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Applying dual analysis for efficiency improvement with application to the Asian lead frame firms

Tien-Hui Chen *

Department of Tourism Management, Far-East University, No. 49, Jhonghua Road, Hsin-Shih, Tainan County 744, Taiwan, ROC

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ABSTRACT

Although faced with a quickly changing business environment, better performing firm can still develop and maintain a competitive advantage. This study applies the dual analysis in data envelopment analysis to consider performance improvement of the Asian lead frame firms, since this can indicate how the associated factors should be adjusted so that input wastages and/or output shortfalls can be eliminated. The advantages of this study are that it can not only provide a practical framework for performance improvement for the lead frame industry, but also the management practices obtained can be used as a reference for the management of lead frame firms during their expansion strategies and the current global financial crisis.

1. Introduction

Performance evaluation is an important issue for managers, since it can be used as a reference in decision making with regard to budget distribution and/or performance improvement for business units. Performance is conventionally defined either as organizational inputs or outputs, or as a relationship between these, usually stated as *efficiency*. Because the evaluation characteristics are generally multi-dimensional, there is no appropriate aggregation schema for them, and the basic problem of performance measurement is how to evaluate the relative performance of business units. To overcome this difficulty, data envelopment analysis (DEA) is a widely utilized technique for such evaluations within a group of decision making units (DMUs), and is often found in the management literature (for example, Bottl, Briec, & Cliquet, 2009; Chang & Chen, 2008; Chen, 2007; Cook & Zhu, 2007; Hwang & Chang, 2003; Kao & Hung, 2008; Kao & Hwang, 2008; Liu & Wang, 2008; Paradi, Smithand, & Schaffnit-Chatterjee, 2002; Shin & Sohn, 2004; Tseng, Chiu, & Chen, 2009; Wang, 2005; Wang, Huang, & Lai, 2008).

DEA is a mathematical programming approach for measuring the relative efficiencies within a group of business units, such as bank branches, hospitals, schools, and so on. The relative efficiency of a unit within the DEA framework is defined as the ratio of multiple weighted outputs to multiple weighted inputs. Given the restriction that no DMU can exceed 100% efficiency, the weights are chosen to give as much efficiency as possible with regard to a specific business unit. If the efficiency score of a DMU is equal to one, then it is classified as efficient, and inefficient otherwise.

There are two types of DEA measurements, radial and non-radial, that can be utilized to obtain the alternative targets of inputs and outputs for inefficient DMUs in order to eliminate inefficiency. A radial measurement gives a dual variable to associate with the normalizing equation in the DEA model, meaning that the adjustment proportions of all inputs or outputs are the same for efficiency improvement. For a non-radial measurement, the normalizing equation is decomposed in order to be associated with different dual variables, and thus the adjustment proportions of factors do not need to be the same. In a DEA evaluation, a by-product is that the dual variables can indicate how the associated factors should be adjusted so that input wastages and/or output shortfalls can be eliminated. Consequently, the dual analysis is a widely utilized tool for inefficient DMUs to eliminate inefficiency.

Based on the excellent performance of the upstream design sector and the wafer fabrication sector, the production value and market share of Taiwan in the semiconductor foundry and assembly/testing industries are both number one worldwide. Since the lead frame is a main component in the assembly/testing industry and Taiwan is an important target market for the lead frame manufacturers, many firms are located in Asia, which has become the main production district of the lead frame industry. To enhance the competitiveness of a firm, any effort for performance improvement should first be considered. Consequently, an investigation of the efficiency improvement of Asian lead frame firms is carried out with the aim of finding out what targets should be set for specific factors, so that inefficient firms can improve. Therefore, this study applies dual analysis to obtain the alternative targets of factors for inefficient business units, through the radial and non-radial measurements, so that they can know what issues to work on in order to eliminate inefficiency and enhance competitiveness.

* Tel.: +886 6 5979566x7686; fax: +886 6 5977960.
E-mail address: thchen@cc.feu.edu.tw

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2. DEA methodology

The measurement of technical efficiency, first implemented by Farrell (1957), has motivated many scholars to develop new measures or to extend the existing ones. Charnes, Cooper, and Rhodes (1978) first applied DEA to the relative efficiency measurement, which stemmed from the Farrell efficiency concept. The relative efficiency of a DMU within the DEA framework is defined as the ratio of multiple weighted outputs to multiple weighted inputs.

2.1. Basic DEA model

If there are n DMUs with s outputs and m inputs to be evaluated, and y_{ik} is denoted as the level of output i, and x_{rk} is denoted as that of input r of DMU_k, the efficiency measurement for DMU_j is the optimal value of the objective function of the following linear programming model, referred to as the CCR model (Charnes et al., 1978)

$$\text{Max} \quad h_j = \sum_{i=1}^{s} u_i y_{ij} \tag{1a}$$

$$\text{s.t.} \quad \sum_{r=1}^{m} v_r x_{rj} = 1, \tag{1b}$$

$$\sum_{i=1}^{s} u_i y_{ik} - \sum_{r=1}^{m} v_r x_{rk} \leqslant 0, \quad k = 1,2,\ldots,n, \tag{1c}$$

$$u_i, v_r \geqslant \varepsilon > 0, \quad i = 1,2,\ldots,s, \; r = 1,2,\ldots,m.$$

u_i and v_r are decision variables associated with output i and input r, respectively, and ε is a positive non-Archimedean infinitesimal. Model (1) is an input-oriented CCR model, since it assumes that inputs are under the control of DMU_j, which aims to maximize its output. Constraint (1b) is referred to as the normalizing equation (Dyson, Allen, Camanho, Podinovski, & Sarrico, 2001). Model (1) allows each DMU to effectively select the best weights in calculating its efficiency score and adopts a radial efficiency measurement.

Because the dual variables can indicate how the associated factors should be adjusted so that input wastages and/or output shortfalls can be eliminated, scholars usually convert the primal model into the dual problem shown as Model (2)

$$\begin{aligned}
\text{Min} \quad & g_j = \theta - \varepsilon\left(\sum_{i=1}^{s} S_i^+ + \sum_{r=1}^{m} S_r^-\right) \\
\text{s.t.} \quad & \sum_{k=1}^{n} \lambda_k x_{rk} - \theta x_{rj} + S_r^- = 0, \quad r = 1,2,\ldots,m, \\
& \sum_{k=1}^{n} \lambda_k y_{ik} - S_i^+ = y_{ij}, \quad i = 1,2,\ldots,s, \\
& \lambda_k, S_r^-, S_i^+ \geqslant 0, \quad k = 1,2,\ldots,n, \; i = 1,2,\ldots,s, \; r = 1,2,\ldots,m, \\
& \theta \text{ unrestricted}.
\end{aligned} \tag{2}$$

where θ and λ_k are dual variables, and DMU_j is efficient if, and only if, $h_j^* = g_j^* = 1$, and all slacks are of zero in the DEA run. A value of $g_j^* = \theta^* < 1$, however, implies that DMU_j is inefficient, since DMU_j could reduce its input r in the proportion $(1-\theta^*)$ without worsening any output. If DMU_k is relatively inefficient, according to the constraints of Model (2), we have $\sum_{k=1}^{n} \lambda_k^* x_{rk} = \theta^* x_{rk} - S_r^{-*}$ and $\sum_{k=1}^{n} \lambda_k^* y_{ik} = y_{ik} + S_i^{+*}$, so for the DMU_k to achieve Pareto efficiency it must decrease input r

$$\Delta x'_{rk} = x_{rk} - (\theta^* x_{rk} - S_r^{-*}) = (1-\theta^*) x_{rk} + S_r^{-*}, \quad r = 1,2,\ldots,m, \tag{3a}$$

and increase output i

$$\Delta y'_{ik} = (y_{ik} + S_i^{+*}) - y_{ik} = S_i^{+*}, \quad i = 1,2,\ldots,s. \tag{3b}$$

According to Eq. (3a), the adjustment proportions of all inputs need to be the same, $(1-\theta^*)$, for the DMU_k to achieve Pareto efficiency. However, this treatment is not the only possibility, and it is worth extending the radial model to a non-radial measurement in the context of performance improvement.

2.2. A non-radial DEA model

If we decompose the normalizing Eq. (1b) into m components, i.e. $v_1 x_{1j} = \alpha_1, \; v_2 x_{2j} = \alpha_2, \ldots, v_m x_{mj} = \alpha_m$ and let $\sum_{r=1}^{m} \alpha_r = 1$, then each input will be associated with a different dual variable, and Model (1) can be converted into Model (4) as a non-radial DEA model

$$\begin{aligned}
\text{Max} \quad & e_j = \sum_{i=1}^{s} u_i y_{ij} \\
\text{s.t.} \quad & v_r x_{rj} = \alpha_r, \quad r = 1,2,\ldots,m, \\
& \sum_{i=1}^{s} u_i y_{ik} - \sum_{r=1}^{m} v_r x_{rk} \leqslant 0, \quad k = 1,2,\ldots,n, \\
& u_i, v_r \geqslant \varepsilon > 0, \quad \alpha_r \geqslant 0, \quad i = 1,2,\ldots,s, \; r = 1,2,\ldots,m.
\end{aligned} \tag{4}$$

The dual problem of Model (4) is shown as Model (5)

$$\begin{aligned}
\text{Min} \quad & f_j = \sum_{r=1}^{m} \alpha_r \theta_r - \varepsilon\left(\sum_{i=1}^{s} S_i^+ + \sum_{r=1}^{m} S_r^-\right) \\
\text{s.t.} \quad & \sum_{k=1}^{n} \lambda_k x_{rk} - \theta_r x_{rj} + S_r^- = 0, \quad r = 1,2,\ldots,m, \\
& \sum_{k=1}^{n} \lambda_k y_{ik} - S_i^+ = y_{ij}, \quad i = 1,2,\ldots,s, \\
& \lambda_k, S_r^-, S_i^+ \geqslant 0, \\
& \theta_r \text{ unrestricted}, \quad k = 1,2,\ldots,n, \; i = 1,2,\ldots,s, \; r = 1,2,\ldots,m.
\end{aligned} \tag{5}$$

Zhou, Poh, and Ang (2007) stated that α_r, $r = 1, 2, \ldots, m$, are the normalized user-specified weights for adjusting the rth input. Based on this argument, α_r's are decision variables when incorporated into the non-radial DEA model, and their linear combination should be equal to one. However, this may result in infinitely many solutions in solving Model (4), and thus it is meaningful and useful to provide a reasonable mechanism in the determination of α_r values. Therefore, Chen, Bao, and Chang (2009) proposed the following procedure to specify α_r's:

Step 1. Run the CCR model to obtain the optimal weights of the inputs, i.e. $v_r^*, \; r = 1,2,\ldots,m$.
Step 2. Let $\alpha_r = v_r^* x_{rj}$.

The major characteristic of the procedure is that it applies the radial measurement to obtain the best weights of inputs for each DMU, and thus the decision maker can utilize these to specify the α_r values in the non-radial DEA model.

2.3. Alternative improvement targets of factors

In practical situations, it is often desirable to set targets for relatively inefficient DMUs to guide them to improve their performance. Such targets provide concrete benchmarks by which DMUs can monitor their performance. For example, if DMU_k is relatively inefficient, i.e. $f_k^* = \sum_{r=1}^{m} \alpha_r \theta_r^* < 1$, then an improvement target for the inefficient DMU_k to eliminate input wastage using the non-radial measurement is to decrease input r in the proportion $(1-\theta_r^*), \; r = 1,2,\ldots,m$. In other words, the