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Application of DEA and SFA on the Measurement of Operating Efficiencies for 27 International Container Ports

Lie-Chien Lin
Associate Professor
Department of Logistics Management
National Kaohsiung First University of Science and Technology
2, Juoy Rd. Kaohsiung, Taiwan
Fax: +886-7-6011040
E-mail: lclin@ccms.nkfust.edu.tw

Lih-An Tseng
Warehouse Officer
Research and Development Department
Kaohsiung Harbor Bureau, MOTC
62, Linhai 2nd Rd. Kaohsiung, Taiwan
Fax: +886-7-5331594
E-mail: p15482@mail.khb.gov.tw

Abstract: The operating efficiency of a port is the critical element for its competitiveness in the international market. Previous research for port operating efficiencies measurement usually adopts either DEA or SFA method, but not both of them. Therefore, this paper is aimed to measure the operating efficiencies of 27 international container ports from 1999 to 2002 by applying both SFA and DEA models with three inputs and single output. The result shows that the total average of operating efficiency scores are $SFA_{TR}(0.8217) > SFA_{CD}(0.7979) > DEA_{BCC}(0.7075) > DEA_{CCR}(0.6150)$, and Hong Kong port demonstrates the best performance in each model. Also, three hypotheses for port performance, including the geographical location of port, port administrative structure, and national economic growth rate, are performed in this paper. The results show that the operating efficiencies are not significantly different with the previous two hypotheses; however, the last hypothesis shows significant difference in DEA model.

Key Words: Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), Port Operating Efficiency, International Container Port.

1. INTRODUCTION

The efficiency of port operation is an important indicator of economic development since more than 80% of the global international trade is conducted by way of maritime transportation. In order to assist the container ports to identify their own strengths, weakness, and the potentially existent threats and opportunities in a competitive environment, it is essentially necessary and critically important to select a set of impartial and objective measures for introducing the efficiency evaluation.

This paper aims to provide efficiency measurement of international container ports by applying two different frontier methods, i.e. DEA (Data Envelopment Analysis) and SFA (Stochastic Frontier Analysis), for same panel data set of container ports. The paper is organized as follows. Section 2 discusses the literatures for port operating efficiency. Section 3 presents the methodologies of DEA and SFA. Section 4 assesses the efficiency ratings of 27 international container ports. Finally, the main results and suggestions for future research are summarized.

2. PORT OPERATING EFFICIENCY

The previous literature about the ports' operating efficiency is relatively modest in comparison to the literature available on other infrastructure activities (Estache, Gonzalez, and Trujillo, 2002). The activities of port production are complex, including pilotage, towage, berthing, cargo and container handling, warehousing, and logistics. Therefore, the improvement for ports' operating efficiency could include: improvement in efficiency through private sector management skills, enhancement of service quality through improved commercial responsiveness, reduction in the fiscal burden of loss making public enterprises, a reduction in the financial demands on central and local government through access to private sector capital, and additional revenue streams (McDonagh, 1999). Dowd and Leschine (1990) propose that, from the standpoint of container terminal productivity, each port's player has his own self-interest and his own definition of productivity. As most port operations have been privatized, private operators aimed to maximize output (container throughput) and operating efficiencies (Heaver *et al.*, 2000).

The operating efficiency of a container port is a mixture of multiple inputs and multiple outputs, which is in compliance with the characteristics of DEA. The DEA with mathematical programming techniques has applied to the measurement of port efficiency for hypothetical port data by Roll and Hayuth (1993). Since then there have numerous papers that have extended and applied alternative models of the DEA methodology, including BCC, Additive, FDH (Free Disposal Hull), *etc*. Martínez, Diaz, Navarro, and Ravelo (1999) apply BCC model to assess global efficiencies of 26 Spain ports using 5 observations for each port from 1993 to 1997 and to examine efficiency evolution of individual port. Tongzon (2001) uses CCR and additive models to make an international comparison of technical efficiencies in 4 Australian and 12 other international container ports in 1996. Wang, Song, and Cullinane (2003) use the CCR, BCC, and FDH models to evaluate production efficiencies of 57 terminals within 28 container ports for year 2001, and find that the FDH model is the best model of port efficiency measurement. Valentine & Gray (2001) also applies CCR model to evaluate relative efficiencies of 31 global container ports in 2001, and adopts cluster analysis to determine whether there is a particular type of ownership and organizational structure that leads to higher efficiency rating.

On the other hand, privatization of container port operation has been prevail in recent years, and private terminal operators aim to maximize profit, which is in compliance with the characteristics of stochastic frontier analysis (SFA). SFA is based on the quantitative economy theory that has been applied to the measurement of technical efficiency by Liu (1993) for 28 Britain ports during 1983~1990. Estache *et al.* (2002) applies SFA with Cobb-Douglas and Translog production function for the half-normal and truncated-normal distributions to estimate production efficiencies of 11 Mexico container ports with two inputs (including labor and capital) and one output (volume of merchandise handled) from 1996 to 1999. Cullinane, Song, and Gray（2002）uses the SFA method with Cobb-Douglas production function for the half-normal, exponential, and truncated-normal distributions to estimate production efficiencies of 15 Asian container ports/terminals with unbalanced-panel data between 1989 and 1998. The research on ports' operating efficiency by applying DEA or SFA is summarized as shown on Table 1.

Additionally, both DEA and SFA methods are also applied simultaneously in transport industry. For example, Lan and Lin (2003) also apply both DEA and SFA methods to estimate the relative productive efficiency for 74 railway systems in 1999, and use the two-stage method of DEA with CCR and BCC models and the SFA method with Translog production function for the half-normal and truncated-normal distributions. The empirical results show that the average technical efficiency is $SFA_{TN} > SFA_{HN} > DEA_{BCC} > DEA_{CCR}$, and Translog production function is more suitable than Cobb-Douglas function to specify the relationship between input and output of railway industry and the assumption of constant returns to scale does not apply to railway industry.

Table 1. The Applications of DEA and SFA Methods on Ports Operating Efficiency

Author	Data Description	Model Evaluation	Input/Output Variables	Efficiency Concept
Roll and Hayuth (1993)	20 ports in the world Cross-section hypothetical port data	DEA	Input: manpower, capital, cargo uniformity. Output: total cargo throughput, level of service, users' satisfaction, ship calls.	Technical efficiency, Sensitivity.
Martínez, Diaz, Navarro, and Ravelo (1999)	26 Spanish ports Panel data in 1993~1997	DEA with BCC model	Input: labor expenditures, depreciation charges, other expenditures Output: Total cargo throughput, revenue for the rent of port facilities	Global efficiency, Slack analysis
Tongzon [2001]	4 Australian and 12 other international container ports Cross-section data 1996	DEA with CCR and Additive DEA models (constant returns to scale and variable returns to scale)	Input: number of cranes, number of container berths, number of tugs, terminal area, delay time, and labor Output: annual container throughput, and ship working rate	Technical efficiency, Slack analysis
Valentine and Gray (2001)	31 world ports Cross-section data 1998	DEA with CCR model	Input: total length of berth, and container berth length Output: container throughput, total cargo throughput	Technical efficiency
Wang, Song, and Cullinane (2003)	28 world ports with 57 container terminals Cross-section data 2001	DEA with CCR, BCC, and FDH models	Input: quay length, terminal area, and number of quayside gantry, yard gantry, and straddle carrier Output: container throughput	Technical efficiency
Liu (1995)	28 UK ports Panel data 1983~1990	SFA with stochastic translog frontier production function (SPF)	Input: labor by total wage payments, and capital by the net-book value of fix asset Output: total turnover	Technical efficiency
Cullinane, Song, and Gray (2002)	15 Asian container ports Panel data 1989~1998	SFA with Cobb-Douglas production function for the half-normal, exponential, and truncated-normal distributions	Input: terminal quay length, terminal area, and number of cargo handling equipments Output: annual container throughput	Productive efficiency
Estache, Gonzalez, and Trujillo (2002)	11 Mexico ports Panel data 1996~1999	SFA with Cobb-Douglas and Translog production function for the half-normal and truncated-normal distributions	Input: the number of workers, length of docks Output: the volume of handling merchandise	Technical efficiency

While the slack analysis of DEA provide insight for add up or reduce input resources to improve efficiency scores, the SFA method focuses on the economic justification and hypothesis testing. A combination of both DEA and SFA support management to have a more comprehensive understanding of the operating efficiency of international container ports and to identify the reasoning of efficiency and causes of inefficiency. Furthermore, both two methods are frontier function to measure efficiencies of all firms with cross-section and panel data, and many container ports' operations may have characteristics of consistency for DEA and SFA. Therefore, we would adopt both DEA and SFA methods to evaluate container ports' operating efficiency.

However, previous research on ports' efficiency usually adopts either DEA or SFA method, but not both of them. Therefore, this paper is aimed to measure the relative operating efficiencies of the 27 international container ports from 1999 to 2002 by first applying SFA with Cobb-Douglas and Translog production function for the truncated-normal distribution, and secondly by applying DEA with CCR and BCC models for panel data.

3. METHODOLOGIES

3.1 Data Envelopment Analysis (DEA)

The DEA method is first introduced by Charnes, Cooper, and Rhodes (1978) and is called CCR model. It is based on Farrell (1957) theory of using a non-parametric piece-wise-linear technology and combined with mathematical programming for efficiency rating. The CCR model used constant returns to scale (CRS) concept to assess relative productive efficiencies of decision making units (DMUs) with multiple inputs and outputs. The CCR model assumes *m* inputs, *s* outputs and *n* DMUs, respectively. The DMU_k is express as:

$$\text{Max} \qquad h_k = \frac{\sum_{r=1}^{s} U_r Y_{rk}}{\sum_{i=1}^{m} V_i X_{ik}} \tag{1}$$

$$s.t. \qquad \frac{\sum_{r=1}^{s} U_r Y_{rj}}{\sum_{i=1}^{m} V_i X_{ij}} \leq 1 \qquad ; j = 1,2,\ldots, n$$

U_r, V_i >0; $r = 1,2, \ldots,s$; $i = 1,2, \ldots,m$;

where: h_k is relative efficiency of the *k*th DMU;
Y_{rj} is *r*th outputs of the *j*th DMU;
X_{ij} is *i*th inputs of the *j*th DMU;
U_r is a weight of *r*th output;
V_i is a weight of *i*th input.

According to formula (1), the relative efficiency scores of CCR model are the maximum of a ratio of weighted outputs to weighted inputs (Charnes *et. al.*, 1978). Because formula (1) is a linear fractional programming problem, it has a linear programming dual that can be transformed as follows:

$$Min \qquad h_k = \theta - \varepsilon \left[\sum_{r=1}^{s} s_r^{+} + \sum_{i=1}^{m} s_i^{-} \right] \tag{2}$$

$$s.t. \quad \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- \leq \theta X_{ij}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ \geq Y_{rj}$$

$$\lambda_j \geq 0,\ s_r^+,\ s_i^- \geq \varepsilon \geq 0;\ \forall\, i, r, j$$

$r = 1, 2,\ldots, s$; $i = 1, 2,\ldots, m$; $j = 1, 2, \ldots, n$

ε is a small positive number;

λ_j is a weight of jth DMU;

s_r^+ is a slack variable of rth output;

s_i^- is a slack variable of ith input.

In 1984, since CCR model assumed DMU to be constant returns to scale for restriction of production possible set, the Banker, Charnes, and Cooper (BCC model) relaxes this restriction to be variable returns to scale (VRS) model, and evaluates technical efficiency and scale efficiency of DMU. BCC model adds the convexity restriction ($\sum_{j=1}^{n} \lambda_j = 1$). The linear programming dual of BCC model is represent by:

$$Min \quad \theta - \varepsilon \left[\sum_{r=1}^{s} s_r^+ + \sum_{r=1}^{m} s_i^- \right] \tag{3}$$

$$s.t. \quad \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- \leq \theta X_{ij}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ \geq Y_{rj}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j,\ s_r^+,\ s_i^- \geq 0;\ \forall\, i, r, j;\ r = 1, 2,\ldots, s;\ i = 1, 2,\ldots, m;\ j = 1, 2, \ldots, n$$

3.2 Stochastic Frontier Analysis (SFA)

The SFA is a parametric method and is based on the quantitative economy theory. According to Farrell (1957) theory of efficiency measurement, Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) independently constructed an error structure of stochastic frontier analysis to measure productive efficiency of firm.

Therefore, this paper applies the SFA models of Cobb-Douglas and Translog production function with truncated-normal distribution for analysis of 27 international container ports' operating efficiency by adopting panel data from 1999 to 2002. This model with three inputs and single output may be expressed as formula (4) and formula (5), respectively:

$$\ln y_{it} = \beta_0 + \beta_1 \ln x_{1it} + \beta_2 \ln x_{2it} + \beta_3 \ln x_{3it} + v_{it} - u_{it}, \quad i=1,2,\ldots,27;\ t=1,2,3,4; \tag{4}$$

$$\ln y_{it} = \beta_0 + \beta_1 \ln x_{1it} + \beta_2 \ln x_{2it} + \beta_3 \ln x_{3it} + \beta_4 (\ln x_{1it})^2 + \beta_5 (\ln x_{2it})^2 +$$

$$\beta_6(\ln x_{3it})^2 + \beta_7(\ln x_{1it})(\ln x_{2it}) + \beta_8(\ln x_{1it})(\ln x_{3it}) + \beta_9(\ln x_{2it})(\ln x_{3it}) + v_{it} - u_{it},$$

$$i=1,2,\ \cdots,27;\ t=1,2,3,4; \qquad (5)$$

where: y_{it} is the output of the *i*th port in the *t*th time period;

x_{1it}, x_{2it}, x_{3it} are the input items of the *i*th port in the *t*th time period;

v_{it} are random variables which are assumed to be *iid* $N(0,\sigma_v^2)$, and independent of the u_{it};

$u_{it} = \{\exp[-\eta(t-T)]\}u_i$, i=1,2, …,27; t=1,2,3,4 ; where the u_{it} are non-negative random variables which are assumed to account for time-varying technical inefficiency in production and are assumed to be *iid* as truncations at zero of the $N(\mu,\sigma_u^2)$ distribution;

$\varepsilon_{it} = v_{it} - u_{it}$, ε_{it} is an error item (or disturbance item); and

β_k is an unknown parameters to be estimated k = 0, 1,…, 9;

η is an unknown scalar parameter to be estimated.

The truncated-normal distribution of the technical inefficiency effect (u_{it}) is $E[u_{it}|\varepsilon_{it}]$ which is the "mean productive inefficiency" for the *i*th container port at any time *t*. It is represented by:

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi\left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)}{\Phi\left(-\frac{\varepsilon_{it}\lambda}{\sigma}\right)} - \left(\frac{\varepsilon_{it}\lambda}{\sigma} + \frac{\mu_i}{\sigma\lambda}\right)\right] \qquad (6)$$

where $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, $\mu_i = -\varepsilon_i\sigma_u^2/\sigma^2$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cumulative distribution and density function. Finally, individual (conditioned) technical efficiency scores will be $TE_i = e^{-E[u_{it}|\varepsilon_{it}]}$

Coelli *et al*. (1997) suggest the one-side generalized likelihood-ratio test to determine the technical inefficiency effect (u_{it}) under both the null and alternate hypotheses. This can be calculated through the generalized likelihood ratio-test that express as follows:

$$LR = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln[L(H_0)]\} - \ln[L(H_1)] \qquad (7)$$

where L(H_0) and L(H_1) are the values of the likelihood function under the null hypothesis H_0: $\gamma = \sigma_u^2/\left(\sigma_v^2 + \sigma_u^2\right) = 0$ and alternative hypothesis H_1: $\gamma > 0$, respectively. This paper will compare with the LR statistic, and find the $\chi^2(2\alpha)$ value (the degree of freedom are restricted sizes of the null hypothesis), then determines to accept or reject the null hypothesis.

3.3 Comparison of SFA and DEA Methods

Although both SFA and DEA methods are efficiency frontier analysis and are originally introduced to the efficiency concepts developed by Farrell (1957), there are essential differences between the econometric approach and mathematical programming methods to construction of a production frontier and calculation of efficiency relative to the frontier as shown in Table 2. DEA is a non-parametric approach and is suited to measure efficiencies of deterministic industry for multiple inputs/outputs information. DEA has been applied to assess performance of non-profit organizations or branches, such as school, hospitals, universities, courts, public sector, agriculture, *etc* (Doyle & Green, 1994; Coelli, 1996). But in recent yeas, more and more scholars have applied it to evaluate performance of profit organizations. On the other hand, SFA is a parametric approach, and is suited to measure efficiencies of stochastic industry for input/output information. SFA needs to assume a production function of the usual regression form and a distribution type of error item which is equal to the sum of two components, the first part is symmetric and captures statistical noise such as weather, luck, machine breakdown and other events beyond the control of firms, and the second part represents technical inefficiency of firms. SFA has been applied to measure performance of profit organizations.

Table 2. The Comparison of SFA and DEA Methods

	Stochastic Frontier Analysis (SFA)	Data Envelopment Analysis (DEA)
Consistency	Both DEA and SFA methods are efficiency frontier analysis, and are similar in that they determine a frontier and inefficiency based on that frontier.	
Characteristic	Parametric method	Non-Parametric method
Efficiency measurement	Technical efficiency, scale elasticity, scale efficiency, allocative efficiencies, technical change and TFP change	Technical efficiency, scale elasticity, scale efficiency, allocative efficiencies, congestion efficiencies, technical change and TFP change
Strengths	1. It doesn't assume that all firms are efficient in advance. 2. SFA makes accommodation for statistical noise such as random variables of weather, luck, machine breakdown and other events beyond the control of firms, and measures error. 3. It doesn't need to price information available. 4. It is capable to hypothesis test. 5. To estimate the best technical efficiencies of firm, rather than average technical efficiencies of firm.	1. It doesn't assume that all firms are efficient in advance. 2. It could handle with efficiency measurement of multiple inputs and multiple outputs. 3. It doesn't need to price information available. 4. It does not need to assume function type and distribution type. 5. While sample size is small, it is compared with relative efficiency. 6.Both the CCR and BCC models have nature of unit invariance.
Weakness	1. It needs to assume functional form and distribution type in advance. 2. It needs enough samples to avoid lack of degree of freedom. 3. The assumed distribution type is sensitive to assessing efficiency scores.	1. It doesn't make accommodation for statistical noise such as measure error. 2. It isn't capable to hypothesis test. 3. When the newly added DMU is an outlier, it could affect the efficiency measurement.
Application	It has applied to measure performance of profit organizations.	It has applied to assess performance of non-profit organizations or branches of firm.

Source: Coelli *et. al* .(1997), Lan *et al.* (2003).

4. EMPIRICAL APPLICATION TO 27 CONTAINER PORTS

4.1 Empirical Results

For this research, the leading container ports in 2002 are initially selected. Because some ports data are not available, including Tianjin, Qingdao, and Guangzhou of China, and Nagoya of Japan, this paper selects 27 international container ports in 18 areas as shown in Table 3. These port data are collected mainly from the *Containerisation International Yearbook* (various issues) and annual statistical data of various port authorities from 1999~2002. There are totally 108 observations.

Table 3. The Selected International Container Ports

No.	2002 Ranking (2001)	Port	Area	2002 (TEUs)	2001(TEUs)	%
1	1(1)	Hong Kong	China	19,144,000	17,800,000	8%
2	2(2)	Singapore	Singapore	16,800,000	15,520,000	8%
3	3(3)	Busan	Korea	9,453,356	8,070,000	17%
4	4(5)	Shanghai	China	8,611,890	6,334,400	36%
5	5(4)	Kaohsiung	Taiwan	8,493,000	7,540,524	13%
6	6(8)	Shenzhen	China	7,613,754	5,076,435	50%
7	7(6)	Rotterdam	Nederland	6,515,449	6,096,502	7%
8	8(7)	Los Angeles	USA	6,105,864	5,183,520	18%
9	9(9)	Hamburg	Germany	5,373,999	4,689,000	15%
10	10(11)	Antwerp	Belgium	4,777,151	4,218,176	13%
11	11(12)	Port Klang	Malaysia	4,533,212	3,759,512	21%
12	12(10)	Long Beach	USA	4,524,038	4,462,958	1%
13	13(13)	Dubai	UAE	4,194,264	3,501,820	20%
14	14(14)	New York/New Jersey	USA	3,749,014	3,316,275	13%
15	16(17)	Tokyo	Japan	3,028,090	2,829,999	7%
16	17(15)	Bremen/Bremerhaven	Germany	2,982,141	2,895,283	3%
17	18(20)	Gioia Tauro	Italy	2,954,571	2,488,332	19%
18	19(22)	Manila	Philippine	2,943,000	2,790,000	5%
19	20(21)	Laem Chabang	Thailand	2,749,194	2,369,995	16%
20	21(16)	Felixstowe	UK	2,700,000	2,650,000	2%
21	22(19)	Tanjunk Priok	Indonesia	2,700,000	2,524,375	7%
22	23(27)	Tanjung Pelepas	Malaysia	2,668,512	2,050,000	30%
23	25(23)	Yokohama	Japan	2,301,000	2,255,882	2%
24	26(24)	Algeciras	Spain	2,229,141	2,151,770	4%
25	28(25)	Kobe	Japan	1,992,949	2,010,342	-1%
26	29(40)	Jawaharlal Nehru	India	1,946,000	1,462,000	33%
27	31(30)	Keelung	Taiwan	1,918,598	1,815,854	6%

Source: *Containerisation International*, March 2004.

To be in compliance with characteristic of consistency for both DEA and SFA, this paper adopts single output and multiple inputs, i.e., this paper initially selected four inputs of container port infrastructures, including number of container gantry cranes, quay length, number of stevedoring equipments, and container yard, and single output of container throughput as shown in Table 4.

Table 4. Description of Initially Selected Input/Output Variables

Variables	Unit	Description
Inputs	Container gantry cranes X_1 (units)	Number of container gantry cranes
	Container quay length X_2 （kilometer）	Total length of container berth
	Stevedoring equipment X_3 (units)	Number of stevedoring equipment in container yard
	Container yard X_4 (hectare)	Area of container yard
Outputs	Container throughput Y (10 thousand TEUs)	Annual container throughput

These inputs are key factors of port/terminal operation, and are related to container throughput of port. To confirm the correlation between selected inputs and outputs, this paper applies analysis of Pearson correlation coefficients at 0.05 significant level (two-tailed), and find that output variable of container throughput (Y) highly correlates with inputs of container gantry cranes (X_1), container quay length (X_2), and stevedoring equipment (X_3), except container yard (X_4) isn't significant with Pearson correlation coefficients of 0.3734, 0.3692, 0.3431, 0.2940 from 1999 to 2002, respectively as shown in Table 5. The input of container yard is not significant therefore it is eliminated, and then this paper finally selected three inputs (X_1, X_2, and X_3) and single output (Y).

Table 5. Pearson Correlation Coefficients of Initially Selected Input/Output Variables

Year	Output (Y_t)	Input			
		X_1	X_2	X_3	X_4
1999	Y_1	0.8401	0.4397	0.7825	0.3734*
2000	Y_2	0.8228	0.5017	0.7823	0.3692*
2001	Y_3	0.7732	0.4455	0.6683	0.3431*
2002	Y_4	0.7482	0.4466	0.6312	0.2940*

Remark: (*) represents not significant at 0.05 the level (2-tailed).

To be in compliance with the rough rule of thumb of DEA, i.e., the number of DMUs should be at lease twice the sums of inputs and outputs (Golany *et al.*, 1989), the selected 27 ports are indeed larger than twice of addition of 3 inputs and 1 output.

4.2 Analysis of Efficiency Scores

Table 6 presents the results of a maximum likelihood estimate of the frontier under these assumptions for SFA with Cobb-Douglas and Translog function for the truncated-normal distribution (SFA_{CD}, SFA_{TR}), and Coelli (1996) FRONTIER Version 4.1 computer software is adopted for calculation. The LR values of SFA_{CD} (57.7869) and SFA_{TR} (31.4398) are larger than the critical values 4.605 and 6.251 of χ^2 distribution, respectively. Therefore, we reject null assumption H_0 and don't reject alternative hypothesis H_1:$\sigma^2 \neq 0$ with technical inefficiency effect. H_0: $\gamma = 0$ to determine existence of technical inefficiency effect. The statistical values 0.5928 and 0.3658 of SFA_{CD} and SFA_{TR} models are smaller than the critical value 7.1191 and 3.0846, and hence both the null assumptions are not rejected, and it means that technical inefficiency must be included. The second test H_0: $\beta_4=\beta_5=\beta_6=\beta_7=\beta_8=\beta_9=0$ suggests that we reject the null hypothesis that a Translog function is better than a Cobb-Douglas as a representation of production technology of the 27 international container ports. The LR value 57.7869 is larger than the critical value 12.592 of χ^2 distribution. However, this paper still uses both Cobb-Douglas and Translog functions to evaluate container port efficiency. Because the η value 0.5778, 0.6604 of SFA_{CD} and SFA_{TR} models are larger than zero, they represented time-varying inefficiency model that depends on increasing period to increase port operating efficiency.

Table 6. Maximum Likelihood Estimates of the SFA Model

Coefficient	SFA_{CD} model		SFA_{TR} model	
	Estimate	Critical value	Estimate	Critical value
β_0 (intercept)	2.6041	7.2696	4.2883	4.5320
X_1=ln(gantry cranes)	0.8710	5.3473	-4.6359	-5.5399
X_2=ln(quay length)	-0.2360	-1.7568	1.0593	1.1263
X_3=ln(stevedoring equipment)	0.1693	1.4791	3.0925	4.6611
$(X_1)^2$			0.9803	2.2673
$(X_2)^2$			-0.2231	-0.3346
$(X_3)^2$			-0.1015	-0.4373
$(X_1 \cdot X_2)$			0.1718	0.7006
$(X_1 \cdot X_3)$			-0.4086	-0.6112
$(X_2 \cdot X_3)$			-0.2238	-0.5290
σ^2	0.2790	5.4333	0.1946	3.0650
γ	0.5928	7.1191	0.3658	3.0846
μ	-0.8134	-1.9715	-0.5336	-0.9358
η	0.5778	5.3799	0.6604	4.0177
Log likelihood function	-62.1944		-63.8910	
LR values	57.7869		31.4398	

On the other hand, the CCR and BCC models of DEA adopt DEA-Solver package to estimate relative operating efficiency of 27 international container ports from 1999 to 2002. Table 7 and Table 8 present the efficiency scores of SFA and DEA models, respectively.

Table 7. Efficiency Scores of SFA_{CD} and SFA_{TR} Models in 27 Ports

Scores	1999				2000				2001				2002			
Port	SFA_{CD}	Rank	SFA_{TR}	Rank	SFA_{CD}	Rank	SFA_{TR}	Rank	SFA_{CD}	Rank	SFA_{TR}	Rank	SFA_{CD}	Rank	SFA_{TR}	Rank
1	0.9341	1	0.9155	1	0.9620	1	0.9546	1	0.9783	1	0.9761	1	0.9877	1	0.9875	1
2	0.8846	2	0.7312	13	0.9322	2	0.8459	13	0.9609	2	0.9157	13	0.9777	2	0.9551	13
3	0.8808	3	0.8755	3	0.9299	3	0.9320	3	0.9595	3	0.9638	3	0.9769	3	0.9810	3
4	0.7931	8	0.7910	10	0.8749	8	0.8824	10	0.9266	8	0.9364	10	0.9578	8	0.9663	10
5	0.8222	7	0.7791	12	0.8933	7	0.8752	12	0.9378	7	0.9324	12	0.9643	7	0.9641	12
6	0.6730	15	0.6861	15	0.7955	15	0.8175	15	0.8777	15	0.8994	15	0.9288	15	0.9462	15
7	0.7405	12	0.7926	8	0.8407	12	0.8834	8	0.9057	12	0.9369	8	0.9455	12	0.9666	8
8	0.7882	11	0.7877	11	0.8717	11	0.8804	11	0.9247	11	0.9353	11	0.9566	11	0.9657	11
9	0.5928	19	0.6549	19	0.7397	19	0.7975	19	0.8422	19	0.8878	19	0.9074	19	0.9398	19
10	0.7044	13	0.8086	6	0.8167	13	0.8930	6	0.8909	13	0.9423	6	0.9367	13	0.9695	6
11	0.4575	23	0.4733	24	0.6389	23	0.6723	24	0.7754	23	0.8122	24	0.8662	23	0.8974	24
12	0.7888	10	0.7920	9	0.8721	10	0.8830	9	0.9250	10	0.9367	9	0.9568	10	0.9665	9
13	0.7899	9	0.8202	5	0.8728	9	0.8999	5	0.9254	9	0.9461	5	0.9570	9	0.9716	5
14	0.4072	24	0.4982	23	0.5983	24	0.6905	23	0.7474	24	0.8236	23	0.8485	24	0.9039	23
15	0.5864	20	0.6033	21	0.7352	20	0.7635	21	0.8393	20	0.8678	21	0.9056	20	0.9288	21
16	0.6058	18	0.6685	17	0.7489	18	0.8062	17	0.8481	18	0.8929	17	0.9110	18	0.9426	17
17	0.8699	4	0.6227	20	0.9231	4	0.7764	20	0.9556	4	0.8754	20	0.9746	4	0.9330	20
18	0.8395	5	0.7264	14	0.9043	5	0.8429	14	0.9443	5	0.9140	14	0.9681	5	0.9542	14
19	0.6473	17	0.5807	22	0.7779	17	0.7483	22	0.8666	17	0.8587	22	0.9221	17	0.9237	22
20	0.6739	14	0.6798	16	0.7961	14	0.8135	16	0.8780	14	0.8971	16	0.9290	14	0.9450	16
21	0.8249	6	0.9073	2	0.8951	6	0.9500	2	0.9388	6	0.9736	2	0.9649	6	0.9862	2
22	0.02007	27	0.04915	27	0.1105	27	0.2085	27	0.2897	27	0.4436	27	0.4985	27	0.6566	27
23	0.3710	25	0.2621	26	0.5678	25	0.4952	26	0.7258	25	0.6935	26	0.8346	25	0.8270	26
24	0.5237	21	0.8322	4	0.6894	21	0.9069	4	0.8094	21	0.9500	4	0.8873	21	0.9737	4
25	0.3526	26	0.3929	25	0.5518	26	0.6104	25	0.7142	26	0.7726	25	0.8271	26	0.8745	25
26	0.6510	16	0.6555	18	0.7805	16	0.7978	18	0.8682	16	0.8880	18	0.9231	16	0.9399	18
27	0.5029	22	0.7959	7	0.6739	22	0.8854	7	0.7990	22	0.9380	7	0.8809	22	0.9672	7
Average scores	0.6565		0.6734		0.7701		0.7968		0.8539		0.8819		0.9109		0.9346	

Table 8. Efficiency Scores of DEA_{CCR} and DEA_{BCC} Models in 27 Ports

Scores	1999				2000				2001				2002			
Port	DEA_{CCR}	Rank	DEA_{BCC}	Rank	DEA_{CCR}	Rank	DEA_{BCC}	Rank	DEA_{CCR}	Rank	DEA_{BCC}	Rank	DEA_{CCR}	Rank	DEA_{BCC}	Rank
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0.7968	5	0.9135	5	0.7866	5	1	1	0.8380	8	0.9425	8	0.8751	8	1	1
3	0.7793	6	0.8497	7	0.8689	3	0.9538	8	0.9940	4	1	1	0.9413	6	0.9758	10
4	0.4422	18	0.4960	17	0.5805	13	0.6582	16	0.6815	14	0.7350	15	0.8459	9	0.8645	14
5	0.6227	13	0.6950	12	0.5989	11	0.7477	14	0.7131	11	0.7370	13	0.7760	11	0.8004	16
6	0.3975	21	0.4059	22	0.4975	17	0.5121	19	0.7113	12	0.7130	17	1	1	1	1
7	0.4560	17	0.4599	19	0.4170	21	0.4177	24	0.3645	23	0.3664	26	0.3756	23	0.3814	25
8	0.9511	3	1	1	0.7332	7	1	1	0.9075	5	1	1	1	1	1	1
9	0.3265	23	0.3608	24	0.3392	23	0.3917	25	0.3953	21	0.4479	21	0.3723	24	0.3963	24
10	0.3836	22	0.4034	23	0.3383	24	0.4275	23	0.3603	24	0.4515	20	0.4062	22	0.4722	22
11	0.2708	25	0.3204	25	0.3595	22	0.4824	20	0.3928	22	0.4163	23	0.5132	20	0.5639	20
12	0.6964	9	0.8029	8	0.5999	10	0.8051	12	0.7736	10	0.7876	12	0.7192	13	0.7648	17
13	0.6824	10	0.6961	11	0.6471	9	0.6622	15	0.8647	6	0.8679	10	0.9565	4	1	1
14	0.2380	26	0.2863	27	0.2418	26	0.3379	27	0.2967	26	0.3986	24	0.2688	26	0.3547	26
15	0.4235	19	0.4364	20	0.4612	18	0.5227	18	0.5122	19	0.5232	19	0.5245	18	0.6160	19
16	0.4234	20	0.4357	21	0.4355	19	0.4588	21	0.4331	20	0.4334	22	0.4319	21	0.5327	21
17	0.7123	8	0.7908	9	0.8077	4	1	1	0.8224	9	1	1	0.9438	5	1	1
18	0.6602	12	0.6840	13	0.7802	6	0.8801	9	0.8391	7	0.8777	9	0.8344	10	0.9114	12
19	0.5022	15	0.6339	16	0.5946	12	0.8635	10	0.5668	17	0.7368	14	0.6230	17	0.8528	15
20	0.6193	14	0.6421	15	0.5141	15	0.6022	17	0.5510	18	0.6503	18	0.5143	19	0.6535	18
21	1	1	1	1	1	1	1	1	1	1	1	1	0.7239	12	0.8902	13
22	0.01166	27	0.6538	14	0.2078	27	1	1	1	1	1	1	0.8900	7	1	1
23	0.4817	16	0.4821	18	0.4237	20	0.4547	22	0.3523	25	0.3803	25	0.3078	25	0.4123	23
24	0.7712	7	0.8817	6	0.5513	14	0.7575	13	0.7080	13	0.8177	11	0.7034	15	0.9476	11
25	0.2836	24	0.2947	26	0.2739	25	0.3414	26	0.2072	27	0.2692	27	0.2036	27	0.3048	27
26	0.8841	4	1	1	0.5124	16	1	1	0.5859	16	1	1	0.6984	16	1	1
27	0.6822	11	0.7169	10	0.6829	8	0.8238	11	0.6317	15	0.7168	16	0.7163	14	1	1
Average scores	0.5740		0.6423		0.5650		0.7075		0.6483		0.7137		0.6728		0.7665	

The average operating efficiency scores of each model from 1999 to 2002 show an increasing situation, except that the average score of DEA_{CCR} model for year 2000 (0.5650) is smaller than that of DEA_{CCR} for year 1999 (0.5740) as shown in Figure 1. The analysis also shows that the total average of operating efficiency scores of SFA_{TR} (0.8217)＞SFA_{CD}(0.7979)＞DEA_{BCC}(0.7075)＞DEA_{CCR}(0.6150) from 1999 to 2002. It is found that the total average scores of SFA_{CD} is larger than other models so SFA_{CD} is better than other models. The total average scores of SFA method are larger than DEA so SFA is also better than DEA. Table 9 presents the Spearman ranking of correlation coefficients that are executed on SPSS 10.0 package. Both DEA_{CCR} and DEA_{BCC} models have the highest Spearman ranking in year 1999, 2001, and 2002, and both SFA_{CD} and DEA_{CCR} models have the highest Spearman ranking of correlation coefficients in year 2000.

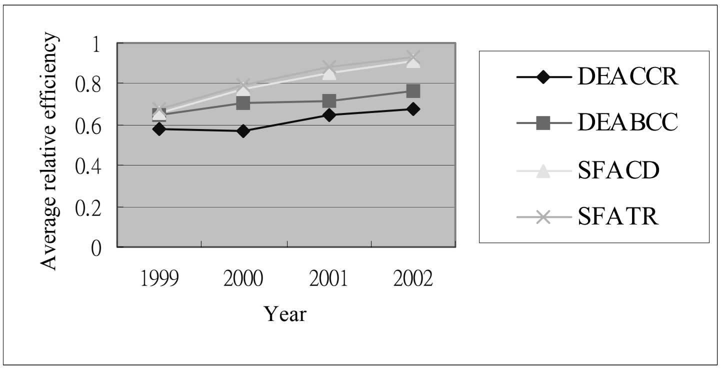

Figure 1. Average Efficiency Scores in Each Model

Table 9. Ranking of Spearman Correlation Coefficients among Alternative Measures

Variables	2002				Variables	2001			
	DEA_{CCR}	DEA_{BCC}	SFA_{CD}	SFA_{TR}		DEA_{CCR}	DEA_{BCC}	SFA_{CD}	SFA_{TR}
DEA_{CCR}	1	0.8881	0.6371	0.4459	DEA_{CCR}	1	0.9125	0.6335	0.4966
DEA_{BCC}	0.8881	1	0.4379	0.3477	DEA_{BCC}	0.9125	1	0.5967	0.4101
SFA_{CD}	0.6371	0.4379	1	0.6526	SFA_{CD}	0.6335	0.5967	1	0.6526
SFA_{TR}	0.4459	0.3477	0.6526	1	SFA_{TR}	0.4966	0.4101	0.6526	1
Variables	2000				Variables	1999			
	DEA_{CCR}	DEA_{BCC}	SFA_{CD}	SFA_{TR}		DEA_{CCR}	DEA_{BCC}	SFA_{CD}	SFA_{TR}
DEA_{CCR}	1	0.7421	0.8118	0.6310	DEA_{CCR}	1	0.9381	0.6866	0.6451
DEA_{BCC}	0.7421	1	0.5345	0.3116	DEA_{BCC}	0.9381	1	0.5931	0.5705
SFA_{CD}	0.8118	0.5345	1	0.6526	SFA_{CD}	0.6866	0.5931	1	0.6526
SFA_{TR}	0.6310	0.3116	0.6526	1	SFA_{TR}	0.6451	0.5705	0.6526	1

Among the 27 ports, operating efficiency scores of Hong Kong is No. 1 and demonstrates the best performance in each of the four models. The remaining ports show variation of performance in different models. DEA_{CCR} has 3 efficient ports including Hong Kong, Shenzhen, and Los Angeles, and DEA_{BCC} has 9 efficient ports on year 2002. SFA_{CD} are Hong Kong, Singapore, and Busan, and SFA_{TR} are Hong Kong, Tanjunk Priok, and Busan in top 3 efficient ports on year 2002. The Port of Tanjung Pelepas has inferior rating in both SFA_{CD} and SFA_{TR} models.

4.3 Slack Analysis

DEA method provides analysis of input excesses and output shortfalls for resource utilization. The slack analysis of DEA is to investigate the utilization of input and output resources to improve efficiency scores, and hence set benchmark for other ports. Since there are only single output and three inputs, we may have at most one output shortfall and two input excesses for relatively inefficient ports. Table 10 presents slack analysis of input excesses of both DEA_{CCR} and DEA_{BCC} models between 1999 and 2002. The maximum value and minimum value are compared with efficiency scores 1 of efficient ports (e.g., Hong Kong) that the input and/or output resources of inefficient ports should be added or reduced for improving the operating efficiencies.

Table 10. Slack analysis of DEA_{CCR} and DEA_{BCC} Models

	Slack	DEA_{CCR}			DEA_{BCC}		
Year		Input excess X_1 (units)	Input excess X_2 (Kilometer)	Input excess X_3 (units)	Input excess X_1 (units)	Input excess X_2 (Kilometer)	Input excess X_3 (units)
1999	max. value	17.4164 Los Angeles	4.2728 Bremerhaven	7.2379 NY/NJ	10.7698 Algeciras	4.3580 Bremerhaven	23.9016 NY/NJ
	min. value	0.0772 PTP	0.0118 PTP	1.7618 Shanghai	0.1194 Kaohsiung	0.0391 Busan	2.9134 Antwerp
	Number	7	22	2	7	20	8
2000	max. value	7.8447 Singapore	2.4100 Antwerp	4.8493 Antwerp	5.5827 Keelung	1.7597 Rotterdam	44.7403 Port Klang
	min. value	0.0235 Laem Chabang	0.0693 Port Klang	0.1392 NY/NJ	0.7249 Algeciras	0.1322 Kaohsiung	0.2401 Shenzhen
	Number	8	21	2	5	10	11
2001	max. value	8.5686 Singapore	3.0954 Antwerp	63.8499 Antwerp	42.6641 Singapore	3.8501 Antwerp	112.375 Antwerp
	min. value	0.3406 Algeciras	0.0037 Laem Chabang	10.6342 NY/NJ	0.3933 Algeciras	0.0637 Laem Chabang	0.7692 Kobe
	Number	5	19	2	4	18	10
2002	max. value	14.8692 Singapore	2.9900 Antwerp	52.8191 Antwerp	5.2341 Long Beach	1.9732 Antwerp	81.9822 Antwerp
	min. value	1.1465 Jawaharlal Nehru	0.0357 Laem Chabang	37.1082 NY/NJ	0.9807 Busan	0.1667 Kaohsiung	5.9136 Laem Chabang
	Number	9	17	2	3	6	3

4.4 Sensitivity Analysis

Sensitivity analysis is to investigate the impact when DMUs are deleted or added to the set being considered or when outputs or inputs are added or withdrawn from consideration (Cooper, Seiford, and Tone, 1999). However, this paper only considers with inputs deleted in DEA_{CCR} and SFA_{CD} models, to identify the strength, weakness, and degree of contribution of each variable to each port. Table 11 presents correlation coefficient matrix of inputs and outputs in 2002, and presents the highest correlation coefficient 0.8107 between gantry cranes (X_1) and quay length (X_2). Besides, the relationship between the inputs (X_1, X_2, X_3) and output (Y) show that the correlation coefficient 0.7482 of X_1 is highest, followed by stevedoring equipment (X_3) 0.6312, and X_2 (0.4466) is the smallest.

Then, the input variables X_1, X_2, X_3 of each port are deleted individually, the average operating efficiency scores of DEA_{CCR} and SFA_{CD} models are compared with original efficiency scores of each port. For example, every input variable in DEA_{CCR} model and input variable X_1 in SFA_{CD} model have higher impact for Hong Kong port, while input variable X_3 in DEA_{CCR} model and input variable X_2 in SFA_{CD} model have higher impact for Singapore. Table 12 presents the strengths of input variables of 27 ports in both DEA_{CCR} and SFA_{CD} models. Most ports have higher degree of sensitivity of input variables X_1 and X_3 in both DEA_{CCR} and SFA_{CD} models.

Table 11. Correlation Coefficient Matrix of Inputs and Outputs in 2002

Variables	X_1	X_2	X_3	Y
X_1	1	0.8107	0.7559	0.7482
X_2	0.8107	1	0.7694	0.4466
X_3	0.7559	0.7694	1	0.6312
Y	0.7482	0.4466	0.6312	1

Table 12. Input Variables of Higher Impact for 27 Ports in DEA_{CCR} and SFA_{CD} Models

<table>
<tr><th>Port</th><th>DEA_{CCR} model</th><th>SFA_{CD} model</th></tr>
<tr><td>1.Hong Kong</td><td>X_1、X_2、X_3</td><td>X_1</td></tr>
<tr><td>2.Singapore</td><td>X_3</td><td>X_2</td></tr>
<tr><td>3.Busan</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>4.Shanghai</td><td>X_1、X_3</td><td>X_1</td></tr>
<tr><td>5.Kaohsiung</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>6.Shenzhen</td><td colspan="2">X_3</td></tr>
<tr><td>7.Rotterdam</td><td>X_1、X_3</td><td>X_1</td></tr>
<tr><td>8.Los Angeles</td><td colspan="2">X_3</td></tr>
<tr><td>9.Hamburg</td><td>X_1、X_3</td><td>X_1</td></tr>
<tr><td>10.Antwerp</td><td colspan="2">X_1</td></tr>
<tr><td>11.Port Klang</td><td>X_3</td><td>X_1</td></tr>
<tr><td>12.Long Beach</td><td>X_3</td><td>X_1、X_3</td></tr>
<tr><td>13.Dubai</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>14.New York/New Jersey (NY/NJ)</td><td colspan="2">X_1</td></tr>
<tr><td>15.Tokyo</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>16.Bremen/Bremerhaven</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>17.Gioia Tauro</td><td>X_1、X_3</td><td>X_1</td></tr>
<tr><td>18.Manila</td><td>X_1、X_3</td><td>X_1</td></tr>
<tr><td>19.Laem Chabang</td><td>X_3</td><td>X_1</td></tr>
<tr><td>20.Felixstowe</td><td>X_3</td><td>X_1</td></tr>
<tr><td>21.Tanjunk Priok</td><td>X_3</td><td>X_1</td></tr>
<tr><td>22.Port of Tanjung Pelepas (PTP)</td><td colspan="2">X_3</td></tr>
<tr><td>23.Yokohama</td><td colspan="2">X_3</td></tr>
<tr><td>24.Algeciras</td><td colspan="2">X_3</td></tr>
<tr><td>25.Kobe</td><td colspan="2">X_1、X_3</td></tr>
<tr><td>26.Jawaharlal Nehru</td><td>X_3</td><td>X_1、X_2</td></tr>
<tr><td>27.Keelung</td><td colspan="2">X_3</td></tr>
</table>

4.5 Hypotheses Testing of Port Efficiency

In order to understand the correlation of ports' operating efficiency with geographical location, port administrative structure, and national economic growth rate, respectively, the 27 ports are divided into two groups, and adopts Mann-Whitney-U test to decide whether this two groups are the same for efficiency scores of DEA_{CCR} and DEA_{BCC} models in year 2002, and understand the correlation with characteristics of international container ports.

4.5.1 Geographical Location of Port

To understand the difference of ports operating efficiency scores in different geographical location (Asian vs. non-Asian), the hypothesis 1 is proposed: H_0: there is no significant differentiation between operating efficiency scores of Asian and non-Asian ports.

Among the 27 ports, there are 17 ports in Asia, the other 10 ports are in Europe or U.S.A. Table 13 presents the p-values of the Mann-Whitney-U test for DEA model are larger than

0.05 significant level in 2002, and hence the null assumption can not be rejected. It means that the two groups have no significant correlation with each other. That is, there is no significant differentiation between operating efficiency scores of Asian vs. non-Asian ports. The reasoning might be that the professional management skills adopted by most ports are standard in the international market. Also, the stevedoring companies, global terminal operators, ocean carries involved in the port operation aim to reduce per container handling cost and maximize their profit, and they have to push the port administrative authority to enhance port operating efficiency under the resource restrictions of container yard and terminal infrastructures. Therefore, the operating efficiencies in different ports seem to grow in the same direction and make no significant differentiation for Asian vs. non-Asian ports.

Table 13. Test of Asian vs. Non-Asian Ports

Model	Mann-Whitney-U test	Z -test	p-value
DEA_{CCR}	55	-1.5072	0.1318
DEA_{BCC}	51	-1.7393	0.0820

4.5.2 Port Administrative Structure

To understand the correlation of ports operating efficiency scores with port administrative structure, the hypothesis 2 is proposed: H_0: there is no significant differentiation between operating efficiency scores of corporate-owned ports vs. public-owned ports.

Among the 27 ports, there are 5 corporate-owned ports, including Shanghai, Shenzhen, Felixstowe, Rotterdam, and Tanjung Pelepas, and the other 22 ports are under control of national or local public administrative organization in 2002. Table 14 presents the results for DEA model of the Mann-Whitney-U test are larger than 0.05 significant levels, and hence the null assumption can't be rejected. It means that the two groups have no significant correlation with each other. Therefore, there is no significant differentiation between operating efficiency scores of corporate-owned vs. public ports. The reasoning may be most port operations have been privatized, and aims to maximize container throughput and operating efficiencies. Every port administrative organization aims to utilize the port facilities, financial resource and state-of-the-art technology full to the maximum degree to increase effectiveness and efficiency; secondly, most ports encourage private participation on a BOT basis (Build, Operate, Transfer) and are willing to provide concession agreement of a given duration (e.g. 30 years) to improve port operating efficiency. Therefore, it makes no significant differentiation between corporate-owned vs. public ports.

Table 14. Test of Corporate-owned vs. Public Ports

Model	Mann-Whitney-U test	Z -test	p-value
DEA_{CCR}	45	-0.6246	0.5323
DEA_{BCC}	52	-0.1908	0.8487

4.5.3 National Economic Growth Rate

To understand the correlation of ports' operating efficiency with the national economic growth rate, the hypothesis 3 is proposed: H_0: there is no significant differentiation between operating efficiency scores and the national economic growth rate.

According to the International Monetary Fund (IMF), the global economic growth rate is 1.9% in 2002. Out of the 27 ports, 16 ports of 10 countries are above-average, the other 10 ports of 7 countries (consist of UK, Nederland, Germany, Belgium, Spain, Italy, and Japan) are below-average except that data of Dubai in United Arab Emirates is not available. Table 15 presents the p-values for DEA models of the Mann-Whitney-U test are smaller than 0.05 significant level in 2002, hence the null assumption is rejected. It means that the two groups have significant correlation with each other. The reasoning might be that surging port cargo volumes from the developing countries, especially China, to the US and Europe have resulted in record-breaking throughput for container terminals, and resulted in higher economic growth rate, on the other hand, the developed countries in Europe and Japan have suffered lower and fix level of economic growth rate recently. Therefore, the countries of lower rate are striving to strengthen their domestic economic activities and expand port plans, including port of Rotterdam Maasvlakte 2 in Nederland, port of Bremerhaven CT4 container terminal in Germany, port of Antwerp Deurganckdok new terminal in Belgium, *etc*. Thus, it makes significant differentiation with national economic growth rate.

Table 15. Test of Above-average vs. Below-average of National Economic Growth Rate

Model	Mann-Whitney-U test	Z -test	p-value
DEA_{CCR}	26	-2.8480	0.0044
DEA_{BCC}	29.5	-2.7006	0.0069

5. CONCLUSIONS

Although DEA doesn't make accommodation for statistical noise such as measure error, SFA makes accommodation for statistical noise such as random variables of weather, luck, machine breakdown and other events beyond the control of firms, and measures error. However, both DEA and SFA are efficiency frontier analysis, and provide a suitable way of treating the measurement of port operating efficiency. Port operations are aimed to maximize output and operating efficiency, so this paper applies the two methods to evaluate operating efficiency of 27 international container ports.

The analysis shows that the total average of operating efficiency scores of SFA_{TR} model is the highest (0.8217), followed by SFA_{CD} model (0.7979), DEA_{BCC} model (0.7075), and DEA_{CCR} model (0.6150) is the smallest. It is found that the total average scores model SFA_{CD} is larger than other models so SFA_{CD} model is better than other models, and SFA method is better than DEA method in measuring port efficiency. Port of Hong Kong demonstrates the best performance in the four models, while the other ports show variation of performance in different models. This paper also examines the correlations between operating efficiencies and three factors, that is, location of port (Asian vs. non-Asian), administrative structure of port (corporate-owned vs. public-owned), and national economic growth rate (above-average vs. below-average). The results show that the operating efficiencies are not significantly different with both location of port and administrative structure of port. However, the DEA model shows significant difference with national economic growth rate. To investigate the long-term performance of leading international container ports, an approach based on both panel data and multi-inputs/outputs should be considered comprehensively.

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