MEASURING THE EFFICIENCY OF KOREAN SHIPPERS USING DATA ENVELOPMENT ANALYSIS

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목 차

I. Introduction

Since 1996, the Korea nationwide commodity flow survey has been periodically conducted very five years. as a means to improve national logistics system. The third and the most recent survey were conducted in 2005 and the results have been stored into a database.

This study is a case study as to the productivity efficiency of Korean shippers. The study, more specifically, analyzes input and output data with respect to business logistics regarding individual shipment and receipt. It is expected that the study is to analyze "What firms are efficient?" on the purpose of production.

The objective of the study is to evaluate the productivity efficiency of transport shippers. The decision making unit is a shipping establishment, or business firm in Korea. There are 7,365 firms from 27 industries from 2005 commodity flow survey being evaluated. The study employs the useful frontier technique; Data Envelopment Analysis (DEA) to identify the productivity and also the scale efficiency for each particular shipping company.

The finding in the study are being as a performance indicator of existing transport shipping in Korea for the government and a guideline for individual firms to improve their productivity efficiency.

The paper is organized as follow: Section II summarizes the DEA methodology utilized in the study; Section III discusses the model specification in measuring shipping efficiency; Section IV shows and discusses the result form data analysis and finally Section V concludes the interpretation from the results and recommend for future studies.

II. DEA approach

1. DEA basic concept

DEA use linear programming to organize and analysis data. It involves an alternative principle for extracting information about a population of independent units characterized by multiple inputs and outputs and optimizes on each individual observation with the objective of calculating a discrete piecewise frontier to identify the best practice and measures the efficiency ratio based on differences between observed units and their efficient frontier. DEA model evaluates multiple inputs and multiple outputs to calculate a relative efficiency score of a DMU (Charnes, et al., 1978). This relative efficiency score has generated from actual field data of all DMU in an interesting activity. Note that a fundamental property of an efficiency measure embedded in DEA model is that it must be independent of units in which the input and output variable are measured.

The ability to model multi-input and multi-output relationships without *a priori* underlying functional form assumption has make DEA has been widely applied to such assorted activities as airline operation, banking, education, and also in transportation and logistics (Clarke and Gouradin, 1991; Chu and Fielding, 1992).

In Korea, researches have used DEA to measure the performance of a transportation activity such as measuring airport performance (Hong and Lee, (2007), Lee and Kim, (2004)), evaluating transit service performance (Hong, (2004), Kim (2003), Oh and Kim (2002)). Most recently research conducted by Ha and Choi, (2007). They apply DEA to analyze the efficiency of Korea's logistics Industry.

2. Envelopment model formulations

The original and classic DEA models, namely, CCR model by Charnes, Cooper and Rodes (1978) and the BCC model by Baker, Charnes and Cooper (1984). Later, the collection of DEA models as a extension of CCR and BCC model, have been proposed by many researcher such as Multiplicative models, Additive model and its extended.

Each model has been developed for identifying the envelope surface named the efficient frontier which serves to characterize efficiency and identify inefficiencies. The main objective in the DEA models is to obtain an efficiency score for each of the DMU under evaluated.

The efficiency score depends on the orientation of the problem. There are two alternatives orientation in DEA to evaluate the efficient frontier; input-oriented and output-oriented. First, in input-oriented, the inputs are minimized and the outputs are kept at their current levels. The process is defined input-efficient if there in no other processes that, produces the same of higher level of output, using smaller amount of inputs. Second, in output-oriented, the outputs are maximized and the inputs are kept at their current levels. And the process is defined output-efficient if there is no other process that, using the same or small amount of input, produces higher level output.

In addition to model orientations, there are four possible models namely the constant returns model, the variable returns model, the increasing returns model, and the decreasing returns model.

Each model is defined by a specific set of economic assumptions regarding the relation between inputs and outputs. Associated with each of the four DEA models, independent of the orientation, there is a production possibility set.

Let n is number of total observed DMUs. For a specific j-th DMU (DMU_j), x_{ij} and y_{rj} are their input and output element. The empirical efficient frontier or best-practice frontier for DMU_j is determined by these total observations. The properties of convexity and inefficiency ensure that a piecewise linear approximation to the efficient frontier and the area dominated by the frontier can be developed. (Zhu (2003)).

Table 1 shows the frame of all possible basic envelopment models employed in the study, where λ_j are non negative scalar.

Table 1: Envelopment models

Input-oriented models	Output-oriented
$\min\ \theta_o$ subject to $\sum_{j=1}^{n} \lambda_{jo} x_{ij} \le \theta_o x_{io}$ all I $\sum_{j=1}^{n} \lambda_{jo} y_{ij} \ge y_{ro}$ all r $\lambda_{jo} \ge 0$ all j (Constant returns)	$\max\ \Phi_o$ subject to $\sum_{j=1}^{n} \lambda_{jo} x_{ij} \le x_{io}$ all i $\sum_{j=1}^{n} \lambda_{jo} y_{ij} \ge \Phi_o y_{ro}$ all r $\lambda_{jo} \ge 0$ all j (Constant returns)
Variable returns constraint $\sum_{j=1}^{n} \lambda_{jo} = 1$ all j	
Non-Increasing returns constraint $\sum_{j=1}^{n} \lambda_{jo} \le 1$ all j	
Non-Decreasing returns constraint $\sum_{j=1}^{n} \lambda_{jo} \ge 1$ all j	

For example, in the input-oriented model with variable returns, the DEA model for the DMU_o which is the DMU under efficient evaluated is

$$\min\ \theta_o$$

subject to

$$\sum_{j=1}^{n} \lambda_{jo} x_{ij} \le \theta_o x_{io} \quad \text{all i}$$

$$\sum_{j=1}^{n} \lambda_{jo} y_{ij} \ge y_{ro} \quad \text{all r}$$

$$\lambda_{jo} \ge 0 \quad \text{all j}$$

$$\sum_{j=1}^{n} \lambda_{jo} = 1 \quad \text{all}$$

θ_o^* that is the feasible solution of those linear programming is so called the efficiency score of DMU_o.

If θ_o^* equal one, then the current input cannot be reduced indicating that the DMU_o is on the frontier. On another word, DMU_o is efficiency. Otherwise, if θ_o^* less than one then DMU_o is dominated by the frontier. This observed DMU is inefficiency.

3. Peers count

Rather than the efficiency score, part of the solution for an observed DMU_o is the set of non-zero optimal λ_{jo}^* which named as activity multipliers. It identify the peer units. This reference set of coefficient use to define the hypothetical efficient DMU or virtual DMU for DMU_o. It shows how inputs can be decreased and outputs increased to make the DMU under evaluation earn the efficiency. Beside, each inefficient DMU will be related to one or more benchmark or peer units and has a positive weight λ_{jo}^* associated with each of its peer from the model solution. The weights λ_{jo}^* are zero for inefficient DMUs not be being peer of DMU_o.

The firm that most frequently appear to be the peer for other DMU can be consider as the best-practice firm.

4. Scale efficiency

The measure of scale efficiency can be derived by taking the ration of the constant returns to the variable returns efficiency scores (Ross and Droge, 2004). If the value of this ratio is one, then the observed DMU is apparently operating at the optimal score. If this ration is less than one then the observed DMU appear to be either too large or too small. To determine whether it may be too small or too large requires running a third variant of DEA subject to non-increasing returns. By comparing the variable and non-increasing returns scores for those DMUs which appear to be not at optimal scale, it is possible to identify on which part of the frontier they fall. If the variable and non-increasing returns scores are the same then the DMU would be too large relative to its optimum size. If the variable returns score is higher than the non-increasing returns efficiency score, then the DMU is would be too small relative to its optimum size. (Ross and Droge, 2004)

III. Model specification and data

1. Input and output variables

Using DEA to measure the shipping productivity efficiency, initially, selecting the inputs and outputs variable which related to the shipping decision is an importance. The study selects fives input variables; employee, firm's area, number of vehicle, price of receipt, and weight for each receipt, and two output variables; price of shipment and weight of shipment. Those inputs and outputs were collected during the present Korea commodity flow survey (2005). The total number of 7,365 shipping companies from 27 industries have been evaluated in the study. Table 2 shows the overall descriptive statistics of the inputs and outputs being evaluated.

Table 2: Descriptive statistic of inputs and outputs data

Inputs/Outputs	Mean	SD
Input:		
Employee (persons)	35	65
Firm's area (m^2)	3,707	11,354
No. of vehicle (veh.)	4	3
Price of receipt (won/ton)	5,966	61,459
Receipt's weight (kg.)	11,679	68,910
Output:		
Price of shipment (won/ton)	10,429	107,087
Shipment's weight (kg.)	8,850	63,518

2. Model analyzed

Existing researches wildly use DEA to measure performance efficiency of DMU. All of them deal with a less than thousand number of DMU. Beside, this study have to evaluated three-forth of ten-thousand observed shipping firms. This can lead to the programming computable difficulty. Consequently, to handle data variability and avoid a wild data which can make the model failure during solving feasible solution of linear programming, the study applied DEA models to test shipping firms based on the same industry.

Shipping firms in an industry are evaluated using both input and output orientation. Each orientation, the constant returns, variable returns, and non-increasing returns are used to evaluate the efficiency score for any observed shipping firm. The results from variable returns both input and output orientation are presented as the shipping productivity efficiency score. The ratio of constant return and variable returns are determine and represented as scale effect of the shipping firms. Then, from comparing the score of variable returns and non-increasing return, the size of observed firm are determined whether they is too large or to small. Finally, the firms which appear as the reference or peer to the other are range to identify the most reference.

However, in a big industry that have to deal with a thousand firms, the study applies two rounds DEA model testing. Frist, the efficiency score are identified from several DEA models as described above but the process of extracting a set of peer is ignored. Then an only efficiency firms are selected and re-evaluated with a subset of inefficiency firms to determine how many time these efficiency firms are refered by an inefficiency firms. Note here that adding a DMU to the firm group which being evaluated would not reflect the efficiency score of observed DMU as long as the DMU added is not the frontier of observed DMU.

IV. Empirical results

LIMDEP is a computer software package for econometric modelling. The most recently released version; LIMDEP 9 has an extension module for DEA frontier analysis. This DEA module fully satisfy the object of this study. So, the study has employed LIMDEP 9 to do DEA shipping efficiency analysis. The shipping efficiency of a shipper under evaluated were determined both input and output orientation approach. The scale efficency then are identified from the comparison result of variable and constant returns model. Finally, the best-practice shipper who are most frequently refferred by the other are introduce.

The study results are presented as follows.

1. DEA Efficiency score

Under performance evaluation based on same industry comparison, the relative efficiency score of all firms in an industry are comparable. Table 3 shows the average efficiency score of shipping firms under evaluated and table 4 shows the range of overall efficiency score.

The results can be drawn that the overall productivity efficiency of Korea shipping under evaluation of input-oriented variable returns model is 0.80 and one under evaluation of output-oriented variable returns model is 0.32. This average efficiency score from output-oriented model is close to the DEA efficiency score of Korea's logistics industry which was conducted by Hun-Koo and A young (2007). In their study, under the output-oriented DEA model, the efficiency score of logistics industry Korea for year of 2005 is 0.3363.

Table 3: Average efficiency score and Scale efficiency (Variable returns)

ID: Industry name	Nos. firms	Productivity efficiency		Scale efficiency	
		Input-oriented	Output-oriented	Input-oriented	Output-oriented
10: 석탄, 원유 및 우라늄 광업	14	0.89	0.61	0.59	0.87
12: 비금속 광물 광업 ; 연료용 제외	35	0.93	0.84	0.61	0.71
15: 음, 식료품 제조업	269	0.73	0.31	0.29	0.77
17: 섬유제품 제조업 ; 봉제의복 제외	452	0.77	0.29	0.28	0.77
18: 봉제의복 및 모피제품 제조업	287	0.85	0.31	0.16	0.57
19: 가죽, 가방 및 신발 제조업	102	0.85	0.58	0.42	0.65
20: 목재 및 나무 제품 제조업 ; 가구 제외	100	0.85	0.60	0.51	0.77

21: 펄프 종이 및 종이제품 제조업	205	0.79	0.45	0.27	0.63
22: 출판, 인쇄 및 기록매체 제조업	351	0.85	0.36	0.23	0.58
23: 코크스, 석유정제품 및 핵연료제조업	5	1.00	0.90	0.76	0.87
24: 화합물 및 화학제품 제조업	225	0.76	0.47	0.43	0.78
25: 고무 및 플라스틱제품 제조업	509	0.69	0.19	0.16	0.76
26: 비금속광물제품 제조업	161	0.79	0.44	0.21	0.58
27: 제1차 금속산업	205	0.76	0.45	0.38	0.73
28: 조립금속제품 제조업 ; 기계 및 가구 제외	739	0.81	0.30	0.25	0.73
29: 기타 기계 및 장비 제조업	944	0.76	0.26	0.25	0.78
30: 컴퓨터 및 사무용 기기 제조업	47	0.86	0.73	0.64	0.79
31: 기타 전기기계 및 전기변환장치 제조업	272	0.77	0.35	0.30	0.74
32: 전자부품, 영상, 음향 및 통신장비 제조업	186	0.83	0.62	0.57	0.81
33: 의료, 정밀, 광학기기 및 시계 제조업	135	0.83	0.50	0.40	0.75
34: 자동차 및 트레일러 제조업	184	0.76	0.59	0.63	0.83
35: 기타 운송장비 제조업	38	0.84	0.78	0.73	0.82
36: 가구 및 기타 제품 제조업	273	0.85	0.39	0.36	0.80
37: 재생용 가공원료 생산업	22	0.98	0.93	0.84	0.89
50: 자동차판매, 차량연료 소매업	93	0.93	0.42	0.34	0.76
51: 도매 및 상품중개업	1,278	0.81	0.11	0.08	0.76
52: 소매업 ; 자동차 제외	234	0.88	0.30	0.12	0.54
OVERALL	7,365	0.80	0.32	0.26	0.73

Table 4: Variable returns efficiency score range based on firms location

Score range	Seoul		KyungKiDo	
	Input-oriented	Output-oriented	Input-oriented	Output-oriented
0.0 - 0.2	7 (0.5%)	863 (56.2%)	9 (0.4%)	1,100 (55.0%)
0.2 - 0.4	83 (5.4%)	225 (14.7%)	169 (8.4%)	319 (15.9%)
0.4 - 0.6	258 (16.8%)	105 (6.8%)	477 (23.8%)	153 (7.6%)
0.6 - 0.8	63 (4.1%)	58 (3.8%)	123 (6.1%)	82 (4.1%)
0.8 - 1.0	1,124 (73.2%)	284 (18.5%)	1,223 (61.1%)	347 (17.3%)
Total	1535	1535	2001	2001
Avg. score	0.86	0.32	0.80	0.33
Score range	Pusan		Incheon	
	Input-oriented	Output-oriented	Input-oriented	Output-oriented
0.0 - 0.2	1 (0.2%)	317 (55.0%)	1 (0.2%)	267 (50.5%)
0.2 - 0.4	42 (7.3%)	73 (12.7%)	47 (8.9%)	96 (18.1%)
0.4 - 0.6	123 (21.4%)	37 (6.4%)	123 (23.3%)	45 (8.5%)
0.6 - 0.8	25 (4.3%)	21 (3.6%)	27 (5.1%)	29 (5.5%)
0.8 - 1.0	385 (66.8%)	128 (22.2%)	331 (62.6%)	92 (17.4%)
Total	576	576	529	529
Avg. score	0.82	0.35	0.80	0.35
Score range	Other location		Entire Korea	
	Input-oriented	Output-oriented	Input-oriented	Output-oriented
0.0 - 0.2	23 (0.8%)	1,584 (58.1%)	41 (0.6%)	4,131 (56.1%)
0.2 - 0.4	362 (13.3%)	462 (17.0%)	703 (9.5%)	1,175 (16.0%)
0.4 - 0.6	680 (25.0%)	162 (5.9%)	1,661 (22.6%)	502 (6.8%)
0.6 - 0.8	141 (5.2%)	106 (3.9%)	379 (5.1%)	296 (4.0%)
0.8 - 1.0	1,518 (55.7%)	410 (15.1%)	4,581 (62.2%)	1,261 (17.1%)
Total	2724	2724	7365	7365
Avg. score	0.75	0.30	0.80	0.32

Rather than analysis the efficiency score employing only one orientation model as most existing DEA researches, the study pay attention on measuring performance both input and output orientation. Comparing the efficiency score resulted of input and output oriented model can give some vision about the characteristics of shipping productivity efficiency. The distribution of efficiency scores for input- and output-oriented model is shown in figure 1. In figure 1, the shipping firms for each location are grouped together and sorted according to the industry ID. Two finding can be drawn from the figure. First, comparing the efficiency score distribution with spatial consideration, the location of the firms seems not influence the efficiency of the shipper.

Second, comparing the distribution of the score based on model orientation, it illustrates that the efficiency resulted of output oriented model is continuous while the one that resulted of input oriented model is more discrete. This can be implied that the shipping decision units are managing their production based on maximized outputs and kept inputs at their current levels. In the other word, the second implication recommended that the output-oriented model is suitable for shipping productivity efficient evaluation.

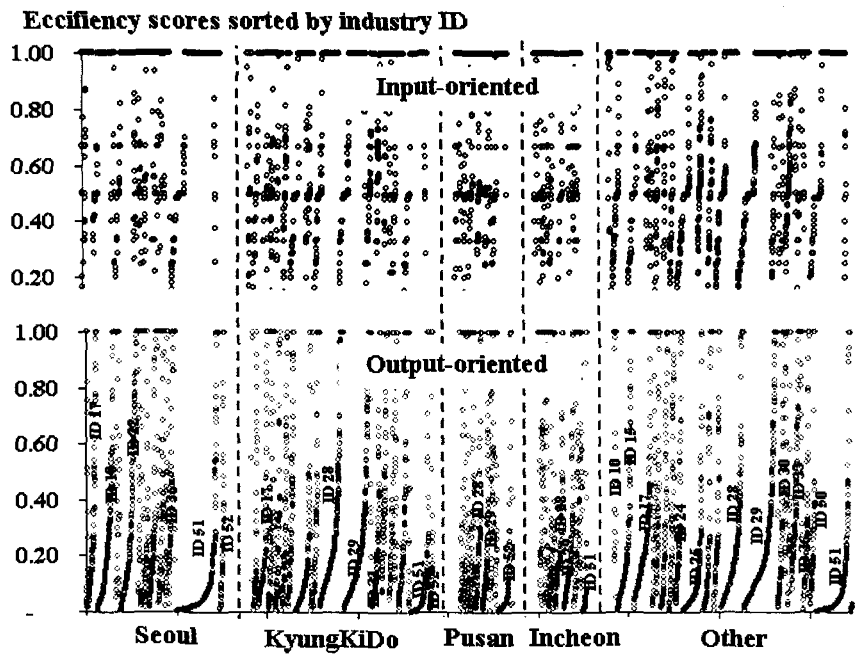

Figure 1: Sorted efficiency score with firm locations

2. Firm size evaluation

Scale efficiency is the ratio of constant returns to variable returns efficiency scores. If the value of this ratio is one, then the observed DMU is operating at the optimal size. The average scale efficiency results of each industry have been tabulated in table 3.

For the firms who are not operating at the optimal size their scale efficiency is not equal one. Comparing the efficiency score of variable returns to the one obtained from the non-increasing returns, the evaluation of firm's size whether they are too large or too small can be identified. Table 5 is the conclusion of firms size evaluation. The result illustrates that mostly the firm's size of shipping company in Korea are too small compared to the optimal. Evaluating firm's size using input-oriented model shows that almost 94% of the shipping company is operating at the small size. There are only 5.3% are operating at the optimal size. Using output-oriented model, the results can be concluded to the same implication. From output-oriented, 67.1% of shipping firm is considered as too small and 11.2% has optimal firm's size. This finding can be concluded that the shipping companies should be extended their operating size.

Table 5: Korea shipping firm's size evaluation

Size evaluation	Number of firms	
Input-oriented model		
Optimal size	392	(5.3%)
Too large	65	(0.9%)
Too small	6,908	(93.8%)
Output-oriented model		
Optimal size	828	(11.2%)
Too large	1,593	(21.6%)
Too small	4,944	(67.1%)

3. Peer count

A part of the solution of DEA model is the set of multiplier indicating the peer for an observed shipping firm. Firms with non zero values of the multiplier have been define to be a set of peers for observed firms in improving the efficiency.

The firm that most frequently appear into a set of other DMU consider as the best-practice firm. Table 6 contains the firm ID who most appear as a reference for other firms in the same industry and together with the number of time they are appeared resulted from peer count.

Table 6: Most reference firms from peer count

ID: Industry name	Input-oriented		Output-oriented	
	Firm ID	Peer count	Firm ID	Peer count
10: 석탄, 원유 및 우라늄 광업	30111	10	30111	12
12: 비금속 광물 광업 ; 연료용 제외	15	18	80	18
15: 음, 식료품 제조업	60004	270	6153	221
17: 섬유제품 제조업 ; 봉제의복 제외	421	221	1142	330
18: 봉제의복 및 모피제품 제조업	1344	92	7289	251
19: 가죽, 가방 및 신발 제조업	3069	68	3069	75
20: 목재 및 나무 제품 제조업 ; 가구 제외	2104	111	2104	69
21: 펄프 종이 및 종이제품 제조업	5165	67	5165	178
22: 출판, 인쇄 및 기록매체 제조업	879	163	1086	295
23: 코크스, 석유정제품 및 핵연료제조업	2697	3	7651	4
24: 화합물 및 화학제품 제조업	631	77	631	99
25: 고무 및 플라스틱제품 제조업	5643	201	5643	488
26: 비금속광물제품 제조업	3599	75	3599	123
27: 제1차 금속산업	6282	65	1837	141
28: 조립금속제품 제조업 ; 기계 및 가구 제외	2712	238	2519	649
29: 기타 기계 및 장비 제조업	2606	353	3132	599
30: 컴퓨터 및 사무용 기기 제조업	3690	31	3690	35
31: 기타 전기기계 및 전기변환장치 제조업	5845	143	559	194
32: 전자부품, 영상, 음향 및 통신장비 제조업	3467	81	1904	86
33: 의료, 정밀, 광학기기 및 시계 제조업	844	68	769	76
34: 자동차 및 트레일러 제조업	7250	79	3591	84
35: 기타 운송장비 제조업	6969	26	6969	25
36: 가구 및 기타 제품 제조업	959	105	680	175
37: 재생용 가공원료 생산업	6461	11	2186	12
50: 자동차판매, 차량연료 소매업	11162	51	11162	66
51: 도매 및 상품중개업	12386	439	9299	705
52: 소매업 ; 자동차 제외	10110	84	9809	181

V. Conclusions

The study measures Korea shippers performance by using DEA techniques to evaluate the productivity efficiency score. The data used in analysis is collected from 2005 commodity flow survey. The number of 7,365 shipping firms from 27 industries were evaluated in the study.

The analysis applied DEA models both input - and output orientation each including variable returns, constant returns, and non-increasing returns model to measure the productivity efficiency score and the scale efficiency of an observed shipper in an same industry. The empirical results show that in overall the average shipping productivity efficiency based on output orientation is 0.32 and based on input orientation is 0.80. Since the output-oriented model is superior than input-oriencted to represent the decision making of shipping manager, the shipping firms in Korean is consider an inefficiency. In addition, the result from scale effect analysis shows that almost 80% of shipping firm in Korea are operating in small level of production compared to the optimal size. The shipper should enlarge the production size. Finally, from peer count, the result herein also determine which firms are the best-pratice interm of most apperence to be a reference for other.

Because of the wide data, the study are still facing the problem when applying the existing DEA models to determine the efficiency comparing all 7,365 shipping firms together. This can be solved from two approaches. First is designing the wide variables into a categorical variables. Second is developing a methodology to integrate data filtering into DEA model. Both approaches will be an extension of the study.

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