물류활동에 종사하는 트럭의 효율성: 데이터 포락 분석 활용

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Efficiency of trucks in logistics: An evaluation with Data Envelopment Analysis

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요 약

This paper proposes a scheme to estimate the technical efficiency of trucks in logistics as performance measure by Data Envelopment Analysis (DEA). The result of technical efficiency estimation shows that there exists a substantial opportunity for improvement in technical efficiency of trucks and also the heterogeneity in the technical efficiency among trucks.

1. Introduction

Over past 20 years, logistics has been developed as one of the most important factors of business competitiveness and one of the most promising service industries. As the production technology has been matured, the establishment of seamless connection among players in a supply chain through logistics becomes an important source of competitiveness because it is almost impossible for firms to get competitive advantage through the innovation of technology. In Korea, total logistics cost in 2006 is over ₩100,000,000 million and it continues to be increased in the future. In this logistics industry, trucks play the most important and popular role in inland logistics. Without trucks, multimodal transportation system cannot be set up at all.

In this situation, the accurate evaluation of trucks' efficiency has become more important for reasonable performance management and compensation. This paper concentrates on the evaluation of technical efficiency for trucks. The reasons why technical efficiency is selected for performance measure are that it is evaluated relatively to best performance trucks not to average trucks and that it can take multiple inputs and outputs into account simultaneously.

Farrell (1957) initially claimed that evaluation of efficiency is useful for decision making units (DMUs) because it provides information on how much a DMU can decrease input without decreasing output (with keeping current output). Equivalently, technically inefficient DMUs can be brought towards efficiency by cutting down overused inputs. Trucks (DMUs) can also reduce the overused inputs (Bad performance) and truck owners evaluate their trucks reasonably through the evaluation of technical efficiency. As the approach to evaluate the technical efficiency, Data Envelopment Analysis (DEA) is employed in this paper because it does not require the assumption of the functional specification between input factors and output factors and also includes multiple outputs unlike stochastic frontier model (SFM). Data for empirical analysis in this paper come from a survey to truck drivers.

One application of DEA to trucks is found (Hjalmarsson and Odeck, 1996). The objectives of this paper are to determine individual-truck level technical efficiency using both radial and nonradial measure for freight truck, to calculate the degree of input overuse. This paper provides the general applicability of nonradial measure.

2. Theoretical Backgrounds

The implications of this problem for the measurement of technical efficiency were recognized by Farrell (1957) and Charnes et al. (1978). The input based measures of Farrell and of Russell efficiency can be defined following these studies for a set of N firms indexed $n=1,...,N$, each with access to the same technology that transforms a vector of variable inputs $x_n \in R_+^I$ into a vector of outputs $y_n \in R_+^J$. More generally, for the set of firms, we can define a ($I \times N$) input matrix, X, and a ($J \times N$) output matrix, Y. Suppose the technology satisfies the augmented regularity conditions adopted by Banker et al. (1984). The production possibilities set for firm n_0 which is evaluated firm can be written as the following piece-wise linear technology:

$$
\begin{aligned}
P = \{(y_{n_0}, x_{n_0}) \mid x_{n_0} \geq \sum_{n=1}^{N} z_n x_n,& \\
y_{n_0} \leq \sum_{n=1}^{N} z_n y_n, \sum_{n=1}^{N} z_n = 1, z \in R_+^N\}& \qquad (1)
\end{aligned}
$$

where $z = (z_1, ..., z_N)$ is the intensity vector with elements indicate the intensity with which

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each firm's production plan is taken into account in the construction of the technology frontier (Cooper et al., 2000). By equation (1), firm n's production plan (x_n, y_n) belongs to the production possibilities set, if and only if, $(x_n, y_n) \in P$. Input-based radial technical efficiency (*RTE*) and input-based nonradial technical efficiency (*NRTE*) are for the firm n_0 as follows.

$$\underset{\lambda_{n_0}, z_n}{Min}\, \lambda_{n_0}$$

$$\sum_{n=1}^{N} z_n x_{n,i} \le x_{n_0,i} \lambda_{n_0}, \; i = 1, 2, \ldots, I \tag{2}$$

$$y_{n_0,j} \le \sum_{n=1}^{N} z_n y_{n,j}, \; j = 1, 2, \ldots, J$$

$$\sum_{n=1}^{N} z_n = 1$$

$$\underset{\lambda_{n_0,i}, z_n}{Min} \sum_{i=1}^{I} \lambda_{n_0,i}$$

$$\sum_{n=1}^{N} z_n x_{n,i} \le x_{n_0,i} \lambda_{n_0}, \; i = 1, 2, \ldots, I \tag{3}$$

$$y_{n_0,j} \le \sum_{n=1}^{N} z_n y_{n,j}, \; j = 1, 2, \ldots, J$$

$$\sum_{n=1}^{N} z_n = 1$$

Equation (2) and (3) illustrates the DEA models developed by Banker et al. (1984), assuming the variable returns to scale (VRS) which implies that outputs (returns to scale) are changed in the amount of inputs used.

3. Data and Empirical Issues

The data on monthly operation records of trucks in 2007 for efficiency evaluation were collected through the interview with truck drivers. The evaluated trucks are, as noted, engaged in logistics. The number of sample is 62.

The model for efficiency evaluation is specified with three output categories (transportation distance, transportation amount, and effective transportation distance) and five variable input factors (labor cost, fuel cost, oil cost, supplies cost, and tax and insurance etc.).

In order to guarantee the robustness of DEA results, it is very important to determine the model specification appropriately because DEA is dependent on extreme points. As a measure for evaluation of appropriateness of model specification, dimensionality (= $\frac{\#\ of\ trucks}{\#\ of\ input\ factors + \#\ of\ output\ factors}$) can be used (Fernandez-Cornejo, 1994). If it is greater than 5, the model specification looks good. Since the dimensionality of this research is greater

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than 5 ($\frac{62}{3+5} \cong 8$), this model specification is acceptable. Table 1 illustrates the summary of data for efficiency evaluation and benchmark analysis.

Table 1. Summary of data for efficiency evaluation

Variables	Minimum	Maximum	Mean	Standard Deviation
Labor cost (₩/month)	1,000,000	3,500,000	2,058,064.52	549,455.29
Fuel cost (₩/month)	100,000	3,000,000	1,084,193.55	498,369.63
Oil cost (₩/month)	20,000	800,000	122,741.94	119,571.22
Supplies cost (₩/month)	20,000	1,200,000	195,806.45	170,866.15
Tax, insurance etc. (₩/month)	100,000	800,000	296,290.32	155,122.73
Transportation distance (km/month)	2,000	13,000	4,683.80	2,468.60
Transportation amount (ton/month)	20	350	84.27	55.42
Effective transportation distance (km/month)	600	13,000	3,692.00	2,806.00

4. Results and Discussion

Technical efficiency for 62 trucks engaged in logistics. Table 2 shows the examples of technical efficiency estimated for 5 trucks. Truck 2's radial efficiency score and all nonradial efficiency scores are 1.0000, which implies that it is efficient and does not need to reduce any inputs given current level of outputs. Truck 1's radial efficiency score is 0.7970, which implies that it

should reduce all inputs by 20.30% in order to be technically efficient keeping current outputs. However, nonradial measure gives us different insight to truck 1. Truck 1 should reduce labor cost by 17.73%, fuel cost by 90.35%, oil cost by 16.39%, supplies cost by 14.74%, and tax and insurance etc. by 18.41% in order to be technically efficient. The results for truck 3, 4, and 5 are interpreted in the same way as the results for truck 1 and truck 2. Moreover, the results in Table 2 illustrate the heterogeneity in inefficiency among trucks. Each truck has different radial efficiency score and different nonradially inefficient inputs.

Table 2. Examples for technical efficiency of trucks

Truck ID	Radial	Nonradial efficiency

	efficiency	Labor cost (₩/month)	Fuel cost (₩/month)	Oil cost (₩/month)	Supplies cost (₩/month)	Tax, insurance etc. (₩/month)
1	0.7970	0.8227	0.0965	0.8361	0.8526	0.8159
2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	0.8044	0.6170	0.2562	0.3982	0.9790	0.3456
4	0.4646	0.4717	0.1258	0.4149	0.4362	0.4764
5	0.7389	0.6968	0.1368	0.6617	0.8796	0.7419

The summary of technical efficiency evaluation also shows the heterogeneity in efficiency of trucks, substantial opportunity for improvement, and the possibility for use of multiple criteria for performance evaluation of trucks. The heterogeneity is shown by the results that the ranges of efficiency are 69.75% for radial measure, 78.07% for nonradial measure of labor cost, 94.45% for nonradial measure of fuel cost, 88.72% for nonradial measure of oil cost, 88.75% for nonradial measure of supplies cost, and 69.95% for nonradial measure of tax and insurance etc.. Moreover, the result that the percent of efficient trucks ranges from 25.81% to 35.48% also shows the heterogeneity. For improvement opportunity, trucks should improve their efficiency by 24.56%, 40.38%, 42.41%, 30.62%, 40.14%and 25.85% averagely for radial efficiency and nonradial efficiency for input factors, respectively. From the results from nonradial measure, we found that truck performance should be measured by multiple criteria.

Table 3. Summary of results from technical efficiency evaluation of trucks

Summaries	Radial measure	Nonradial efficiency				
		Labor cost (₩/month)	Fuel cost (₩/month)	Oil cost (₩/month)	Supplies cost (₩/month)	Tax, insurance etc. (₩/month)
Average efficiency (%)	75.44%	59.62%	57.59%	69.38%	59.86%	74.15%
# of efficient trucks	16	16	17	20	17	22
% of efficient trucks	25.81%	25.81%	27.42%	32.26%	27.42%	35.48%
Minimum	30.25%	21.93%	5.65%	11.28%	11.25%	30.05%

efficiency (%)						

5. Conclusion

This paper deals with topic how to evaluate the performance of trucks engaged in logistics. Technical efficiency based on production function of trucks was chosen as the performance measure and DEA was implemented in order to estimate technical efficiency. As the result, it was possible to confirm some meaningful findings and get some important intuition.

Trucks engaged in logistics show the substantial heterogeneity in technical efficiency. While some trucks are efficient, other trucks are inefficient by considerable amount. Trucks show also the different pattern in technical inefficiency. Some trucks are inefficient in labor cost, some trucks are inefficient in fuel cost, and some trucks are inefficient in other input factors, which also implies that each truck should be evaluated in multiple dimensions.

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