Efficiency Measurement Theory and its Application to Airport Benchmarking

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Abstract

Efficiency measurement is critical for industries where firms do not face strong competition, as we cannot rely on the market to discipline the firms effectively. Airports are a typical example. At the same time, the fact that airports produce multiple outputs using a common set of inputs calls for a delicate and sophisticated treatment in measuring their efficiencies. The current paper starts out by presenting the conventional methodologies of efficiency measurement such as DEA, Stochastic Frontier method, Productivity Index, and some recent developments in efficiency measurement literature. We then provide a review of the existing literature on airport efficiency measurement results, recent advancement on the airport efficiency measurement, and some recent empirical estimates of the effects of ownership forms and governance structures on airport’s efficiency.

Keywords: efficiency measurement, productivity index, airport benchmarking

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1. Introduction

Efficiency measurement and benchmarking is an important topic whether one is interested in comparing efficiency of a firm or a sub-unit of a firm (a decision making unit, or a DMU in short) relative to its peers/competitors, learning to improve one’s efficiency performance relative to a benchmark unit, or investigating effects of a public policy or a regulation.

Efficiency measurement is critical for industries where firms do not face strong competition in the market. Examples include transport infrastructure providers such as airports, seaports, highways, urban transit systems, etc., public utilities such as electricity, water, public schools, hospitals, and other subsidized programs, and regulated industries where market can not discipline firms effectively.

The literature on efficiency measurement and benchmarking has been advanced significantly during the last three decades. The most widely used methodologies for measuring and analyzing efficiency are Data Envelopment Analysis (DEA), Econometric production (or cost) function method, and Productivity Index Number approach. These and other methodologies, at times, may yield significantly different results on relative efficiency of firms. Furthermore, especially in transport and logistics industries, the definition of outputs and/or inputs is not always clear since the production processes often involve many intermediate inputs and outputs. For example, the efficiency rankings of airports vary wildly depending on whether or not non-aeronautical services (commercial services including duty free sales) are included as an output. These and other issues require in-depth investigation in order to enhance credibility of efficiency ranking and to make efficiency benchmarking useful to managers and policy makers.

This chapter starts out in the following section by reviewing the conventional theory of efficiency measurement and its recent developments. One of the most relevant extensions in the theory is made recently in how to treat undesirable outputs in efficiency measurement. We will present how three different methodologies stated above (namely DEA, econometric method, and index number approach) incorporate the undesirable outputs such as green house gas and congestion delay. Then we focus our discussion on the case of airports, by providing a chronological review of the literature. Researches on efficiency measurement emerged following the deregulation in aviation industries, which advanced through the 1980’s in the US and then followed by EU and other parts of the world. Literature on airport efficiency measurement accumulated as the effects of deregulation in aviation industry manifest. Now, the public concern on the global environment is growing, and this gives rise to a new stream of efficiency measurement research where undesirable outputs are existent. Section 3 will present these evolutions of the literature on airport efficiency measurement.

2. Theory of Efficiency Measurement and Recent Developments

2.1. Basic Concepts of Efficiency Measurements

Methodologies of measuring the performance of economic entities can be divided into several categories. The economic entities whose performances are measured are often called decision-making units or DMUs in short. One and natural way of measuring the performance of an DMU is to compare its inputs used and outputs produced. This idea is
often referred to as the productivity ratio. When DMUs produce multiple outputs sharing 
the same set of inputs, measuring their performance is not as straightforward as taking 
simple ratio of an output and an input. Distance function measures the relative deviation 
of any given pair of input and output vectors from the production possibility frontier. 
Another way of defining the performance of a DMU uses cost/revenue/profit functions, 
where the performance is measured relative to these functions. This section provides these 
basic concepts of efficiency measurement.

2.1.1. Distance Function Approach

Production Possibility Set Let $\mathbf{x}$ be an input vector and $\mathbf{y}$ be an output vector. 
Production possibility set $S$ is a set of combinations of input and output such that

$$S = \{ (\mathbf{x}, \mathbf{y}) \mid \mathbf{x} \text{ can produce } \mathbf{y} \}. \quad (2.1)$$

Output set $P(\mathbf{x})$ is a set of outputs that can be produced by a given input vector $\mathbf{x}$:

$$P(\mathbf{x}) = \{ \mathbf{y} \mid \mathbf{x} \text{ can produce } \mathbf{y} \}$$

$$= \{ \mathbf{y} \mid (\mathbf{x}, \mathbf{y}) \in S \}. \quad (2.3)$$

Input set $L(\mathbf{y})$ is then a set of inputs that can produce a given output vector $\mathbf{y}$:

$$L(\mathbf{y}) = \{ \mathbf{x} \mid \mathbf{x} \text{ can produce } \mathbf{y} \}$$

$$= \{ \mathbf{x} \mid (\mathbf{x}, \mathbf{y}) \in S \}. \quad (2.5)$$

Properties associated with the production technology includes the following (see Chambers [12] for details.) Note, however that in productivity/efficiency measurement, not all 
of these properties are assumed a-priori.

- Non-negativity implying that $\mathbf{x}$ is an $m$-vector and $\mathbf{y}$ is an $n$-vector whose elements 
  are all positive real numbers, i.e., $\mathbf{x} \in R^m_+$ and $\mathbf{y} \in R^n_+$ where $m, n$ are the numbers 
  of inputs and outputs respectively.

- Weak essentiality implying that for any non-zero output vector, its input set does 
  not include the zero vector, i.e., $L(\mathbf{y}) \not\subseteq 0$ for any $\mathbf{y} \neq 0$.

- Disposability (or monotonicity) in inputs: increase in an input will not decrease 
  output, i.e., if $\mathbf{x}_0 \leq \mathbf{x}_1$ then $P(\mathbf{x}_0) \subseteq P(\mathbf{x}_1)$.\(^1\)

- Disposability of outputs: any portion of outputs can be disposed without any cost, 
  i.e., if $\mathbf{y}_1 \in P(\mathbf{x})$ and $\mathbf{y}_0 \leq \mathbf{y}_1$ then $\mathbf{y}_0 \in P(\mathbf{x})$.

- Concavity in inputs: if $\mathbf{x}_0, \mathbf{x}_1 \in L(\mathbf{y})$ then $\lambda \mathbf{x}_0 + (1 - \lambda) \mathbf{x}_1 \in L(\mathbf{y})$, $\forall \lambda \in [0,1]$ (and 
  similar for outputs.)

\(^1\)This is often termed strong disposability (see section 2.3 of [19].) Weak disposability is, instead $\forall \lambda > 1$ 
and $\mathbf{x} \neq 0$, $P(\mathbf{x}) \subseteq P(\lambda \mathbf{x})$. Thus weak disposability allows isoquant to be “bending backward” or “upward sloping.”
Distance Functions

**Output-oriented Distance Functions** Output-oriented distance function is defined on the domain of output set $P(x)$ for a given input vector $x$:

$$d_O(x, y) = \min \{\theta | (y/\theta) \in P(x)\}.$$  \hfill (2.6)

Technical Efficiency for the output-oriented distance function $TE_O$ is defined as

$$TE_O = d_O(x, y).$$  \hfill (2.7)

**Input-oriented Distance Functions** Input-oriented distance function is, in turn defined on the domain of input set $L(y)$ for a given output vector $y$:

$$d_I(x, y) = \max \{\rho | (x/\rho) \in L(y)\}.$$  \hfill (2.8)

Technical Efficiency for the input-oriented distance function $TE_I$ is then defined as

$$TE_I = 1/d_I(x, y)$$  \hfill (2.9)

Input-oriented efficiency measurement captures how efficiently inputs are used for the given output level. See chapter 3 of [17] and [15] for properties of these concepts and further discussions.

**Scale Economies** Production transformation function $T(x, y)$ is defined as an implicit function such that

$$T(x, y) = 0$$  \hfill (2.10)

where

$$d_O(x, y) = d_I(x, y)$$  \hfill (2.11)

$$= 1.$$  \hfill (2.12)

That is, production transformation function $T(x, y)$ is the boundary of the production possibility set $S$.

Define the overall (local) elasticity of scale $E_{yx}$ as the percentage increase in all outputs in response to a percentage increase in all inputs, when all outputs are increased at the same rate where $(x, y)$ is such that $T(x, y) = 0$. Then the overall (local) elasticity of scale $E_{yx}$ is computed as

$$E_{yx} = \left[ \sum_{i=1}^{n} \left( \sum_{j=1}^{m} E_{yixj} \right)^{-1} \right]^{-1}$$  \hfill (2.14)

$s.t. \ T(x, y) = 0,$  \hfill (2.15)

where $m, n$ are the numbers of inputs and outputs respectively, $x_j$ ($y_i$) is the $j$th ($i$th) element of input (output) vector, and $E_{yx}$ is an elasticity of $y$ with respect to $x$. 

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2.1.2. Cost, Revenue, and Profit Function Approach

Let us continue to consider multi-output, multi-input DMUs. When price data are available, the relationship between inputs and outputs can be expressed compactly in one equation as either cost, revenue, or profit functions.

**Cost-Function Approach** Cost function is represented as

\[ c(w, y) = \min_{x} w'x \tag{2.16} \]

\[ s.t. \ (x, y) \in S \tag{2.17} \]

where \( w \) is an input-price vector. After specifying appropriate functional form and error distribution, cost function is estimated. Then such minimum (estimated theoretical) cost is compared to the actual cost to obtain cost efficiency. For cost-function approach to be applicable, it must be reasonable to assume that DMUs are cost minimizers.

Applying Shephard's lemma to the cost function gives input demand function:

\[ x_i(w,y) = \frac{\partial c(w,y)}{\partial w_i}. \tag{2.18} \]

When the cost function (2.16) is specified as an anonymous approximation function such as the translog function, then the cost function (2.16) has to be estimated simultaneously with input demand functions (as cost shares) through an appropriate econometric method such as SUR (seemingly unrelated regressions.) See, for example, Murakami (2006) and Murakami and Uranishi (2006) for details.

Economy of scale can be alternatively computed from cost elasticities:

\[ E_c = \left[ \sum_{i=1}^{n} \frac{\partial \ln c(w,y)}{\partial \ln y_i} \right]^{-1}. \tag{2.19} \]

This measure of scale economy \( E_c \) does not in general coincide with \( E_{yx} \) as \( E_c \) permits unequal rates of increase in inputs so as to minimize the increase in cost, for example if the production technology is not homothetic.

**Revenue-Function Approach** Revenue function is represented as

\[ r(p, x) = \max_{y} p'y \tag{2.20} \]

\[ s.t. \ (x, y) \in S \tag{2.21} \]

where \( p \) is an output-price vector. That is, for a given input vector \( x \), output mix needs to be optimized so as to maximize the revenue. Revenue-function approach is much less utilized than cost-function approach in productivity measurement, and is more popular in the field of macro-economics and international trade.

Applying Shephard's lemma to the revenue function gives revenue-maximizing output allocation given output prices and inputs:

\[ y_i(p, x) = \frac{\partial r(p, x)}{\partial p_i}. \tag{2.22} \]
**Profit-Function Approach** Profit function is represented as

\[ \pi (p, w) = \max_{x,y} p'y - w'x \]
\[ s.t. (x,y) \in S. \]  

(2.23)  

(2.24)

Profit-function approach is the most comprehensive approach in the sense that it captures all the potential sources of inefficiency of DMUs. However, its data requirement is the highest: both input and output price data are required. Also, it must be reasonable to assume that DMUs are profit maximizers.

Applying Hotelling’s lemma to the obtained profit function yields (provided that the profit function is twice continuously differentiable) supply function:

\[ q_t(p, w) = \frac{\partial \pi (p, w)}{\partial p_t}. \]

(2.25)

2.1.3. Other Issues

**Identifying the Sources of Inefficiency** Efficiency can be decomposed into several parts, including (pure) technical efficiency, allocative efficiency, and scale economies. It is possible that a DMU is technically efficient but inefficient in allocative sense or in production scale. Appropriate method and assumptions will separate these sources of inefficiency (see chapter 3 of Coelli et al [17] for details.)

For example, allocative efficiency is defined as follows. Let \( x^* \) be the solution the to the cost-minimization problem given in (2.16) above and \( c^* \) be the resulting minimum cost. Then allocative efficiency of inputs \( AE_I \) is

\[ AE_I \equiv \frac{w'x^*}{d_I w'x}. \]

(2.26)

Recall that technical efficiency is

\[ TE_I = 1/d_I (x,y) \]

(2.27)

and combining together we have the cost efficiency \( CE \):

\[ CE = \frac{w'x^*}{w'x} = AE_I : TE_I. \]

(2.28)  

(2.29)

Similar argument applies to outputs as well. For outputs, allocation efficiency implies optimal output mix in maximizing revenue \( r \) in (2.20) above, given inputs \( x \) and output prices \( p \).

**Technological Change and Productivity Growth: Malmquist Index** Performance of a DMU changes not only because of efficiency change of such DMU itself but also by the technological change. Malmquist index captures both of them and hence decomposing it separates and identifies these two effects. Caves, Christensen, and Diewert [11], Fare and Grosskopf [18], and chapter 9 of Fare et al [19] explains the concept in details,
however, in this section we review briefly some of their results. Malmquist input-oriented productivity index is defined as follows.

\[
M_{t+1}^{t+1} = \left[ \frac{d_I(x^{t+1}, y^{t+1})}{d_I(x^t, y^t)} \right]^{\frac{1}{2}} \left( \frac{TE_I[x, y, s]}{TE_I[x, y, s+1]} \right)^{\frac{1}{2}} \left( \frac{TE_I[x^{t+1}, y^{t+1}, s^{t+1}]}{TE_I[x^{t+1}, y^{t+1}, s^{t+1}]} \right)^{\frac{1}{2}}
\]

where superscript indicates time of observation and \( M_{t+1}^{t+1} \) is the Malmquist input-oriented productivity index. Note that \( M_{t+1}^{t+1} \) above can be alternatively written as

\[
M_{t+1}^{t+1} = \frac{TE_I[x, y, s]}{TE_I[x, y, s+1]} \left[ \frac{TE_I[x^{t+1}, y^{t+1}, s^{t+1}]}{TE_I[x^{t+1}, y^{t+1}, s^{t+1}]} \right]^{\frac{1}{2}}.
\]

The square root of the terms in square brackets gives the technology change as the geometric mean of the shifts in production possibility set measured at observed inputs and outputs in periods \( t \) and \( t+1 \). Terms outside the brackets gives the ratio of efficiencies in two periods.

2.2. Conventional Methods of Efficiency Measurement

2.2.1. Index Numbers and Total Factor Productivity

An index is exact if it is derived from aggregator functions (e.g., production functions and utility functions.) An exact index is superlative if the aggregator function is a flexible, second-order approximation function of some anonymous function. One example of a superlative index is the Fisher Ideal index, and another is the Tornqvist index (see Fisher [22] for Fisher Ideal index and Tornqvist [51] and Theil [48] for Tornqvist index.) A desirable index number should possess properties such as reversality and circularity (or transitivity). Fisher Ideal index does not satisfy circularity. Caves, Christensen, and Dievert [10] develops a multilateral superlative indices basing upon Tornqvist Index. We reproduce their results in the following section.

Tornqvist Index As mentioned above, Tornqvist index is superlative and its aggregator function is a homogeneous translog function. For example, Tornqvist output index is derived from a translog production function.\(^2\) Tornqvist multilateral output index \( \delta \) has the form such that

\[
\ln \delta = \frac{1}{2} \sum_{i=1}^{n} \left( R_i + \bar{R}_i \right) \left[ \ln y_i - \ln \bar{y}_i \right],
\]

and Tornqvist multilateral input index \( \rho \) is such that

\[
\ln \rho = \frac{1}{2} \sum_{i=1}^{m} \left( W_i + \bar{W}_i \right) \left[ \ln x_i - \ln \bar{x}_i \right],
\]

\(^2\)For details of derivation see Caves, Christensen, and Dievert. For translog function and its properties see, for example Berndt and Christensen [9].
where \( R_i \) \((W_i)\) is the revenue (cost) share of the \(i\)th output (input), \( y_i \) \((x_i)\) is the \(i\)th element of the output (input) vector \(y\) \((x)\), and the bar \((-\)) indicates arithmetic mean. In its derivation, Tornqvist output \((input)\) index assumes constant-return production technology and revenue maximization \((cost\ minimization)\) of DMUs.

It is derived \(\text{not defined}\) in Caves, Christensen, and Diebolt \[10\] that Tornqvist productivity index, say \(\lambda\) equals to the ratio between Tornqvist output and input indices:

\[
\ln \lambda = \ln \left( \frac{\delta}{\rho} \right)
\]

\[
= \frac{1}{2} \sum_{i=1}^{n} \left( R_i - \bar{R_i} \right) \left[ \ln y_i - \ln \bar{y}_i \right] - \frac{1}{2} \sum_{i=1}^{m} \left( W_i + \bar{W_i} \right) \left[ \ln x_i - \ln \bar{x}_i \right].
\]

Oum and Yu \[38\] applies this index number method to TFP measurement of airlines.

### 2.2.2. Data Envelopment Analysis

Data envelopment analysis \(\text{(DEA)}\) is applied to assess relative productivity or efficiency of DMUs that produce multiple outputs using common multiple inputs. Twenty years after the pioneering work by Farrel \[20\], an innovative work by Charnes, Cooper, and Rhodes \[13\] triggered a rapid accumulation of the research on and using data envelopment analysis \(\text{(DEA)}\). Banker, Charnes, and Cooper \[6\] extended the literature, and Gillen and Lall \[24\] applies DEA to airport productivity.

DEA is a non-parametric method of identifying production possibility set and computing efficiency as the distance function approach. The benefit of DEA is that it only requires physical data, and not financial/nominal data; free of a-priori assumptions on functional forms; and applicable to multi-output productions. The weakness is that it is extremely sensitive to outliers; generates multiple best performers; and is inefficient as it utilizes only a subset of observations in identifying production possibility set. See chapter 6 of Coelli et al \[17\] for concise explanation and applications of DEA.

DEA can be combined with Malmquist approach to separate and measure the technological advance and efficiency improvement over the different time points \(\text{(see Coelli and Rao} \[16\])}.

**The DEA Model** In the original DEA model developed in Charnes et al, the efficiency of a DMU is measured by solving the following maximization problem:

\[
\max_{u_{i}v_{j}} \frac{\sum_{j=1}^{m} u_{j} y_{j}}{\sum_{j=1}^{m} v_{j} x_{j}} \tag{2.37}
\]

\[
\text{s.t.} \quad \frac{\sum_{j=1}^{m} u_{j} y_{j}}{\sum_{j=1}^{m} v_{j} x_{j}} \leq 1 \quad \forall l = 1, \ldots, L \\
\quad u_{i}, v_{j} \geq 0 \quad \forall i = 1, \ldots, n, \quad \forall j = 1, \ldots, m
\]

where \(L\) is the number of DMUs, \(y_{jl}\) and \(x_{jl}\) are the \(i\)th output and \(j\)th input of the \(l\)th DMU respectively, and \(m\) and \(n\) are the number of inputs and outputs respectively. The efficiency of a DMU is measured as the maximum ratio of a linear combination of outputs
to a linear combination of inputs, controlling nonnegative parameters \( u \)'s and \( v \)'s, subject to the constraint that such ratio must be less than or equal to unity for every DMU.

The following linear programming problem is a reduced form derived from the above maximization problem:

\[
\begin{align*}
\min_{\lambda_1, \ldots, \lambda_L} & \quad h_0 \\
\text{s.t.} & \quad \sum_{i=1}^L \lambda_i y_{i0} = y_{00} \quad \forall i = 1, \ldots, n \\
& \quad \sum_{i=1}^L \lambda_i x_{i0} = h_0 x_{j0} \quad \forall j = 1, \ldots, m \\
& \quad \lambda_1, \ldots, \lambda_L, h_0 \geq 0.
\end{align*}
\]  

(2.38)

The solution of this linear programming \( h_0 \) indicates “input-oriented” efficiency of each DMU. We focus on this input-oriented DEA efficiency in the following analysis. Note that this model assumes constant return to scale (CRS) for production technology. This CRS DEA model can be readily extended to the variable-return-to-scale (VRS) DEA model. We obtain the VRS specification by adding the following concavity condition as constraints to the above linear programming problem in (2.38):

\[
\sum_{i=1}^L \lambda_i = 1. 
\]  

(2.39)

Note that the following inequality is always satisfied:

\[
h_0|_{VRS} \geq h_0|_{CRS}.
\]  

(2.40)

As Banker et al [6] argues, VRS DEA efficiency measured as \( h_0 \) above indicates only technical efficiency, and does not include scale efficiency. The difference between CRS and VRS DEA efficiencies then gives such scale efficiency.

2.2.3. Stochastic Frontier Analysis

Stochastic frontier analysis, or SFA in short, is initiated by Aigner, Lovell, and Schmidt [3]. The idea is to assume two components consists the disturbance term in estimating parametric production frontier. These two components are namely white noise and inefficiency. While the white noise is a two-tailed symmetric distribution, inefficiency has only one tail. Maximum likelihood method is conventionally utilized in estimating the production frontier as well as parameters for the noise and inefficiency distributions. This idea can be adopted in estimating not only production functions but also cost/profit functions, which enables efficiency measurement under multiple-output situation.\(^3\)

In the following we introduce the empirical model utilized in Oum et al [35] in which they estimated cost efficiencies of worldwide airports using SFA. They estimated a variable cost function in the form of

\[
\ln C_{it} = \ln C^* (Q_{it}, W_{it}, K_{it}, t) + \Delta_i + \varepsilon_{it} 
\]  

(2.41)

\(^3\)See Greene [26] and Kumbhakar and Lovell [28] for more comprehensive discussions of SFA. Recently, Tone and Tsutsui [50] proposes to use SFA results in DEA in multi-stage analysis.
where $\varepsilon_{it}^\ast$ is the white noise for the airport $i$ in time $t$; $Q_{it}, W_{it}$ and $K_{it}$ are the vectors of outputs, variable input prices, and fixed capital inputs respectively. Here, $\Delta_i$ is the deviation of actual cost for airport $i$ from the cost frontier $C^\ast$. Since $\Delta_i$ is the inefficiency in the cost, it takes only positive values. Their assumption is that $\Delta_i$ is a random draw conditional on the airports attributes, i.e., ownership form. The probability density function of $\Delta_i$ is

$$\Delta_i = \exp(Z_i \Gamma_i)$$

(2.42)

where

$$\Gamma_i \sim N(\bar{\Gamma}_i, \Omega),$$

(2.43)

and $Z_i$ is the ownership-form dummy vector representing characteristics of airport $i$. Variance-covariance matrix $\Omega$ is assumed to be diagonal. After specifying the minimum cost function $\ln C^\ast$ as a translog function, they estimate it together with the cost-share function for variable inputs. This improves the efficiency of estimation, as stated above.

### 2.3. Recent Developments in Theory

#### 2.3.1. Production with Undesirable Outputs

Production of desirable outputs (e.g., transport services) is often accompanied by production of undesirable outputs (pollution, congestion delays, noise, and risk of accidents) as by-products. Chung et al. [14] introduced the directional distance function approach to calculate production relationships involving goods and bads. Atkinson and Dorfman [5] treated the bad as a technology shifter of an input distance function while Pathomsiri et al [42] has defined a new output distance function in the framework of DEA to incorporate the delays associated with airport operations.

**Distance-Function Approach**  Let us denote $y$, $b$, and $x$ as vectors of desirable outputs (goods), undesirable outputs (bads), and inputs respectively. One way of treating the undesirable outputs is to treat them symmetrically to the ordinary outputs. Then the input distance function with undesirable outputs, $d^I_{yi}$ say, is defined as

$$d^I_{yi}(x, y, b) = \max \{ \rho | (x/\rho) \in L(y, b) \}$$

(2.44)

where $L(y, b)$ is the set of input vectors that can produce the output combination of $y$ and $b$.

Unfortunately, when treating desirable and undesirable outputs symmetrically the output distance function is in general not well defined, even under a standard set of assumptions on the production possibility set. This is due to the fact that the amount of goods and bads can increase together even when the amount of inputs is held constant, unlike ordinary goods that are in trade-offs.

Atkinson and Dorfman [5] uses input distance function in measuring efficiency of electric utilities industry with air pollution as bads, however, they treat the bads as technology shifter. Let $t$ be the parameter for the state of production technology, which depends on the quantity of bads $b$. That is, production possibility set $S$ (and therefore the input set $L$) expands as the quantity of bads increases. They specified the input distance function as follows:

$$d^I_{yi}(x, y, t|b) = \max \{ \rho | (x/\rho) \in L(y, t|b) \}.$$  

(2.45)
Output distance function can be computed in this specification, and that corresponds to measuring the distance to the production frontier from the output combination \((y, b)\) in the direction that \(y\) is increasing while holding \(b\) as given. Atkinson and Dorfman specifies the distance function as translog, then applies SFA method for econometric estimation.

**DEA-Based Approach** Methodology employed by Pathomsiri et al [42] is essentially DEA oriented, and they define the production possibility set in a way that the output set \(P(x)\) defined above is given as follows:

\[
P(x) = \{y, b| \sum_{i \in I} \lambda_i y_i \geq y_i, \quad i = 1, \cdots, N,
\sum_{i \in I} \lambda_i b_{ji} = b_j, \quad j = 1, \cdots, J,
\sum_{i \in I} \lambda_i x_{ki} \leq x_{ki}, \quad k = 1, \cdots, M,
\lambda_l \geq 0, \quad l = 1, \cdots, L\}
\]  

(2.46)

where \(b\) is a \(J\)-vector of undesirable outputs; on the right-hand side of constraints \(y_i\), \(b_j\), and \(x_k\) are respectively \(i\)th, \(j\)th, and \(k\)th element of \(y, b\), and \(x\) vectors whereas on the left-hand side, \(b_j\) is the \(j\)th undesirable output of airport \(l\), and so on. Production possibility set defined as above is compact and convex, implying that shrinking all three vectors \(y, b,\) and \(x\) in the production possibility set at the same rate will result in a set of vectors that is still in the production possibility set. Also, above expression implies weak disposability, i.e., for any given combination of undesirable outputs \(b\) and inputs \(x\) one can reduce the amount of desirable outputs \(y\) and still in the production possibility set.

In their analysis, inefficiency is computed by using the directional output distance function, not the above-mentioned ordinary output oriented distance function. Unlike the ordinary DEA, inefficiency cannot be computed by contracting the output vector \((y, b)\), since as stated above, it will simply reduce to a zero vector. Instead, their method finds the minimum distance to the boundary from the output combination \((y, b)\) in the direction that \(y\) is increasing and \(b\) is decreasing (see Pathomsiri et al [42] for more details.)

**Index-Number Approach** Pittman [44] extended the original index-number approach developed by Caves, Christensen, and Diewert [10] to include the undesirable outputs. As Caves et al, Pittman specifies the production transformation function as translog:

\[
F(\ln Y^k, \ln x^k, k) = 1
\]  

(2.47)

\[
Y^k = [y^k, b^k]
\]  

(2.48)

where \(y^k, b^k,\) and \(x^k\) are respectively desirable and undesirable outputs and inputs, for firm \(k\). Production transformation function \(F\) is firm specific, as it has technology parameter \(k\) as the forth argument. In comparing productive efficiency of two firms, the factor of proportionality \(\delta_k\) is redefined as the contraction factor for desirable outputs while undesirable outputs are expanded by the same factor, i.e.,

\[
F\left(\ln \frac{y^k}{\delta_k}, \ln \delta_k b^k, \ln x^l, l\right) = 1.
\]  

(2.49)
The bilateral output index is then obtained as

$$\ln \delta_{kl} = -\sum_i \left[ \frac{1}{2} F_i \left( \ln Y_{ik}^k, \ln x_i^k, k \right) + \frac{1}{2} F_i \left( \ln Y_{il}^l, \ln x_i^l, l \right) \right] \ln \left( \frac{Y_{ik}^k}{Y_{il}^l} \right)$$

(2.50)

where $Y_{ik}^k$ is the $i$th element of a vector $Y^k = [y^k, b^k]$. This expression of output index is identical to the original bilateral output index without the undesirable outputs developed in Caves et al. Hence the multilateral output index follows the same way as in the Caves et al, even with the existence of undesirable outputs. It is also shown by Pittman that the multilateral input index has the same form as that of Caves et al, where all outputs are desirable.

One practical difficulty, however, arises due to the fact that the prices for undesirable outputs may well be unobservable. Pittman uses the shadow prices of undesirable outputs, obtained through the constrained profit maximization problem, where total admissible amounts of emission of bads are constraints.

2.3.2. Other Margins of Theoretical Developments

**Dynamic Efficiency** When production uses durable inputs, a DMU’s decision process becomes that of dynamic optimization.\(^4\) There, what is an optimal choice in static (or one-time) sense does not have to be optimal in the long-run dynamic sense. Therefore, the measurement of performance requires appropriate method. One of such methods is dynamic DEA. In dynamic DEA, there are two kinds of inputs, namely variable inputs and quasi-fixed inputs. The quasi-fixed inputs are durable, and therefore, the choice is to adjust its stock at every time point, thus entailing dynamic optimization. Dynamic DEA solves for the dynamic cost frontier through linear programming. See Nemoto and Goto [32] and Nemoto and Goto [33] for its details. Yoshida and Yamaguchi [54] recently developed a parametric counterpart to the dynamic DEA. In these methodologies, overall cost efficiency is decomposed into dynamic and static efficiency. Further, this static efficiency is decomposed into allocation efficiency and technical efficiency, as described above.

**Reconciling Different Methodologies** There have not been sufficient research comparing, analyzing and reconciling the differences in efficiency measurement results using different methods, in particular, between non-parametric methods (DEA, Productivity Index number approach, etc.) and econometric production/cost function methods. Theoretically bridging different methodologies would enable reconciling differential results in efficiency rankings and benchmarking obtained by using different methodologies: DEA, Stochastic Frontier method, and Productivity Index.

**Quality Attributes of Services** In many service industries, not only the quantity, but also the quality provided should be taken into account in efficiency measurement. Further research should include improving the ways to handle variations in service quality in each of the three key methods namely DEA, Econometrics, and Productivity Index number approaches.

\(^4\)Contrast with the Malmquist concept which is merely comparative statics.
Reflecting Strategic Environment  Traditional DEA and Econometric approach to efficiency measurement assumes static environment for firms (facing no competition). Increasingly, airports, seaports and other infrastructures are being commercialized. Thus, their production and investment decisions become strategic, taking competition into account. We will try to reflect this oligopoly market structure in our model for efficiency measurement.

Efficiency Measurement at Sub-unit Levels of an Agency.  There is an increasing need for measuring, comparing and benchmarking efficiency for various sub-units within a firm or agency (e.g., an airport’s airside services business, terminal side business, and non-aeronautical services including car parking, concessions, rentals, etc.). Efficiency measurement and analysis at sub-unit levels are essential in order to provide guidance to management about how to improve efficiency vis-à-vis benchmark firms.

Other Econometrical / Methodological Developments

Parametric Estimation of Production Transformation Function  Though DEA is a versatile methodology in the sense that it only requires physical data and can handle multi-outputs, and that there is no a-priori assumptions such as cost minimization or CRS production. However, it generates multiple best performers, and utilizes only a subset of observations in identifying the frontier, and cannot allow IRS production. Yoshida [52] and Yoshida and Fujimoto [53] proposes and uses parametric approach of estimating productive efficiency called endogenous-weight TFP. Endogenous-weight TFP is a parametric method which estimates production transformation function with multiple outputs directly by using physical data only. Thus it overcomes all of the shortcomings of DEA mentioned above. However, choice of a functional form is critical for a successful measurement of efficiencies.

Corrected Ordinary Least Squares  The idea of corrected ordinary least squares (COLS) is to first estimate the production function with OLS, and then to shift it “upward” as much as the maximum positive error to construct the production frontier. Coelli [15] applies COLS to productivity measurement of European railway using the distance function approach. Greene [26] provides comprehensive discussion of production frontier estimation using COLS.5

Slacks-Based Measures (SBM)  Tone [49] proposes non-radial measures of efficiency in the framework of DEA. Unlike the conventional method, SBM contracts input vector non-radially, in other words, inputs are reduced in varying proportions to maximize the rate of reduction. This measure provides efficiency as a unique intermediate value between input- and output-oriented efficiencies.

5It also discusses about modified ordinary least squares (MOLS) in conjunction with the SFA.
3. Empirical Analysis of Airport Productivity: a Chronological Overview

This section treats recent empirical analysis of airport productivity that uses efficiency measurement techniques discussed in earlier sections. It attempts to give an historical overview of airport productivity analysis. The section concludes by addressing future research opportunities.

3.1. Initial Stage of Airport Productivity Analysis

The first series of productivity analysis of airports came out in the late 1990’s. Since advent of deregulation in the airline industry that starting in US and then in Europe and other areas of the world, there were growing emphasis on improvement of airport performance. Airlines were now in a position to strategically select airports and develop their network. However, it was not after airport privatization that took place in UK and Australia in the late 1980’s that productivity analysis was applied to airports.

Gillen and Lall (1997) and Hooper and Hensher (1997) were first two papers that shed light on this topic. Gillen and Lall (1997) applied Data Envelopment Analysis (DEA) on twenty-one US airports and used the efficiency measurement of terminal service and aircraft movements derived from DEA in a Tobid regression to identify how much variation in productivity index is attributable to managerial factors. They identified higher terminal efficiency when gates were commonly used by a number of air carriers compared to when gates were used exclusively by specific air carriers. Preferential use of gates provided airlines to exercise monopoly power and deter new entry. Compensatory financing had higher level of efficiency for terminal service, while the opposite was true for the airside, implying the importance of incentives. Exploratory work by Hooper and Hensher (1997), on the other hand, used Tornqvist index to measure productivity of six Australian airports. Gross TFP index was regressed against the size of the output level to compute output-adjusted TFP which significantly altered the overall productivity ranking. This paper served as a lead to subsequent papers that focused on scale economies of airports.

Another important step in airport productivity analysis was to assess the impact of public policy. Parker (1999) was the first to assess efficiency impact of airport privatization. DEA was applied to panel data of twenty-two UK airports including those managed by British Airports Authority (BAA). He found no evidence of technical productivity improvement from BAA privatization. This important paper inspired researchers and policy makers to take a deeper look at the optimal governance structure and regulation of airports.

3.2. The Second Phase: Theoretical and Methodological Evolution

A number of studies that followed not only assessed airports in different parts of the world but also adopted new methodological approaches.

Salazar de la Cruz (1999) analyzed sixteen major airports in Spain with DEA. Mid-sized airports exhibited constant returns to scale whereas large airports showed signs of decreasing returns to scale. Another DEA analysis of thirty-three Spanish airports by Murillo-Meldor (1999) broke down productivity change into technical efficiency and scale
efficiency. Larger airports were constant or decreasing returns to scale, while small regional airports omitted in Salazar de la Cruz (1999) turned out to be increasing returns to scale. Malmquist indices derived henceforth attempted to reveal the dynamic productivity change.

Sarkis (2000) calculated various efficiency scores using a variety of DEA-based models and provided a robust observation that average efficiency of major US airport experienced general increase during the period. He also performed a non-parametric analysis (Mann-Whitney U-test) of DEA based indices to identify characteristics that affected airport efficiency. Hub airports were more efficient than others, while there was no statistically significant difference between multi-airport system and single airport system. Gillen and Lall (2001) updated their previous work on US airports and constructed Malmquist index of productivity change and decomposed it into scale efficiency, technical efficiency and technological change. Significant variation was identified in the twenty-two airports that they analyzed. They also found that higher productivity for terminal service does not always imply high productivity for airside activities. Another interesting observation was to identify ‘innovator airports’ that pushed the frontier to a more efficient level.

Pels et al. (2001) analyzed thirty-four European airports using DEA and stochastic frontier analysis. By calculating most productive scale sizes they contended that given the current input-mix most airports were operating under increasing returns to scale. DEA analysis of thirty-seven Spanish airports by Martin and Roman (2001) concludes that twenty of which are operating under increasing returns to scale. They also identify some spatial concentration of airports performing in the frontier.

Adler and Berechman (2001) introduced an innovative way of reflecting airlines’ perception of airport quality into productivity analysis. They collected detailed questionnaires from airlines and after confirming with canonical correlation analysis that these subjective data could be explained by objective data, they applied DEA-based super-efficient techniques on the subjective and objective attributes of twenty-six airports, of which sixteen are European airports. In order to avoid lack of differentiation between DMUs, the number of outputs was reduced by principal component analysis. They found some specific west European airports such as Geneva and Milan consistently lead the efficiency scale.

Abbott and Wu (2002) conducted DEA analysis of twelve Australian airports and contended that although technological change was recorded during 1990’s technical and scale efficiency had not improved. Regression analysis of DEA efficiency against characteristics of airports and operating environments revealed that productivity improvement had been higher for more profitable, heavily asset accumulating airports. They added twelve airports outside Australia to conduct benchmarking and found that Australia’s largest airports such as Sydney and Melbourne appear to be on or close to the efficient frontier. Correlation between X-values under the price-cap regulation and the efficiency scores derived from DEA was not identified.

Fernandes and Pacheco (2002) analyzed thirty-five Brazilian airports with DEA and compared the efficient capacity with existing demand forecast to assess the timing of future capacity expansion. They argued that although majority of efficient airports would suffer capacity shortage even in the short-run, some inefficient airports have slacks available to utilize before they reach the capacity limit for the next fifteen years.

Bazargan and Vasigh (2003) studied total of forty-five US airports, fifteen each from
large, medium and small hub airports, to identify efficiency difference between the three airport categories. They introduce virtual super-efficient airports in the DEA analysis to cope with majority of airports being on or close to the frontier. Resulting efficiency scores from the adjusted DEA was statistically verified by non-parametric tests and found the small hubs consistently outperformed the large hubs.

3.3. Reaching Out into the World: Global Airport Benchmarking

In 2001, Air Transport Research Society (ATRS) embarked on the first comprehensive world-wide airport benchmarking. Oum et al (2003) and Oum and Yu (2004) highlights major findings from the ATRS initiative. Oum et al (2003) computed productivity of fifty major airports in Asia Pacific, Europe and North America using endogenous-weight TFP method (EW-TFP). Asia-Pacific airports appeared to be more efficient than those in North America, which in turn were relatively more efficient than European airports. The productivity index was then regressed against factors beyond and under managerial control. From the regression analysis, larger airports appear to have higher gross TFP due to economies of scale and not necessarily because they are technically efficient. Airport ownership structure does not seem to have any statistically significant effect on TFP, while diversification into non-aeronautical activities leads to higher productivity. Oum and Yu (2004) focuses on operating efficiency of airports. They compute gross Variable Factor Productivity (VFP) that considers labor and soft cost as inputs and then residual VFP is estimated by removing factors beyond managerial control form. In addition to similar analytical results from Oum et al (2003), in terms of residual VFP, Auckland, Christchurch, Sydney, Copenhagen, Amsterdam, Oslo, Zurich, Gatwick, Atlanta, Charlotte, Raleigh-Durham, Vancouver, Cincinnati and Calgary were high performers.

A number of productivity analyses were also conducted in different corners of the world. Yoshida and Fujimoto (2004) applied DEA and EW-TFP to sixty-seven airports in Japan and conducted Tobid regression to assess efficiency of local and new airports. They found inefficiency in small regional airports on the mainland and similar inefficiency in airports opened since 1990’s. Barros and Sampaio (2004) conducted DEA analysis for ten major airports in Portugal and breaks productivity into technical and allocative efficiency. Productivity index from DEA is regressed against various spatial factors and contends that location of airport plays an important role in determining its efficiency. Fung et al (2007) applied DEA on twenty-five airports in mainland China and found the average rate of productivity growth to be 3%, although significant discrepancy existed between airports in different geographical locations. Using a Gaussian kernel smoothing technique the source of growth was attributed mostly to technological improvement rather than technical efficiency gains.

3.4. New Avenues of Airport Productivity Analysis

Pacheco and Fernandes (2003) conducted a bi-dimensional analysis of thirty-five Brazilian airports through DEA analysis of variables that are related to ability to raise financial returns and capacity utilization. They plot the outcome into an efficiency matrix to identify which airport not only needs capacity expansion but also has the necessity to raise capital. Pels et al (2003) conducted stochastic frontier analysis and DEA for thirty-three
European airports. In the former, efficient frontier of air transport movements (ATM) is first estimated and predicted value of ATM is then used to estimate air passenger movements (APM). Similarly, in the later, number of runways is sued as fixed factor. This enables them to distinguish between efficiency in terms of aircraft movement and passenger throughput. They contend that an average airport is operating under constant returns to scale for ATM and increasing returns to scale for APM. This is consistent with Gillen and Lall (1997). Overall they identify rooms for efficiency improvement in many European airports and find no specific correlation between specific region and airport efficiency.

Sarker and Talluri (2004) applied DEA on forty-four major US airports and conducts cross-efficiency analysis to rank their performance. It appears that Fort Lauderdale and Oakland were good performers while Jacksonville, Kansas City, Milwaukee and New Orleans were least efficient. They utilized these results to undergo hierarchical clustering analysis so as to identify different categories of benchmarking. Thirteen clusters were identified. Similar to the result in Sarker (2000), airports in warm and stable weather regions, as well as large hub airports turned out to be performing well.

A number of recent researches have started to take undesirable outputs into consideration. Yu (2004) introduced social cost of aircraft noise as undesirable outputs as well as population as environmental factors into DEA analysis of airports. He calculated DEA productivity scores for fourteen airports in Taiwan and argued that conventional methodology that uses normal outputs undermines the relative efficiency performance. Yu et al (2007) assessed productivity growth of four Taiwanese airports using modified Malmquist index that accommodated undesirable output, the aircraft noise. Omission of undesirable outputs overestimates TFP growth almost by threefold. Considering that TFP growth on average was found to be driven mainly by efficiency gains, they stress the importance of upgrading air traffic facilities to enhance efficiency through reduction in aircraft noise. Pathomsiri et al (2008) incorporates delays as an undesirable output into DEA analysis of fifty-six US airports. Luenberger productivity index is used to assess inter-temporal productivity change. When delay was excluded from outputs many large and congested airports were the ones on the efficient frontier accounted, however, when delay was accounted for, many small and less congested airports joined the group of efficient airports.

4. Concluding Remarks

When the firms does not face strong competition, market mechanism fails to discipline these firms or to achieve the best efficient use of limited resources. In this situation, efficiency measurement gains an important role in learning to improve one’s efficiency performance relative to a benchmark unit, or investigating effects of a public policy or a regulation. Typical example of such industries without strong competition is a transportation sector, including airports and seaports. One complication here is that these firms provide multiple outputs share a common set of inputs in producing these multiple outputs. This calls for a delicate and sophisticated treatment in measuring their efficiencies.

The current paper started out by presenting the methodologies to measure efficiencies under these difficulties. They include DEA, Stochastic Frontier method, and Productivity Index approaches. Also, it presented recent developments in efficiency measurement theory, especially in the case with undesirable outputs. It then provided a review of the
existing literature on airport efficiency measurement results and recent advancement on the airport efficiency measurement with the existence of undesirable outputs such as pollution and congestion. It became clear that advancement of deregulation in aviation industry motivated the accumulation of the literature on airport efficiency measurement, while recent growing concern on the environmental degradation started a new stream of research on airport efficiency measurement with undesirable outputs.

References


