African Journal of Business Management Vol. 5(12), pp. 4746-4754, 18 June, 2011
Available online at http://www.academicjournals.org/AJBM
DOI: 10.5897/AJBM10.653
ISSN 1993-8233 ©2011 Academic Journals

Full Length Research Paper

Local government efficiency evaluation: Consideration of undesirable outputs and super-efficiency

Sheng-Chieh Pan[1] Shiao-Yen Liu[2] Chia-Jui Peng [2] and Po-Chin Wu[3]*

[1]Department of Leisure and Recreation Management, China University of Technology, 56 Sec. 3, Shinglung Road, Wenshan Chiu, Taipei, Taiwan.
[2]College of Business, Chung Yuan Christian University, 200 Chung Pei Road, Chung Li, Taiwan.
[3]Department of International Trade, Chung Yuan Christian University, 200 Chung Pei Road, Chung Li, Taiwan.

Accepted 16 December, 2010

The efficiency of the personnel involved in local government is considered to be critical for significant progress in global competition and development. This study adopted a super-efficiency Data Envelopment Analysis (DEA) model with undesirable outputs to evaluate the operating performance of Taiwan's local governments. We also employed the concept of the Sharpe ratio to combine desirable and undesirable outputs and then, form modified outputs. The study revealed that, neglecting undesirable outputs would underestimate (on average) governments' operating efficiency and cause incorrect efficiency rankings. Moreover, given specific real disposable income per capita, undesirable outputs regarding the volume of garbage clearance and air pollution are over-produced on average; however, unemployment rates are almost optimal. We therefore propose that, environmental protection policies are crucial for local governments to increase their performance and that the evaluated efficiency scores can be used by central governments as reference indices to subsidize local governments actively engaging in environmental protection based on the difference between the average output slack and each government's output slack.

Key words: Undesirable outputs, super-efficiency, data envelopment analysis, Sharpe ratio.

INTRODUCTION

In evaluating a country's competitiveness, the International Institute for Management Development (IMD) and the World Economic Forum (WEF) both take the management effectiveness of government into account. Local governments are the basic executive organizations of a country; therefore, their overall operating performance influences a country's competitiveness. In other words, a country's competitiveness is closely related to the operating performance of local governments (Alam, 2009). To improve their competitiveness, developed countries, including the United States, England and the European Union, have been actively assessing the executive efficiency of local governments. We expect this trend will spread to the developing countries (Alam et al., 2010).

Data Envelopment Analysis (DEA) is a well-known mathematical programming technique for evaluating the efficiency of a given set of similar decision-making units (DMUs). The approach is unnecessary to specify a functional form for the relationship between multiple inputs and multiple outputs and it can measure technological efficiency, pure technological efficiency and scale efficiency, which makes it possible to perform a comprehensive evaluation of achievements. Thus, the DEA model has been applied extensively to various fields, including governmental organization (De Borger and Kerstens, 1996; Grossman et al., 1999; Worthington and Dollery, 2000; Tsai et al., 2009), power stations (Andersen and Petersen, 1993), hospitals (Steinmann and Zweifel, 2003), manufacturing (Zelenyuk and Zheka, 2006; Sufian and Habibullah, 2009), agriculture (Latruffe

*Corresponding author. E-mail: pochin@cycu.edu.tw. Tel: +886-2-9376566. Fax: +886-3-2655299.

et al., 2004; Mauyo et al., 2007), finance (Avkiran and Morita, 2010; Cummins et al., 2010) and education (Moreno and Tadepalli, 2002; Pierre and Valerie, 2005).

In performing efficiency evaluations, the standard DEA models (the BCC and CCR models) consider only desirable outputs (i.e., outputs generating positive utility) such as income, consumption and profit. In addition to these desirable outputs, there are some situations in which undesirable outputs, such as unemployment, taxation, inflation, air pollution, or garbage release, are produced together with desirable outputs. Fare et al. (1989) argue that, the performance rankings of DMUs turn out to be highly sensitive to whether undesirable outputs are included. That is, in evaluating a government's executive performance, we need to consider desirable and undesirable outputs. Neglecting or inappropriately accounting for undesirable outputs may lead to misleading results.

Although, recent studies have proposed various methods for including undesirable outputs in the efficiency scores of DEA models (Fare et al., 1989; Yaisawarng and Klein, 1994; Seiford and Zhu, 2002; Silva Portela et al., 2004; Jahanshahloo et al., 2005; Amirteimoori et al., 2006), their methods encounter some constraints when empirically applied. First, most of them involve complicated mathematical calculations, which cause the application to be inconvenient. (Baten and Kamil, 2010) Second, they use methods in which undesirable outputs are directly deducted from a specified constant or undesirable outputs are regarded as inputs, which might neglect differences in the relative importance of desirable and undesirable outputs and the scale effect of DMUs. (Ali and Seiford, 1990; Tyteca, 1996, 1997; Scheel, 2001) Thus, their estimated efficiency indices are less than fully persuasive. Most importantly, their approaches cannot assess whether undesirable outputs are over-produced relative to desirable outputs. This is extraordinarily important for a country trying to reduce environmental destruction (i.e., undesirable environment outputs) while maintaining sustainable development.

To resolve these shortcomings in previous studies regarding undesirable outputs, this paper employed the concept of the Sharpe ratio derived in 1966 by William Sharpe. The Sharpe ratio is defined as the excess return (or risk premium) per unit of risk in an investment asset or portfolio. This excess return is similar to a desirable output and the asset or portfolio risk for risk-averse investors corresponds to an undesirable output in the production process. The Sharpe ratio thus, reflects a portfolio's historical risk-adjusted performance. Therefore, the concept of the Sharpe ratio is appropriate for the construction of a modified desirable output variable that contains a desirable output/undesirable output pair for use in evaluating DEA efficiency scores.

To our knowledge, the method of constructing modified desirable outputs by utilizing the concept of the Sharpe ratio is rarely mentioned in the literature and it has the following two advantages: (1) It integrates any combination of one desirable output and one undesirable output into a new modified single desirable output; that is, the amount of the desirable output is expressed per unit of undesirable output. Therefore, the higher the value of the modified desirable output, the higher the efficiency value it will achieve under a specific set of inputs; (2) by combining estimated efficiency scores with modified output slacks, analysts can easily investigate whether an undesirable output is over-produced relative to a specific desirable output under a given set of inputs.

In addition to providing another method for dealing with undesirable outputs via the Sharpe ratio, this paper also employed the super-efficiency model ranking method proposed by Andersen and Petersen (1993), to perform the efficiency rankings among local governments, which cannot be executed by the standard DEA models. Essentially, the super-efficiency model executes the standard DEA models, but it does so under the assumption that the DMU being evaluated is excluded from the reference set. This allows a DMU to be located above the efficiency frontier, that is, to be super-efficient. (Chen et al., 2010) In other words, this procedure allows for more effective ranking of efficient units, while the scores for inefficient DMUs remain the same as in the standard DEA models.

Problem statement

Based on the considerations mentioned earlier, this paper made two improvements to DEA model-based evaluations of the operating performance of local governments. First, we employed the concept of the Sharpe ratio to deal with the coexistence of desirable outputs and undesirable outputs. Second, we also adopted the super-efficiency DEA model to perform performance rankings of units with an efficiency score of 1 in standard DEA models. To assess the utility of these improvements, we compared the results of evaluating a research sample of 22 local Taiwanese governments using each of three DEA-based performance evaluation models: a DEA model without undesirable outputs, a DEA model with undesirable outputs and a super-efficiency model with undesirable outputs. The findings of this paper not only contribute to performance measurement methodology, but they also have policy implications for central and local Taiwanese governments.

The procedures used to perform our empirical analysis are as follows. First, we constructed a super-efficiency DEA model that allowed researchers to compare relative achievements among local governments in a standard DEA model. Second, we replaced nominal income (a representative desirable output universally adopted in the literature to characterize a government's operating performance) with real disposable per capita income, which reflects the impact of undesirable outputs, including inflation and taxation and population scale, on operating performance. Third, in addition to real disposable per capita income, we also considered three undesirable outputs: unemployment rate, garbage generation and air pollution. To take the relative importance between desirable and undesirable outputs into account, we employed the Sharpe ratio and divided the desirable output by each undesirable output to form three new modified outputs: real disposable income per capita over unemployment rate, garbage generation and air pollution.

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature on DEA models with undesirable outputs. Section 3 briefly introduces the standard DEA model and the super-efficiency DEA model with undesirable outputs. Section 4 describes the selection of input and output variables and data sources. Section 5 presents the empirical results and discussion and Section 6 draws conclusions.

LITERATURE REVIEW

Since Charnes et al. (1978), DEA has been extensively applied to measure the performance of various kinds of DMUs. Examples involving governmental organizations include De Borger and Kerstens (1996), Grossman et al. (1999), Worthington and Dollery (2000) and Tsai et al. (2009). In these studies, traditional inputs are used to produce desirable or marketable outputs. However, there are some situations in which undesirable outputs (e.g., unemployment, inflation, air pollutants and garbage release) are produced together with desirable outputs. Ignoring such undesirable outputs could produce misleading results.

Recently, the issue of handling undesirable outputs has attracted research attention. Fare et al. (1989) relax the strong disposability of outputs to allow for the fact that, undesirable outputs may be freely disposable and they re-evaluate DMU efficiency. Their results show that, the efficiency rankings of DMUs are very sensitive to whether undesirable outputs are included. Thus, given the fact that undesirable outputs are jointly produced with desirable outputs, it makes sense to credit a DMU for its provision of desirable outputs and to penalize it for its production of undesirable outputs when evaluating its performance.

Yaisawarng and Klein (1994) construct a DEA model to measure the effects of SO_2 control on the efficiency of US coal-fired power plants in the 1980s. Following Fare et al., the authors assume weak disposability for undesirable outputs and further extend their DEA model to include an undesirable input, namely the sulfur content in the fuel. However, because SO_2 emissions can only come from the combustion of sulfur and they are expected to be strongly correlated with the sulfur content of the fuel, the inclusion of both variables synchronously in the DEA may actually reduce the discriminating power of the DEA model.

Tyteca (1996) provides a survey of the literature on environmental performance measurement. He proposes three DEA variations in terms of how undesirable outputs are included. Similar to those used in Tyteca (1996), Korhonen and Luptacik (2004), use several variants of DEA models to measure the eco-efficiency of coal-fired power plants. The authors treat emissions directly as inputs in the sense that, given a certain amount of desirable output, both inputs and undesirable outputs should be minimized. Their results show that all the DEA model variants lead to similar results.

Seiford and Zhu (2002) propose employing data translation as a means of integrating undesirable outputs and inputs into DEA models. By reversing the bad outputs, they can be readily included in the standard DEA model and the usual scaling will actually reduce the bad outputs.

Although, this recognizes the fact that increases in undesirable outputs and inputs are not desirable, it does not resort to the usual *ad hoc* treatment of undesirable outputs as inputs. By using the classification invariance property, Amirteimoori et al. (2006) show that, the standard DEA model can be used to improve performance through increasing desirable outputs and decreasing undesirable outputs.

The recently introduced directional distance function generalizes existing distance functions by accounting for both input contractions and output improvements. Furthermore, the directional distance function is flexible due to the variety of direction vectors it allows for. To accommodate eventual negative data, Silva Portela et al. (2004) proposed a variation on the directional distance function that is a very general distance function akin to the profit function. Jahanshahloo et al. (2005), present a method for dealing with undesirable inputs and outputs in non-radial DEA models.

In summary, although the stated studies have provided specific methods for evaluating the efficiency of DMUs, these methods encounter difficulties in empirical applications. First, most of them involve complicated mathematical calculations (Baten and Kamil, 2010). Second, methods of directly deducting the undesirable output from a specified constant or of treating undesirable outputs as inputs might neglect differences in the relative importance of the desirable and undesirable outputs, and the scale effect of the DMUs (Tyteca, 1996; Korhonen and Luptacik, 2004).

Most importantly, their methods cannot determine whether undesirable outputs are over-produced relative to desirable outputs. This paper employs the concept of the Sharpe ratio to construct a modified output that combines desirable and undesirable outputs to overcome the earlier mentioned problems.

MODEL

This section briefly introduces the DEA models we use to evaluate the operating performance of governments.

The CCR model

The CCR model is based on the assumption of constant return to scale and it is used to evaluate the technical effi-ciency (TE) of DMUs. Denote x_{ik}, i =1,…,*m* and y_{rk}, r =1,…,*s* as the *i*-th input and *r*-th outputs, respectively, of DMU_k (*k*=1,…,*n*). The efficiency score of each DMU_k in the output-oriented CCR model can be derived from the following model:

$$Max \;\; E_k = \theta + \varepsilon\left(\sum_{i=1}^{m} S_{ki}^{-} + \sum_{r=1}^{s} S_{kr}^{+}\right)$$

$$s.t. \;\; \sum_{k=1}^{n} \lambda_k x_{ki} - x_{ki} + S_{ki}^{-} = 0\,,\; i = 1,...,m$$

$$\sum_{k=1}^{n} \lambda_k y_{kr} - S_{kr}^{+} = \theta\, y_{kr}\,,\; r = 1,...,s$$

$$\lambda_k, S_{ki}^{-}, S_{kr}^{+} \geq 0\,,\; k = 1,...,n \tag{1}$$

Where E_k is the relative efficiency score of DMU *k*, E_k =1 indicates efficiency and E_k <1 indicates inefficiency. ε (≧0) is an infinitesimal constant. S_{ki}^{-} and S_{kr}^{+} represent the *i*-th input slack and *r*-th output slack for DMU *k*, respectively.

Another version of the conventional DEA model fre-quently used is the Banker et al. (1984) BCC model. The BCC model is more flexi-ble and allows variable returns to scale; consequently, it measures only the pure technical efficiency (PTE) for each DMU. That is, for a DMU to be considered CCR efficient, it must have both scale efficiency and pure technical efficient. Moreover, the scale effi-ciency (SE) index can be derived by estimating the CCR-efficiency to BCC-efficiency ratio.

In its evaluations of government operating perfor-mance, this paper allows for the coexistence of desirable and undesirable outputs instead of just desirable outputs as in the specifications of the conventional CCR model and the BCC model.

The super-efficiency model

To proceed with the efficiency rankings of DMUs with an efficiency score of 1 in conventional DEA models, this study applies the super-efficiency model proposed by Andersen and Petersen (1993). Super-efficiency indicates the extent to which efficient products exceed the efficiency frontier formed by other efficient units. The super-efficiency indices of an output-oriented DEA model with constant return to scale are derived from the linear programming model (2).

$$\max_{\lambda} \;\; \theta$$

$$s.t. \;\; \sum_{k=1}^{n} y_{kr}\lambda_k \geq \theta\, y_{lr} \qquad r = 1,..., s$$

$$\sum_{k=1}^{n} x_{ki}\lambda_k \geq x_{li} \qquad i = 1,..., m$$

$$\lambda_l = 0$$

$$\lambda_k \geq 0 \qquad\qquad k = 1,\cdots,n\,;\, k \neq l \tag{2}$$

The derived efficiency score θ in the DEA model specifies the super-efficiency of DMU *k*. In the output-oriented DEA model, the value of θ ranges in the interval (0, 1) for the DMUs identified as efficient, with smaller values indicating increasing efficiency. θ ranges in the interval (1, ∞) for the DMUs identified as inefficient, with larger values indicating decreasing efficiency.

If the goal is to identify a production frontier, then conventional technical efficiency measurement with the interval [1, ∞) is appropriate and efficient DMUs are compared only to themselves. In that model, any efficient DMU that increases its outputs or reduces its inputs can increase its efficiency; however, the efficiency score of 1 remains unchanged in spite of its improved performance. In contrast, in the super-efficiency model (2), as inefficient or efficient DMUs change their performance, their effi-ciency scores change simultaneously. Moreover, super-efficiency scores always benchmark a target DMU based on the efficiency of its peers regardless of its own efficiency level.

Another reason for using super-efficiency scores is to avoid a limited-value response variable in second-stage regressions, as argued by Coelli et al. (2005). Conventional technical efficiency scores yield a variable of limited value because an efficient DMU's score of 1 will remain unchanged even if it becomes more efficient by increasing outputs or decreasing inputs. Super-efficiency scores are an observable proxy for latent variables underlying conventional efficiency scores. Because their range is not limited, they can preclude the need to esti-mate such latent values using sample-selected truncated regression.

The DMUs used in this study are 22 local Taiwanese governments (*j* = 1… 22). In performing its executive functions, we assume that each government adopts two inputs *x* (*n*=1, 2) and ob-tains three modified desirable outputs *y* (*m*=1, 2, 3). We will explain the formation and definition of the modified desirable outputs later.

Overall, this paper employs a super-efficiency output-oriented DEA model with undesirable outputs to generate efficiency indices for 22 local Taiwanese governments. In particular, we provide an alternative method for dealing with the problem of the coexistence of desirable and undesirable outputs in DEA models. The DEAs were conducted with Scheel's (2000) EMS Software.

Selection of variables

The DMUs used in the present paper are 22 Local Governments in Taiwan in 2007 and the inputs and outputs were selected as follows:

Inputs

Production factors mainly include labor, capital, land and entrepreneurship. For a local government, its executive power serves as an appropriate proxy variable for entrepreneurship and is embedded in its operating performance. The executive domain of a government, a proxy variable for land, is less variable; therefore, it is exogenous to the government. Thus, the inputs we choose to evaluate the efficiency of local governments primarily focus on labor and capital, which are measured by employment (EM) and the accumulation of fixed assets (AFA), respectively.

Outputs

Income is typically used as a proxy variable to represent the econo-mic level of a specific country or area and it is a desirable output in the DEA model. As mentioned earlier, we replace nominal income with real disposable income per capita (RDIPC). To focus the effi-ciency analysis on the issue of the existence of undesirable outputs in DEA models, we use only this one desirable output. Regarding

Table 1. Data measurement.

Symbol	Variable	Measure (Unit)
EM	Employment	Thousands of people
AFA	Accumulation of fixed assets	Millions of NT dollars
RDIPC	Real disposable income per capita	NT dollars
UR	Unemployment rate	%
VGC	Volume of garbage clearance	Kilos per capita per year
AP	Air pollution	The emissions of ozone and sulfur dioxide (ppm / year)

Regarding undesirable outputs, this paper selects three important variables: unemployment rate (UR), garbage generation (VGC) and air pollution (AP) measured as emissions of ozone and sulfur dioxide. To assess the relative importance of desirable and undesirable outputs and to assess whether undesirable outputs are over-produced relative to desirable outputs, we combine desirable outputs and undesirable outputs to form a new modified desirable output. The procedures for constructing the new modified desirable outputs in our model are as follows:

First, this paper replaces nominal income with real disposable income per capita to capture the influences of price level, taxation and population on nominal income. Second, by employing the concept of the Sharpe ratio, we divide real disposable income per capita (that is, the desirable output) by each of the three undesirable outputs to construct three new modified desirable outputs: real disposable income per capita with respect to unemployment rate, garbage generation and air pollution, which are named Outputs 1, 2 and 3, respectively. All the data comes from National Statistics, Taiwan, R.O.C. and the measures employed are displayed in Table 1.

RESULTS

In this section, the results derived from three different DEA models are presented and discussed in detail: The standard DEA model without and with undesirable outputs (Model 1 and 2, respectively) and the super-efficiency DEA model with undesirable outputs (Model 3 or Equation 2). Table 2 (Figure 1) presents the efficiency evaluations of 22 Taiwanese city/County governments in 2007. The inputs in the three models are employment and the accumulation of fixed assets. The output in Model 1 is real disposable income per capita; in Model 2 and Model 3, the outputs are ratios of real disposable income per capita to unemployment rate, the volume of garbage generated and air pollution. Technical efficiency (crtse) can be examined by decomposing it into pure technical efficiency (vrtse) and scale efficiency (scale).

There are some notable findings. First, in Models 1 and 2, the average indices of technical efficiency are 0.387 and 0.429, those of pure technical efficiency are 0.812 and 0.822 and those of scale efficiency are 0.453 and 0.490, respectively. Evidently, considering the appearance of undesirable outputs and treating the coexistence of desirable and undesirable outputs increases all three efficiency indices similarly. In other words, neglecting the undesirable outputs would lead to underestimates, on average, of governmental operating efficiency, including technical efficiency, pure technical efficiency and scale efficiency. This underestimation phenomenon occurs with most of the city/County governments. In addition, decomposition in Models 1 and 2 indicates that, 21 (95.55%) and 19 (86.36%) local governments are technically ineffcient, respectively. However, the means show that the technical inefficiency mainly comes from the scale inefficiency.

Second, in Model 1 the only government satisfying both technical efficiency and pure technical efficiency is that of Taichung County, whereas Keelung city, Hsinchu and Taipei cities reach pure technical efficiency. When the three undesirable outputs are taken into account and three modified outputs are constructed, in addition to Taichung County, Hsinchu city and Hualien County now also reach both technical efficiency and pure technical efficiency; whereas Chiayi and Taichung cities newly achieve pure technical efficiency (Model 2).

As to the efficiency rankings of the 22 local governments, there is a slight difference between the evaluations of Model 1 and 2. Taking technical efficiency as an example, in descending order the governments are Chiayi city, Hsinchu County, Chiayi County, Tainan city, Yunlin County, Kaohsiung city, Changhua County and Taoyuan County; in ascending order they are Hualien County, Hsinchu city, Ilan County, Taichung city, Tainan County, Taipei city and Taichung County. Again, the omission of undesirable outputs can result in biased efficiency indices and efficiency rankings.

Although, the evaluation results in Model 2 consider the existence of undesirable outputs in the standard DEA model, the priority rankings of the local governments for both technical efficiency and pure technical efficiency remain unresolved. However, this can be achieved by employing the super-efficiency model, (Model 3). From the evaluation results in Model 3 we find that, Taitung County has the highest technical efficiency among the three technical efficiency governments and the highest pure technical efficiency among the six pure technical efficiency units. Moreover, by employing the super-efficiency model, the three technical efficiency governments identified in Model 2 are ranked as follows (from high to low): Hualian County, Hsinchu City and Taitung County. Obviously, the super-efficiency model is useful for ranking

Table 2. Efficiency indices for local Taiwanese governments in 2007.

DMU	Model 1			Model 2			Model 3		
	Efficiency score			Efficiency score			Super-efficiency score		
	Crste	Vrste	Scale	Crste	Vrste	Scale	Crste	Vrste	Scale
Taipei County	0.063 (22)	0.674	0.094	0.065 (22)	0.657	0.099	15.36	1.523	10.09
Ilan County	0.462 (07)	0.840	0.550	0.591 (06)	0.865	0.682	1.693	1.156	1.465
Taoyuan County	0.140 (20)	0.740	0.189	0.145 (21)	0.739	0.196	6.910	1.353	5.107
Hsinchu County	0.481 (06)	0.736	0.653	0.571 (07)	0.890	0.641	1.752	1.124	1.559
Miaoli County	0.398 (08)	0.732	0.544	0.407 (08)	0.735	0.554	2.454	1.360	1.804
Taichung County	0.138 (21)	0.600	0.230	0.151 (20)	0.631	0.240	6.601	1.586	4.162
Changhua County	0.154 (18)	0.642	0.239	0.167 (19)	0.636	0.263	5.985	1.572	3.807
Nantou County	0.351 (09)	0.732	0.480	0.396 (09)	0.720	0.550	2.524	1.390	1.816
Yunlin County	0.278 (12)	0.611	0.455	0.311 (13)	0.681	0.456	3.219	1.469	2.191
Chiayi County	0.344 (10)	0.740	0.465	0.344 (11)	0.746	0.461	2.904	1.340	2.167
Tainan County	0.183 (17)	0.603	0.304	0.182 (15)	0.608	0.300	5.486	1.645	3.335
Kaohsiung County	0.188 (16)	0.738	0.254	0.174 (16)	0.680	0.256	5.751	1.470	3.912
Pingtung County	0.270 (14)	0.854	0.316	0.270 (14)	0.855	0.316	3.705	1.170	3.167
Taitung County	1.000 (01)	1.000	1.000	1.000 (01)	1.000	1.000	0.646	Big	
Hualien County	0.699 (04)	0.954	0.732	1.000 (01)	1.000	1.000	0.982	0.735	1.336
Keelung city	0.649 (05)	1.000	0.649	0.647 (05)	0.938	0.689	1.546	1.066	1.450
Hsinchu city	0.864 (03)	1.000	0.864	1.000 (01)	1.000	1.000	0.967	0.683	1.416
Taichung city	0.278 (11)	0.$948	0.294	0.378 (10)	1.000	0.378	2.648	0.809	3.273
Chiayi city	0.911 (02)	0.958	0.950	0.966 (04)	1.000	0.966	1.036	0.990	1.046
Tainan city	0.320 (11)	0.926	0.345	0.329 (12)	0.954	0.345	3.043	1.049	2.901
Taipei city	0.142 (19)	1.000	0.142	0.170 (18)	1.000	0.170	5.888	0.639	9.214
Kaohsiung city	0.191 (15)	0.845	0.226	0.173 (17)	0.760	0.227	5.795	1.316	4.403
Average efficiency	0.387	0.812	0.453	0.429	0.822	0.490	3.950		
Efficiency units	1	4	1	3	6	3	3	6	1
Inefficiency units	21	18	21	19	16	19	19	16	21

Notes: The efficiency indices are evaluated by utilizing a standard output-oriented DEA model in Model 1 and Model 2, and by employing a super-efficiency DEA model in Model 3. The inputs in the three Models are employment and the accumulation of fixed assets. The output variable in Model 1 is real disposable income per capita; in Model 2 and Model 3 they are the ratios of real disposable income per capita to unemployment rate, the volume of garbage generated, and air pollution (measured as the emissions of ozone and sulfur dioxide). crste: technical efficiency from a constant return to scale DEA; vrste: pure technical efficiency from a variable return to scale DEA; scale: scale efficiency = crste / vrste. Super-efficiency scores marked "Big" indicate that the DMU remains efficient under arbitrarily increased inputs (input-oriented) or decreased outputs (output-oriented). The figures in parentheses indicate the efficiency rankings.

useful for ranking the operating performance of County/city governments with efficiency scores of 1 in the standard DEA model.

To further investigate whether undesirable outputs are over-produced relative to specific desirable outputs, the modified output slacks evaluated from super-efficiency Model 3 are displayed in Table 3. Regarding the main sources of inefficiency, output 1 is almost optimal, because the slack that it presents approaches zero. However, output 2 and 3 should increase by 2.105 and 7.796%, respectively. According to the definitions of Outputs 2 and 3, this means that given a desirable real disposal income per capita, undesirable volumes of garbage and levels of air pollution are over-produced. This dual overproduction in Outputs 2 and 3 is especially obvious for three local governments: those of Taipei County, Pingtung County and Tainan city.

Taking Taipei County as an example, the slack in output 2 is 10.34% and the real disposal income per capita and the volume of garbage clearance are 262,347 NT dollars per capita per year and 229.95 kilos per capita per year, respectively; therefore, relative to the desirable output (i.e., real disposable income per capita), the garbage stream should optimally be abated to 206.173 kilos per capita per year. Moreover, the slack in Output 3 is12.401% and given the real disposable income per capita per year, the optimal level of air pollution should be abated from an annual average of 0.034 to 0.0298 ppm. Apparently, employing the Sharpe ratio to combine desirable and undesirable outputs and construct new modified output terms allows the relative importance of desirable and undesirable outputs to be easily assessed.

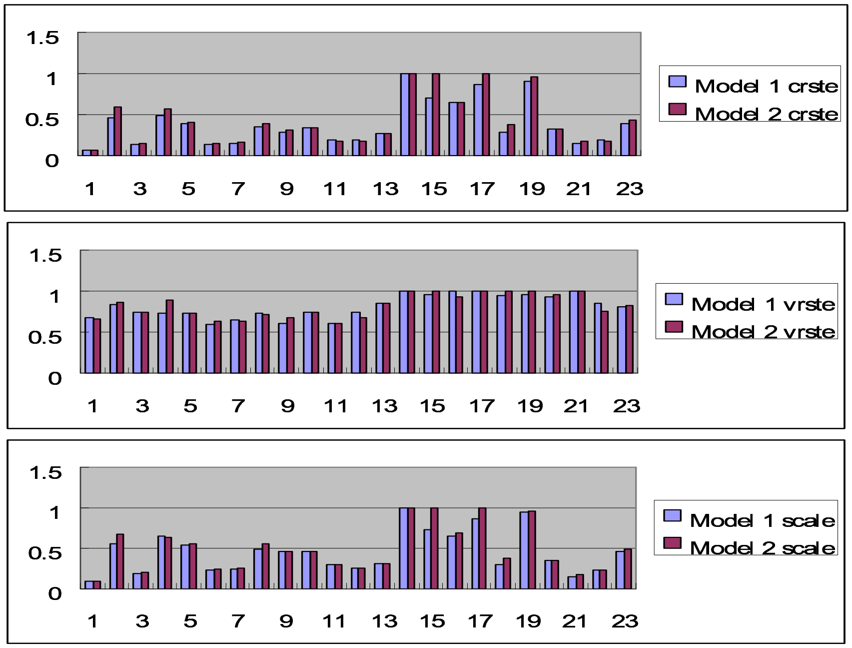

Figure 1. Bar chart of efficiency indices in Models 1 and 2. Note: 1: Taipei County; 2: Ilan County; 3: Taoyuan County; 4: Hsinchu County; 5: Miaoli County; 6: Taichung County; 7: Changhua County; 8: Nantou County; 9: Yunlin County; 10: Chiayi County; 11: Tainan County; 12: Kaohsiung County; 13: Pingtung County; 14: Taitung County; 15: Hualien County; 16: Keelung city; 17: Hsinchu city; 18: Taichung city; 19: Chiayi city; 20: Tainan city; 21: Taipei city; 22: Kaohsiung city; 23: Average efficiency.

Readers can proceed with similar derivations to obtain the optimal abatements of undesirable outputs for the other inefficiency governments.

DISCUSSION

Based on the stated empirical results, this article offers the following policy suggestions:

First, to improve governmental operating performance, reducing the volume of garbage generated and air pollution emissions are more effective methods than reducing the unemployment rate. That is, environmental protection policies are crucial for local governments to increase their performance.

Second, our evaluated efficiency scores can be regarded as reference indices for central governments seeking to subsidize local governments actively engaging in environmental protection. For example, if we consider the three efficiency scores in Model 3 simultaneously, then Taitung County, Hsinchu city and Hualien County are the first three local governments that should be rewarded for their achievements in environmental protection.

Third, based on the means of the technical efficiency scores, pure technical efficiency scores and scale efficiency scores in Model 2, we find that nearly 41% of local governments (Taipei County, Taoyuan County, Taichung County, Changhua County, Yunlin County, Chiayi County, Tainan County, Kaohsiung County and Kaohsiung city) have three efficiency scores below their respective means; therefore, these cities/counties need to actively improve their efficiency indices by (especially) reducing the volume of garbage generated and air pollution emitted.

Finally, rewards or subsidies to governments for their environmental protection achievements can be indexed based on the difference between the average output slack and each government's output slack. For example, a specific amount of rewarded funds could be allocated to governments with output slack less than the average output slack according to weights calculated from the ratio of the difference between the average output slack and each government's output slack to the summation of the difference between the average output slack and each government's output slack.

Conclusions

The operating performance of local governments has a strong influence on a country's competitiveness. Although, previous studies have employed various kinds of DEA models to evaluate the relative efficiency of local

Table 3. Summary of output slacks: Super-efficiency DEA model for local Taiwanese governments in 2007.

DMU	Output slack (%)			Original output variable			
	Output 1	Output 2	Output 3	RDIPC	UR	VGC	AP
Taipei County	5.856E-07	1.034E+01	12.401	262347	3.8	229.95	0.034
Ilan County	1.434E-09	4.247E-08	0.000	226849	4	182.5	0.027
Taoyuan County	1.461E-07	3.096E-08	9.030	282758	4	200.75	0.034
Hsinchu County	1.537E-07	1.388E-07	22.886	242715	3.9	175.2	0.033
Miaoli County	8.097E-08	6.995E-07	8.945	234813	3.9	211.7	0.034
Taichung County	4.495E-07	5.897E-08	7.084	227322	4	189.8	0.033
Changhua County	6.955E-08	2.279E-01	3.117	213289	3.8	215.35	0.032
Nantou County	8.174E-08	2.715E-08	5.353	202299	4.2	186.15	0.031
Yunlin County	1.341E-09	5.766E-10	17.168	219773	3.9	186.15	0.035
Chiayi County	3.878E-10	1.554E+01	6.865	204772	3.8	248.2	0.036
Tainan County	2.144E-08	2.695E-08	14.467	225952	3.9	222.65	0.035
Kaohsiung County	3.727E-09	9.763E-08	17.607	250609	4.1	233.6	0.04
Pingtung County	1.089E-07	1.600E+01	13.907	250350	3.8	248.2	0.038
Taitung County	0.000	0.000	0.000	250159	3.8	208.05	0.035
Hualien County	0.000	0.000	0.000	247331	4.1	167.9	0.024
Keelung city	6.312E-07	1.735E-06	0.903	263625	4.2	215.35	0.035
Hsinchu city	0.000	0.000	0.000	367087	3.8	262.8	0.029
Taichung city	0.000	0.000	0.000	306741	4	153.3	0.03
Chiayi city	0.000	0.000	0.000	240144	3.8	288.35	0.033
Tainan city	9.205E-08	6.360E+00	9.111	271140	3.7	219	0.035
Taipei city	0.000	0.000	0.000	389064	3.7	200.75	0.029
Kaohsiung city	2.586E-09	3.727E-08	14.803	299804	4.2	237.25	0.039
Average slack (%)	0.0000001	2.105	7.796				

Notes: the output slacks are obtained from the evaluation results in Model 3, i.e., the super-efficiency output-oriented DEA model in Eq. (2). The inputs in the model are employment and the accumulation of fixed assets. Output 1, output 2, and output 3 are defined as the ratios of real disposable income per capita to unemployment rate, the volume of garbage generated, and air pollution (measured as the emissions of ozone and sulfur dioxide), respectively. RDIPC, UR, VGC, and AP denote real disposable income per capita (NT dollars per capita per year), unemployment rate (%), the volume of garbage clearance (kilos per capita per year), and air pollution (ppm / year), respectively.

governments, most of them either neglect undesirable outputs or deal with them with inappropriate methods.

In evaluating local governments' operating performance, this paper provides another method of dealing with undesirable outputs in standard DEA models and super-efficiency DEA model. We integrate one desirable output and one undesirable output into a new modified output. The modified desirable output is defined as the amount of the desirable output created per unit of undesirable output. The inspiration to build the modified output comes from the Sharpe ratio, an index combining return (a desirable result) and risk (an undesirable result) for use by risk-averse investors to measure the risk-adjusted performance of an asset or portfolio.

The treatment of undesirable outputs in this paper has the following two advantages: First, by adding undesirable outputs into the DEA models, we can evaluate the efficiency indices more correctly. Second, from the evaluated output slacks and the modified outputs, we can detect whether the undesirable output is over-produced relative to the desirable output and this provides available information about how to reduce undesirable outputs, such as unemployment rate, garbage and air pollution and reach an efficient modified output level.

In addition, our method of dealing with undesirable outputs can be easily extended to the efficiency analysis of DEA models with undesirable inputs and undesirable outputs. Moreover, by combining our method and panel data to form a panel Tobit model, researchers can also evaluate efficiency with multi-stage DEA models and stochastic DEA models using undesirable inputs and outputs.

REFERENCES

Alam GM (2009). The role of science and technology education at network age population for sustainable development of Bangladesh through human resource advancement. Sci. Res. Essays, 4(11): 1260-1270.

Alam GM, Hoque KH, Rout GK, Priyadarshini N (2010). Who does gain from EFA: State business of education or private higher education in developing nation: A study to understand the policy impact in Bangladesh? Afr. J. Bus. Manage., 4(6): 770-789.

Ali AI, Seiford LM (1990). Translation invariance in data envelopment analysis. Oper. Res. Lett., 9: 403-405.
Amirteimoori A, Kordrostami S, Sarparast M (2006). Modeling undesirable factors in data envelopment analysis. Appl. Math. Comp., 180: 444–452.
Andersen P, Petersen NC (1993). A procedure for ranking efficient units in data envelopment analysis. Manag. Sci., 39(10): 1261–1264.
Avkiran NK, Morita H (2010). Predicting Japanese bank stock performance with a composite relative efficiency metric: A new investment tool. Pacific-Basin Finance J., 18: 254–271.
Banker RD, Charnes A, Cooper WW (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag. Sci., 30: 1078-1092.
Baten MA, Kamil AA (2010). A stochastic frontier model on measuring online bank deposits efficiency. Afr. J. Bus. Manag., 4(12): 2438-2449.
Charnes A, Cooper WW, Rhodes E (1978). Measuring the efficiency of decision making units. Eur. J. Oper. Res., 2: 429-444.
Chen C, Hu J, Liao J (2010). Tourists' nationalities and the cost efficiency of international tourist hotels in Taiwan. Afr. J. Bus. Manag., 4(16): 3440-3446.
Chen Y, Yung-ho C, Huang C (2010). Measuring super-efficiency of financial and non- financial holding companies in Taiwan: an application of DEA models. Afr. J. Bus. Manag., 4(13): 3122-3133.
Cummins JD, Weiss MA, Xie X, Zi H (2010). Economies of scope in financial services: A DEA efficiency analysis of the US. J. Bank. Finance, 34: 1525–1539.
Deng CG, Liu T, Wu J (2007). Efficiency analysis of China's commercial banks based on DEA: Negative output investigation. China-USA Bus. Rev., 6(2): 50-56.
De Borger B, Kerstens K (1996). Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA, and econometric approaches. Reg. Sci. Urban Econ., 26: 145–170.
Färe R, Grosskopf S, Lovell CAK, Pasurka C (1989). Multilateral productivity comparisons when some outputs are undesirable: A non parametric approach. Rev. Econ. Stat., 71(1): 90-98.
Grossman PJ, Mavros P, Wassmer RW (1999). Public sector technical inefficiency in large U.S. cities. J. Urban Econ., 46: 278–299.
Jahanshahloo GR, Lotfi FH, Shoja N, Tohidi G, Razavyan S (2005). Undesirable inputs and outputs in DEA models. Appl. Math. Comp., 169: 917–925.
Kerstens K, Van de Woestyne I (2009). Negative data in DEA: A simple proportional distance function approach. Working Papers ECO-03, IESEG School of Management.
Korhonen P, Luptacik M (2004). Eco-efficiency analysis of power plants: An extension of data envelopment analysis. Eur. J. Oper. Res., 154: 437- 446.
Latruffe L, Balcombe K, Davidova S, Zawalinska K (2004). Determinants of technical efficiency of crop and livestock farms in Poland. Appl. Econ., 36(12): 1255-1263.
Lovell CAK, Rouse APB (2003). Equivalent standard DEA models to provide super-efficiency scores. J. Oper. Res. Soc., 54 (1): 101-108.
Mauyo LW, Okalebo JR, Kirkby RA, Buruchara R, Ugen M, Mengist CT, Anjichi VE, Musebe RO (2007). Technical efficiency and regional market integration of cross-border bean marketing in western Kenya and eastern Uganda. Afr. J. Bus. Manag., 1(4): 77-84.
Moreno AA, Tadepalli R (2002). Assessing academic department efficiency at a public university. Manage. Dec. Econ., 23(7): 385-397.
Pastor J, Ruiz J (2007). Variables with negative values in DEA. in Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis, ed. By Zhu J, Cook W. 63-84. Springer, Berling.
Pierre Q, Valerie V (2005). An evaluation of the efficiency of Quebec's school boards using the data envelopment analysis method. Appl. Econ., 37(14): 1643-1662.
Scheel H (2001). Undesirable outputs in efficiency valuations. Eur. J. Oper. Res., 132(2): 400-410.
Seiford LM, Zhu J (2002). Modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res., 142: 16-20.
Sharpe W (1966). Mutual fund performance. J. Bus., 39(S1): 119–138.
Steinmann L, Zweifel P (2003). On the (in)efficiency of Swiss hospitals. Appl. Econ., 35(3): 361-370.
Sufian F, Habibullah MS (2009), Do mergers and acquisitions leads to a higher technical and scale efficiency? Evidence from Malaysia. Afr. J. Bus. Manag., 3 (8): 340-349.
Tsai HT, Tzeng SY, Fu HH, Wu JCT (2009). Managing multinational sustainable development in the European Union based on the DPSIR framework. Afr. J. Bus. Manag., 3(11): 727-735.
Thanassoulis E, Portela MCAS, Despic O (2008). DEA: The mathematical programming approach to efficiency analysis. In The Measurement of Productive Efficiency and Productivity Growth, ed. by Fried HO, Lovell CAK, Schmidt SS. Oxford University Press, New York. 251-420.
Tyteca D (1996). On the measurement of the environmental performance of firms: A literature review and a productive efficiency perspective. J. Environ. Manag., 46 (3): 281-308.
Tyteca D (1997). Linear programming models for the measurement of environmental performance of firms: Concepts and empirical results. J. Prod. Anal., 8(2): 183-197.
Worthington AC, Dollery BE (2000). An empirical survey of frontier efficiency measurement techniques in local government. Local Gov. Stud., 26: 23–52.
Yang HL, Pollitt M (2007). Incorporating both undesirable outputs and uncontrollable variables into DEA: the performance of Chinese coal-fired power plants. CWPE 0733 and EPRG 0712.
Zelenyuk V, Zheka V (2006). Corporate governance and firm's efficiency: The case of a transitional country, Ukraine. J. Prod. Anal., 25(1): 143-157.