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Ching-Jung Ting
Yuan-Ze University

Hsueh-Lin Fang
Yuan-Ze University

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Ching-Jung Ting and Hsueh-Lin Fang
Department of Industrial Engineering and Management
Yuan Ze University

Abstract

There has been considerable interest worldwide in last few years in the growth of third party logistics (3PL) providers. 3PL distribution center (DC) enables firms to achieve reduced operating costs, increased revenues, and to focus on their core competence. This research aims to find the key performance indicators through a survey of a set of DCs and then evaluate their efficiency over the period 2005-2007 using data envelopment analysis (DEA) models based on selected performance indicators as inputs and outputs. Three inputs and two outputs for all DCs from the surveyed performance indicators were selected in this study. DEA is a non-parametric linear programming technique used to evaluate the efficiency of decision making units (DMUs) where multiple inputs and outputs are involved. We adopted both the input-oriented CCR model and the BCC model that were designed to derive weights instead of being fixed in advance and handle positive inputs/outputs. A Malmquist productivity index (MPI) analysis further evaluates efficiency change and productivity growth between two time points. Our empirical results show that scale inefficiency is the major reason for the inefficient DMUs. For the future research, more DC data should be collected and different DEA models could be applied for other benchmark studies.

1. Introduction

With the increasing global competition, companies across industries and around the world regard logistics and supply chain management as key components of their overall business success (2009 3PL Study [25]). Third-party logistics (3PL) provider is one that provides or manages one or more logistics services for its customers. Outsourcing of logistics services to a 3PL enables firms to reduce their payroll and their warehousing fixed costs and to focus on their core competency. The 3PL distribution centers (DCs) often have an advantage over individual companies, owing to the presence of economies of scale and scope. With recent economic downturn and increasing competition, 3PL DC managers have to measure the performance relative to its competitors and its previous years to continuously improve its market competitive strength. Thus, benchmarking seems to be the most suitable way of setting a reliable standard and then measuring the operational efficiency of the 3PL DC.

In the warehouse industry, traditionally productivity benchmark is measured as a ratio of a single output to a single input, called single ratio productivity measures (Tompkins et al. [26]). However, as production processes have become more complex as in the 3PL DC, multiple inputs are often used to produce more than one output. This leads to a set of single ratio productivity measures which can be confusing to evaluate – a typical multiple criteria evaluation problem. Warehouse performance therefore, has multiple dimensions. Data envelopment analysis (DEA), using the linear programming techniques, provides a suitable way to establish a multiple inputs and multiple outputs empirical efficient function as described by Farrell [11]. The relationship between DEA and single ratio productivity measure has been investigated and described in Chen and McGinnis [4].

DEA requires the inputs and outputs for each decision-making units (DMUs) to be specified. It will then compute efficiency score for each DMU as a ratio of weighted sum of outputs to a weighted sum of inputs, where all efficiency scores are restricted to lie between 0 and 1. The strength of the DEA is that it allows each DMU to select the weights that maximize its own efficiency. On the other hand the efficiency does not mean that the DMUs are absolutely efficient but they are relatively efficient among the other units. Literature reviews, such as the excellent bibliography in Seiford [24] and Cook and Seiford [6], reveal that few researches examining the use of mathematical programming and associated statistical techniques to aid decision-making in warehousing benchmarking.

In addition to comparing the relative performance of a set of DMUs at a specific period, some researches extended the DEA to include more than a single time period and treat each DMU at different period as different units. Some also used DEA with window analysis to evaluate the efficiency trend over multiple year data. However, it is difficult to tell the DMUs at latter time period are inherently advantageous over the former ones because technological advance has been regularly made overtime. Caves et al. [2] proposed a Malmquist productivity index (MPI) which measures several DMUs at several time points and differentiates the productivity change results from efficiency change or technological change. The most popular method is the one proposed by Färe et al. [9] which takes the geometric mean of two MPIs calculated from two time periods. By observing the MPI over time, a relatively inefficient DMU determined by using DEA, may be the one with the greatest productivity growth. MPI is very useful for calculating the productivity change of a DMU, and many applications have been reported in logistics.

The remainder of the paper is organized as follows. In section 2 we briefly review the related literature. Section 3 introduces DEA as a benchmarking method and the Malmquist productivity index. In section 4 we describe the data collection and inputs and outputs variables. In section 5 we present our empirical results and section 6 gives some concluding remarks.

2. Related Literature

Schefcyzk [23] showed that for internal benchmarking, traditional ratio approaches correlate with simple DEA models. The case study of sixteen warehouses performance evaluation showed that simple cost-based measures to be suitable for internal benchmarking. Cohen et al. [5] conducted an industrial survey of service parts logistics and defined relevant performance measures and measured the achieved values of such measures. However, the comparative results were based on a number of normalized ratios of specific financial and service performance variables.

Hackman et al. [14] argued that ratio-based performance measures are inaccurate and inappropriate for warehousing. Data envelopment analysis (DEA) is regarded as an appropriate tool for this task because of its capability to capture simultaneous all the relevant inputs (resources) and outputs (performances), to construct the best performance frontier, and to reveal the relative shortcomings of inefficient warehouses. Ross and Droge [22] measured 102 distribution centers' productivity, and identified distribution centers with consistent best performance using facet analysis, and detected performance trends using DEA window analysis of 4 years data.

An internet-based DEA system (iDEA) for warehouses was designed by the Keck Lab at Georgia Tech (McGinnis et al. [19]). Because of price sensitivity and service requirements among customers, increasing efficiency is of critical importance. Thus, DC managers in the competing 3PL environment would like to identify improvements through the development of standards for comparison to similarly situated DCs. Johnson et al. [16] described the development of large-scale internet benchmarking instance, iDEAs-W and their findings from this ongoing collaboration between academia and the warehousing industry.

Hamdan and Rogers [15] proposed a new weight-restricted DEA model with four inputs, labor, space, technology cost and material handling equipment cost, and three outputs, shipping volume, order filling and space utilization, to evaluate 19 warehouses. Zhou et al. [27] developed two DEA models to measure the operational efficiency of ten leading 3PL in China with multiple year data. Min and Joo [20][21] also applied DEA on evaluating the 3PL providers in USA. De Koster and Balk [8] evaluated the efficiency of 65 European distribution centers (EDCs) and compare for years 2000 and 2004. They found that public EDC warehouses run by logistics service providers are more efficient than own-account EDC warehouses. Manrodt and Vitasek [18] identified common metrics that impact both distribution and manufacturing. They found that 3PLs are being required, measured and rewarded on driving performance for value for their customers. Senior management is paying more attention to performance measures to gain better understanding of the turmoil in the economy and cut costs through efficiencies. Gu et al. [13] reviewed the benchmarking and analytical models for warehouse performance evaluation in terms of cost, throughput, space utilization, and service provides.

To our knowledge, there is only one research applying MPI to evaluate the warehouse performance by De Koster and Balk [8]. However, they only compared two time points which are 4 years apart (2000-2004) not for consecutive time periods. Our research is the first to apply MPI to evaluate the 3PL distribution centers in a period of consecutive years. In this paper, we adopt both the Charnes, Cooper and Rhodes (CCR) model and Banker, Charnes and Cooper (BCC) model among several different types of DEA models. The CCR model differs from the BCC model in that the former considers constant returns to scale, whereas the latter considers variable (decreasing or increasing) returns to scale and thus mitigates the impact of economies of scale on the efficiency.

3. Methodology

DEA is a non-parametric mathematical programming approach for measuring relative efficiencies of comparable DMUs with respect to multiple inputs and outputs in a specific situation. With the use of DEA, the most appropriate set of weights for all the inputs and outputs are determined so that the resulting efficiency scores are less than or equal to one. Consider a set of n DMUs, with each DMU j (j = 1, …, n), using m inputs x_{ij} (i = 1, …, m) and generating s outputs y_{rj} (r = 1, …, s). In the absence of priori knowledge on weights, v_i, u_r associated with inputs i and outputs r, the DEA model allows each DMU to choose the weights of its inputs and outputs in order to maximize its own efficiency score with respect to the others. Charnes et al. [3] solved the particular non-linear programming problem to obtain the appropriate weights for a given DMU. Specifically, the CCR model for measuring the technical efficiency of that targeted DMU$_0$ is given by the solution to the fractional programming problem as follows.

$$\begin{aligned}
&\underset{u,v}{Max} \quad e_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \\
&S.T. \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad \forall j \\
&\qquad\quad u_r, v_i \ge 0 \qquad\qquad \forall i, r
\end{aligned} \tag{1}$$

This model which involves the weighted ratio of outputs to inputs is referred to as the input-oriented model. CCR model assumes constant returns to scale (CRS). Applying the theory of fractional programming, CCR can be converted to a linear programming model as follows.

$$\begin{aligned}
&\underset{u}{Max} \quad e_0 = \sum_{r=1}^{s} u_r y_{r0} \\
&S.T. \quad \sum_{i=1}^{m} v_i x_{i0} = 1 \\
&\qquad\quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad \forall j \\
&\qquad\quad u_r, v_i \ge 0 \qquad\qquad \forall i, r
\end{aligned} \tag{2}$$

By duality, this problem is equivalent to the linear programming problem.

$$
\begin{aligned}
&\underset{\theta}{Min} \quad \theta_0 - \varepsilon(\sum_{r=1}^{s} s_r^+ - \sum_{i=1}^{m} s_i^-) \\
&S.T. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0} \qquad \forall i \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0} \qquad \forall r \\
&\qquad \lambda_j, s_i^-, s_r^+ \geq 0 \qquad \forall i, j, r \\
&\qquad \theta_0 \text{ unconstrained}
\end{aligned}
\tag{3}
$$

The slack variables for the *i*th input and the *r*th output are, respectively, represented by s_i^- and s_i^+, which indicate the input excess and output shortfall, respectively. The variable λ_j denotes the weight of DMU_j while assessing the performance θ_0 of the object DMU_0. ε is the non-Archimedean constant.

The above model is solved *n* times to evaluate the relative efficiency score of each DMU. Note that the weight v_i, u_r associated with inputs *i* and outputs *r* will be optimally determined by maximizing the efficiency score of the targeted DMU_0. An efficiency score of 1 indicates that the targeted DMU is efficient relative to other DMUs and lies on the efficiency frontier, which is composed of the set of efficient DMUs. An efficiency score of less than one indicates the targeted DMU is inefficient.

3.1 BCC Model

Banker et al. [1] (BCC) extended the earlier work of Charnes et al. [3] by providing for variable returns of scale (VRS) and thus mitigates the impact of economies of scale on the operational efficiency. The BCC model adds an additional variable u_0 to identify the returns of scale of the targeted DMU. The linear programming model of BCC is

$$
\begin{aligned}
&\underset{u}{Max} \quad e_0 = \sum_{r=1}^{s} u_r y_{r0} - u_0 \\
&S.T. \quad \sum_{i=1}^{s} v_i x_{i0} = 1
\end{aligned}
\tag{4}
$$

$$\sum_{r=1}^{s} u_r y_{rj} - u_0 - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad \forall j$$
$$u_r, v_i \geq 0 \qquad \forall i, r$$
u_0 unconstrained in sign

The dual for which is given by the following.

$$\begin{aligned}
&\underset{\theta}{Min} \quad \theta_0 - \varepsilon\left(\sum_{r=1}^{s} s_r^+ - \sum_{i=1}^{m} s_i^-\right) \\
&S.T. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0} && \forall i \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0} && \forall r \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j, s_i^-, s_r^+ \geq 0 && \forall i, j, r \\
&\theta_0 \text{ unconstrained}
\end{aligned} \tag{5}$$

where θ_0 is the resource input efficiency ratio for DMU_0. Compared to the CCR, BCC has the additional convexity constraint $\sum_j \lambda_j = 1$ causes the feasible region of the BCC to be a subset of the CCR. The optimal solution to (5) implies that DMU_0 is efficient if and only if the followings hold: (1) θ_0^* = 1.00 and (2) all slacks $s_i^- = s_r^+ = 0.00$. DEA generates an efficiency frontier consisting of the piece-wise linear combinations of the efficient DMU called the reference set.

3.2 Malmquist Productivity Index

Malmquist productivity index (MPI) first introduced by Malmquist [17] has further been studied and developed in Färe et al. [9][10]. Färe et al. [9] constructed the DEA-based MPI as the geometric mean of the two Malmquist productivity indices of Caves et al. [2] – one measures the change in technical efficiency and the other measures the shift in the frontier technology. Färe et al. [10] developed it into the output-based Malmquist productivity change index. The input-oriented Malmquist productivity index of a DMU can be expressed as

$$M_0(x_0^t, y_0^t, x_0^{t+1}, y_0^{t+1}) = \left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^t, y_0^t)} \right]^{\frac{1}{2}} \tag{6}$$

M_0 measures the productivity change between periods t and t + 1, productivity declines if M_0 < 1, remains unchanged if M_0 = 1 and improves if M_0 > 1. The frontier technology determined by the efficient frontier is estimated using DEA for a set of DMUs. However, the frontier technology for a particular DMU under evaluation is only represented by a section of the DEA frontier or a facet. Färe et al. [10] decomposed the MPI in eq. (6) into two terms, as shown in eq. (7), that makes it possible to measure the change of technical efficiency and the shift of the frontier in terms of a specific DMU_0. This implies that productivity change includes efficiency change as well as technical change component.

$$\overline{M}_0(x_0^t, y_0^t, x_0^{t+1}, y_0^{t+1}) = \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \left[\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \frac{D_0^t(x_0^t, y_0^t)}{D_0^{t+1}(x_0^t, y_0^t)} \right]^{\frac{1}{2}} \tag{7}$$

The first term on the right hand side captures the change in technical efficiency (EC) between periods t and t + 1. EC > 1 indicates that technical efficiency change improves while EC <1 indicates efficiency change declines. The second term measures the technology frontier shift (TECH) between periods t and t + 1. A value of TECH >1 indicates progress in the technology, a value of TECH < 1 indicates regress in the technology. TECH = 1 indicates no shift in technology frontier. The technical efficiency change can further be decomposed into scale efficiency change (SECH) and pure technical efficiency change (PTEC) which is similar with the DEA-BCC model (Färe et al. [9]).

4. Data and Inputs/Outputs

4.1 Data

The assessment of operational efficiency using DEA begins with the selection of appropriate input and output measures. The input and output variables for measuring the efficiency of warehousing industry tends to be diversified in the literature, due to the lack of uniform performance evaluation criteria. Considering data availability and summarizing from what were used in the past studies, we first listed a set of performance metrics for the participants to select what are considered important for evaluating the distribution center performance. This survey was conducted in February-March 2009 with responses solicited by the members of the Logistics Association in Taiwan. Personnel interviews were also conducted to understand the specifics of their businesses and to clarify their responses to the questions. All results are presented in an anonymous manner, to preserve respondent confidentiality.

The participants were asked to rate each key performance indicator on a scale from 1 to 5, with 1 best the least important and 5 being the most important. The collected data were then analyzed to derive the rank for KPIs. Table 1 presents the top 10 KPIs from the survey. These KPIs can be considered as five sets, customer, operational, financial, capacity/quality and employee, which is consistent as those defined by Manrodt and Vitasek (2009).

Table 1. The Top 10 Used Key Performance Indicators in DCs

Performance indicator	Score	rank
Order picking accuracy	4.8462	1
On-time shipment	4.5385	2
Employee productivity	4.5385	2
Distribution cost per order	4.5385	2
Average warehouse capacity used	4.4615	5
Order picking productivity	4.3077	6
Inventory turnover	4.3077	6
Revenue per area	4.1538	8
Asset turnover rate	3.9231	9
Return order process	3.9231	9

In March-April 2009, we sent out the second questionnaires to collect data for years 2005-2007 from the DCs who returned the first questionnaire. 11 distribution center operators and managers returned the second questionnaire. The number of DCs is less than we expected. It is found that some confidential data is difficult to be obtained as companies may not want to share out the data or some data were not recorded or maintained across all participating DCs. To comply with the rule of thumb, the number of units should be at least twice the number of inputs and outputs considered (Golany and Roll [12]), we select three inputs and two outputs. The descriptive statistics of these variables are listed in Table 2. Sections 4.2 and 4.3 presented these variables.

Table 2. Descriptive Statistics of Inputs and Outputs during the Three-year Span

	Item	Maximum	Minimum	Average	Std. dev.
Inputs	Number of imperfect orders	8,200	8	761.364	1,853.939
	Number of employees	280	5	98.303	79.899
	Average warehouse capacity used (%)	145.2	24.4	81.59	24.39
Outputs	Revenue (in NT$1,000)	1,430,000	40,000	326,689.85	401,950.28
	Total number of orders	7,500,000	4,560	887,817.42	1,955,984.69

4.2 Inputs

1. Number of imperfect orders – A perfect order must fulfill the following components: delivered on time, shipped complete, shipped damage free, and correct documentation. If one or more of the four components are not achieved, that order will be count as an imperfect order.
2. Number of employees – the index constructed to represent the labor input is the sum of the number of direct and indirect labor performing all operations in the warehouse.
3. Average warehouse capacity used – the ratio of average capacity used (measured in number of pallets) and capacity available (measured in the number of pallets that a warehouse can store). At some distribution center, if the pallet rack cannot accommodate all the pallets, the pallets will be put on the aisles. Thus, some of the average warehouse capacity used is more than 100%. Since we want to minimize the input, we use the reciprocal of average capacity utilization as the third input.

4.3 Outputs

1. Revenue – better service quality and more efficient utilization of DC resources will enhance revenue.
2. Total number of orders – the picking/shipping workload is driven by the number of orders. Since these DCs do not track the number of cases or lines for the orders, we can only use the total number of orders as the output.

We view those inputs as discretionary inputs, since a warehouse manager can exercise a reasonable degree of control over these inputs. Since the output of a warehouse is typically not within the control of the warehouse manager, we focused on this input-oriented DEA instead of the out-oriented DEA, which determines the increased level of output that could be obtained using no more than the current levels of input. After selecting the inputs and outputs, we used Person correlation analysis to test whether they are isotonic, i.e. increasing inputs should not reduce outputs. As shown in Table 3, the variables selected are positively correlated.

Table 3. Person Correlation Coefficients of Inputs and Outputs

	Number of employees	Number of imperfect orders	Average warehouse capacity used
Total number of orders	0.171	0.322	0.712
Revenue	0.188	0.699	0.258

5. Empirical Results

In general, DEA solutions require solving a linear programming model for each DMU. Because of the risk of degeneracy even for small datasets, calculations with standard LP software are subject to inaccuracies. Therefore, this study used DEA solver – Pro 6.0 [7] to compute efficiency scores and MPI.

Each DC's efficiency score (TE) under constant returns to scale and pure technical efficiency (PTE), scale efficiency (SE) and returns to scale (RTS) under variable returns to scale over the period 2005-2007 are presented in Table 4 where the last row shows the annual average score. According to Table 4, average efficiency scores show an upward trend from 2005 to 2007. Trends of PTE and SE are similar to that of TE. The implication of this rise is that DCs not only operated at the proper size but that the resources were well managed.

Table 4. Annual TE, PTE, SE and Return to Scale for Each DC

	2005				2006				2007			
DMU	TE	PTE	SE	RTS	TE	PTE	SE	RTS	TE	PTE	SE	RTS
A	0.504	0.877	0.575	IRS	0.475	0.924	0.514	IRS	0.443	0.906	0.489	IRS
B	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
C	0.305	0.619	0.493	IRS	0.317	0.664	0.477	IRS	0.354	0.957	0.370	IRS
D	0.505	0.890	0.568	IRS	0.629	0.900	0.699	IRS	0.589	0.790	0.745	IRS
E	0.341	0.892	0.383	IRS	0.567	1.000	0.567	IRS	0.919	1.000	0.919	IRS
F	0.206	1.000	0.206	IRS	0.270	1.000	0.270	IRS	0.253	1.000	0.253	IRS
G	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
H	0.515	0.870	0.593	IRS	0.738	0.912	0.809	IRS	0.917	0.975	0.940	IRS
I	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
J	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
K	0.351	0.785	0.447	IRS	0.358	0.901	0.398	IRS	0.334	0.864	0.387	IRS
Avg.	0.612	0.903	0.660		0.669	0.936	0.703		0.710	0.954	0.737	

In terms of efficiency score alone in Table 4, we can find that four of the 11 DCs, B, G, I and J, are considered to be efficient DMUs over the entire period. The relatively high number of efficient DMUs could result from the fact that we used only 11 DMUs. In checking each DMU, DC F shows that the inefficiency is due to its scale inefficiency. DMUs E and H show persistent progress in efficiency score during the three-year period, while DC A's efficiency score declines year by year due to its scale inefficiency. In terms of returns to scales, those four efficient DCs show constant returns to scale while the rest of 7 relatively inefficient DCs are experiencing increasing returns to scale. This indicates that these inefficient DMUs should invest more on the resources to increase the efficiency. Table 5 presents the average TE, PTE and SE for each DUM over the three year period. Four DCs' (A, C, D, and K) three kinds of average scores are all below the average. DCs F and K show that the inefficient score are due to scale inefficient, while DC H's inefficient is because of pure technical inefficient.

Table 5. Average TE, PTE and SE for Each DC

DMU	TE	PTE	SE
A	0.474	0.902	0.526
B	1.000	1.000	1.000
C	0.325	0.747	0.447
D	0.574	0.860	0.671
E	0.609	0.964	0.623
F	0.243	1.000	0.243
G	1.000	1.000	1.000
H	0.723	0.919	0.781
I	1.000	1.000	1.000
J	1.000	1.000	1.000
K	0.348	0.850	0.410
Avg.	0.663	0.931	0.700

Table 6 displays each DC's original Malmquist productivity index (MPI), technology frontier shift (TECH) and change in technical efficiency (EC) over the period 2005-2007. The last row shows the average scores while the last columns present the average MPI, TECH, and EC for each DMU, respectively. Note that, if a DMU's productivity grows from period t to t+1, its MPI is larger than 1. EC measures whether the DMU has moved closer to or away from the frontier, and TC measure whether the frontier has moved outward or inward. Note that, in Table 6 only DC A does not show technical efficiency progress from 2005 to 2007; on the other hand, we can conclude that other DCs show improvement and decline in technical efficiency change. DCs E and H improve their performance over the average year after year. For all the DCs, technical efficiency improves 13.1% from 2005 to 2006 and improves 5.0% from 2006 to 2007.

It can be seen in Table 6 that on average, the technology frontier improves 3.8% from 2005 to 2006, and improves 7.8% from 2006 to 2007. Only DC I show negative shift in technology frontier between 2005 and 2007, though I is technical efficient in all three years. It can also be observed, on average, that there is about a 17.4% productivity gain from 2005 to 2006, while from 2006 to 2007 there is about 13.2% productivity gain.

Table 6. Each DC's MPI, TECH and EC

	2005 vs. 2006			2006 vs. 2007			Average		
DMU	MPI	TECH	EC	MPI	TECH	EC	MPI	TECH	EC
A	1.086	1.152	0.942	1.140	1.225	0.931	1.113	1.189	0.937
B	1.330	1.330	1.000	0.993	0.993	1.000	1.162	1.162	1.000
C	1.099	1.059	1.038	1.102	0.986	1.118	1.101	1.023	1.078
D	1.246	1.000	1.246	0.965	1.032	0.936	1.106	1.016	1.091
E	1.427	0.859	1.661	1.824	1.125	1.621	1.626	0.992	1.641
F	1.331	1.015	1.311	0.952	1.015	0.938	1.142	1.015	1.125
G	1.111	1.111	1.000	1.313	1.313	1.000	1.212	1.212	1.000
H	1.283	0.895	1.433	1.397	1.125	1.241	1.340	1.010	1.337
I	0.959	0.959	1.000	0.992	0.992	1.000	0.976	0.976	1.000
J	1.033	1.033	1.000	1.016	1.016	1.000	1.025	1.025	1.000
K	1.102	1.079	1.021	1.015	1.088	0.933	1.059	1.084	0.977
Avg.	1.174	1.038	1.131	1.132	1.078	1.050	1.153	1.058	1.091

Examining MPI, we can observe that all warehouses except warehouse I have positive productivity change between 2005 and 2007. Between 2005 and 2006 only DC I shows negative productivity growth, however, four DCs show productivity loss between 2006 and 2007. DCs E and H are relatively inefficient DUM determined by using DEA, however, they are both with the greatest productivity growth. On the other hand, DC I persistently lying on the efficient frontier is the one needing the most technological advance. Without the MPI measures, we may draw a misleading conclusion. The average MPI scores and EC scores of DCs E and H are the highest two of all. As both DCs' average TECH scores are below the overall average, it implies that DCs E and H's productivity growth were driven more by efficiency improvement than technological advance. In this context, we can find that the trend of continuous improvement of DEA efficiency score is also reflected by observing the efficient change of the MPI.

6. Conclusion

As competition in the 3PL industry has intensified and cost pressure has mounted over the last few years, today's 3PL distribution centers are faced with daunting challenges of continuously improving their operational efficiency and competitiveness. This paper applied both CCR and BCC DEA models and the Malmquist productivity index to measure the efficiency score and productivity growth changes of 3PL distribution centers in Taiwan. The primary objective of this paper is to identify potential sources of inefficiency, recognize best-practice 3PLs, and provide useful insight for the continuous improvement of operational efficiency. We first identify the key performance indicators through a survey of a set of 3PL DCs. Then collect data of those KPIs from 11 participating DCs over the period from 2005 to 2007 for evaluating their performance. The three inputs are the number of employees, number of imperfect orders and average warehouse capacity used, and two outputs are revenue and total number of order received.

To summarize, the main contribution of this paper includes the application of both CCR and BCC DEA models to the performance measurement of 3PL distribution centers. The proposed DEA models can be extended to include other inputs and/or outputs and a greater number of 3PLs across the globe. To our knowledge, this paper is the first one to evaluate Malmquist productivity index over a period of three consecutive years. Based on our empirical results, most of the inefficient distribution centers are due to the scale inefficient. All the inefficient DCs exhibit increasing return of scales, which means they still have to invest more on the input resources to improve the efficiency scores. When considering the DEA results and without the MPI measures, we may draw a misleading conclusion. One major shortcoming of this research is the limited number of decision making units. Although our number of DMUs follows the rule of thumb that the number of DMUs should be at least twice the sum of the numbers of inputs and outputs, it only has one more DMU. Increasing the number of DMUs could provide a better performance evaluation results.

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