\Lambda_j - S^g_r \tag{3c}$$

$$ty_k^b = \sum_{j=1}^{n} y_j^b \Lambda_j + S^b \tag{3d}$$

$$t + \frac{1}{R}\sum_{r=1}^{R}\frac{S_r^g}{y_{rk}^g} = 1 \tag{3e}$$

$$S_i \geq 0,\ S_r^g \geq 0,\ S_r^b \geq 0, \Lambda_j \geq 0. \tag{3f}$$

In the above model, the efficiency scores ρ_k have values between 0 and 1, where 1 indicates that the coastal ferry operator k (DMU_k) is efficient. If the DMU_k is inefficient, i.e., $\rho_k < 0$, it can be improved and become efficient by deleting the excess in input slack S_i for all i and the shortage of desirable output slack S_r^g for all r.

3.2. Selection of Variables

The variables to be assigned into the operational efficiency model of coastal ferry operators and the measurement criteria of the relevant data were defined considering the previous studies and the characteristics of coastal ferry operations. Table 2 shows the criteria for measuring the input and output variables, and the selected variables used for measuring the operational efficiency of coastal ferry operators.

Table 2. Input/output variables for operational efficiency measures of coastal ferry operators.

Variables		Measurement Criteria
Input 1	Number of ferries	$\frac{\text{Actual operation period of vessels(Days)}}{\text{Observation period(Days/Vessels)}}$
Input 2	Number of actual ferry services	The number of scheduled ferry services during the observation period – The number of cancelled ferry services during the observation period
Input 3	Total passenger capabilities	Sum of the allowable number of passengers on board the ferries
Desirable Output (DO)	Number of passengers	Number of passengers onboard the vessels during the observation period
Undesirable Output (UDO)	Marine accident records	Number of marine accident damages occurring during the observation period

The input variables Input 1, Input 2 and Input 3 were selected as they are closely related to the number of passengers aboard the ship, which determines the transportation sales of a coastal ferry operator. Additionally, as the safety management legal structure for coastal ferries changes depending on the three selected variables; these variables are also related to the safety of the coastal ferry. The output variables were classified into desirable and undesirable outputs. The desirable output was the number of passengers, which can represent company profitability, whereas the undesirable output was set as marine accident occurrence, which has a negative effect on profitability. The frequency of marine accidents and the resulting economic losses can reflect the safety performance of the company [80]. However, it is practically impossible to gather these data, as the economic losses of companies from marine accidents are not made public. Even if these data are collected, there may be deviations between the companies depending on the calculation method of the losses. Therefore, this study focuses on the frequency of actual marine accidents. However, there is a qualitative difference in the safety performance perceived by the ferry operator depending on the extent of damage caused by the marine accident. If each marine accident is summed up equally without considering the extent of damage, the efficiency score can become distorted. Therefore, it is necessary to standardize the various possible types of marine accidents before assigning the records of marine accidents as undesirable outputs. Eight possible types of damage from marine accidents are shown in Table 3.

Table 3. Classification of damage types from marine accidents.

Classification	Damage Type	Description
Ship damage	Total loss	The vessel has sunk, gone missing, or is otherwise unsalvageable, i.e., it no longer functions as a ship, or the costs of repair are beyond economic feasibility owing to reasons such as running aground or onboard fire.
	Significant damage	The vessel is unable to operate under its own power, or it requires significant repairs to regain operability.
	Minor damage	Damage not categorized as total loss or significant damage
	No damage	No damage to the vessel despite accident occurrence
Casualties	1st class casualties	2 or more fatalities or missing persons
	2nd class casualties	1 or 0 fatalities or missing persons, or 2 or more severely injured persons
	3rd class casualties	Injuries not categorized as 1st class or 2nd class casualties
	No casualties	No injuries from the accident

Source: Korean Maritime Safety Tribunal.

In addition, the relative importance between the eight damage types was estimated using analytic hierarchy process (AHP) proposed by Saaty [81], which is commonly used in multiple criteria decision-making. To enable a pairwise comparison of damage types from marine accidents, a nine-point questionnaire was formed to survey 60 safety managers and ferry operations managers. From the 47 people who responded, the data from 22 participants who had a consistency index (CI) of within 0.1 were used to calculate the relative weighting of each marine accident damage type. Table 4 shows the results of estimating the relative weights of damage types from marine accidents.

Table 4. Estimating the relative weights of damage types from marine accidents with AHP.

Damage Type	Total Loss	Significant Damage	Minor Damage	No Damage	1^{st} class casualties	2^{nd} Class Casualties	3rd Class Casualties	No Casualties
	S_1	S_2	S_3	S_4	C_1	C_2	C_3	C_4
Weight	0.238	0.092	0.030	0.019	0.410	0.145	0.048	0.019

In the event of a marine accident, casualties and ship damage occur in combination. Table 5 is the result of identifying 16 types of marine accidents that can occur depending on the extent of casualties and ship damage. The values in Table 5 are in numbers of negligible accident (No damage of ship + No casualties) units, converted using Equation (4). When measuring the actual efficiency of each coastal ferry operator in Section 4, the marine accident record is classified based on Table 3, and the undesirable output value is assigned based on the number of negligible accident (No damage of ship + No casualties) units in Table 5.

$$\text{Negligible accident units per one accident} = \left(\frac{\text{Weight of } S_i + \text{Weight of } C_i}{0.019}\right)/2 \tag{4}$$

where S_i is type of ship damage and C_i is type of casualties $(i = 1, 2, 3, 4)$.

Table 5. Conversion of 16 accident types into negligible accident units. (Units: Negligible accident units per one accident).

Casualties	Ship Damage			
	S_1	S_2	S_3	S_4
$\mathbf{C_1}$	17.3	13.4	11.8	11.5
$\mathbf{C_2}$	10.3	6.4	4.7	4.4
$\mathbf{C_3}$	7.6	3.8	2.1	1.8
$\mathbf{C_4}$	6.9	3.0	1.3	1.0

3.3. Data Description

For an equal comparison of efficiencies, of the 60 companies (100 routes, 169 vessels) holding coastal ferry licenses as of December 2018, 44 (185 vessels) that have continuously operated for the past five years (2013–2017) were chosen as DMUs. Because a group of DMUs is used to evaluate each other for the purpose of securing relative comparison, performing DEA requires a minimum sample size. Banker et al. (1984) argued that the number of DMUs to be assessed should be at least three times greater than the sum of inputs and outputs. Boussofinance et al. [82] argued that the number of DMUs should be at least two times greater than the product of the number of inputs and outputs. This was corroborated by Dyson et al. [83]. In light of the preceding theories on the suitable number of observations, the number of DMUs selected for this study was deemed to be reasonable.

Table 6 shows the summary statistics of DMU input and output data. The collection period of this data was between 2013 and 2017.

Table 6. Summary statistics of input and output variables.

Classification	Input 1	Input 2	Input 3	Desirable Output	Undesirable Output
	Number of Ferries	Number of Actual Ferry Services	Total Passenger Capabilities	Number of Passengers	Marine Accident Records
N	44	44	44	44	44
Mean.	3.0	27,991.5	835.2	1,465,384	4.6
Median	2.6	17,263.0	491.1	1,188,432	3.4
Standard deviation	2.3	32,696.4	745.5	1,015,692	4.4
Minimum	1.0	834.0	195.0	166,061.0	0
Maximum	14.3	173,636.0	3287.1	3,881,355.0	17.8

To obtain meaningful results, the data set used in the DEA analysis should satisfy isotonicity (nondecreasing) [36,84]. In other words, increasing the input during the production process should make it possible to increase the output. To check nondecreasing, a correlation matrix among the input and output variables based on the collected data was constructed, as shown in Table 7. All variables confirmed positive correlations at a significance level of 1%.

Table 7. Correlation among the input and output variables.

Classification		Input 1	Input 2	Input 3
		Number of Ferries	Number of Actual Ferry Services	Total Passenger Capabilities
Desirable Output	Number of passengers	0.508 **	0.450 **	0.638 **
Undesirable Output	Marine accident records	0.732 **	0.205 **	0.614 **

** $p < 0.01$.

Furthermore, it was assumed that all the variables in the DEA model have a value greater than zero. As no marine accidents occurred in the years of the study period (2013–2017), further action is required by DMUs where the undesirable output is zero. However, currently, there is no clear methodology for processing zero undesirable output data in an SBM model. In this study, the method of substituting zero undesirable output data with a negligibly small positive number (i.e., 10^{-8}) proposed by Yeh [72] was applied to address this issue while mitigating the effects on the efficiency analysis. Although not intended for an SBM model, Bowlin [85] also proposed the use of a small positive value substitution if the variable is zero output variable.

4. Efficiency Measurement Results

The operational efficiency of coastal ferry operators was measured by utilizing MaxDEA 7 Ultra, a specialized program capable of implementing DEA models under various production assumptions. Table 8 shows the summarized results of operational efficiency scores of coastal ferry operators. The efficiency score ρ and ρ^* denote each value obtained from the normal SBM model and the safety-constrained SBM model. The normal SBM model, which only considers passenger transportation records, had a total of 7 DMUs (No. 14, 18, 30, 34, 35, 37, 40) that had a measured efficiency score of "1," indicating strong efficiency. In contrast, the safety-constrained SBM model, which also considered marine accident records, had a total of 17 DMUs (No. 3, 9, 12, 14, 18, 20, 25, 29, 30, 33, 34, 35, 37, 38, 39, 40, 42) that had efficiency scores of "1." A comparison of efficiency score rankings between the normal SBM model and the safety-constrained SBM model showed that the ranking of these 37 DMUs changed depending on marine accident records. However, DMUs 14, 18, 30, 34, 35, 37, and 40, which had strong efficiency in the normal SBM model, also had strong efficiency in the safety-constrained SBM model, resulting in no change in ranking. The correlation coefficient between the efficiency scores (ρ, ρ^*) of the two models was 0.77, indicating a strong positive correlation. This indicates that DMUs with high efficiency scores in the normal SBM, which represents the economic operational efficiency of the ferry operator, tend to achieve higher efficiency scores in the safety-constrained SBM. Thus, the coastal ferry operators with a high economic operational efficiency were relatively less affected by changes in production resulting from the occurrence of marine accidents.

Table 8. Comparison of the efficiency scores between normal SBM and safety-constrained SBM.

DMU	Normal SBM		Safety-Constrained SBM		Change of Rank (R–R*)	Efficiency Score Ratio (ρ/ρ^*)
	Efficiency Score (ρ)	Rank (R)	Efficiency Score (ρ^*)	Rank (R*)		
1	0.458	25	0.588	31	−6	0.78
2	0.281	39	0.281	44	−5	1.00
3	0.44	28	1	1	+27	0.44
4	0.432	30	0.516	35	−5	0.84
5	0.214	43	0.318	42	+1	0.67
6	0.761	13	0.771	20	−7	0.99
7	0.533	24	0.731	22	+2	0.73
8	0.352	33	0.549	32	+1	0.64
9	0.452	26	1	1	+25	0.45
10	0.716	15	0.736	21	−6	0.97
11	0.286	38	0.31	43	−5	0.92
12	0.191	44	1	1	+43	0.19
13	0.452	27	0.546	33	−6	0.83
14	1	1	1	1	0	1.00
15	0.312	36	0.512	36	0	0.61
16	0.239	41	0.465	37	+4	0.51
17	0.396	32	0.437	39	−7	0.91
18	1	1	1	1	0	1.00
19	0.541	23	0.661	28	−5	0.82
20	0.921	9	1	1	+8	0.92
21	0.824	12	0.839	19	−7	0.98
22	0.228	42	0.394	41	+1	0.58

Table 8. *Cont.*

DMU	Normal SBM		Safety-Constrained SBM		Change of Rank (R–R*)	Efficiency Score Ratio (ρ/ρ^*)
	Efficiency Score (ρ)	Rank (R)	Efficiency Score (ρ^*)	Rank (R*)		
23	0.321	35	0.54	34	+1	0.59
24	0.258	40	0.396	40	0	0.65
25	0.628	20	1	1	+19	0.63
26	0.434	29	0.628	30	−1	0.69
27	0.618	21	0.686	26	−5	0.90
28	0.573	22	0.715	24	−2	0.80
29	0.676	17	1	1	+16	0.68
30	1	1	1	1	0	1.00
31	0.641	19	0.717	23	−4	0.89
32	0.678	16	0.713	25	−9	0.95
33	0.941	8	1	1	+7	0.94
34	1	1	1	1	0	1.00
35	1	1	1	1	0	1.00
36	0.856	11	0.88	18	−7	0.97
37	1	1	1	1	0	1.00
38	0.754	14	1	1	+13	0.75
39	0.668	18	1	1	+17	0.67
40	1	1	1	1	0	1.00
41	0.349	34	0.681	27	+7	0.51
42	0.884	10	1	1	+9	0.88
43	0.397	31	0.639	29	+2	0.62
44	0.293	37	0.445	38	−1	0.66

Notably, the efficiency score ratio (ρ/ρ^*) of the two SBM models shown in Table 8 has values between 0 and 1, which appears to be a form of index. The efficiency scores in the safety-constrained SBM model are equal to or higher than those in the normal SBM model. This indicates that the production possibility set has been reduced following the reflection of marine accident records in the safety-constrained SBM model via Equation (2d). Specifically, the results showed smaller or equal slack of the input and output variables required by the DMU to reach the projected point on the reduced production frontier. Ultimately, the ratio (ρ/ρ^*) dictates the degree of impact of marine accident records on the operational efficiency of the DMU.

5. Discussion and Implications

Marine accident records represent the level of safety of a coastal ferry operator. The occurrence rate of marine accidents varies depending on the voluntary safety management efforts made by the coastal ferry operator. It can be said that marine accidents are output-oriented quantitative safety performance indicators. Considering these points, the efficiency score ratio (ρ/ρ^*) of the two SBM models can be alternatively interpreted as the effect of safety management performance by a coastal ferry operator on its operational efficiency. For example, when the ratio (ρ/ρ^*) is 1, the normal SBM efficiency score (ρ) and the safety-constrained SBM efficiency score (ρ^*) are the same. This indicates that there is no effect on the operational efficiency in production change reflected by safety management performance, which represents marine accidents. In this case, it is acceptable for the DMU to maintain its current safety level, as it indicates that no additional investment is required for safety management improvement. In contrast, if the ratio (ρ/ρ^*) is smaller than 1, it indicates that the occurrence of marine accidents is affecting the operational efficiency of DMUs by reducing production. Marine accidents result in excess inputs and the loss of desirable output relative to a hypothesized efficient DMU. Coastal ferry operators must consider additional investment in safety for the improvement of current safety management standards, which affects the operational efficiency, to reduce marine accidents.

Accordingly, the ratio (ρ/ρ^*) could be defined as the index of safety management performance impact on operational efficiency, and will be called the SMPI index here. Quantitatively, the degree of safety management impact can be measured by (1-SMPI). This idea originated from a study by Zhou et al. [68], in which environmental regulatory impacts on the economic efficiency of OCED countries were measured by applying the SBM model. According to Zhou et al. [59], similar ideas can be found in Boyd and McClelland [63], Zaim and Taskin [86], and Picazo-Tadeo et al. [87].

Furthermore, many DMUs experienced production shortages or excess input in operational efficiency owing to the production restrictions caused by marine accident occurrences. As described earlier, implementing additional safety investments to improve this aspect result in the loss of the corresponding production investment opportunities. This can be perceived as a production opportunity cost for DMUs. If it is assumed that these series of effects ultimately lead to a loss of passenger transportation sales for the coastal ferry company, the loss of passenger transportation sales can be defined as an opportunity cost of safety management performance. Such an opportunity cost can be approximated by Equation (5), shown below.

$$\text{Opportunity cost from safety management performance} = \\ \text{(1-SMPI)} \times \text{sales from passenger transportation} \quad (5)$$

The opportunity cost of safety management performance, shown in Table 9, was estimated by substituting the passenger transportation sales of 44 coastal ferry operators from the five-year observation period. The opportunity cost of safety management performance by the 44 DMUs was an average of USD 2.11 million. DMU 7 had the highest cost, at approximately USD 19.21 million, whereas by excluding DMUs 14, 18, 30, 34, 35, 37, and 40, which had SMPI values of 1, DMU 11 had the lowest cost, at approximately USD 0.21 million.

Table 9. Estimate of the opportunity cost of DMUs from safety management performance.

DMU	SMPI	1-SMPI	Transportation Sales (Million USD)	Opportunity Cost (Million USD)
1	0.78	0.22	13.10	2.90
2	1.00	0.00	3.76	0.00
3	0.44	0.56	3.54	1.98
4	0.84	0.16	1.81	0.29
5	0.67	0.33	0.91	0.30
6	0.99	0.01	57.81	0.75
7	0.73	0.27	70.93	19.21
8	0.64	0.36	4.95	1.78
9	0.45	0.55	8.60	4.71
10	0.97	0.03	38.77	1.05
11	0.92	0.08	2.66	0.21
12	0.19	0.81	1.91	1.55
13	0.83	0.17	14.90	2.57
14	1.00	0.00	11.97	0.00
15	0.61	0.39	3.09	1.21
16	0.51	0.49	0.83	0.40
17	0.91	0.09	2.84	0.27
18	1.00	0.00	3.59	0.00
19	0.82	0.18	18.26	3.31
20	0.92	0.08	16.23	1.28
21	0.98	0.02	59.60	1.07
22	0.58	0.42	8.76	3.69
23	0.59	0.41	5.27	2.14
24	0.65	0.35	7.93	2.76
25	0.63	0.37	47.30	17.60
26	0.69	0.31	2.94	0.91
27	0.90	0.10	3.90	0.39
28	0.80	0.20	10.25	2.04
29	0.68	0.32	3.86	1.25
30	1.00	0.00	8.43	0.00
31	0.89	0.11	2.64	0.28
32	0.95	0.05	11.00	0.54

Table 9. *Cont.*

DMU	SMPI	1-SMPI	Transportation Sales (Million USD)	Opportunity Cost (Million USD)
33	0.94	0.06	8.10	0.48
34	1.00	0.00	42.82	0.00
35	1.00	0.00	70.32	0.00
36	0.97	0.03	9.57	0.26
37	1.00	0.00	15.27	0.00
38	0.75	0.25	2.77	0.68
39	0.67	0.33	7.81	2.59
40	1.00	0.00	2.86	0.00
41	0.51	0.49	10.32	5.03
42	0.88	0.12	16.45	1.91
43	0.62	0.38	3.92	1.49
44	0.66	0.34	11.85	4.05
	Average		14.9	2.11

Additionally, based on the DMU transportation sales in Table 9, the fuzzy c-means (FCM) clustering algorithm was used to group and compare the degree of opportunity costs arising from the characteristics between groups. The FCM clustering algorithm was first studied by Dunn [88] and generalized by Bezdek [89]. It is one of the most popular data mining methods for dealing with data cluster problems [90].

Table 10 shows the result of classifying groups based on transportation sales volumes using FCM. The classification according to the FCM was as follows: group 1 had four ferry operators with a transportation sales volume of over USD 65 million, group 2 had three ferry operators with over USD 43.47 million, group 3 had 18 ferry operators with over USD 12.32 million and group 4 had four operators with over USD 3.39 million. Studying the group characteristics shows that group 1 had the largest average number of operational vessels; however, there was no significant difference compared with groups 2, 3 and 4. Furthermore, group 1 had the highest number of actual ferry services, i.e., almost five times greater than that of group 4, which had the fewest. The average total passenger capability, which shows ferry size, was larger in groups 3 and 4, which had smaller transportation sale volumes, than groups 1 and 2. Group 3, the largest group, was almost four times larger than the smallest group, group 2. In summary, coastal ferry operators with high transportation sales maintain an appropriate fleet size but focus on strategies to provide more transportation services to passengers, whereas coastal ferry operators with low transportation sales have adopted the strategy of deploying relatively large vessels to transport more passengers at a lower frequency.

Table 10. Classification of groups according to FCM clustering of the size of transportation sales.

Group	Number of DMUs	Cluster Value (Million USD)	Avg. Number of Ferries	Avg. Number of Actual Ferry Services	Avg. Total Passenger Capabilities
1	4	65.00	3.92	2,562.62	9,215.25
2	3	43.47	3.34	1,276.86	8,127.33
3	18	12.32	3.60	820.81	34,934.50
4	19	3.39	2.16	415.41	28,503.21

Table 11 shows the results of calculating the average transportation sales and the average opportunity costs of each group classified using FCM clustering. Group 2 had the highest opportunity cost from safety management, at an average of USD 6.22 million, followed by group 1 at USD 5.26 million, group 3 at USD 2.12 million and group 4 at USD 0.8 million. However, in terms of the average ratio of opportunity cost to transportation sales per group (average opportunity cost/average transportation sales), group 4, which had the lowest transportation volume sales, had the highest value at 0.26, followed by group 3 at 0.18, group 2 at 0.14, and group 1 at 0.08. Group 4, with the largest ratio, was approximately 3.3 times larger than group 1 with the smallest ratio. Although the opportunity cost of safety performance is high for large ferry operators with high transportation sale volumes, the impact of these opportunity costs on company management is larger for smaller ferry operators with low transportation sales volumes.

Table 11. Comparison of the average opportunity costs from safety management performance according to FCM clustering of the size of transportation sales.

Group	(a) Average Transportation Sales (Million USD)	(b) Average Opportunity Cost (Million USD)	(b)/(a)
1	64.67	5.26	0.08
2	42.96	6.22	0.14
3	11.60	2.12	0.18
4	3.06	0.80	0.26

The above results have significant implications for the direction of coastal ferry safety policies pursued by the government. Unfortunately, it should be recognized that ferry operators may prioritize pursuing profits through commercial ship operations rather than through thorough safety management. In the short term, strengthening the enforcement of safety regulations can reduce marine accidents involving coastal ferries. However, in the long term, the benefits of safety management will decrease owing to an increase in opportunity costs from safety management, leading to a disparity in adherence to strict safety regulations between large and small coastal ferry operators. This suggests that the effects of strengthened safety regulations on reducing marine accidents are limited over time. Even if the government perfectly implements institutional frameworks on safety, coastal ferry operators are eventually required to practically implement them in the field. Marine accidents will continue to occur in the future if operators fail to implement safety measures faithfully due to time and resource constraints. In shipping operations, as in any other industry, there is a trade-off between efficiency and thoroughness [91,92]. Therefore, to effectively reduce marine accidents in the long term, the strengthening of safety management regulations should be accompanied by the development and implementation of customized positive policies for ship operators, such as safety management consultation support and vessel modernization support. This implication would also be valuable for ship operators on a global scale, because they are operating on the uniform IMO instrument boundary, regardless of their business size. International maritime safety regulations were enhanced in the wake of a series of major accidents, from the Titanic accident in 1912 to the Costa Concordia accident in 2012. It is time for a fundamental change, i.e., to the systemic approach which looks at safety and economics in a balanced manner. Schröder-Hinrichs et al. [92] also stressed that actual safety improvement should start from a systemic view of accident causation, rather than from firm confidence in the efficacy of new or improved technical regulations.

6. Conclusions

This study analyzed the operational efficiency of coastal ferry operators from a safety perspective. For this purpose, two SBM models were built to compare the effects of marine accidents, which represent safety management performance, on operational efficiency. One is the normal SBM model, which only reflects the desirable output of passenger transportation performance. The other is a safety-constrained SBM model, which includes marine accident records, an undesirable output, with the desirable output of passenger transportation performance. The operational efficiency of 44 coastal ferry operators that have been continuously operating between 2013 and 2017 was measured. The input variables selected for use in the operational efficiency measurements were the number of operational vessels, the number of actual ferry services and the total number of passengers.

Comparing the efficiency scores measured using the two SBM models showed that the operational efficiency of 37 coastal ferry operators was affected by production changes resulting from marine accident occurrence. In particular, coastal ferry operators with high efficiency scores in the normal SBM model, which indicates economic operational efficiency, were also observed to have high operational efficiency in the safety-constrained SBM model, which reflects marine accident records. Thus, an index between 0 and 1 was created from the ratio of efficiency scores from the two SBM models. This was defined as the index of safety management performance impact on operational efficiency (SMPI). If the index value is 1, it indicates that the operational efficiency of the DMUs is not affected by production change, which reflects the level of safety management represented by marine accidents. If the index value is smaller than 1, it indicates that there are production losses arising from the level of safety management implemented by the coastal ferry operator. In this study, this form of production loss was defined as the production opportunity cost resulting from safety management performance.

Finally, the opportunity cost of safety management performance was measured based on the passenger transportation sales of 44 DMUs over the observed five-year period, i.e., between 2013 and 2017. The results showed that the opportunity cost of safety management performance was higher for large ferry operators, which have greater transportation sales volumes than small ferry operators. However, in contrast to transportation sales, the ratio of opportunity costs from safety performance was observed to be higher in small ferry operators than in larger ferry operators. The impact of safety management performance on company operations was greater for ferry operators with smaller transportation sales. Therefore, to reduce marine accidents effectively, the implementation of positive policies that provide a sound economic environment where small coastal ferry operators can thrive is as important as strengthening the enforcement of government safety regulations.

Of course, it might be very difficult, but the top-down and bottom-up methods need to be compatible in ship safety. In other words, top executives should be aware of safety as an overriding priority of management, and at the same time, the crew working onboard should implement safety management faithfully; the wider the gap between these two actors, the harder it becomes to secure safety. To bridge the gap between them, the continued development and application of education and training programs are necessary. Indeed, international organizations, governments, research institutes and universities need to collaborate to develop and provide customized safety-oriented education and training programs for small-business companies and developing economies.

This study differs from existing efficiency analysis studies on coastal ferry operations in that it devised a more realistic method of measuring the operational efficiency of coastal ferry operators by considering actual marine accident records, which is a key performance indicator of safety management. The author will continue to conduct research on the development of a safety management performance analysis model that comprehensively accounts for the safety management level and operational efficiency of coastal ferry operators.

Author Contributions: Conceptualization, H.K. and J.K.; methodology, H.K. and J.K.; software, J.K.; validation, H.K. and G.L.; formal analysis, J.K.; investigation, J.K.; resources, H.K. and J.K.; writing—original draft preparation, J.K.; writing—review and editing, G.L.; visualization, J.K. and G.L.; supervision, H.K.; project administration, H.K.; funding acquisition, H.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2019R1F1A1059037).

Acknowledgments: We sincerely thank the anonymous reviewers for their constructive and valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

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