Journal of Korea Trade Vol. 26, No. 3, May 2022, 23-44
https://doi.org/10.35611/jkt.2022.26.3.23
ISSN 1229-828X

Economic Efficiency of the Korean Container Terminals: A Stochastic Cost Frontier Approach*

JKT 26(3)

Received 12 August 2021
Revised 5 May 2022
Accepted 6 May 2022

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Abstract

Purpose – Recent issues such as vessel enlargement, strengthening of environmental regulations, and port smartization are expected to increase costs and intensify competition in the port industry. In the new normal era, when external growth has reached its limit, the efficient operation of ports is becoming indispensable for achieving sustainable growth. This study aims to identify the determinants of inefficiency by examining the cost structure and efficiency of container terminals in Korea and furthermore propose the political implications to derive the maximization of efficiency.

Design/methodology – This study estimates the cost function of container terminal operators and identifies the efficiency of container terminals using stochastic cost frontier (SCF) in the first stage. In the second step, the SCF results are compared with the data envelopment analysis (DEA). Last, this paper proposes efficiency determinants on container terminal operation to establish appropriate strategies. Out of the 29 container terminal operators in South Korea, 13 operators participated in the survey. The translog cost function was estimated utilizing a total of 116 observations collected over the 2007-2017 period.

Findings – Empirical analysis shows that economies of scale exist in Korea's container ports, which provides a rationale for the government's policy to establish the global terminal operator by integrating small terminal operators to enhance competitiveness. In addition, as a result of the determinants analysis, container throughput, weight of direct employment costs, and labour cost share have positive effects on improving cost efficiency, while inefficiency increases as the length of quay increases. More specifically, cost efficiency improves as the proportion of direct employment costs to outsourcing service costs increases.

Originality/value – This study contributes to analyzing the inefficiency factors of container terminals through efficiency analysis with respect to a cost function. In addition, this study proposes the practical and political implications, such as establishing a long-term manpower pool, the application of the hybrid liner terminal system, and the construction of a statistical data system, to improve the cost inefficiency of terminal operators.

Keywords: Container Terminals, Cost Efficiency, Data Envelopment Analysis, Inefficiency Assessment, Stochastic Frontier Analysis
JEL Classifications: D12, F14, O53

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1. Introduction

The use of container ports in global supply chains has been vital in linking transportation modes and activating trades among different nations. Lately, due to the high economies of scale and increased competitiveness associated with handling cargo using containers, the production efficiency of ports has become an important issue (Wang, et al., 2003). Despite the slow growth of the global economy, the competition among global ports is intensifying with the continued development of new ports worldwide and the reorganization of global alliances in container shipping. In Korea's major container ports, the increase in container throughput is slowing down due to changes in the logistics environment, thus adding to the importance of the Korean port industry structure, which has a significantly higher proportion of transhipment business as compared to major ports in the world. Moreover, in recent years, the port industry has experienced issues such as enlarged ships, strengthened environmental regulations, and port automation and smartization. These issues have been accompanied by increased costs associated with improving existing port facilities, developing new facilities, and introducing a new operating system. This has motivated the need for stakeholders to reduce costs and strengthen the competitiveness of container ports worldwide by optimizing port operations.

In 2019, the import-export to GDP ratio in Korea was 81.5%, with more than 90% of these import-export transactions made through ports under geographical constraints (Statistics Korea, 2021). Additionally, containerization has affected transhipment volumes by enabling multimodal transport, i.e., using different modes of transportation. Transhipment volume reached 3.31 million tons in 2019 (Statistics Korea, 2021), with Busan port serving as a buffer during the COVID-19 global economic recession and transhipment cargo rising by 3% year-on-year (Busan Port Authority, 2021). In this regard, more careful attention to improving container terminal efficiency is required since the ports industry accounts for a significantly large proportion of the national economy and to secure value-added productivity through transhipment cargo.

As various cost factors and uncertainties surrounding the port industry increase, the government is concentrating investment on enhancing the competitiveness of logistics and revitalizing high value-added industries that utilize the port industry. Port authorities, which are responsible for evaluating the benefits and costs of development in general, have focused on developing the facilities of port terminals (Stein and Acciaro, 2020). However, unlike past development, there is a limit to quantitative growth, such as an increase in cargo volume that can be obtained through investment in infrastructure facilities. According to Munim and Schramm (2018), in developing countries, gradual improvement in port infrastructure significantly contributes to logistical performance, seaborne volume, and thus economic growth. However, in developed countries, this relationship has somewhat weakened. In addition, ports in developed countries are also required to maintain high infrastructure quality. Since there is a limit to the quantitative growth of infrastructure, it is necessary to achieve qualitative growth simultaneously by increasing cost efficiency. It is obvious that cost reduction and the efficient use of inputs are directly related to the survival of the port industry. However, as far as we know, it is few studies conducting comprehensively and quantitatively analyzing the cost structure of container terminals in Korea. Moreover, previous efficiency measurement studies through cost functions examined only a simple cost structure. To fill this gap, this study aims to analyze the cost structure of the container port industry and identify more precisely the determinants of the inefficient factors affecting the optimal operation of terminals through the Tobit model. Therefore, this study estimates the cost function of container terminal operators and identifies the efficiency of container terminals using stochastic frontier analysis (SFA) in the first stage. In the second stage, the SFA results are compared with the data envelopment analysis (DEA) results. Finally, this paper suggests policy directions for maximizing the cost efficiency of terminal operators by appropriately controlling its determinants.

The remainder of this paper is organized as follows. Section 2 reviews previous research on port efficiency. The theoretical background of cost function and economic efficiency is explained in Section 3. Section 4 presents the empirical analysis and results. Finally, Section 5 presents the concluding remarks with the implications and limitations of the study.

2. Literature Review

2.1. Port Efficiency and Cost Function

Efficient port operations play a vital role in promoting national competitiveness and corporate profits as well as regional economic growth (Cullinane, et al., 2002). Competition among port authorities to secure global cargo volume is becoming increasingly fierce, and this competition is also taking place between ports in a country. Along with this trend, many previous studies have examined port competitiveness in the following ways: determinant analysis (Tongzon and Heng, 2005; Yeo, et al., 2011; Yuen, et al., 2012), evaluation of performance or service quality (Tongzon and Ganesalingam, 1994; Lee and Hu, 2012; Talley, et al., 2014), port selection (Slack, 1985; Wiegmans, et al., 2008; Onut, et al., 2011), and sustainability (Oh, et al., 2018; Lim, et al., 2019). In accordance with these studies, port efficiency analysis solves complex optimization problems and provides decision-makers with implications for port operation. Especially, Clark et al. (2004) addressed that port inefficiency negatively affects not only transport costs but also port service quality, which has been recognized as an important factor in supply chains. Therefore, it is essential to analyze the efficiency of ports and terminals using appropriate methodologies that present the managerial implications of maximizing outputs or minimizing costs from the perspective of port authorities and supply chain members.

With limited resources, it is important to make appropriate investments to improve port efficiency. Port authorities and policymakers should consider the direction of investment in port facilities depending on whether they are developed or developing countries (Munim and Schramm, 2018; Portugal-Perez and Wilson, 2012). In some studies, port size and efficiency were not significantly correlated (Wang, et al., 2003; Tongzon, 2001). On the other hand, some studies show that smaller ports have higher efficiency (Coto-Millan, et al., 2000). There is an obvious limit to the quantitative growth in cargo volume that the port industry can achieve by physically investing in infrastructure facilities. Therefore, qualitative growth, achieved by improving cost efficiency via cost function, is also required along with quantitative growth. There are several literatures examining cost functions related to the port industry. Jara-Diaz et al. (2005) utilized a multi-output cost function model to analyze the cost structure of ports using the monthly data of three corporates at a Spanish port. This research suggested appropriate policy implications for the Spanish port through the estimation of marginal costs, economies of scale, and economies of scope. Talley and Ng

(2016) proposed a port's cost function that considered the port output as a service supply rather than physical output. They distinguished the service supply of ports in terms of port cargo services, port vessel services, and port vehicle services. It is insufficient that research analyzes the cost structure of container ports by estimating the cost function for container terminal operation in Korea. Therefore, it is necessary that a quantitative approach through cost function estimation that can reasonably determine the optimal input factors such as manpower, unloading equipment, and operating costs for container terminal operators.

2.2. Research Methods for Port and Terminals Efficiency

A majority of prior literature that measured the efficiency of ports and terminals applied either DEA or SFA. DEA is a nonparametric approach that deals with mathematical programming techniques and can be used to analyze multiple inputs and outputs. In contrast, SFA is a parametric approach that deals with econometric techniques and can address the distribution of errors such as statistical noise and technical inefficiency. While these two methodologies have their pros and cons depending on the research purpose and industry characteristics, both economic analysis methodologies provide strong policy directions for evaluating the effectiveness of government and public affairs (Cullinane, et al., 2002). Due to the nature of port terminal research, the SFA method with a solid economic theoretical background is more suitable for achieving the purpose of this paper.

Many of the preceding literature has applied the stochastic production frontier (SPF) model to measure the efficiency of ports or terminals. Cullinane and Song (2003) applied an SPF model to measure the efficiency of container terminals efficiency based on the degree of port autonomy. They found that the higher the level of port privatization, the greater the production efficiency of the terminal. Lin and Tseng (2005) evaluated the operational efficiency of 27 international ports based on the production frontier. Cullinane et al. (2006) also used an SPF model to measure the technical efficiency of 57 container ports and terminals and compared it with results from a DEA. On the other hand, a few studies on port efficiency utilized the stochastic cost frontier (SCF) model. Coto-Millan et al. (2000) applied an SCF model to examine 15-year panel data of 27 ports located in Spain to measure their economic efficiency using a translog cost function. In this study, total costs, which include labour costs, depreciation, and intermediate consumptions, were used as a dependent variable and three inputs, i.e., labour, capital, and intermediate consumption, were extracted as independent variables. In particular, the outputs included port cargo volume, the number of vehicles with passengers, and the number of passengers. Barros (2005) employed an SCF model with a translog function to analyze the inefficiency and technical change of seaports in Portugal. This study considered two inputs, labour and capital costs, and two outputs, number of ships and total cargo volume, and added the trend variable for technical change. To our knowledge, no previous research has estimated the cost efficiency of container terminals in South Korea using the SCF model.

In general, DEA is mainly used in efficiency analysis in various fields. Also, it is a widely adopted method in port or terminal efficiency evaluation to understand their operational status. There is an advantage of being able to handle multiple inputs and outputs that affect port performance. Roll and Hayuth (1993) initially utilized DEA to compare the performance of 20 hypothetical individual ports and measure their relative efficiency. Tongzon (2001) compared the efficiencies of Australian and international ports by utilizing the Charnes, Cooper, and Rhodes CCR DEA and additive models, and identified inefficient ports to provide the scope for performance improvements so that port operators can improve port performance. Martinez-Budria et al. (1999) adopted the Banker, Charnes, and Cooper (BCC) DEA model taking account into economies of scale to the efficiency of Spanish port performance. Park and De (2015) proposed an alternative four-stage DEA method to measure port efficiency in Korea by considering seaport performance in the light of productivity, profitability, and marketing. Furthermore, a few studies have utilized both methodologies simultaneously to compare each result and increase the justification of the results. Lin and Tseng (2005) evaluated the operational efficiency of 27 international ports by applying both the DEA and SFA methods to the same dataset. Cullinane et al. (2006) applied the two methodologies to 57 container ports and terminals and observed a high correlation between the technical efficiency results. Park (2010) attempted to expand the scope of research related to the measurement of port efficiency by applying the DEA and SFA to eight container terminals in Korea. The combination of the SFA and DEA methodologies can provide more comprehensive management implications for stakeholders than when they are used individually (Lin and Tseng, 2005). However, there is little research that comprehensively estimates the cost functions of container terminals in Korea through two main efficiency methodologies. Given the advantages and disadvantages of the two alternative major methodologies, operators and policymakers can draw balanced conclusions under each circumstance (Cullinane, et al., 2006). This study sheds light on identifying the determinants of inefficiency by examining the cost structure and efficiency of container terminal operators in Korea.

To increase the accuracy of the analysis and the applicability of the empirical function, this study focused on container terminals rather than overall ports and identified the cost structure of 13 container port operators in Korea. This study aims to contribute to improving technical efficiency and competitiveness by presenting significant insights derived from the SCF model to container terminal operators. In addition, it intends to measure the correlation with the DEA results and to identify the determinants that affect the efficiency of container terminals.

3. Methodology

For a cost function, Coelli et al. (2005) suggested some common parametric functional forms such as linear, Cobb-Douglas, quadratic, translog, and generalized Leontief functions, emphasizing that flexibility, parametric linearity, regularity, and parsimoniousness conditions should be considered when selecting a specific function. In previous studies, either the Cobb-Douglas or translog function has been widely used. However, since the translog is a generalized version of the Cobb Douglas, it is more appropriate to use the translog unless more restrictions are necessary.

3.1. Translog Cost Function

If the translog cost function of a container terminal is defined using the inputs of container throughput, labour cost, capital cost, and operation cost, it can be expressed as follows.

$$C = \mathrm{c}(q, w_l, w_r, w_o;\ \beta) \tag{1}$$

where C is the total cost, q is the container throughput, w_l, w_r, w_o are the input prices of labour, capital and operation, respectively. By applying translog function with the second-order Taylor expansion to the equation (1), the translog cost function can be obtained as shown in equation (2).

$$\ln C = \beta_0 + \beta_1 \ln q + \frac{1}{2}\beta_{qq}(\ln q)^2 + \sum_n \beta_n \ln w_n$$
$$+\tfrac{1}{2}\textstyle\sum_n \sum_m \beta_{nm} \ln w_n \ln w_m + \sum_n \beta_{qn} \ln q \ln w_n + \varepsilon, \quad (n, m = l, r, o) \tag{2}$$

While it is possible to include terms to account for technological progress, the specification used here assumes that cost is independent of time. Using Shepherd's lemma, the derived demand equations are as follow.

$$s_n = \beta_n + \beta_{nq} \ln q + \textstyle\sum_m \beta_{nm} \ln w_m \tag{3}$$

where $s_n = \frac{w_n x_n}{C}$ is the cost share of the nth input and x_n is the amount of nth input. Concerning homogeneity of the first degree and symmetry of the second derivatives, the following two conditions can be applied.

$$\text{(homogeneity condition)} \textstyle\sum_n \beta_n = 1,\ \sum_m \beta_{nm} = 0,\ \sum_n \beta_{nq} = 0 \tag{4}$$

$$\text{(symmetry condition)} \qquad \beta_{nm} = \beta_{mn} \qquad \text{for all } n \neq m \tag{5}$$

In this paper, we use the iterative seemingly unrelated regression(ITSUR) method to estimate the parameters of the cost function. Equation (2) and Equation (3), excepting s_o, are estimated simultaneously to avoid linear dependency. From the estimated cost function, it is possible to derive useful economic indicators, such as economies of scale, price elasticity, and elasticity of substitution, as shown in Appendix A.

3.2. Stochastic Cost Frontier Analysis

Since its introduction by Aigner et al. (1977), SFA has been widely used as a method for measuring the efficiency of industries or individual companies. While initial research focused on the production frontier, later studies paid more attention to the cost frontier. To utilize SFC analysis, the cost function in Equation (1) is revisited as follows.

$$c_i = \mathrm{c}(w_{li}, w_{ri}, w_{oi}, q_i; \beta) + \epsilon_i \tag{6}$$

where c_i is total cost of ith company, w_{ni} is price of nth input, q_i is container throughput of ith company, β is the parameter to be estimated, and ϵ_i is a random error. It is also assumed that $c(\cdot)$ is a cost function that satisfies the conditions of monotone increase with respect to price, linear homogeneity, and concavity. In the SCF analysis, the error term is divided into two variables as shown in Equation (7), and different distributions are assumed for each.

$$\epsilon_i = v_i + u_i \tag{7}$$

where ν_i is a random error which follows a two-sided symmetric distribution, $N(0, \sigma_v^2)$, while $u_i \geq 0$ is the cost inefficiency of ith company and is assumed to follow an one-sided distribution. For the distribution of u_i, Aigner et al. (1977) proposed a half-normal distribution and an exponential distribution. Later, Stevenson (1980) suggested a truncated normal distribution, while Greene (1980) used a gamma distribution. Applying Equation (7), the cost function in Equation (6) is rewritten as follows.

$$\begin{aligned} c_i &= \mathrm{c}(w_{li}, w_{ri}, w_{oi}, q_i; \beta) + \nu_i + u_i \\ &= c_i^* + \nu_i + u_i \end{aligned} \tag{8}$$

Since u_i is assumed to be non-negative, $c_i - (c_i^* + \nu_i) = u_i \geq 0$ implies that $c_i^* + \nu_i$ is always less than the company's total cost, c_i and can be defined as the minimum cost frontier. If $u_i = 0$, it indicates that a company is on the minimum cost frontier and is thus cost efficient. Following Jondrow et al. (1982) [33], it is assumed that $v \sim N(0, \sigma^2)$ and $u \sim N^+(0, \sigma^2)$ are distributed independently of the input variables as well as of one another. Therefore, the joint probability density function of ν and u is as follows.

$$f(\nu, u) = f(\nu)f(u) = \frac{1}{\pi\sigma_v\sigma_u}\exp\left[\frac{-1}{2\sigma_u^2}u^2 - \frac{1}{2\sigma_v^2}\nu^2\right] \tag{9}$$

By substituting $\nu = \epsilon - u$ in Equation (9), the joint probability density function of u and ϵ is

$$f(u, \epsilon) = \frac{1}{\pi\sigma_v\sigma_u}\exp\left[\frac{-1}{2\sigma_u^2}u^2 - \frac{1}{2\sigma_v^2}(u^2 + \epsilon^2 - 2u\epsilon)\right] \tag{10}$$

Meanwhile, Aigner et al. (1977) presented the probability density function of ϵ as follows.

$$f(\epsilon) = \frac{2}{\sqrt{2\pi}\sigma}(1 - F)\exp\left[-\frac{1}{2\sigma^2}\epsilon^2\right] \tag{11}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u/\sigma_v$ and F is the standard normal distribution function at $\epsilon\lambda/\sigma$. Utilizing Equations (10) and (11), the conditional probability density function of u given ϵ is as follows.

$$f(u|\epsilon) = \frac{f(u,\epsilon)}{f(\epsilon)} = \frac{1}{\sqrt{2\pi}\sigma_v\sigma_u}\frac{1}{(1-F)}\exp\left[\frac{-1}{2\sigma_u^2}u^2 - \frac{1}{2\sigma_v^2}(u^2 + \epsilon^2 - 2u\epsilon) + \frac{1}{2\sigma^2}\epsilon^2\right] \tag{12}$$

Letting $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$, the following equation is obtained:

$$f(u|\epsilon) = \frac{1}{\sqrt{2\pi}\sigma_*}\frac{1}{(1-F)}\exp\left[\frac{-1}{2\sigma_*^2}\left(u - \frac{\sigma_u^2\epsilon}{\sigma^2}\right)^2\right] \tag{13}$$

Thus, $u|\epsilon \sim N^+(\mu_*, \sigma_*^2)$ where $\mu_* = \frac{\sigma_u^2\epsilon}{\sigma^2}$. Next, the mean and mode of $u|\epsilon$ in Equations (14) and (15), respectively, are used as a point estimator of u.

$$E(u|\epsilon) = \mu_* + \sigma_*\frac{f(-\mu_*/\sigma_*)}{1-F(-\mu_*/\sigma_*)} = \sigma_*\left[\frac{f(-\epsilon\lambda/\sigma)}{1-F(-\epsilon\lambda/\sigma)} + \left(\frac{\epsilon\lambda}{\sigma}\right)\right] \tag{14}$$

$$M(u|\epsilon) = \epsilon(\sigma_u^2/\sigma^2) \;\text{ if }\; \epsilon \geq 0, \qquad = 0 \quad \text{otherwise} \tag{15}$$

In this paper, the corrected ordinary least squares (COLS) method is used to estimate the cost inefficiency. COLS is known to provide an efficient estimate even when there are few observations and is easier to use than the maximum likelihood estimation (MLE) method. In the COLS method, the parameters are first estimated using the conventional cost function estimation method to obtain the residuals. Next, cost inefficiencies are estimated using the second and third moments of the residuals. Kumbhakar and Lovell (2000) represented the mean, variance and third moment of u_i, and the second and third moments of ϵ_i, as follow.

$$E(u_i) = \sqrt{2/\pi}\sigma_u \tag{16}$$

$$V(u_i) = [(\pi - 2)/\pi]\sigma_u^2 \tag{17}$$

$$E(u_i^3) = -\sqrt{2/\pi}(1 - 4/\pi)\sigma_u^3 \tag{18}$$

$$E(\epsilon_i^2) = \sigma_v^2 + [(\pi - 2)/\pi]\sigma_u^2 \tag{19}$$

$$E(\epsilon_i^3) = \sqrt{2/\pi}(1 - 4/\pi)\sigma_u^3 \tag{20}$$

Letting Equation (19) and (20) be equal to m_2 and m_3 ($m_r = 1/n\sum_i^n \epsilon_i^r$), i.e., the second and third moments of ϵ_i, $\hat{\sigma}_u^2$ and $\hat{\sigma}_v^2$ are derived as follows.

$$\hat{\sigma}_u^2 = \left(\sqrt{\frac{\pi}{2}}\left(\frac{\pi}{4-\pi}\right)m_3\right)^{2/3} \tag{21}$$

$$\hat{\sigma}_v^2 = m_2 - \left(1 - \frac{2}{\pi}\right)\hat{\sigma}_u^2 \tag{22}$$

Therefore, Equation (2), with $\epsilon_i = v_i + u_i$, is rewritten as follows.

$$\ln c_i = \beta_0 + \beta_q \ln q_i + \frac{1}{2}\beta_{qq}(\ln q_i)^2 + \sum_n \beta_n \ln w_{ni} + \frac{1}{2}\sum_n\sum_m \beta_{nm} \ln w_{ni} \ln w_{mi} + \sum_n \beta_{qn} \ln q_i \ln w_{ni} + v_i + u_i \tag{23}$$

By applying Equations (21) and (22) to Equations (19) and (20), the u_i in Equation (23) is measured by the estimated mean or mode of $u|\epsilon$. Finally, the cost efficiency of each company (CE_i) is derived from the following equations.

$$CE_i = \exp\left(-\hat{E}(u_i|\epsilon_i)\right) \text{ if the mean of } u|\epsilon \text{ is used} \tag{24}$$

$$= \exp\left(-\widehat{M}(u_i|\epsilon_i)\right) \text{ if the mode of } u|\epsilon \text{ is used} \tag{25}$$

With $0 \leq CE_i \leq 1$, a company is perfectly cost efficient when $CE_i = 1$ and the cost inefficiency of each company is computed using $1 - CE_i$.

3.3. Determinants of Cost Efficiency

To identify which factors have a significant impact on the cost efficiencies estimated in Equations (24) and (25), a Tobit regression model is utilized to avoid obtaining an inconsistent estimate. In previous literatures, Turner et al. (2004) derived the efficiency determinants of North American ports based on container port size, vessel size, and the number of railroads. Park and Kim (2012) used berth area, yard productivity, and the presence of an incoming railroad as factors that affected the efficiency of four major container ports in Korea.

In this paper, three types of variables are considered as possible independent variables. The first type includes variables that are directly used to estimate the cost function such as container throughput, input element prices, and input element cost ratios. The second type includes variables associated with the size and facility status of terminals, such as the total area of the terminal, quay length, and the number of gantry cranes. The last type includes variables that reflect the characteristics of individual operators, such as ownership type, location, and operating period. The final model applied in this paper is shown in Equation (26).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \epsilon_i \tag{26}$$

where y_i is the cost inefficiency, x_1 is the container throughput(in twenty-foot equivalent units, TEUs), x_2 is quay length, x_3 is the ownership type (private=1, lease=0), x_4 is ratio of direct employment in the labour cost, x_5 is the number of standard equipment, and x_6 is the cost share of labour.

4. Application to Korean Container Terminals

4.1. Variables

As shown in Equation (1), the independent variables in the cost function include the output in the form of container throughput and the input prices of labour, capital, and operation. Labour(Coto-Millan, et al., 2000; Baros, 2005; Jara-Diza, et al., 2005; Ramos-Real and Tovar, 2010), capital(Coto-Millan, et al., 2000; Baros, 2005; Jara-Diza, et al., 2005; Rodriguez-Alvarez, et al., 2007; Ramos-Real and Tovar, 2010), and operating costs(Coto-Millan, et al., 2000; Jara-Diza, et al., 2005; Rodriguez-Alvarez, et al., 2007; Ramos-Real and Tovar, 2010) are the main factors frequently used in previous studies. In general, the labour in container terminals comprises on-site manpower for container unloading work and operation/management personnel. In financial statements, labour cost includes salaries, retirement benefits, and welfare benefits. Additionally, terminal operators do not directly hire the manpower required for on-site personnel but obtain manpower through external service companies, the costs of which do not appear in the form of salary but are classified as "outsourcing service expenses" in financial statements. Manpower management for direct and external employees and accounting for the labour costs are different for each terminal operator. In this paper, the sum of direct employee's salary and outsourcing service expense is defined as labour cost.

Capital cost includes lease rental fees for leased terminals, port management and operation right fees for private terminals, and the cost of tangible and intangible assets such as equipment, buildings, and software. The lease of a terminal involves paying rent in exchange for use of dock space, which appears as a "lease rental fee" in financial statements. In contrast, in the case of private terminals, the investment costs for port development are depreciated over a long period under the title of "port management right" in the financial statements and are treated as annual expenses. Additionally, "depreciation expenses" and "paid rent" for equipment, such as Q/C, T/C, and Y/T, are included as capital costs.

Operation cost includes power costs, maintenance costs, insurance fees, education, and training costs, and any other costs that are directly linked to terminal operations except labour and capital costs. Among these costs, power cost, which is the cost of electric power and oil required to operate equipment, accounts for a relatively high proportion of the operation cost.

Moreover, the input prices of each cost item are required to estimate the cost function. However, the data used in this analysis is limited in its ability to grasp the exact input amount for each cost item since each cost item comprises several sources. For example, in the case of labour costs, it is common to calculate the amount of input as the number of workers, but the labor costs defined in this study include a combination of directly hired employee's salary and outsourcing service expenses. Therefore, in the case of labour and operation costs, input prices are calculated by dividing each cost by container throughput under the assumption that input cost is determined based on the annual container throughput. In contrast, in the case of capital cost, input price is derived by dividing cost by the annual container loading capacity under the assumption that terminal lease fees, which account for the largest proportion of the capital cost, are calculated based on the annual loading capacity of each terminal. Table 1 summarizes the definitions of the input cost items and measures of their input amounts.

Table 1. Definition of input cost items and their measures

Item	Definition	Input amount(measure)	Reference
Labour	Salary for directly hired employee, Outsourced service expenses	Container throughput(TEU)	Coto-Millan, *et al.*(2000), Baros(2005), Jara-Diaz, *et al.*(2005), Ramos-Real and Tovar(2010)
Capital	Lease rental fee(lease terminal), Port management right(private terminal), depreciation expenses and paid rent for equipment	Loading capacity of a terminal(TEU)	Coto-Millan, *et al.*(2000), Baros(2005), Jara-Diaz, *et al.*(2005), Rodriguez-Alvarez, *et al.*(2007), Ramos-Real and Tovar(2010)
Operation	Power, Maintenance, Insurance, Education and training costs, etc.	Container throughput(TEU)	Coto-Millan, *et al.*(2000), Jara-Diaz, *et al.*(2005), Rodriguez-Alvarez, *et al.*(2007), Ramos-Real and Tovar(2010)

Source: Author.

Additionally, total cost and the cost of each input are deflated to the 2010 constant prices using the Bank of Korea producer price index as of 2010 prior to the analysis.

4.2. Data Sources

The questionnaire in this paper was collected through the Korea Port Logistics Association and individually sent to the non-member operators by e-mail. The survey was conducted from June to July 2018. By the end of 2017, there were 11 container ports that were operated by 29 terminal operators in Korea. Out of these 29 operators, 13 participated in a survey, providing a total of 116 observations for the period 2007~2017. The 13 terminal operators include PNIT, HJNC, HPNT, HKTL, BPT, DPCT, PNC, BNCT in Busan, KIT in Gwangyang, PCTC in Pyeongtaek, E1CT, ICT in Incheon, and GCT in Gunsan. The annual container throughput in TEUs handled by the 13 operators in 2017 was 22.3 million, accounting for more than 85% of the total annual container throughput in Korea. Unlike the production function, cost function estimation requires unit prices, and if unit prices are disclosed externally, operators may harm their bargaining power with shippers, shipping companies, and other competing operators. Therefore, in this research, data was provided by operators on the condition that only unidentifiable information should be disclosed without disclosing raw data shortly.

4.3. Descriptive Statistics

The average total cost of the 13 terminal operators was about 57.3 billion won (KRW), which included a labour cost of 23.1 billion, a capital cost of 19.2 billion, and an operation cost of 15 billion. However, the standard deviation of the total cost reached 43.8 billion and the maximum value exceeded 70 times the minimum value, showing that there were significant differences in the size of terminal operators included in the data. The average container throughput was 1.22 million TEUs; however, the maximum value was 4.63 million TEUs and the minimum value was only 12,000 TEUs. Table 2 summarizes the total cost, costs of each input item, and the container throughput of the 13 container terminal operators examined in this analysis.

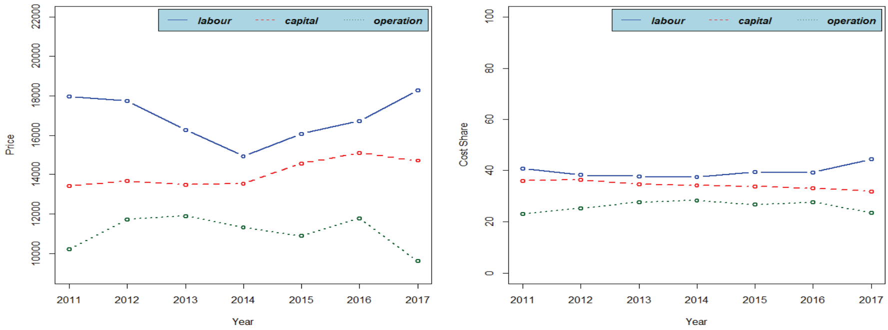
Table 2. Variable descriptive statistics

Category		Average	SD	Min	Max
Total cost (in billion KRW)		57.3	43.8	23.1	176.1
Input item cost (in billion KRW)	Labour	23.1	21.2	0.6	92.9
	Capital	19.2	14.9	0.7	54.3
	Operation	15.0	13.2	0.8	50.5
Container throughput (in million TEUs)		1.22	1.05	0.012	4.63

Source: Author.

Fig. 1 shows the trend of changes in average input prices and cost shares by year during the period 2011~2017. Labour prices gradually declined until 2014 and then began to rise again. The capital cost, which accounts for a large proportion of fixed costs, such as rent and depreciation, did not change significantly. In contrast, the operation cost had been gradually decreasing since 2012. There were no significant annual changes in cost shares. Labour cost accounted for the largest share, followed by capital and operation costs.

Fig. 1. (a) Average input prices by year (b) Average cost shares by year



Source: Author.

5. Results

5.1. Estimated Translog Cost Function

When estimating a cost function and derived demand equations simultaneously under the ITSUR method, it is necessary to exclude one of the derived demand equations to avoid a linear dependency, wherein the sum of the cost shares is 1. Therefore, this paper excludes the share of operation cost. Table 3 shows the estimation results of the translog cost function with the constraints of homogeneity and symmetry conditions. Most of the coefficients are found to be statistically significant. In particular, the coefficients of the second term are significant, showing that the translog form is sufficient and no additional model constraints are necessary for the Cobb-Douglas function. Additionally, the adjusted coefficients of determination for the cost function are calculated to be 0.9764, indicating that the model fits the data sufficiently.

Table 3. Result of estimated translog cost function

Parameter	Estimate	Std.Err.	t-sata.	P-value
β_l	-0.0268	0.0522	-0.51	0.6092
β_{ll}	0.1386	0.0051	27.44	<.0001 ***
β_{lr}	-0.0449	0.0047	-9.49	<.0001 ***
β_{lo}	-0.0937	0.0018	-50.85	<.0001 ***
β_{lq}	0.0280	0.0037	7.60	<.0001 ***
β_r	1.1695	0.0657	17.80	<.0001 ***
β_{rl}	-0.0449	0.0047	-9.49	<.0001 ***
β_{rr}	0.1238	0.0048	25.65	<.0001 ***
β_{ro}	-0.0790	0.0028	-28.34	<.0001 ***
β_{rq}	-0.0610	0.0046	-13.17	<.0001 ***
β_o	-0.1428	0.0426	-3.35	0.0011 ***
β_{ol}	-0.0937	0.0018	-50.85	<.0001 ***

Table 3. (Continued)

Parameter	Estimate	Std.Err.	t-sata.	P-value
β_{or}	-0.0790	0.0028	-28.34	<.0001 ***
β_{oo}	0.1727	0.0023	73.74	<.0001 ***
β_{oq}	0.0330	0.0031	10.83	<.0001 ***
β_{0}	6.1868	0.6597	9.38	<.0001 ***
β_{q}	0.4256	0.0898	4.74	<.0001 ***
β_{qq}	0.0302	0.0062	4.91	<.0001 ***

Note: *, **, *** mean that coefficients of variables are statistically significant under 10%, 5%, 1% critical values respectively.
Source: Author.

The cost function is estimated by assuming that the homogeneity and symmetry conditions hold. Table 4 shows the results of the significance test on the restrictions.

Table 4. Variable descriptive statistics

Restriction		t-stat.	p-value
homogeneity condition	$\beta_l + \beta_r + \beta_o = 1$	0.16	0.8745
	$\beta_{ll} + \beta_{lr} + \beta_{lo} = 0$	-1.10	0.2733
	$\beta_{rl} + \beta_{rr} + \beta_{ro} = 0$	-2.52	0.0111 **
	$\beta_{ol} + \beta_{or} + \beta_{oo} = 0$	0.47	0.6407
	$\beta_{lq} + \beta_{rq} + \beta_{oq} = 0$	-0.06	0.9502
symmetry condition	$\beta_{lr} = \beta_{rl}$	3.05	0.0020 ***
	$\beta_{lo} = \beta_{ol}$	-5.07	<.0001 ***
	$\beta_{ro} = \beta_{or}$	-8.12	<.0001 ***

Note: *, **, *** mean that coefficients of variables are statistically significant under 10%, 5%, 1% critical values respectively.
Source: Author.

5.1.1. Economies of Scale

The economies of scale are analyzed using the estimates of the translog cost function presented in Table 3. First, cost elasticity is calculated by applying the parameter estimates and the average input prices and container throughput for each year and operator, respectively. Subsequently, Equation (A1) is used to calculate the economies of scale. Table 5 shows the economies of scale by year and terminal operator.

The above results show that the container terminals in Korea achieved economies of scale in all periods and for all operators, implying the industry has not yet reached the point where economies of scale are disappearing. This means that the size of container terminals in Korea must be further expanded to fully enjoy economies of scale.

Table 5. Result of economies of scale by year and operator

Year	Cost elasticity	Economies of scale	Operator	Cost elasticity	Economies of scale
2007	0.6355	0.3645	A	0.6301	0.3699
2008	0.6458	0.3542	B	0.6331	0.3669
2009	0.6441	0.3559	C	0.6285	0.3715
2010	0.6421	0.3579	D	0.6393	0.3607
2011	0.6384	0.3616	E	0.6182	0.3818
2012	0.6410	0.3590	F	0.6261	0.3739
2013	0.6421	0.3579	G	0.6478	0.3522
2014	0.6415	0.3585	H	0.6608	0.3392
2015	0.6407	0.3593	I	0.6125	0.3875
2016	0.6415	0.3585	J	0.6573	0.3427
2017	0.6433	0.3567	K	0.6690	0.3310
-	-	-	L	0.6229	0.3771
-	-	-	M	0.6408	0.3592

Source: Author.

5.1.2. Price Elasticity and Elasticity of Substitution

Table 6 presents the results regarding the price elasticities of demand as defined in Equation (A2). The diagonal elements of the price elasticity matrix indicate its own-price elasticity and confirm that the values for all three factors are negative. In contrast, all non-diagonal elements exhibiting cross-price elasticity have positive values. In particular, the price elasticities of labour and capital are relatively high. For example, 0.2092, the 1×2 element of the price elasticity matrix, can be interpreted as the increase in labour demand by 0.2092% when the price of capital rises by 1%. However, the absolute values of all the elements in the price elasticity matrix are less than 1. Thus, changes in the demand for inputs are found to be inelastic to price changes.

Table 6. Result of price elasticities of demand

	Labour	Capital	Operation
Labour	-0.2537	0.2092	0.0444
Capital	0.2602	-0.2933	0.0332
Operation	0.0637	0.0382	-0.1019

Source: Author.

Table 7 presents the results regarding the elasticity of substitution, an index that measures whether replacements among production input elements are easy while maintaining a constant level of production. The Hicks-Allen elasticities of substitution, estimated using Equation (A3), appear as a symmetric matrix. The non-diagonal elements in the matrix are all positive, which means that it is possible to partially replace the input elements of labour, capital, and operation. However, since the observed elasticities of substitution are all less than 1, the possibility of substitution among inputs remains low.

Table 7. Result of Hicks-Allen elasticities of substitution

	Labour	Capital	Operation
Labour	-0.6346	0.6509	0.1593
Capital	0.6509	-0.9125	0.1189
Operation	0.1593	0.1189	-0.3654

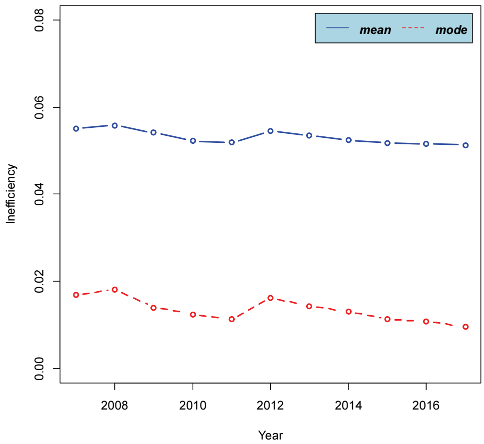
Source: Author.

5.2. Stochastic Cost Frontier Analysis Results

5.2.1. Estimated Cost Efficiency

Applying a total of 116 observations from 13 operators to Equations (24) and (25), the cost efficiency for each observation is estimated. When the mean of $u|e$ in Equation (24) is applied, the overall average cost inefficiency is 0.0528, the standard deviation is 0.0093, the minimum value is 0.0315, and the maximum value is 0.0849. In contrast, when the mode of $u|e$ in Equation (25) is used, the overall average cost inefficiency is 0.0131, the standard deviation is 0.0149, the minimum value is 0, and the maximum value is 0.0710. Overall, the cost inefficiency is very low and the deviation between observations is not significant, implying that the cost inefficiency of terminal operators is not significantly high compared to that of the leading companies.

Fig. 2. Average cost inefficiency by year



Source: Author.

Meanwhile, results regarding the average cost inefficiency by year and operator are shown in Figure 2 and Table 8. As shown in Figure 2, there are no dramatic changes in the cost inefficiency values for each year, with the values gradually decreasing since 2012. This shows that the cost inefficiencies of terminal operators gradually decrease in comparison with leading companies, indicating improved efficiency. Regarding the average cost inefficiency by the operator, Operator I is found to be the most cost-efficient, followed by Operators F and M.

Table 8. Result of average cost inefficiency by year and operator

Year	SFA		DEA	Operator	SFA		DEA
	Mean	Mode			Mean	Mode	
2007	0.0551	0.0169	0.1080	A	0.0573	0.0186	0.1712
2008	0.0558	0.0182	0.1089	B	0.0566	0.0174	0.1442
2009	0.0541	0.0140	0.1398	C	0.0513	0.0042	0.0643
2010	0.0522	0.0124	0.1331	D	0.0532	0.0093	0.1234
2011	0.0518	0.0113	0.1272	E	0.0564	0.0175	0.0471
2012	0.0546	0.0163	0.1363	F	0.0433	0.0000	0.0326
2013	0.0534	0.0143	0.1045	G	0.0540	0.0113	0.1909
2014	0.0524	0.0131	0.0927	H	0.0536	0.0104	0.1375
2015	0.0517	0.0113	0.0815	I	0.0361	0.0000	0.0000
2016	0.0516	0.0108	0.0805	J	0.0603	0.0256	0.0322
2017	0.0513	0.0096	0.0703	K	0.0589	0.0229	0.0969
-	-	-		L	0.0724	0.0502	0.2503
-	-	-		M	0.0440	0.0000	0.0892

Note: DEA(Data Envelopment Analysis) scores are estimates of cost inefficiency using cost-minimization DEA method under the assumption of variable returns to scale.

Source: Author.

In addition, the estimated cost inefficiencies obtained from the stochastic cost frontier analysis are compared to those from the DEA. The Pearson's correlation coefficient was found to be 0.6235, showing the results of the two methods were analyzed to be in great agreement. This shows empirically that the overall performance of SFA is equivalent to that of DEA. In addition, although DEA is often preferred because of its ease of use, it can be seen that SFA with a strong theoretical background can also be fully utilized.

5.2.2. Determinants of Cost Efficiency

Table 9 presents the results of the Tobit regression model presented in Equation (26). The p-values for each of the coefficients in the model are given. Although two of the six coefficients are found to be not statistically significant, the likelihood ratio test for overall goodness-of-fit is associated with a p-value of less than .0001, indicating that the overall effect of the model is statistically significant. Meanwhile the coefficient of determination, i.e., 0.6393, implies that the model fits the data relatively well.

Table 9. Result of the Tobit regression model

Parameter	Estimate	Std.Err.	Z-stat.	p-value	
β_0	0.0604	0.0028	21.676	<.0001	***
β_1	-4.72E-09	1.09E-09	-4.324	<.0001	***
β_2	1.47E-05	2.39E-06	6.151	<.0001	***
β_3	0.0017	0.0024	0.719	0.4723	
β_4	-0.0055	0.0022	-2.534	0.0113	**
β_5	2.41E-05	4.21E-05	0.573	0.5669	
β_6	-0.0384	0.0051	-7.527	<.0001	***

Note: *, **, *** mean that coefficients of variables are statistically significant under 10%, 5%, 1% critical values respectively.

Source: Author.

The implications of the significance test for each coefficient are summarized as follows. First, the coefficient of container throughput has a negative value and is significant at the 1% significance level. This indicates that cost inefficiency decreases as individual operators increase their container throughput, assuming that the inputs of other variables are fixed. Second, the coefficient of quay length has a positive value and is also significant at the 1% significance level. In general, quay length is regarded as an indicator of the size of a terminal operator. It is considered that the larger the size of a terminal, the higher its efficiency. However, since an increase in quay length mainly leads to an increase in capital cost, the results imply that terminal operators in Korea are not increasing their output cost-effectively as compared to the increase in costs due to the increase in quay length. Third, the coefficient of ownership type is estimated to be 0.0017; however, this value is not statistically significant. This indicates that there is no difference in cost inefficiency between leased and private terminals. Fourth, the coefficient of the direct employment to labour cost ratio is significant at the 5% significance level. Since the sign of the coefficient is negative, it can be interpreted that the cost inefficiency decreases as the proportion of direct employment cost to outsourced service cost increases. Fifth, the coefficient of the amount of standard equipment is not statistically significant, implying that expanding the amount of equipment does not always lead to an improvement in cost efficiency. Lastly, the coefficient of the cost share of labour is statistically significant at the 1% significance level. In the service industry, the high proportion of labour cost in a given year usually indicates an increase in output for that year. If economies of scale exist in an industry, more output leads to decreased labour cost per output unit, thus improving cost efficiency.

6. Conclusions

As the growth of global trade slows down, competition at both the inter-port and intra-port levels has intensified. Environmental changes in global container terminals, such as the emergence of mega-ships, strengthened regulations, and port automation and smartization, are causing additional physical investment expenditure in the industry. In the past, securing volume (maximizing production) through the expansion of large-scale facilities and equipment was an urgent task to strengthen competitiveness. However, in the global environment, there are limits to the improvement in the competitiveness of ports that can be derived from simply increasing investment in physical infrastructure. Therefore, in order to improve port competitiveness more efficiently, it is vital to consider not only quantitative but also qualitative factors.

In particular, it is necessary to understand the characteristics of the port industry and implement measures to improve cost efficiency by conducting a cost analysis of container terminal operators, one of the main stakeholders in the port industry. Container terminal operators can check the cost structure and economies of scale through cost function analysis, and it is useful for identifying unnecessary input factors to derive implications for efficient operation. Hence, in addition to simply analyzing the cost structure and measuring efficiency in previous studies, this study further identifies the determinants affecting cost inefficiency through the Tobit model. This would be a starting point for not only the competitiveness of individual ports but also securing the preoccupation of the global supply chain in Korea by reducing shipping costs.

The analysis showed that the economies of scale figures were all above 0.0 and below 0.4 by year and terminal operators, respectively. This implies that the analyzed container terminals in Korea can achieve higher operational efficiency. The results of SCF analysis showed that cost inefficiency by year has been consistently decreasing since 2012. This means that the cost inefficiency of domestic container terminal operators is gradually decreasing compared to leading operators, thus improving efficiency. More specifically, the overall value of the cost inefficiency of individual terminal operators did not exceed 0.1, indicating that most firms were efficient, with Operator I being the most cost-efficient, followed by Operators F and M. Furthermore, a high-level Pearson correlation of 0.6244 was indicated between the results of DEA and SFA approaches.

The container throughput, quay length, direct employment to labour cost ratio, and proportion of labour cost were all identified as the determinants of cost inefficiency in container terminals and had statistically significant values. Factors that negatively affected inefficiency, i.e., the greater the volume of input, the higher the terminal efficiency, were container throughput, direct employment to labour cost ratio, and proportion of labour cost in the total cost. Specifically, cost inefficiency could improve as the proportion of direct employment costs to outsourcing services increases. In other words, terminal operators can enhance terminal productivity by directly hiring workers with professional skills and high productivity, instead of providing relatively high wages and job security. In contrast, a factor that positively affected inefficiency was quay length. This suggests that increased investment in physical infrastructure, such as quay length, is less correlated with container terminal efficiency. This finding is consistent with the results obtained by Tongzon (2001), Wang et al. (2003), and Coto-Millan et al. (2000).

The political implications of this study are the following three. First, it is to establish a long-term manpower pool to secure stable skilled technical employees. The result that the higher the proportion of direct employment, the lower the cost inefficiency indicates that individual operators can improve cost efficiency through rational manpower management. They can achieve prolonged cost savings by strengthening the vocational education system and establishing cooperation with labour unions to reduce the mismatch in manpower supply and demand. Second, it is worth considering the adoption of a hybrid liner terminal system. The system optimally operates facilities in units of ports rather than individual terminals by delegating the authority to negotiate rates and berths for all terminals to a virtual integrated entity. It prevents the physical integration of terminal operators, which is difficult to solve in a short period of time, and at the same time has the effect of expanding the size of port terminal operators, thereby realizing economies of scale. Through this operating system, shipping companies can expect reduced waiting or lead time, seamless work tasks of port-related services, and reduced operating costs, and the perspective of terminals operators have advantages of increasing container volume, strengthening bargaining power, and increasing profits through optimization of facility utilization. In addition, port authorities can secure publicity. Lastly, it is the construction of a statistical data system in a collective and unified form. Currently, the financial statements of operators disclosed through the DART (the electronic disclosure system of the Financial Supervisory Service) have different ways to present and standards for each operator, making it difficult to collect consistent and continuous data. Accordingly, it is effective for the Ministry of Oceans and Fisheries or the Port Authority, a central administrative agency, to periodically accumulate the raw data by assigning the terminal operator the obligation to provide the necessary information. By doing this, it is possible to present a reasonable strategy or policy to enhance the competitiveness of container ports.

This study aimed to identify ways in which the competitiveness of container terminals in Korea could be improved in a situation of increasing uncertainty due to global environmental changes by using mathematical economic analysis. In terms of the academic significance of this study, few attempts were made to comprehensively analyze the cost structure of Korean container terminals. Therefore, this study has academic value in that it explores determinants of the efficiency of container terminals in Korea by estimating a cost function and conducting a cost-efficiency analysis. Moreover, this paper not only adapted the SCF model to container ports but can also help decision-makers to consider the managerial implications by using the financial statements of container terminal operators to enhance their cost competitiveness in the global market. Last but not least, this study attempted to subdivide the input factors of terminal operation by dividing labour cost items into direct employment and external (outsourcing) employment. The result has enabled terminal operators to derive more significant strategies for labour cost factors. However, this paper does not consider suppliers' costs. Therefore, it is necessary for future research to pay attention to this factor. For example, even if an individual operator is cost-efficient, it may still be inefficient in terms of its overall profit, considering the demand sector. Additionally, due to regulatory and structural changes in the port industry, the managerial decisions of individual operators may be contradictory to the results of this paper. Therefore, to develop more realistic policies that can enhance the competitiveness of the port industry, further analysis is necessary to comprehensively consider areas that individual operators cannot control, such as demand and regulations.

Appendix A

1. Economies of scale

Economies of scale are the cost advantages obtained by an industry due to its scale of operations and based on the relationship between the amount of output and cost per unit of output. Economies of scale can be estimated using the below formula:

$$\varepsilon_c = 1 - \frac{\partial lnC}{\partial lnq} = 1 - (\beta_q + \beta_{qq} lnq + \textstyle\sum_n \beta_{nq} ln\omega_n) \qquad \text{(A1)}$$

2. Price elasticity

Price elasticity is an index that measures the percentage change in demand when price changes by 1%. The equations for own-price elasticity and cross-price elasticity are as follow:

$$\begin{aligned} \eta_{nm} &= \frac{\beta_{nm}}{s_n} + s_m \ \text{ for all } n \neq m \ \text{ and} \\ \eta_{nn} &= \frac{\beta_{nn}}{s_n} + s_n - 1 \ \text{ for all } n \end{aligned} \qquad \text{(A2)}$$

3. Hicks-Allen elasticity of substitution

Elasticity of substitution is an index to measure how easy to replace a input element with another while maintaining the production level at a constant level. Hicks-Allen elasticity of substitution is one of the methods widely used to estimate the elasticity of substitution, given by the following formula:

$$\sigma_{nm}^{HA} = \frac{1}{s_n s_m}\beta_{nm} + 1 \quad \text{for all } n \neq m \quad \text{and}$$
$$\sigma_{nn}^{HA} = \frac{1}{s_n^2}\beta_{nn} s_n^2 - s_n \quad \text{for all } n \qquad \text{(A3)}$$

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