The measurement of productivity and efficiency: theory and applications

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No, life has not disappointed me! On the contrary, I find it truer, more desirable and mysterious every year,ever since the day when the great liberator came to me, the idea that life could be an experiment of the seeker for knowledgeand not a duty, not a calamity, not a trickery! And knowledge itself: let it be something else for others, for example, a bed to rest on, or the way to such a bed, or a diversion, or a form of leisure,for me it is a world of dangers and victories in which heroic feelings, too, find places to dance and play. "Life as a means to knowledge"with this principle in one's heart one can live not only boldly but even gaily and laugh gaily, too! And who knows how to laugh anyway and live well if he does not first know a good deal about war and victory?

Friedrich Nietzsche
The Gay Science (Section 234)

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Chapter 1

Introduction

In economic literature it is common to discuss about the performance of producers. And It is usual to discuss on *productivity* and *efficiency* of producers. By the *productivity* of a producer, we mean the ratio of its inputs to its outputs. If the producer has only one input and one output, the ratio is easy to compute. But, when there are more inputs and more outputs and more producers, it is needed to aggregate the production factors and to compare the several firms. We refer these tecniques like *Index Numbers*.

By the *efficiency* of a producer, we mean a comparison between a producer and a optimal value. The economic theory underlying efficiency analysis dates to the work of Koopmans (1951), Debreu (1951), and Farrell (1957), who made the first attempt at empirical estimation of efficiencies for a set of observed production units. A presence of inefficiency can be attributed to differences in production technology, differences in the scale of operation, difference in operating efficiency and differences in the operating environment in which production occurs (Fried et al. 2008). It is a measure that enables the management to gain information about the (X-)inefficiency (Leibenstein 1966) referred to the production process of any unit, which may be influenced by economic factors internal to any firm (the first three factors above) and other factors not tightly under the control of the management (the fourth). Proper attribution is important to for the adoption of managerial pratices and the design of public policies intended to improve productivity performance.

To be able to discuss on previous economic implication, we need to have techniques for that aim. In the next subsection, we introduce the economic model to measure the efficiency. In chapter 2 we present an application of index numbers, in chapter 3 and 4 two different nonparametric techniques to measure the efficiency.

1.1 Definition and measure of the efficiency frontiers

Given vectors $\boldsymbol{x} \in \mathbb{R}_+^p$ of p input quantities and $\boldsymbol{y} \in \mathbb{R}_+^q$ of q output quantities, standard microeconomic theory of the firm posits a production set at time t represented by

$$\mathcal{P}^t \equiv \{(\boldsymbol{x}, \boldsymbol{y}) \mid \boldsymbol{x} \text{ can produce } \boldsymbol{y} \text{ at time } t\}. \tag{1.1}$$

For purposes of efficiency measurement, the upper boundary of $\mathcal{P}^t$, label $\mathcal{P}^{t\partial}$, is of interest. $\mathcal{P}^{t\partial}$ is referred as efficiency boundary or *production frontier*. In the interior it contains all firms that are technically inefficiency and on it there are the efficiency firms. For both efficiency and inefficiency firms it is possible to define distances from $\mathcal{P}^{t\partial}$. The Debreu-Farrell input measure of efficiency for a given point $(\boldsymbol{x}, \boldsymbol{y})$ is:

$$\theta(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \equiv \inf\left\{\theta > 0 \mid (\theta\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t\right\} \tag{1.2}$$

By costruction $\theta \leq 1$ for all $(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t$; and a firm will be efficiency (in a Debreu-Farrel sense) if $\theta = 1$. The Debreu-Farrell output measure of efficiency for a given point $(\boldsymbol{x}, \boldsymbol{y})$ is:

$$\lambda(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \equiv \sup\left\{\lambda > 0 \mid (\boldsymbol{x}, \lambda\boldsymbol{y}) \in \mathcal{P}^t\right\}, \tag{1.3}$$

By costruction $\lambda \geq 1$ for all $(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t$; and a firm will be efficiency (in a Debreu-Farrel sense) if $\lambda = 1$.

The Debreu-Farrel input and output oriented measure of efficiency are not the only measure of efficiency defined in literature. In the applications, sometimes it is more easy to refear at the Shephard (1970) input or output distance functions given by

$$\delta^{in}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \equiv \sup\left\{\delta > 0 \mid (\delta^{-1}\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t\right\} \tag{1.4}$$

and

$$\delta^{out}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \equiv \inf\left\{\delta > 0 \mid (\boldsymbol{x}, \delta^{-1}\boldsymbol{y}) \in \mathcal{P}^t\right\}, \tag{1.5}$$

(respectively) to measure distance from an arbitrary point $(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{p+q}$ to the boundary $\mathcal{P}^{t\partial}$ in the input direction or the output direction. The Shepard measures of efficiency are the reciprocal of Debreu-Farrel measure of efficiency, then $\theta(\boldsymbol{x}, \boldsymbol{y}) = [\delta^{in}(\boldsymbol{x}, \boldsymbol{y})]^{-1}$ and $\lambda(\boldsymbol{x}, \boldsymbol{y}) = [\delta^{out}(\boldsymbol{x}, \boldsymbol{y})]^{-1}$. Clearly, the choice of type of distance, does not have effect on efficiency firms. Instead the choice of orientation (input or output) can have an impact on the efficiency firms because the frontiers in inputs and output orientation could be different. Usually, the choice of orientation is left to economic consideration, considering the different implication of it. Färe et al. (1985) proposed measuring efficiency along a hyperbolic path from the point of interest to $\mathcal{P}^{t\partial}$. The hyperbolic-graph distance function given by

$$\gamma(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \equiv \sup\left\{\gamma > 0 \mid (\gamma^{-1}\boldsymbol{x}, \gamma\boldsymbol{y}) \in \mathcal{P}^t\right\} \tag{1.6}$$

measures distance from the fixed point $(\boldsymbol{x}, \boldsymbol{y})$ to $\mathcal{P}^{t\partial}$ along the hyperbolic path $(\gamma^{-1}\boldsymbol{x}, \gamma\boldsymbol{y})$. Note that for $(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t$, $\gamma(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) \geq 1$ by construction.

Untill now, we discuss about the definition of efficiency in a Debreu-Farrel sense. Koopmans (1951) provide a definition of technical efficiency if an increase in any output is possible only by decreasing one other output and if a reduction in any input is possible only by increasing one other input. the difference with the definition of efficiency provides by Debreu-Farrell is that the second is a radial measure of efficiency and regards *equiproportionate* reduction of all inputs or maximum expansion of all outputs.

In the application, $\mathcal{P}^t$ and $\mathcal{P}^{t\partial}$ (and then the distance functions) are unknown and we need to estimate their. Typically, we know only a sample of observations:

$$\mathbb{X}_n = \{(\boldsymbol{x}_i, \boldsymbol{y}_i), i = 1, .., n\} \tag{1.7}$$

in the sector of interest. Starting from $\mathbb{X}_n$, we obtain estimates of $\mathcal{P}^t$ and $\mathcal{P}^{t\partial}$. For this aim, it is possible to use parametric and nonparametric techniques[1]. Here, we discuss about the second. Between the nonparametric techniques, the most famous is the Data Envelopment Analysis (DEA). DEA uses a linear program to estimate the efficiency and it was developed from Charnes et al. (1978). Its popularity is due to its flexibility, because no one parametric structure of production process or frontier is imposed. Only in the last year, its statistical properties have been investigated. However, this is a deterministic frontier model, where all observation are assumed to be technically attainable. DEA is not the only nonparametric technique: assuming $\mathcal{P}^t$ as free disposability, we have the free disposal hull (FDH) estimator. In the last years, new theories on efficiency measurements are appearing: from a side, there is the study on property of DEA estimator and how to do inference on it (Simar and Wilson, 1998,2000b); in the other side, there are robust nonparametric estimators based on the concept of partial frontiers (Cazals et al., 2002; Daouia and Simar, 2007, Daraio and Simar, 2007b, Wheelock and Wilson, 2008a).

[1]For an introduction on parametric techniques, see Kumbhakar and Lovell (2000).

1.2 Data Envelopment Analysis

1.2.1 The data generation process

Farrell (1957) was the first to use a linear program in an application to measure the efficiency, but only with Charnes et al. (1978) it became popular and it was label Data Envelopment Analysis (DEA)[2]. For several years, and for many researchers today, the use of DEA was a mere resolution of a linear program. The contribution of some researchers, has allowed to uderstand it could not be only that[3]. The first aim regards the concept of *estimator*: data envelopment analysis yields *estimates* of efficiency $(\widehat{\theta}, \widehat{\lambda})$ and an *estimator* of $\mathcal{P}^{t\partial}$ (label $\widehat{\mathcal{P}}^{t\partial}$). So, when we use DEA estimator, we define a probabilistic model.

Kneip et al. (1998), Kneip et al. (2007) and Park et al. (2000) define a flexible and reasonable statistical model.

Assumption 1.2.1. *The production set $\mathcal{P}^t$ is compact and free disposal, i.e., if $(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t$, $(\widetilde{\boldsymbol{x}}, \widetilde{\boldsymbol{y}}) \in \mathcal{P}^t$, and $\widetilde{\boldsymbol{x}} \geq \boldsymbol{x}$, then $(\widetilde{\boldsymbol{x}}, \widetilde{\widetilde{\boldsymbol{y}}}) \in \mathcal{P}^t \ \forall\ \mathbf{0} \leq \widetilde{\widetilde{\boldsymbol{y}}} \leq \boldsymbol{y}$.*

Assumption 1.2.2. *$(\boldsymbol{x}, \boldsymbol{y}) \notin \mathcal{P}^t$ if $\boldsymbol{x} = 0$, $\boldsymbol{y} \geq 0, \boldsymbol{y} \neq \mathbf{0}$, i.e., all production requires use of some inputs.*

This assumption is also called "no free lunch", i.e., it is not possible procude any output without any inputs.

Assumption 1.2.3. *The sample $\mathbb{X}^t_{n_t} = \{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^{n_t}$ of n_t observations on input and output quantities at time t are realizations of identically, independently distributed (iid) random variables with probability density function $f^t(\boldsymbol{x}, \boldsymbol{y})$ with support over $\mathcal{P}^t$; that is*

$$Prob((\boldsymbol{x}_i, \boldsymbol{y}_i) \in \mathcal{P}^t = 1). \tag{1.8}$$

So, we are assuming that all observations are assumed to be technical efficiency[4].

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[2]Nowadays there are several books on DEA: for an exhaustive discussion on DEA models, it is possible to read Coelli et al. (2005), Cooper et al. (2006), Thanassoulis et al. (2008).

[3]For an a survay on the argument, it is possible to read Simar and Wilson (2000b), Daraio and Simar (2007a) and Simar and Wilson (2008).

[4]This is also called deterministic frontier model.

Assumption 1.2.4. *At the frontier, the density f^t is strictly positive, i.e.,* $f_0^t = f^t(\boldsymbol{x}_0^{t\partial}, \boldsymbol{y}_0^{t\partial}) > 0$, *and it is continous in any direction toward the interior of* $\mathcal{P}^t$.

Assumption 1.2.5. $\mathcal{P}^t$ *is convex: if* $\{(x_1, y_1), (x_2, y_2)\} \in \mathcal{P}^t$, *then* $\forall \alpha \in [0, 1]$ *we have:* $(x, y) = \alpha(x_1, y_1) + (1 - \alpha)(x_2, y_2)$, *and* $(x, y) \in \mathcal{P}^t$

1.2.2 The estimator of production set

Let $\boldsymbol{Y} = \{\ \boldsymbol{y}_i, i = 1, .., n\}$, the matrix $q \times n$ of the set of outputs and let $\boldsymbol{X} = \{\boldsymbol{x}_i, i = 1, .., n\}$, the matrix $p \times n$ of the set of inputs; an estimator of production set, can be constructed using linear program from the observed input-output:

$$\widehat{\mathcal{P}}_{DEA} = \left\{(\boldsymbol{x}, \boldsymbol{y} \in \mathbb{R}_+^{p+q})|\ \boldsymbol{y} \leq \boldsymbol{Y}\kappa,\ \boldsymbol{x} \geq \boldsymbol{X}\kappa, \kappa \geq 0\right\} \tag{1.9}$$

.

λ is a vector $n \times 1$ of weights. Its "role" should be clear in the next sections

1.2.3 Costant return to scale model

Charnes et al. (1978) assume the convexity of the production set $\mathcal{P}$, obtaining a model analogus at that of Farrell (1957). In this way, they assume a technology with costant return to scale (CRS). Their production set is the convex cone of (1.9).

Output orientation

Considering output-orientation, the efficiency for the firm i, will be:

$$\widehat{\lambda}(\boldsymbol{x}_i, \boldsymbol{y}_i) = sup\left\{\lambda|(\boldsymbol{x}, \lambda\boldsymbol{y}) \in \widehat{\mathcal{P}}_{DEA}\right\} \tag{1.10}$$

.

A solution for (1.10) is the following linear program:

$$\begin{aligned} max_{\lambda,\kappa} \quad & \lambda \\ s.t. \quad & \lambda \boldsymbol{y}_i - \boldsymbol{Y}\kappa \leq 0 \\ & \boldsymbol{x}_i - \boldsymbol{X}\kappa \geq 0 \\ & \kappa \geq 0 \end{aligned} \tag{1.11}$$

.

λ is a scalar and it is the efficiency estimate. Then at the optimum, (1.11) returns the efficiency estimator for the i firm and for a set of firms, it is need to resolve (1.11) n times. The first constraint in (1.11) is repeated q times (one time for each output): from a mathematical point of view, it forces λ to be greater than (or equal to) 1. The second constraint is repeated p times. Then a firm will be efficiency if λ is equal to 1.

Input orientation

Analogus, for the input function (1.2), it is possible to define a linear program to compute the estimator $\widehat{\theta}$ with the reference set $\widehat{\mathcal{P}}_{DEA}$:

$$\begin{aligned} min_{\theta,\kappa} \quad & \theta \\ s.t. \quad & \boldsymbol{y}_i - \boldsymbol{Y}\kappa \leq 0 \\ & \theta \boldsymbol{x}_i - \boldsymbol{X}\kappa \geq 0 \\ & \kappa \geq 0 \end{aligned} \tag{1.12}$$

.

Here θ is a scalar and to obtain efficiency estimator for a set of firm, the linear program (1.12) will be resolve n times. According to definition of distance function (1.2), θ will be greater than 0, and a firm will be effciency if θ is equal to 1.

1.2.4 Variable return to scale model

Banker et al. (1984) relax the assumption of costant return to scale, allowing variable retur to scale (VRS) in the technology. Their production set is the convex hull of (1.9).

Output orientation

For the output oriented case, the the DEA estimator with variable return to scale is computed by the following linear program:

$$\begin{aligned} max_{\lambda,\kappa} \quad & \lambda \\ s.t. \quad & \lambda \boldsymbol{y}_i - \boldsymbol{Y}\kappa \leq 0 \\ & \boldsymbol{x}_i - \boldsymbol{X}\kappa \geq 0 \\ & \sum_{i=1}^{n} \kappa_i = 1 \\ & \kappa \geq 0 \end{aligned} \tag{1.13}$$

.

The difference between (1.11) and (1.13) is the convexity constraint $\sum_{i=1}^{n} \lambda_i = 1$. It evelops the data more tightly than (1.11) model, so the efficiency estimates from (1.13) will be always equal or more efficiency (i.e. more close to 1) than CRS model.

Variable return to scale allows to the estimate frontier to be either increasing, constant or deacrising.

Input orientation

With input orientation and variable return to scale assumption, we gain efficiency scores from:

$$\begin{aligned} min_{\theta,\kappa} \quad & \theta \\ s.t. \quad & \boldsymbol{y}_i - \boldsymbol{Y}\kappa \leq 0 \\ & \theta \boldsymbol{x}_i - \boldsymbol{X}\kappa \geq 0 \\ & \sum_{i=1}^{n} \kappa_i = 1 \\ & \kappa \geq 0 \end{aligned} \tag{1.14}$$

.

Hyperbolic orientation

A DEA hyperbolic oriented is possible, using the distance function (1.6) and the reference set (1.9), but the resulting model is nonlinear. However, it is possible to resolve it with approximate algorithms (Wheelock and Wilson 2008a). In the last year, some authors (Wheelock and Wilson, 2008a, 2008b) are using the hyperbolic distance, but not in a DEA environment (see section 1.4).

1.2.5 Non increasing return to scale model

Other estimator can be defined by modifying the constraint $\sum_{i=1}^{n} \lambda_i = 1$, in particular, it is possible to define an estimator for non increasing return to scale (NIRS). For the output oriented case, the linear program is computed by:

$$\begin{aligned} max_{\lambda,\kappa} \quad & \lambda \\ s.t. \quad & \lambda \boldsymbol{y}_i - \boldsymbol{Y}\kappa \leq 0 \\ & \boldsymbol{x}_i - \boldsymbol{X}\kappa \geq 0 \\ & \sum_{i=1}^{n} \kappa_i \leq 1 \\ & \kappa \geq 0 \end{aligned} \tag{1.15}$$

With NIRS, return to scale along the frontier are either constant or deacrinsing, but not increasing. For brevity, we obmit here the formulation of input oriented NIRS model, which is analogus to the (1.15).

1.2.6 Changing the reference set

Sometimes it could be of interest, to eximate the efficiency of the the firm i respect to another reference set. As we will discuss in section 1.3, this is one of the key points to do statistical inference with DEA.

Given another reference set $\mathbb{X}^* = \{\boldsymbol{X}^*, \boldsymbol{Y}^*\}$ of (pseudo)-observations, it is possible to compute with DEA an estimate of distance function. The estimate of the output oriented distance function under CRS ($\widehat{\lambda}^*$), respects to the reference set $\mathbb{X}^*$ is computed by:

$$
\begin{aligned}
max_{\lambda,\kappa} \quad & \lambda \\
s.t. \quad & \lambda \boldsymbol{y}_i - \boldsymbol{Y}^* \kappa \leq 0 \\
& \boldsymbol{x}_i - \boldsymbol{X}^* \kappa \geq 0 \\
& \kappa \geq 0
\end{aligned}
\tag{1.16}
$$

.

1.2.7 Free disposability hull

Deprins et al. (1984) proposed a more general version of DEA estimator, relying only on the free disposability and relaxing the assumption 1.2.5. So they obtained the FDH estimator. This estimator has an attractive property, since it is difficult to find theoretical justification for postulating convex production set in efficiency analysis.

The FDH estimator measures the efficiency for a given firm which produces $\boldsymbol{x}, \boldsymbol{y}$, relative to the boundary of the Free Disposal Hull of the sample $\boldsymbol{X}, \boldsymbol{Y}$. The FDH estimator is computed, in the output case, by:

$$
\begin{aligned}
max_{\lambda,\kappa} \quad & \lambda \\
s.t. \quad & \lambda \boldsymbol{y}_i - \boldsymbol{Y} \kappa \leq 0 \\
& \boldsymbol{x}_i - \boldsymbol{X} \kappa \geq 0 \\
& \sum_{i=1}^{n} \kappa_i = 1 \\
& \kappa \in \{0, 1\}
\end{aligned}
\tag{1.17}
$$

For the input case, the formulation is similar. Note the differences between 1.17 and 1.13.

1.2.8 Property of FDH/DEA estimator

Before to apply and to use an estimator, it should be important to investigate its property. In particular, the basic property that an estimator should have, it is the consistence. The asymptotic properties of the distance function estimation, are discussed by Simar and Wilson (2000b, 2008).

Althought its large use, the first result on concistence of DEA estimator appears in Banker (1993). Banker shows the consistence of the input efficiency estimator under VRS ($\widehat{\theta}_{VRS}$) but no information on rate of convergence. More general result was obtained by Kneip et al. (1998). In particular, they show:

$$\widehat{\theta}_{VRS} - \theta_{VRS} = O_p(n^{-\frac{2}{p+q+1}}). \tag{1.18}$$

Then, the DEA estimator, under VRS, converge to the theoretical estimator with the rate showed in (1.18). The result is equal for output orientation too. The rate of convergence depend from the dimensionality of the problem, that is, the number of inputs and outputs. Kneip et al. (1998) called that "curse of dimensionality". It is important to note that the increase of the number of input and output will result in more observations lying on the frontier of the estimator $\widehat{\mathcal{P}}_{VRS}$.

The curse of dimensionality results from the fact that the set of observation are projected in an increasing number of orthogonal directions and the Euclidean distance between the observations necessarily must increase (Simar and Wilson 2008). In the next section, we will discuss one of the technique to "mitigate" this problem of DEA estimator.

The convergence of FDH estimator was provided by Park et al. (2000), in particular,

$$\widehat{\theta}_{FDH} - \theta_{FDH} = O_p(n^{-\frac{1}{p+q}}). \tag{1.19}$$

So, the FDH estimator converge slowly than DEA estimator and the curse of dimensionality is here a strong problem. This is the main drawback to the pratical use of FDH estimator.

Finally, FDH and DEA estimators are biased by construction (Simar and Wilson 2000b). This bias could be relevant: starting from Simar and Wilson (1998), some methods based on bootstrap, to correct that bias were proposed (see section 1.3).

1.2.9 Reduction of dimensional spaces

Daraio and Simar (2007a) show a procedure applicable in case of high correlation among the variables belonging to the same class (input and output).

In particular, if we want to aggregate H inputs, it permits to compute a new input vector, here called "input factor", according to the following expression:

$$F^{inp} = (f_1^{inp}, f_2^{inp}, ..., f_n^{inp}) = \sum_{h=1}^{H} \alpha_h \bar{\boldsymbol{x}}_h \tag{1.20}$$

where $\bar{\boldsymbol{x}}_h$ is h the column vector of normalized input[5] and the scalar α_h is the first eigenvector of the matrix $\bar{x}'\bar{x}$ associated to its largest eigenvalue ν_1. It represents the "inertia" associated to the F^{inp} . Thus, the ratio $\nu_1 / \sum_{h=1}^{H} \nu_h$ measures the percentage of inertia, that is information, explained by the first factor. Values of the ratio close to 1 suggest that most information, contained in the original input matrix of dimension nxH, can be summarized by the first factor in a nx1 dimension space.

Similarly, for K it is possible to compute the new output vector, called "output factor", according to the following expression:

$$F^{put} = (f_1^{out}, f_2^{out}, ..., f_n^{out}) = \sum_{k=1}^{K} \alpha_k \bar{\boldsymbol{x}}_k \tag{1.21}$$

Consequently, with this tool, it is possible to reduce the dimensional spaces and to apply DEA estimator when we have few observations.

1.3 Statistical inference with DEA

The efficiency estimation performed solving the linear programming, described by (1.11)-(1.15), neglects the fact that estimates are obtained from a finite sample of observations and, hence, does not take into account their sensitivity to the sampling variations of the obtained frontier. A bootstrap

[5] The normalization is carried out dividing the original input vectors by their respective means.

approach it is possible to assess whether the efficiency distribution is influenced by stochastic effects and to build the confidence intervals for the point estimates and to correct for the bias.

The bootstrapping is based on the idea of repeatedly simulating the Data-Generating Process (DGP), by resampling the sample data and applying the original estimator, given by one of (1.11)-(1.15), to each simulated sample. Since the "naïve" bootstrap[6] yields inconsistent estimates in the context of frontier estimation (Simar and Wilson, 1999a, 1999b), we employ the smoothed bootstrap procedure implemented by Simar and Wilson (1998, 2008).

This procedure is based on the approximation[7] $\widehat{\lambda}_i(\boldsymbol{x},\boldsymbol{y})-\lambda_i(\boldsymbol{x},\boldsymbol{y})$ of the unknown sampling distribution of in a "simulated world" by the bootstrap distribution $\widehat{\lambda}_i^*(\boldsymbol{x},\boldsymbol{y})-\widehat{\lambda}_i(\boldsymbol{x},\boldsymbol{y})$, where $\widehat{\lambda}_i^*(\boldsymbol{x},\boldsymbol{y})$ are the bootstrap estimates, obtained by simulating the DGP. This approximation is available thought the Monte Carlo realizations (method) and provides important statistical properties of the DEA estimators of the real efficiency levels. This approximation of the sampling distribution is proved to be consistent by Kneip et al. (2007).

Hence, once approximations of DGP are obtained, it is possible to implement the confidence intervals. The algorithm we compute can be summarized in the following steps.

1. Compute with (1.11) the estimation of the efficiency scores $\widehat{\Lambda}_n = \left\{\widehat{\lambda}_1,...,\widehat{\lambda}_n\right\}$, from the original data set $\mathbb{X}_n$.

2. Select a value for the bandwidth h_{CV} using the Least Square Cross Validation (LSCV) method[8].

3. Generate a bootstrap sample $\beta_1^*,..,\beta_n^*$, drawing random sample of size

[6]Naïve bootstrap consists of drawing pseudo-observations $\{(x_i^*,y_i^*), i=1,..,n\}$ independently, uniformly, and with replacement from the set $\mathbb{X}$ of original observations.

[7]Here the procedure is discussed for output orientation under CRS. The procedure is the same for other retur to scale assumption and for input orientation.

[8]The LSCV is a data driven method of unbiased cross validation and it assures the minimization of Mean Integrated Square Error (MISE) (see Silverman, 1986 and Efron and Tibshirani, 1993 for details).

n from the set $\widehat{\Lambda}_{2n}$, obtained by reflection estimated efficiency scores[9].

4. Generate the sample $\beta_1^{**},..,\beta_n^{**}$ perturbing these draws by setting $\beta_i^{**} = \beta_i^* + h_{CV} \cdot \epsilon_i^*$, $\forall i = 1,..,n$, where ϵ_i^* are independent draws from the kernel density function $K(\bullet)$[10].

5. Generate the sample $\beta_1^{***},..,\beta_n^{***}$ from the sample $\beta_1^{**},..,\beta_n^{**}$, correcting it regarding the mean and variance[11] in the following way:

$$\beta_i^{***} = \bar{\beta}^* + \frac{\beta_i^{**} - \bar{\beta}^*}{(1 + h_{CV}^2 \sigma_K^2 \sigma_\beta^{-2})^{1/2}} \tag{1.22}$$

where:

$$\begin{aligned} \bar{\beta}^* &= n^{-1} \sum_{i=1}^{n} \beta_i^* \\ \sigma_\beta^2 &= n^{-1} \sum_{i=1}^{n} (\beta_i^* - \bar{\beta}^*) \end{aligned} .$$

6. Compute the sample $\widehat{\Lambda}_n^* = \left\{ \widehat{\lambda}_1^*, ..., \widehat{\lambda}_n^* \right\}$, to come back to measure greater than one, by computing:

$$\widehat{\lambda}_i^* = \begin{cases} 2 - \beta_i^{***} & \forall \beta_i^{***} < 1 \\ \beta_i^{***} & otherwise \end{cases} \tag{1.23}$$

.

7. Define the bootstrap sample $\mathbb{X}_n^* = \{(\boldsymbol{x}_i, \boldsymbol{y}_i^*), i = 1,..,n\}$ where $\boldsymbol{y}_i^*$ is given by:

$$\boldsymbol{y}_i^* = \frac{\widehat{\lambda}_i}{\lambda_i^*} \boldsymbol{y}_i$$

.

[9] The reflection method was proposed by Silverman (1986) and it is used because the efficiency estimates have a boundary since $\delta^{out} \geq 1$ by definition.

[10] β_i^{**}s are random sample from standar kernel density estimator of $\widehat{\Lambda}_{2n}$. This technique is called smoothing techniques (Silverman 1986) and it overcome the problems of na¨ie boostrap discussed above. For further details on non parametric tecnique it is possible to read Li and Racine (2007).

[11] Whith the smoothing technique, the smoothed values will not have the same mean and variance of the boostrap sequences (Efron and Tibshirani 1993), then it is need to correct the value with (1.22).

8. Compute DEA efficiency estimates $\widehat{\Lambda}_n^* = \left\{\widehat{\lambda}_1^*, ..., \widehat{\lambda}_n^*\right\}$, using the reference set $\mathbb{X}_n^*$ in (1.16).

9. Repeat steps 3-8 B times to obtain a set of boostrap estimates $\{\widehat{\Lambda}_{n,b}^*,\ b = 1, .., B\}$.

Simar and Wilson (1998) suggest to set B=2000 to have an accurate convergence. The previous algorithm was implemented in a free software package *FEAR* (Wilson 2007) for *R* software[12].

Moreover, as well known, the DEA estimators are biased by construction. Thus, it is possible to use the empirical bootstrap distribution to estimate the bias (Efron and Tibshirani 1993) for the observation i as follows:

$$\widehat{BIAS}(\widehat{\lambda}_i) = \frac{1}{B}\sum_{b=1}^{B}\widehat{\lambda}_{i,b}^* - \widehat{\lambda}_i. \tag{1.24}$$

Therefore, we construct a bias-corrected estimator by computing:

$$\widehat{\widehat{\lambda}}_i = \widehat{\lambda}_i - \widehat{BIAS}(\widehat{\lambda}_i). \tag{1.25}$$

However, the bias correction introduces additional noise and could have a higher mean square error then the original point estimates. The estimator of sample variance of $\widehat{\lambda}_{i,b}$ is:

$$\widehat{\sigma}_i^2 = \frac{1}{B-1}\sum_{b=1}^{B}(\widehat{\lambda}_{i,b}^* - \frac{1}{B}\sum_{b=1}^{B}\widehat{\lambda}_{i,b}^*)^2. \tag{1.26}$$

It yields to avoid this correction in (1.24) (Efron and Tibshirani 1993) if:

$$\mu = \frac{\left|\widehat{BIAS}(\widehat{\lambda}_i)\right|}{\widehat{\sigma}_i} \leq 0.25. \tag{1.27}$$

Finally, the confidence intervals are constructed following the modified percentile method (Simar and Wilson 2000b), which automatically corrects for bias without explicit use of the noisy biased estimator. The main idea

[12] www.R-project.org

is to compute the quantiles from the empirical bootstrap distribution of the pseudo estimates, exploiting the approximation of the unknown distribution of $\widehat{\lambda}(\boldsymbol{x},\boldsymbol{y}) - \lambda(\boldsymbol{x},\boldsymbol{y})$ by the distribution of $\widehat{\lambda}^*(\boldsymbol{x},\boldsymbol{y}) - \widehat{\lambda}(\boldsymbol{x},\boldsymbol{y})$. If we know the distribution of $\widehat{\lambda}(\boldsymbol{x},\boldsymbol{y}) - \lambda(\boldsymbol{x},\boldsymbol{y})$, it would be trivial to find the values a_α and b_α, such that $Prob(-b_\alpha \leq \widehat{\lambda}(\boldsymbol{x},\boldsymbol{y}) - \lambda(\boldsymbol{x},\boldsymbol{y}) \leq -a_\alpha) = 1-\alpha$. Since a_α and b_α are unknown, we use the empirical distribution of $\widehat{\lambda}^*_{i,b}$, to find the values $\widehat{a}_\alpha$ and $\widehat{b}_\alpha$ such that:

$$Prob(-\widehat{b}_\alpha \leq \widehat{\lambda}_i(\boldsymbol{x},\boldsymbol{y}) - \lambda_i(\boldsymbol{x},\boldsymbol{y}) \leq -\widehat{a}_\alpha) = 1-\alpha. \tag{1.28}$$

Some algebraic transformations yield an estimated $(1-\alpha)$-percent confidence interval, of the real value:

$$\widehat{\lambda}_i + \widehat{a}_\alpha \leq \lambda \leq \widehat{\lambda}_i + \widehat{b}_\alpha \tag{1.29}$$

where $\widehat{a}_\alpha$ and $\widehat{b}_\alpha$ are the endpoints obtained deleting $(\alpha/2 \times 100)$-percent of the sorted elements of the distribution of $\widehat{\lambda}^*_i(\boldsymbol{x},\boldsymbol{y}) - \widehat{\lambda}_i(\boldsymbol{x},\boldsymbol{y})$.

Simar and Wilson (2000b) show in a Monte Carlo experiment, the performance of Simar and Wilson (1998)'s algorithm: they check the coverage in which the estimated confidence intervals included the true efficiency score. Kneip et al. (2007) analyze the property of this tecniques and they prove that the bootstrap provides consistent approximation of the sampling distribution of $\widehat{\lambda}(\boldsymbol{x},\boldsymbol{y}) - \lambda(\boldsymbol{x},\boldsymbol{y})$.

1.3.1 Testing hypothesis of return to scale

Simar and Wilson (2002) discuss how to test hypotheses regarding returns to scale in the context of non-parametric models of technical efficiency. They present bootstrap estimation procedures which yield appropriate critical values for the test statistics. It regards the inconsistent estimation arising from a priori assumption on the true, but unknown, reference technology $\mathcal{P}$ (Simar and Wilson 2002).

In hyphotesis testing, the p-value of a null hypothesis can be estimated with boostrap: a null hypothesis H_0 will be rejected at the desidered level (usually $\alpha = 5\%$ when the p-value is lower than α.

A two steps inference procedure is available: it allows determining whether a particular technology is due to the real analyzed process or merely due to the sampling variation. Formally, the procedure is given by $Test1$,

$H_0:\ \mathcal{P}$ is globally CRS,

against the alternative hypothesis

$H_1:\ \mathcal{P}$ is globally VRS.

If the null hypothesis H_0 is rejected, before accepting the alternative hypothesis H_1, a second test is performed with a less restrictive null hypothesis. Thus, Test 2 is performed and it tests

$H_0:\ \mathcal{P}$ is globally $NIRS$,

against

$H1:\ \mathcal{P}$ is globally VRS.

For testing return to scale, it is needed to define a sensible statistic. Simar and Wilson (2002) propose the ratio of means DEA_{CRS} on DEA_{VRS} scores, that is:

$$\tau = \frac{n^{-1}\sum_{i=1}^{n}\widehat{\delta}_{crs}^{out}(\boldsymbol{x}_i,\boldsymbol{y}_i)}{n^{-1}\sum_{i=1}^{n}\widehat{\delta}_{vrs}^{out}(\boldsymbol{x}_i,\boldsymbol{y}_i)}. \tag{1.30}$$

Where $\widehat{\delta}_{crs}^{out}$ are the Shepard output oriented CRS efficiency scores and $\widehat{\delta}_{vrs}^{out}$ are the Shepard output oriented VRS efficiency scores[13]. The use of Shepard distance function in (1.30) is due to the construction of an appropriate statistic. In this case, τ will be close to 1 if the null hypothesis is true.

[13]Compute Shepard distance function is very simple, remember from section 1.1 that $\delta^{out}(\boldsymbol{x}_i,\boldsymbol{y}_i) = [\lambda(\boldsymbol{x}_i,\boldsymbol{y}_i)]^{-1}$.

The p-value is defined by

$$p - value = Prob(\tau \geq \tau_{obs} \; |H_0), \tag{1.31}$$

where τ_{obs} is the value of the statistic obtained from the sample. It is possible to approximate (1.31) by a bootstrap distribution (Efron and Tibshirani 1993):

$$\widehat{p} - value = Prob(\tau^* \geq \tau_{obs} \; |\mathbb{X}_n, H_0) \tag{1.32}$$

where τ^* is the bootstrap distribution of τ. So, the empirical $\widehat{p} - value$ is computed by:

$$\widehat{p} - value = \sum_{b=1}^{B} \frac{\#\{\tau^* \geq \tau_{obs}\}}{B}. \tag{1.33}$$

B is the number of boostrap replications. Note that (1.32)-(1.33) are conditional on H_0, so it need to generate the boostrap sample under the null hypothesis H_0.

τ^* is obtained through the same bootstrap algorithm described in section 1.3, with the accurance to set the appropriate DEA model (CRS or VRS). To generate the boostrap sample under H_0, it is need to resample from a smooth estimate of the distribution of the $\widehat{\delta}_{crs}^{out}$ (Simar and Wilson 2002).

1.4 The Quantile approach

Cazals et al. (2002) discuss a probabilistic interpretation of the Debreu-Farrel efficiency scores, providing a new way of description of nonparametric FDH estimators.

Assume that there exists a joint probability density $f^t(\boldsymbol{x}, \boldsymbol{y})$ at time t with bounded support over $\mathcal{P}^t$ [14]. The density $f^t(\boldsymbol{x}, \boldsymbol{y})$ implies a probability function

$$H^t(\boldsymbol{x}_0, \boldsymbol{y}_0) = \Pr(\boldsymbol{x} \le \boldsymbol{x}_0, \boldsymbol{y} \ge \boldsymbol{y}_0). \tag{1.34}$$

This is a non-standard probability distribution function, given the direction of the inequality for $\boldsymbol{y}$; nonetheless, it is well-defined. This function gives the probability of drawing an observation from the probability density function $f^t(\boldsymbol{x}, \boldsymbol{y})$ that weakly *dominates* the DMU operating at $(\boldsymbol{x}_0, \boldsymbol{y}_0) \in \mathcal{P}^t$; an observation $(\widetilde{\boldsymbol{x}}, \widetilde{\boldsymbol{y}})$ weakly dominates $(\boldsymbol{x}_0, \boldsymbol{y}_0)$ if $\widetilde{\boldsymbol{x}} \le \boldsymbol{x}_0$ and $\widetilde{\boldsymbol{y}} \ge \boldsymbol{y}_0$. Clearly, $H^t(\boldsymbol{x}_0, \boldsymbol{y}_0)$ is monotone, nondecreasing in $\boldsymbol{x}_0$ and monotone, non-increasing in $\boldsymbol{y}_0$. Using $H^t(\cdot, \cdot)$, the hyperbolic distance function in (1.6) can be written as

$$\gamma(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t) = \sup \left\{ \gamma > 0 \mid H^t(\gamma^{-1}\boldsymbol{x}, \gamma \boldsymbol{y}) > 0 \right\}. \tag{1.35}$$

All studies of efficiency, productivity, etc., involve comparison of observed performance to some benchmark. In traditional, non-parametric studies, the frontier $\mathcal{P}^{t\partial}$ serves as the benchmark, but other benchmarks can also be used to measure efficiency. Consider the hyperbolic α-quantile distance function defined by

$$\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t) = \sup \left\{ \gamma > 0 \mid H^t(\gamma^{-1}\boldsymbol{x}, \gamma \boldsymbol{y}) > (1 - \alpha) \right\} \tag{1.36}$$

for $\alpha \in (0, 1]$, where $\mathscr{F}_t$ denotes the law of the random $(p+q)$-tuple $(\boldsymbol{x}, \boldsymbol{y})$ at time t implied by the distribution function $H^t(\boldsymbol{x}_0, \boldsymbol{y}_0)$. If $\alpha = 1$, then $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t) = \gamma(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{P}^t)$. For $0 < \alpha < 1$ and a fixed point $(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{p+q}$, $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t) >$ (respectively, $<$) 1 gives the proportionate, simultaneous decrease (increase) in inputs and increase (decrease) in outputs required to

[14] $f^t(\boldsymbol{x}, \boldsymbol{y})$ is zero for all $(\boldsymbol{x}, \boldsymbol{y}) \notin \mathcal{P}^t$, strictly positive for all $(\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^{t\partial}$, and continuous in an interior neighborhood of $\mathcal{P}^{t\partial}$.

move from $(\boldsymbol{x}, \boldsymbol{y})$ along a path $(\gamma^{-1}\boldsymbol{x}, \gamma\boldsymbol{y})$, $\gamma > 0$, to a point with probability $(1-\alpha)$ of being weakly dominated. The hyperbolic α-quantile frontier is defined by

$$\mathcal{P}_{\alpha}^{t\partial} = \left\{ (\gamma_{\alpha}(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)^{-1}\boldsymbol{x}, \gamma_{\alpha}(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)\boldsymbol{y}) \mid (\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{P}^t \right\}. \tag{1.37}$$

It is easy to show that $\mathcal{P}_{\alpha}^{t\partial}$ is monotone in the sense that if $(\boldsymbol{x}_0, \boldsymbol{y}_0) \in \mathcal{P}_{\alpha}^{t\partial}$, $(\widetilde{\boldsymbol{x}}, \widetilde{\boldsymbol{y}}) \in \mathcal{P}_{\alpha}^{t\partial}$, and $\widetilde{\boldsymbol{x}} \geq \boldsymbol{x}_0$, then $\widetilde{\boldsymbol{y}} \geq \boldsymbol{y}_0$.

The idea of *dominance* in the sense used here dates at least to the work of Deprins et al. (1984). As a practical matter, the idea is quite useful from the perspective of managers, policy makers, and others. While a set of firms may be ranked in terms of their estimated technical efficiencies or some other criteria, the manager of an inefficient firm may have little to learn from a more efficient firm unless the two firms use a similar mix of inputs to produce a similar mix of outputs. In other words, the more efficient firm may not be a relevant role model for the less efficient firm if they operate in very different regions of the input-output space. By contrast, a firm that *dominates* a less efficient firm is able to produce more with less, and consequently is likely to have management practices or other features that the less efficient firm should emulate.

Figure A.1 provides an illustration of the hyperbolic quantile where $p = q = 1$ and with $f(x, y)$ uniform over a quarter-circle so that the technology displays variable returns to scale. The solid line shows the full frontier $\mathcal{P}^{t\partial} = \{(x, y) \mid x \in [0, 1],\ y = (2x - x^2)^{1/2}\}$. Wheelock and Wilson (2008b, equation 3.10) derived the joint distribution $H^t(x_0, y_0)$ for this problem; using their result, the hyperbolic α-quantile $\mathcal{P}_{\alpha}^{t\partial}$ can be traced out. In Figure A.1, this has been done for $\alpha = 0.99$; $\mathcal{P}_{\alpha}^{t\partial}$ is illustrated by the dashed curve.

The probabilistic formulation used here and in Wheelock and Wilson (2008a, 2008b) is closely related to the work of Daouia and Simar (2007), which builds on earlier work by Daouia (2003) and Aragon et al. (2005). Daouia and Simar defined input- and output-oriented *conditional* α-quantiles and corresponding efficiency measures. In Figure A.1, these input and output conditional α-quantiles are shown by the dotted curves for $\alpha = 0.99$. The steeper of the two shows the input-oriented conditional α-quantile; the other shows the output-oriented conditional α-quantile; details of derivations are given in Wheelock and Wilson (2008b). For any $\alpha \in (0, 1)$, the input- and output-oriented conditional α-quantiles differ from one another. The input-oriented conditional α-quantile $\mathcal{P}^{t\partial}_{x,\alpha}$ will necessarily have steeper slope than $\mathcal{P}^{t\partial}$, while the output-oriented conditional α-quantile $\mathcal{P}^{t\partial}_{y,\alpha}$ will have less steep slope than $\mathcal{P}^{t\partial}$; see Wheelock and Wilson (2008b) for additional discussion.

Before proceeding, note that if $\alpha = 1$, then the hyperbolic α-quantile distance function defined in (1.36) becomes equivalent to the Shephard-type hyperbolic distance function defined in (1.6). In this case, the distance function in (1.36) measures distance to $\mathcal{P}^{t\partial}$, rather than to a quantile lying within the interior of the set $\mathcal{P}^t$. Choosing $\alpha < 1$, however, avoids some of the problems associated with estimation of boundaries of support (or distance to such boundaries) as discussed in the next section.

1.4.1 Estimating technical efficiency with α-quantile estimator

Estimation of the Shephard input and output distance functions defined in (1.4) and (1.5), as well as of the hyperbolic distance function defined in (1.6), requires an estimator of the production set $\mathcal{P}^t$. Let $\mathcal{S}^t_{n_t}$ denote a sample of n_t input/output vectors at time t; in other words, $\mathcal{S}^t_{n_t}$ is a set of n_t $(p+q)$-tuples drawn from the density $f^t(\boldsymbol{x}, \boldsymbol{y})$ with bounded support over $\mathcal{P}^t$.

Estimation of the unconditional, hyperbolic α-quantile distance function $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)$, and hence $\mathcal{P}^{t\partial}_\alpha$, is straightforward. The empirical analog of the distribution function defined in (1.34) is given by

$$\widehat{H}^t(\boldsymbol{x}_0, \boldsymbol{y}_0 \mid \mathcal{S}^t_{n_t}) = n^{-1} \sum_{i=1}^{n} I(\boldsymbol{x}_i \leq \boldsymbol{x}_0, \boldsymbol{y}_i \geq \boldsymbol{y}_0 \mid (\boldsymbol{x}_i, \boldsymbol{y}_i) \in \mathcal{S}^t_{n_t}), \quad (1.38)$$

where $I(\cdot)$ denotes the indicator function. Then an estimator of $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)$ is obtained by replacing $H^t(\cdot, \cdot)$ in (1.36) with $\widehat{H}^t(\cdot, \cdot \mid \mathcal{S}^t_{n_t})$ to obtain

$$\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}^t_{n_t}) = \sup \left\{ \gamma > 0 \mid \widehat{H}^t(\gamma^{-1}\boldsymbol{x}, \gamma\boldsymbol{y} \mid \mathcal{S}^t_{n_t}) > (1 - \alpha) \right\}. \quad (1.39)$$

Computing $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}^t_{n_t})$ is essentially a univariate problem. Given a point of interest $(\boldsymbol{x}_0, \boldsymbol{y}_0)$, it is easy to find initial values γ_a, γ_b such that

$\gamma_a < \gamma_b$ bracket the solution so that $\widehat{H}^t(\gamma_a^{-1}\boldsymbol{x}_0, \gamma_a \boldsymbol{y}_0 \mid \mathcal{S}_{n_t}^t) > (1-\alpha)$ and $\widehat{H}^t(\gamma_b^{-1}\boldsymbol{x}_0, \gamma_b \boldsymbol{y}_0 \mid \mathcal{S}_{n_t}^t) < (1-\alpha)$, and then solve for $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}_0, \boldsymbol{y}_0 \mid \mathcal{S}_{n_t}^t)$ using the bisection method. This method can be made accurate to an arbitrarily small degree. Wheelock and Wilson (2008a, 2008b) list the steps that comprise an algorithm using this idea, and discuss some computational issues. The algorithm presented here has been implemented in the freely-available *FEAR* library provided by Wilson (2007).

Wheelock and Wilson (2008a) derived asymptotic results under mild assumptions for the to the hyperbolic α-quantile distance function estimator $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}_{n_t}^t)$ of $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)$. In particular,

- $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}_{n_t}^t)$ converges completely and hence is a strongly consistent estimator of[15] $\gamma_\alpha(\boldsymbol{x}, \boldsymbol{y} \mid \mathscr{F}_t)$ (Wheelock and Wilson, 2008a, Theorem 4.2);
- $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}_{n_t}^t)$ is asymptotically normally distributed, with convergence at the classical, parametric root-n rate (Wheelock and Wilson, 2008a, Theorem 4.3); and
- $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}_{n_t}^t)$ can be viewed as a robust estimator of $\gamma(\boldsymbol{x}, \boldsymbol{y})$ when α is regarded as a sequence in n tending to 1 at an appropriate rate (Wheelock and Wilson, 2008a, Theorem 4.4).

See Wheelock and Wilson (2008a) for precise statements of the assumptions required for these results.

The root-n convergence rate attained by the unconditional, hyperbolic α-quantile distance function estimator is remarkable for a non-parametric estimator, and is partly due to the summation that appears in (1.38) as is apparent from inspection of the proof of Theorem 4.3 in Wheelock and Wilson (2008a). This result means that the unconditional, hyperbolic α-quantile efficiency estimator $\widehat{\gamma}_{\alpha,n_t}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}_{n_t}^t)$ does not suffer from the curse of dimensionality that plagues most non-parametric estimators since its convergence rate depends solely on the sample size n and involves neither p nor

[15] A sequence of random variables $\{\zeta_n\}_{n=1}^\infty$ converges completely to a random variable ζ, denoted by $\zeta_n \xrightarrow{c} \zeta$, if $\lim_{n\to\infty} \sum_{j=1}^n \Pr(|\zeta_j - \zeta| \geq \epsilon) < \infty \; \forall \; \epsilon > 0$; this type of convergence was introduced by Hsu and Robbins (1947), and is a stronger form of convergence than almost-sure convergence, which is implied by complete convergence.

q. Of course, when viewed as an estimator of distance to the full frontier, $\widehat{\gamma}_{\alpha(n),n}(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{S}^t_{n_t})$ trades its root-n convergence rate when α is fixed for the slow convergence rate of FDH estimators, but retains the advantage of robustness.

It is important to note that the results described above do not hold if $\alpha = 1$. In particular, if $\alpha = 1$, the hyperbolic α-quantile estimator defined in (1.39) measures distance along a hyperbolic path to the FDH of the sample data. In this case, the estimator has an asymptotic Weibull distribution, with convergence rate $n^{-1/(p+q)}$. Similarly, if $\alpha = 1$, the conditional α-quantile distance function estimators described by Daouia and Simar (2007) become equivalent to FDH estimators of Shephard (1970) input and output distance functions, which converge at the rate $n^{-1/(p+q)}$, as noted earlier.

1.4.2 Malmquist indices with the hyperbolic α-quantile estimator

In the case of one input and one output, productivity could be assessed by the ratio of output to input quantities. If $\mathcal{P}^{t\partial}$ exhibits constant returns to scale everywhere, there is little conceptual difference between productivity and technical efficiency, although the two might be measured differently.

Where there are multiple inputs and multiple outputs, productivity cannot be measured reliably by simple ratios. Instead, in dynamic contexts, Malmquist indices are typically used to measure *changes* in productivity. These indices are usually defined in terms of the Shephard input and output distance functions defined in (1.4) and (1.5), which in turn are estimated by the DEA estimators as discussed in Section 1.4.1; see Färe and Grosskopf (1996) for examples and discussion.

Wheelock and Wilson (2008b) showed that Malmquist indices can also be defined in terms of the unconditional, hyperbolic α-quantile measures discussed above in Section 1.4. Along the lines of Wheelock and Wilson (2008b), define

$$\mathcal{P}^t_\alpha = \left\{ (\boldsymbol{x}, \boldsymbol{y}) \mid \boldsymbol{x} \geq \widetilde{\boldsymbol{x}},\ \boldsymbol{y} \in [0, \widetilde{\boldsymbol{y}}]\ \forall\ (\widetilde{\boldsymbol{x}}, \widetilde{\boldsymbol{y}}) \in \mathcal{P}^{t\partial}_\alpha \right\}. \tag{1.40}$$

Then $\mathcal{P}^{t\partial}_\alpha$ is the closure of the compliment of the closed set $\mathcal{P}^t_\alpha$, just as $\mathcal{P}^{t\partial}$ is the closure of the compliment of $\mathcal{P}^t$.

Now define the operator $\mathcal{V}(\cdot)$ so that $\mathcal{V}(\mathcal{A})$ denotes the convex cone of a set $As \subset \mathbb{R}_+^{p+q}$. to denote the convex cone of a set in $\mathbb{R}_+^{p+q}$. Then $\mathcal{P}_\alpha^t \subseteq \mathcal{V}(\mathcal{P}_\alpha^t)$. As noted previously, different distance functions can be defined by replacing $\mathcal{P}^t$ in (1.6) with some other set to measure distance from $(\boldsymbol{x}, \boldsymbol{y})$ to the boundary of the other set; e.g., $\gamma(\boldsymbol{x}, \boldsymbol{y} \mid \mathcal{V}(\mathcal{P}_\alpha))$ measures distance from $(\boldsymbol{x}, \boldsymbol{y})$ along a hyperbolic path $(\gamma^{-1}\boldsymbol{x}, \gamma\boldsymbol{y})$, $\gamma > 0$ to the boundary of the set $\mathcal{V}(\mathcal{P}_\alpha^t)$.

In order to measure the change in productivity of a firm operating at times t_1 and t_2, define the Malmquist-type index

$$\mathcal{M}_{\alpha,i}(t_1, t_2) \equiv \left[\frac{\gamma\left(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_1})\right)}{\gamma\left(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_1})\right)} \times \frac{\gamma\left(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_2})\right)}{\gamma\left(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_2})\right)} \right]^{\frac{1}{2}} \tag{1.41}$$

along the lines of Wheelock and Wilson, where $\boldsymbol{x}_{it}$ and $\boldsymbol{y}_{it}$ denote the observed input and output vectors for firm i at time t. This index is analogous to those proposed by Färe et al. (1992, 1994), but with two important differences. First, productivity is benchmarked against the boundaries of $\mathcal{V}(\mathcal{P}_\alpha^{t_1})$ and $\mathcal{V}(\mathcal{P}_\alpha^{t_2})$, rather than the boundaries of $\mathcal{V}(\mathcal{P}^{t_1})$ and $\mathcal{V}(\mathcal{P}^{t_2})$. Second, the hyperbolic direction is used, rather than an input or output direction, avoiding the ambiguity discussed in Section 1.4

The index $\mathcal{M}_{\alpha,i}(t_1, t_2)$ in (1.41) consists of a geometric mean of two ratios appearing inside the square brackets in (1.41). The first ratio inside the square brackets measures the change in productivity using as a benchmark the convex cone of the set bounded by the hyperbolic α-quantile $\mathcal{P}_\alpha^{t_1\partial}$ prevailing at time t_1, while the second ratio measures productivity change using as a benchmark the convex cone of the set bounded by the quantile $\mathcal{P}_\alpha^{t_2\partial}$ prevailing at time t_2. A particular firm either moves closer to each benchmark (becoming more productive), farther from each benchmark (becoming less productive), or closer to one and farther from the other. Values of the Malmquist index defined in (1.41) less than (equal to, greater than) unity indicate an increase (no change, a decrease) in productivity.

Malmquist indices can be decomposed to identify the sources of changes in productivity, and various decompositions of output- and input-oriented Malmquist indices have been proposed in the literature (see Wheelock and Wilson, 1999 for an example). Although many decompositions are possible, a measure of efficiency change and a measure of technical change are common to most decompositions that have appeared in the literature. In terms of unconditional hyperbolic α-quantiles, efficiency change from time t_1 to time t_2 for firm i is measured by

$$\mathcal{E}_{\alpha,i}(t_1,t_2) = \left(\frac{\gamma_\alpha(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2} \mid \mathscr{F}_{t_2})}{\gamma_\alpha(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1} \mid \mathscr{F}_{t_1})}\right). \tag{1.42}$$

This index measures the change in efficiency experienced by firm i between times t_1 and t_2, relative to the unconditional, hyperbolic α-quantiles at times t_1 and t_2; values less than (equal to, greater than) unity indicate an increase (no change, decrease) in efficiency between times t_1 and t_2.

Technical change encountered by the ith firm is measured by

$$\mathcal{T}_{\alpha,i}(t_1,t_2) \equiv \left[\frac{\gamma_\alpha\left(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1} \mid \mathscr{F}_{t_1}\right)}{\gamma_\alpha\left(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1} \mid \mathscr{F}_{t_2}\right)} \times \frac{\gamma_\alpha\left(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2} \mid \mathscr{F}_{t_1}\right)}{\gamma_\alpha\left(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2} \mid \mathscr{F}_{t_2}\right)}\right]^{\frac{1}{2}}. \tag{1.43}$$

where $\gamma_\alpha\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \mathscr{F}_{t_k}\right)$ measures distance from the firm's location at time t_j to the hyperbolic α quantile $\mathcal{P}_\alpha^{t_k}$ prevailing at time t_k, along a hyperbolic path. The right-hand side of (1.43) is a geometric mean of two ratios that measure the shift in the α-quantile relative to the ith firm's position at times t_1 and t_2. The first ratio will be less than (equal to, greater than) unity when distance from the point $(\boldsymbol{x}_{it_1}, \boldsymbol{y}_{it_1})$ along the hyperbolic path $(\gamma^{-1}\boldsymbol{x}_{it_1}, \gamma\boldsymbol{y}_{it_1})$, $\gamma > 0$, to the hyperbolic α-quantile increases (remains the same, decreases) from time t_1 to t_2. Similarly, the second ratio will be less than (equal to, greater than) unity when distance from the point $(\boldsymbol{x}_{it_2}, \boldsymbol{y}_{it_2})$ along the hyperbolic path $(\gamma^{-1}\boldsymbol{x}_{it_2}, \gamma\boldsymbol{y}_{it_2})$, $\gamma > 0$, to the hyperbolic α-quantile increases (remains the same, decreases) from time t_1 to t_2. Hence $\mathcal{T}_\alpha(t_1,t_2)(<,=,>)1$ indicates that on average, the hyperbolic α-quantile (shifts upward, remains unchanged, shifts downward).

As discussed by Wheelock and Wilson (2008b), estimators of the indices $\mathcal{E}_{\alpha,i}(t_1,t_2)$ and $\mathcal{T}_{\alpha,i}(t_1,t_2)$ are obtained by replacing the unknown distance functions on the right-hand sides of (1.42) and (1.43) with the corresponding quantile-based estimators discussed above in Section 1.4.1. In the case the quantile-based Malmquist index defined in (1.41), distance functions $\gamma\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_k})\right)$ must be estimated for $j,k \in \{1,2\}$, but this is straightforward.

In order to estimate $\gamma\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_k})\right)$, first compute estimates $\widehat{\gamma}_i^{t_j|t_k} = \widehat{\gamma}_{\alpha,n_k}\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \mathcal{S}_{n_{t_k}}^{t_k}\right)$ for all $\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j}\right) \in \mathcal{S}_{n_{t_j}}^{t_j}$. Then set $\boldsymbol{x}_i^{\partial,t_j|t_k} = \left(\widehat{\gamma}_i^{t_j|t_k}\right)^{-1} \cdot \boldsymbol{x}_{it_j}, \boldsymbol{y}_i^{\partial,t_j|t_k} = \widehat{\gamma}_i^{t_j|t_k}\boldsymbol{y}_{it_j}\ \forall\ i = 1,\ \ldots,\ n_j$. Then an estimate $\gamma\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \widehat{\mathcal{V}(\mathcal{P}_\alpha^{t_k})}\right)$ of $\gamma\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \mathcal{V}(\mathcal{P}_\alpha^{t_k})\right)$ is given by the square root of the estimate $\delta^{out}\left(\boldsymbol{x}_{it_j}, \boldsymbol{y}_{it_j} \mid \widehat{\mathcal{V}(\mathcal{P}_\alpha^{t_k})}\right)$, which can be computed as the solution of the linear program (1.16).

Inference about the indices $\mathcal{M}_{\alpha,i}(t_1, t_2)$, $\mathcal{E}_{\alpha,i}(t_1, t_2)$, and $\mathcal{T}_{\alpha,i}(t_1, t_2)$, is straightforward, again because partial frontiers, instead of the full frontier $\mathcal{P}^\partial$, are estimated. Bootstrap samples can be constructed by drawing from the empirical distribution of the observations in $\mathcal{S}_{n_t}^t$ in each time period, and computing bootstrap analogs of the estimates $\widehat{\mathcal{M}}_{\alpha,i}(t_1, t_2)$, $\widehat{\mathcal{T}}_{\alpha,i}(t_1, t_2)$, and $\widehat{\mathcal{E}}_{\alpha,i}(t_1, t_2)$. See Wheelock and Wilson (2008b) for additional discussion.

1.5 Index numbers to measure total factor productivity

Index numbers are usually instruments to measure the changes in total factor productivity (TFP)[16]. With those indices we want to measure the ability for the firm, to convert inputs as capital and labor in outputs as goods and services. Measuring productivity changes necessarily involves measuring changes in the levels of output and the associated changes in the input usage. Such changes are easy to measure in the case of a single input and a single output, but are more difficult when inputs and outputs are considered.

In this section we introduce the Tornqvist index number to measure the productivity. Let y_{ij}, p_{ij} quantity and price for the output i $(i = 1, .., N)$ at the time j $(j = 1, ..T)$, then the logarithmic Tornqvist index for two periods s and t is:

$$\ln Y_{st} = \sum_{i=1}^{N} \frac{w_{is} + w_{it}}{2} (\ln y_{it} - \ln y_{is}) \tag{1.44}$$

where:

$$w_{ij} = \frac{p_{ij} \cdot y_{ij}}{\sum_{i=1}^{N} p_{ij} \cdot y_{ij}} \qquad i = 1, \dots, N; \; j = s, t$$

$w_i j$ is weights given by the value shares. Preference for the use of the Torqvist index formula is due to the many important economic-theoretic properties attributed to the index by Caves et al. (1982a). In the same way, it is possible to define X_{st} the Tornqvist index for the input let $x_k j$ and $b_k j$ quantity and price for the k-th input $(k = 1, .., M)$ at the time j $(j = 1, ..T)$:

$$\ln X_{st} = \sum_{k=1}^{M} \frac{v_{ks} + v_{kt}}{2} (\ln x_{kt} - \ln x_{ks}) \tag{1.45}$$

where:

[16] For an a exhaustive discussion on index numbers, it is possible to read Coelli et al. (2005) and Fried et al. (2008).

$$v_{kj} = \frac{b_{kj} \cdot x_{kj}}{\sum_{k=1}^{M} b_{kj} \cdot x_{kj}} \qquad k = 1, \ldots, M; \; j = s, t$$

Then, the TFP in period s and t is:

$$\begin{aligned} \ln TFP_{st} = \frac{\ln Y_{st}}{\ln X_{st}} = & \frac{1}{2} \sum_{i=1}^{N} (w_{is} + w_{it})(\log y_{it} - \log y_{is}) \\ & - \sum_{k=1}^{M} (v_{ks} + v_{kt})(\ln x_{kt} - \ln x_{ks}) \end{aligned} \tag{1.46}$$

The main trouble of 1.46 is the non transitivity[17] of the relation when there is a change in the base period. Caves et al. (1982b) derived a modified formula to gain the transitive property:

$$\begin{aligned} \ln TFP^{*}_{st} = & \left[\frac{1}{2} \sum_{i=1}^{N} (w_{it} + \overline{w_i})(\ln y_{it} - \ln \overline{y_i}) - \frac{1}{2} \sum_{i=1}^{N} (w_{is} + \overline{w_i})(\ln y_{is} - \ln \overline{y_i}) \right] \\ & \left[\frac{1}{2} \sum_{i=1}^{N} (v_{kt} + \overline{v_k})(\ln x_{kt} - \ln \overline{x_k}) - \frac{1}{2} \sum_{k=1}^{N} (v_{ks} + \overline{v_k})(\ln x_{ks} - \ln \overline{x_k}) \right] \end{aligned} \tag{1.47}$$

where:

$$\begin{aligned} \ln \overline{w_i} &= \frac{1}{T} \sum_{h=1}^{T} w_{ih} \\ \ln \overline{y_i} &= \frac{1}{T} \sum_{h=1}^{T} y_{ih} \qquad i = 1, \ldots, N \\ \ln \overline{v_k} &= \frac{1}{T} \sum_{h=1}^{T} w_{kh} \\ \ln \overline{x_k} &= \frac{1}{T} \sum_{h=1}^{T} x_{kh} \qquad k = 1, \ldots, M. \end{aligned} \tag{1.48}$$

The expressions in 1.48 are simple mean of outputs, inputs and value share on T comparisons, and their weights on the same interval. In this way,

[17] Let s, t, r, three time periods, an index I_{st} is transitive if $I_{st} = I_{sr} \times I_{rt}$.

when we add or remove an observation, it is needed to recalculate all the interval.

Chapter 2

The evolution of Total Factor Productivity of Alitalia

2.1 Introduction

From an historic point of view, the principles of liberalization of the air transport services can be found in the Airline Deregulation Act (1978). For the US air transport industry, it was the end of the regulation period and the return to a lassaiz-faire economy. In fact, since 1938 the air transport industry was slightly controlled. Starting from that date, the fear of a market failure pressed US Government to drastically reduces the degree of competition in the industry. In 1978, US Government moved towards liberalization, culminated in the creation of a competitive market. The pursued aim was to reduce the price control, increase competition through the rise of licenses and remove monopolistic situations. The results were promising: the fares were 40% cheaper and the number of passengers grew by 140% (Thierer 1998). Moreover, between 1976 and 1986 the eight largest US carriers exert costs that were $4 billion per year less than those of the eight largest European carriers (Good et al. 1995). Oum et al. (2005) point out as a share of the cost differential could be generated by the existence of X-inefficiency which are typical of the non competitive market. Thus, the liberalization of the air transport in US has had twofold advantage: the passengers have benefit from lower fares and the governments have had a lower engagement, with a reduction of the costs for the public finances. The liberalization process in Europe was slowly. At the begin, only the bilateral agreements between countries granted the “Third and the Fourth Freedom”[1]. Precursors were Netherland and Great Britain: in 1984 they drew up a bilateral agreement which allows to each flag carrier to carry out flights with any fare or frequency until both countries disapproved it. After that, the growth in bilateral agreements was significant: more than 200 signed. However, an analysis of that agreements shows us a great control of the governments in the choices on supply and stages. So, only one carrier might flight between the two countries and the fares were usually administrate. The result was the creation of duopoly markets between pairs of countries. The European reforms ended in 1993 with the “Eighth freedom”[2]. Before 1993, only small regional airports were fully liberalized. The main aim of the present paper is to investigate the impact of liberalization on the efficiency of the Italian flag company from 1992, the year prior the last European reform, to 2006. Alitalia is a listed company controlled by Italian government through the Treasury Minister which holds 51% of the shares. At the moment, the carrier has economic and financial crisis: several managements rounded at the control, but no solution was founded[3]. In January 2007, the Italian government announced its willingness to sell its shares in order to fully privatize Alitalia. After the bids, only Air-France was able to buy the Italian company, but there was not an agreement on the amount of dismissed employees (April 2008) and the deal failed. At the moment the carrier works through the support of a l oan of 300 million euro from Italian government. However, such a procedure is not allowed by the European laws on state aid and some European carriers have invoked the intervention of the European Court of Justice.

Previous studies on Alitalia concern mainly the performance of the com-

[1]The Freedoms of the air were formulated in the Convention on International Civil Aviation of 1944. The Third freedom is the right to carry passengers or cargo from one’s own country to another. The Fourth Freedom is the right to carry passengers or cargo from another country to one’s own.

[2]The Eighth freedom (true cabotage) permits to carry passengers and cargo between two airports in a foreign country.

[3]The last strategic plan was presented in 2005 (Alitalia 2005), but it failed to achieve its aim (Boitani and Gallo 2006).

pany compared to those of the other European carriers in the last years (Arrigo 2005, Barone and Bentivogli 2006, Gitto and Minervini 2007, Barbot et al. 2008) or the conducts settled to maintain its monopolistic position in a competitive market (Giannaccari 2003). In this chapter, the employed methodology, i.e. Tornqvist index number, allows to analyze the impacts of liberalization and management decisions on the productivity of the Italian flag company from 1992 to 2006.

2.2 The air transport industry

The air transport industry can be considered like a differentiated oligopoly[4]. It is a network industry, where there are flight paths (edges) that connect pairs of airports (nodes). Like many network industry, there are externality due to its characteristics: then, revenues and costs are strong dependent on the routes and there are scale, scope and density economies. Scale economies derive from the possibility to reduce the unit cost employing aircrafts with more capacity; so, the benefits result from fixed and semi-fixed costs (like pilots and cabin crews) which are divided by a different number of passengers. Further, the stage lengths can be a source of scale economies: indeed longer stage length permit a better use of the airplanes since their use (given by times of flight) should increase. The density economies derive from a growth of the number of flights for the same flight path; in this case there are two benefits: from one side there is a better use of the airplanes, to the other, more flights reduce the waiting time for the business customers who exert an inelastic demand[5]. Morrison and Winston (1986) have shown that double frequency in national flight in the US increases the business demand of 21%. It is possible to individuate two alternative sources of scope economies in the air transport services. The first stems directly from the possibility to transport passengers and freights into the same airplane (for instance, the companies in order to reach such a cost advantages have introduced a limit for the weight of baggage). The second one, is due to the complementary

[4]In a differentiated oligopoly, few firms produce products a commodity which differs enough to have their own sloping demand curve.

[5]The so called Mohring (1972)'s effect.

of stages. In fact it is reasonable to think about individual stages as distinct products. Then, the average cost is lower when an airline increases adjacent stages in a hub and spoke network (Hanlon, 1999). To increase the cost advantages due to the scope economies, companies have increased the strategic alliances. In this new environment, 71% of world passenger traffic is generated by the three global alliances (Alliance, SkyTeam and Oneworld) composed by about forty carriers (University 2005). To enforce this cost leverage, the carriers of the same alliance usually use the same frequent flyer program with the purpose to retain the clients. But this business model, heavily based on hub and spoke network, is not the only one in the air transport industry. Starting from 1970s in United States, a new model has been employed in the air services industry at the worldwide level the so called "low cost" (**LC**). One of the most important difference is represented by the network structure of the low cost carriers which are characterized by point to point connections. Other differences stem by the type of clients, mainly leisure and the reduction of some expenses such as personal, marketing and sales (AGCM 2005). Bigelli and Pompeo (2002) show that a "low cost" carrier exerts, on average, cost that are about 50% of a "full service" carrier. So, **LC** carriers aim directly to specific market, entering where and when the demand is relevant. Further, **LC** carriers look at the more elastic part of the demand, trying in that way to differentiate the service. Tretheway (2004) suggests the business model adopted by the **LC** carriers is more robust and in the future, the full service carriers will take a smaller market share. Thus, at the moment it is possible to individuate two alternative business models to operate air transport services:

- the full service company, with hub and spoke network;
- the low cost company, with point to point network.

Due to the differences in these models, once chosen a strategy a carrier has to set all its efforts to support it. In fact, if the company does not support adequately the choice business model, adopting a clear strategy and following actions, it increases dramatically its exposure to the failure. In Italy, the market share for the LC carriers amounts to 26% in 2007 (E.N.A.C. 2001–2007).

2.3 Data

Index numbers are usually employed to analyze the changes in TFP. In fact, they allow to measure the ability of firms to convert inputs, as capital and labor, in outputs, as goods and services. In this chapter, following the literature on the measure of productivity in air transport (Oum and Yu, 1995, Oum-Yu-1998) a modified Tornqvist index (Caves et al. 1982b), showed in the expression (1.47) has been used.

Economic data has been obtained from annual Alitalia reports. In particular, we employ the consolidated annual reports, from 1995 to 2006, and the annual report of Alitalia SpA, from 1992 to 1994. In fact, until 1994, Alitalia was the owner of Aeroporti di Roma SpA (airport management company of Roma Fiumicino and Ciampino airports) and consequently, consolidated report could be source of bias. Traffic data are taken from Association of European Airlines (AEA) and Italian Air Civil Authority (Ente Nazionale Aviazione Civile, ENAC). Fleet composition is obtained by annual reports while technical information about airplanes are taken from their websites.

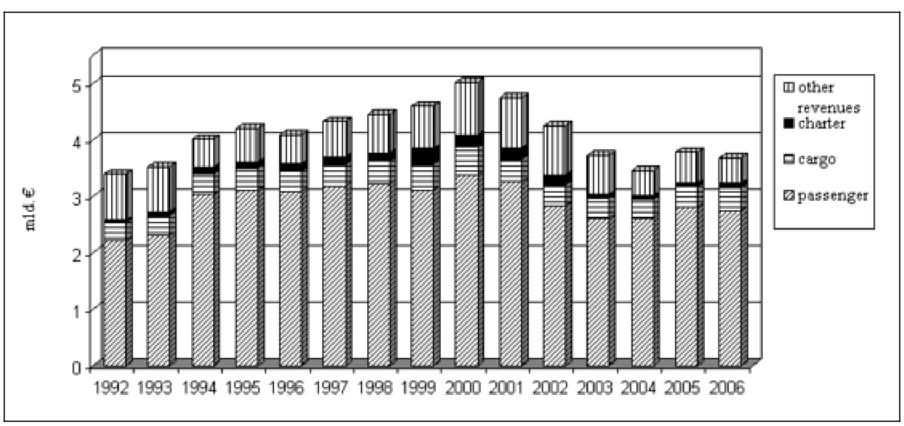
Table 2.1: Descriptive statistics of Alitalia.

	1992	1996	2000	2004	2006
Total Revenues (million €)	2,978	4,250	5,661	4,302	4,724
Total operating expenses (million €)	2,898	4,215	5,913	4,818	5,190
Operating profit (loss) (million €)	80.2	35.5	(252.8)	(515.5)	(465.4)
Net profit (loss) (million €)	(8.7)	(621.2)	(255.5)	(812)	(625.6)
Debt ratio	0.75	0.94	0.68	0.90	0.79
Total asset (million €)	2,176	3,223	4,700	4,476	4,184
Number of employees	19,256	19,410	22,184	21,539	11,466
Number of airplanes	105	138	175	190	188
Load factor (%)	65	69	72	71	74

In Tab.2.1 some synthetic data are reported. From the Tab.2.1 it can be noticed as the increase of the debt has not allow to achieve a net profit for most of years. The company has obtained a net profit only in 1997, 1999 and 2002. The carrier increases the fleet and reduces drastically the employs in 2006 when it spins out services related to aviation maintenance, airport assistance, IT and telecommunications in Alitalia Servizi. Load factor of the airline is low, if it is compared with those of Ryanair, Easyjet (80%) and Air France-KLM (81%).

Following Good et al. (1995), Forsyth (2001), Oum and Yu, (1995, 1998), Oum et al. (2005) the productivity evolution has been analyzed by employing four outputs and five inputs. The outputs are: scheduled passengers service (measured in revenue passenger kilometers, RPK), charter passenger service (measured in revenue passenger kilometers, CRPK), scheduled cargo services (measured in revenue ton kilometers, RTK) and other services. The other services include revenues from no-core services as ground handling, aircraft maintenance, airport and technical assistance. In order to apply (1.47), a quantity index for the other services has been obtained by deflating other revenues with consumer price index. The outputs evolution is depicted in Fig. 2.1.

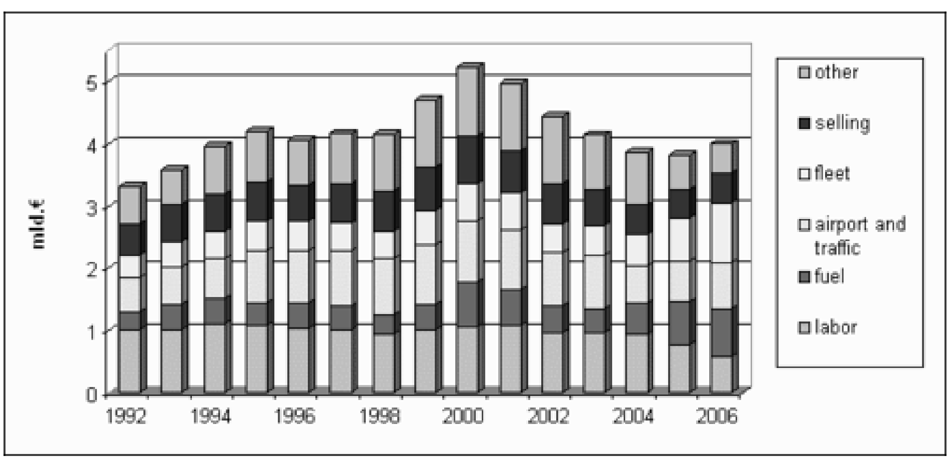
Figure 2.1: Composition of Revenues of Alitalia. Constant price (base= 1995).



The five inputs are: labor, flight equipment, fuel, average stage length, and other inputs. Labor is measured by full time equivalent employees, which allows a better comparison due to seasonal characteristics of air transport industry; labor price is obtained dividing labor cost by full time equivalent employees. Flight equipment is measured by the typical volumetric payload of airplanes[6]. We use this index as proxy of capital since it allows to capture the difference in size and capacity of the fleet. Flight equipment price is obtained dividing leasing, rental and amortization expenses for aircrafts by flight equipment index. Fuel is measured in gallons of fuel consumed and its expense is reported in the notes of consolidated financial statement. How has been pointed out in Section 2.2, the network structure has a great impact on cost structure for an airline, so we introduce such variable measured by the average stage length. Its price has been obtained by dividing total traffic and airport expenses on average stage length. Finally, other inputs concern the residual airline expenses; quantity index has been obtained by deflating other expenses (given by difference between total operating expenses and previous expenses) with consumer price index.

Now, before applying the methodology, we want to highlight some peculiarities of the cost structure of the Italian flag carrier.

Figure 2.2: Composition of expenses of Alitalia. Constant price (base= 1995).



[6]An index is obtained by multiplying typical volumetric payload of an aircraft for its frequency.

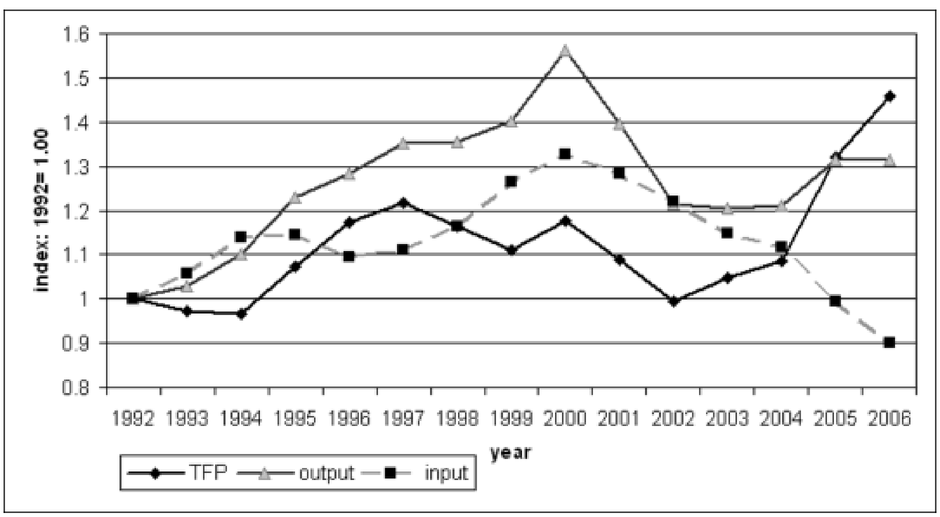
From the Figure 2.2 it can be noticed as Alitalia exerts relevant expenses for selling. Such variable includes cost due to brokerage fees, advertising and promotional expenses. The impact of travel agent in limiting competition in airline industry has been pointed out by Barrett (2006) and Bailey and Williams (1998). This strategic conduct has been partially offset in recent years by the diffusion of internet as selling device. Jarach (2002) noticed as "the application of e-commerce solutions have had a considerable positive impact on containing carriers' costs by smoothing their dependence on computer reservation system (CRS) interfaces and on travel agents' commercial practices".

2.4 Results

2.4.1 Empirical results

The evolution of TFP, from 1992 to 2006, and its two component, the output and input index, are reported in Fig. 2.3.

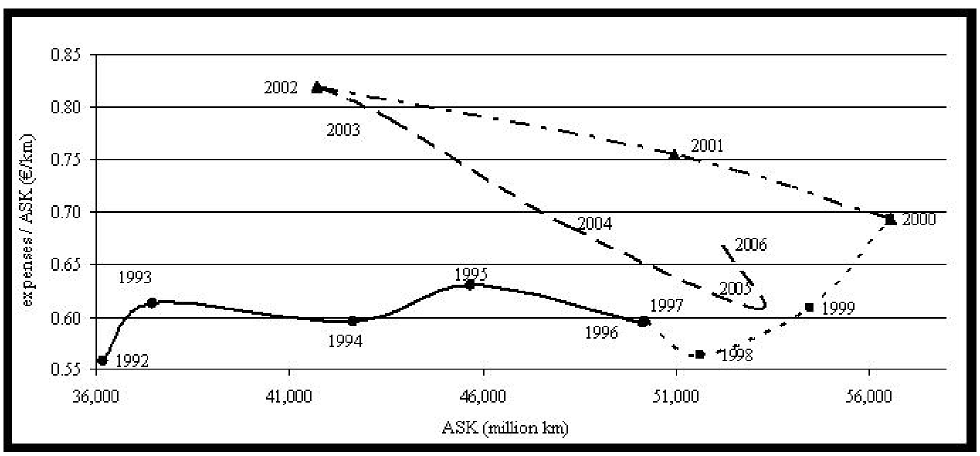
Figure 2.3: Total Factor Productivity, Output and Input Index of Alitalia. 1992-2006.



After the liberalization process, Alitalia increases the productivity until 1997 (17% more than 1992). This result can be explained by two factors:

the increase of the air transport market (30%) and more efficient resource allocation as consequence of the increase of competition (Oum et al. 2005). After 1997, the slowdown in the productivity index has been caused by an extraordinary expansion of inputs. It is important to notice that in 1998 Malpensa airport becomes the second hub for the Italian flag company. A network configuration with two hubs is not so common in air-transport industry. For example, Air France-KLM and few American carriers, have two hubs, but they have huge markets in terms of destinations and traffic, not comparable to that one of Alitalia. To better asses the strategy adopted by the company during 90s, we compare the evolution of its supply, given by available seat kilometer (ASK) and an index of unit cost, given by the ratio aeronautical expenses (personnel, fuel, airport and traffic, amortization and leasing) on ASK in Fig.2.4.

Figure 2.4: Evolution of market and costs of Alitalia. 1992-2006.



Looking at the Fig.2.4 it can be noticed four phases. The first phase, from 1992 to 1998, has been characterized by a costless growth of the supply at the same average cost. Staring from 1998 (second phase), the slope of average cost change drastically due mainly to the new hub of Malpensa and the increase of the fuel price. The third phase marks the Alitalia crisis: increase of costs and supply reduction. The period is characterized by the tragic events of the September 11th and it is denoted by the difficulty for the company to found alliances to support the previous input expansion[7]. The fourth phase begins in 2002: the Italian flag company tries to reduce its cost; for this aim, in 2006 there was the spin-off of Alitalia Servizi. More insights can be obtained by the analysis of figures 2.5, 2.6 and 2.7.

Figure 2.5: ASK evolution: Alitalia and main European airlines. 1992-2006.

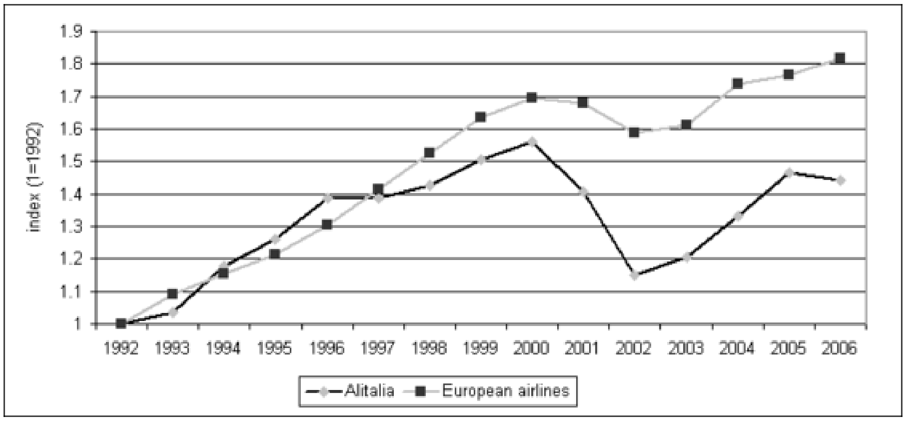


Figure 2.5 compares the ASK index for Alitalia and the main European airlines (Air France, Lufhansa, KLM, British, Iberia). Figures 2.6 and 2.7 describe its national and international market[8] evolution.

In fact, looking at Fig. 2.5, after 1997 the company increases its gap from the main European companies in terms of supply. In the domestic market the liberalization process has drastically reduce the market share of national passengers (Fig. 2.6). The market share of international passengers shows a moderate reduction since its dominant position in some stages between Italy and other countries (Fig. 2.6 and 2.7). Looking at the worldwide market (Fig. 2.7) Alitalia has reduced its market share where the level competition is high (Europe and Asia). However, the stability of American market is the result of the presence of bilateral agreements which reduce the competition.

[7]On April 2000 there was the failure of partnership with KLM ("KLM Ends Venture with Alitalia", Wall Street Journal, May 1st 2000).

[8]In Fig. 2.6 and 2.7, we considered the flights with origin and destination in Italy as relevant market of Alitalia.

Figure 2.6: Evolution of market share and number of passengers of Alitalia, 1995-2006.

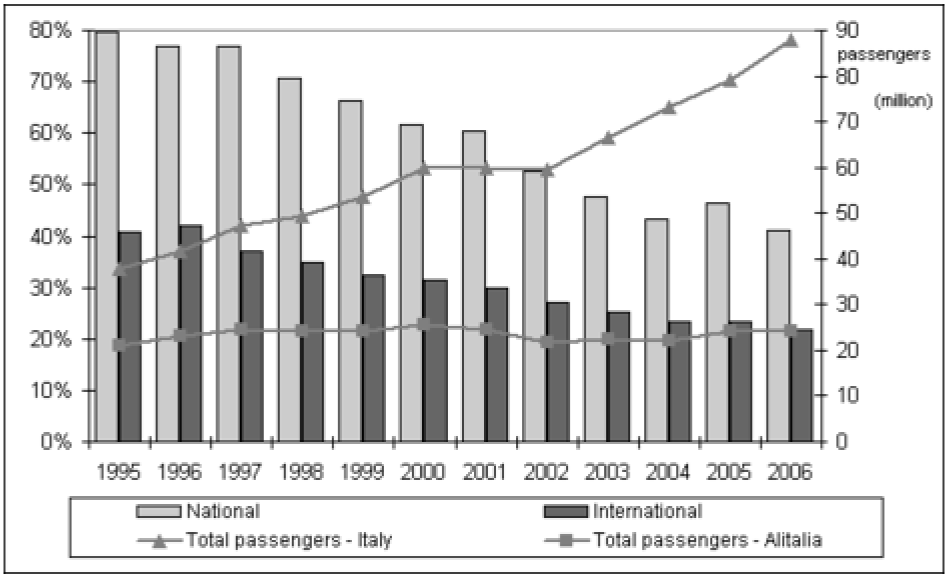
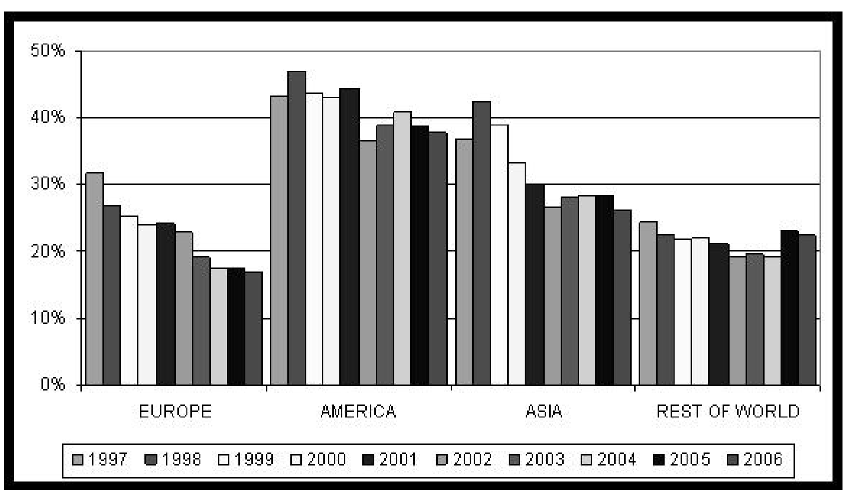


Figure 2.7: International market share of Alitalia: 1997-2006.



2.4.2 Alitalia conduct

The above empirical evidences are strictly connected to the decisions operated by the company and by the Italian Government in new contest of liberalization. The company from 1992 to 2000 increased the fleet of 25%. The objective of such a conduct is controversial: in fact, to one hand the capital expansion can be explained by the market growth, to the other it could mask an aggressive strategy pursued to block new entries in the internal market. Moreover as discussed above, in 1998 the Government decision to open the second hub of Milano Malpensa has dramatically increased expenses of the company. With such a strategy, it is need to undertake conducts to support the market growth. In other terms the success of a full service airlines after liberalization depends from the decisions made by companies to enhance a supply-oriented strategy; this means mainly increasing the number of aircrafts and destinations (Gitto and Minervini 2007). The destinations increase has been marginally pursued by the Italian company. In fact, market expansion in the air transport industry can be reached mainly through merger process and strategic alliances (Fan et al. 2001). However, such cooperation agreement failed in 2000 and the strategic alliances have been slowly enforced since 2001, when the company joined Skyteam alliance with nine big international carries (Northwest, KLM-Air France, Continental, Delta Airlines, Korean Air, Aeromexico, CSA Czech Airlines and Aeroflot).

The Italian domestic market is classified by Association of European Airlines as one of the European "top domestic market". However the Italian flag company has loosed market shares as consequence of the increased competition (Fig. 2.6). In this new environment the conduct of the incumbent seems anticompetitive: the use of slots to block new entries, code-sharing agreements to increase the tariffs on domestic stages, over commissions to travel agents for discriminate the other Italian airlines and the use of the same extra-fees with other Italian carriers to increase revenues (Italian Antitrust decision n.2169 in 1994, n.4398 in 1996, n.6793 in 1999, n.9693 in 2001, n.10981 in 2002, n.11038 in 2002; see Giannaccari, 2003 for a discussion).

To sum up the company once incurred in new capital investments has not been able to support a supply-oriented strategy with the consequence of the reduction in its TFP till 2000. Afterward the new growth on productivity, started in 2002, has been caused mainly by the cost reduction policy adopted by the company. However the high cost structure is still a problem for Alitalia[9].

2.5 Conclusions

Employing the index number methodology we study the productivity evolution of the Italian flag company from 1992 to 2006. In fact since the second half of 90's, the Italian air-transport market, as those of most European countries, has been characterized by new competitive paradigm, stemming from the liberalization process, which has affected the strategies of the incumbent and its majority shareholder: the Italian Government.

The slowdown in the company productivity is linked to the absence of a clear supply-oriented strategy, which should follow the expansion of inputs occurred since 1992 and finished with the creation of the second Italian hub. The company has suffered on the domestic market by the raise of competition and by slow capacity to change its strategy, sometime more interested in preserving its incumbent position rather than exploiting or retaining new markets. On the international market the failure of the agreement with KLM, partially compensated by the participation to the Skyteam alliance, has not allowed an expansion of its market. Company privatization and consolidation of domestic market seems the only solution; (Macchiati and Siciliano 2007), analyzing the experience of British, Iberia and Lufthansa, highlight as the consolidation and the privatization have produced increases in labor productivity and profitability of airlines.

[9] The company has received State aid yet in 2008.

Chapter 3

Liberalization of air transport and airports

3.1 Introduction

Since the mid-1980s, the worldwide air transport sector has been characterized by significant structural, institutional and regulatory changes. In particular, the deregulation policies in the air transport services, started in US after the mid-1980s and followed by Europe at the end of 80s, were designed to foster competition in both domestic and international markets and to enhance carriers' performance Oum and Yu (1995). At the same time, most governments have adopted policies whose effects have impacted on airport management and ownership structure. In particular, commercialization and privatization of airports have become the worldwide trend Oum et al. (2006), although the processes of implementation have been very different and heterogeneous among countries. The common aim of governments in promoting airport privatization includes a desire to: remove airports from the public sector, increase capital investment in existing airports, protect airport administration from political interference and impose commercial disciplines on airport management Lin and Hong (2006).

The Italian scenario has been permeated by deeply institutional changes, enabled by national and European directives. Such directives proposed changes for concession agreements, government and entrance of private capital in the airport management companies. In turn, these institutional forces have set up high standards to the diffusion of mixed private-government ownership and the disappearance of 100% government corporation ownership.

In this new context characterized by a complex and dynamic structure, the need to intensify the monitoring of airport performances from investors and governments perspective has been risen. In general, the performance measures could be helpful in policy decision to choose the best framework to organize the airport system. Indeed, they provide meaningful insights across the airports, identify the best performers and determine the main variables that impact on airport performance.

As well known, the performance of airports is measured in terms of their productivity and efficiency. Thus, the efficiency analysis of airport industry has been becoming a "hot" topic and it is handled as a general methodology in evaluating the effects of regulatory reform on airports' performance. Many scientific papers have been published on the airport performances but there is still room for new researches. Indeed, most of them have focused on productivity and efficiency analysis of US and major international airports (Gillen and Lall 1997, Sarkis 2000, Martìn and Romàn 2001, Pels et al. 2001, Oum et al. 2006), omitting the role played by regional airports in attracting air-transport services operated by low cost companies. Moreover, there are few papers dealing with the Italian airport industry, some of which take into account the two Italian systems (Roma and Milano).

The objective of the present chapter is twofold. The first is to analyze the performance of a representative sample of Italian airports in terms of technical efficiency by means of a robust non parametric method over the 2000-2004. The methodological approach is based on the theoretical developments introduced by Simar and Wilson (1998, 2000a, 2002) in the efficiency analysis. The DEA estimators are used to define the estimated production frontier, conditioned to the original data while the bootstrap procedure to correct the efficiency bias as well as allow whether the efficiency are really determinated by the analyzed process or merely inducted by sampling variations. Moreover, the bootstrapped procedure is employed to test globally return to scale. Since the complexity of the system (e.g. difference in life cycles of the airport, management, government policy, market structures), the inferential approach is able to provide a more accurate analysis. The second objective is to identify the avenues to improvement in the ability to generate financial returns and use the airport capacity. To provide more insights to the airport management companies and political decision makers, a Physical and a Revenue Model are evaluated; further, the statistical analysis is interpreted in terms of managerial strategy, by means of a scatter plot-matrix (Pacheco and Fernandes, 2003).

3.2 Previous study on efficiency of Italian airport sector

Barros and Dieke (2007, 2008) propose two studies to empirically address the operational and financial efficiency of the Italian airports sector, investigating also for the main drivers of the inefficiency, by using a double bootstrap procedure (Simar and Wilson 2007). Although their innovative approach of applying the two stage methodology, certainly accurate from an econometric point of view, both papers suffer from some pitfalls. The drawbacks concern the lack of an accurate (a) choice of the variables to use, in terms of endogenous and exogenous variables with regard to the production problem, (b) characterisation of the airports (in terms of public vs private) and (c) analysis of the efficiency estimates (in terms of sensitivity to the sampling variation), with the consequence of non-robust policy implications.

In particular, about Barros and Dieke (2008), it is possible to individuate the following drawbacks:

1. **Management Status** (see Table1, pag 1041). Most Italian airport companies are associated forms constituted by more shareholders (public and/or private). To determinate the management status (as Barros and Dieke called it), it is need to look at the majority ownership. From the Italian Statistical register of Air Transport, it is possible to derive the composition. In particular:

    - Puglia regional government (Regione Puglia) holds 99.31% of the shares in Aeroporti di Puglia SPA (Bari - Palese Macchie, Brindisi-Papola Casale, Foggia Gino Lisa, Taranto Grottaglie) (so, public status). The authors classify Bari - Palese Macchie with a private management status.

- SAC SPA (Catania - Fontanarossa) is full owned by ASAC, a mix of public and private company where the majority is private (so, private status). The authors classify it with a public management status.
- Aeroporto di Genova S.p.a. (Genova - Sestri) is 60% owned by Local Port Authority (Autorit Portuale di Genova) and 25% by Chamber of Commerce of Genova (so public status). The authors classify it with a private management status.
- S.E.A. SPA (Milano Linate and Milano Malpensa) is 84.56% owned by Local Council of Milano (so public status). The author classify it with a private management status.
- S.A.C.B.O. S.p.A. (Bergamo - Orio al Serio) is 49.9% owned by S.E.A. SPA (see above) and 33.6% by Local governments of Bergamo (so, public status). They classify it with a private management status.
- SAGAT S.p.A. (Torino - Caselle) is 51% owned by Local governments of Torino (Local Council, Province, Region) (so, public status). The authors characterized it with a private management status.

The authors use these information in the second stage regression of their paper, to conclude: "Airports that are partially private contribute to efficiency (Fung et al. 2008, Pels et al. 2003). This is an expected result, since private airports seem to be more efficient than public".

2. **Exclusion of most important airports** (see pag 1045). The authors do not include in analysis the most important airports like Roma Ciampino ($1,765,930$ passengers in 2003, 14th Italian airport) and Milano Linate ($8,755,871$ passengers in 2003, 3th Italian airport).

3. **Concession Agreement**. The authors do not discuss about the role played by concession agreements between the central government and airport companies. It is important because the agreement typology has impact on the airport revenues.

4. **Data misspecification** (see Table 1, pag. 1041). the authors use as data source the Italian Statistical register of Air Transportation. It reports costs and revenues (in a ratio form) for the companies that manage the airports instead of cost and revenues for each airport. It means, for instance, costs and revenues of A.D.R. SPA are the sum of costs and revenues for the airports of Roma Fiumicino and Roma Ciampino. This is the situation for the airports of Bari - Palese Macchie, Brindisi - Papola Casale, Foggia Gino Lisa, Taranto Grottaglie (Aeroporti di Puglia SPA.) and Milano Linate and Milano Malpensa (S.E.A. SPA), too. The authors neglect this fact and assign aggregate measures (related to more than one airport) to some variables, mixing data (such as passengers, movements, etc..) of an airport with costs and revenues of many.

5. **Lack of accuracy in the application of the double bootstrap procedure** (see pag. 1045). The authors claim: "We use the parametric bootstrap for regression to construct the bootstrap confidence intervals for the estimates of parameters $(\delta, \sigma_\epsilon^2)$, which incorporates information on the parametric structure and distributional assumption". Oppositely, they do not show the most significant results of this procedure such as the confidence intervals and do not provide any information about that. Moreover, it is not clear which algorithm they apply for estimating the second stage regression, since Simar and Wilson (2007) proposed two algorithms to apply for different pursuits.

6. **Misspecification of the estimated technology frontier** (see pag.1046). The authors state: "To estimate the cost frontier, we used balanced panel data on 31 Italian airport authorities for the years 2001-2003". Oppositely, they estimate a production frontier, using Data Envelopment Analysis (DEA). Even more, and always in contradiction with

what they do, in some lines below they claim "We measured the production of the airport authorities according to a generalized Cobb-Douglas production function". I point out that the Cobb-Douglas is one of the functional forms to assume in the parametric approach to estimate the production function. Since they use DEA approach, it is not needed of functional form (i.e. the functional form has not to been assumed).

7. **Curse of dimensionality** (see pag. 1046). They state: "The combination of the measured indicators ensures adherence to the DEA convention that the minimum number of DMU observations should be greater than three times the number of inputs plus outputs $[120 \geq 3(6+3)]$ (Raab and Lichty, 2002)." Currently, there are some papers that prove the rate of convergence of DEA-VRS model (see Kneip et al.,1998 and Simar and Wilson, 2008 for more details), making meaningless, from a statistical viewpoint, some *Rules of thumbs*, like that one used in the paper. The Curse of dimensionality (Simar and Wilson 2008) states that the number of observations has to increase exponentially (not linearly proportional) respect to the number of inputs and outputs to maintain the same order of estimation error. This problem is severe and needs attention because the number of inputs and outputs strongly determines the number of how many DMUs are close or on the efficiency frontier. This consideration makes their results dubious. Indeed, on pag.1047, they find "The overall conclusion is that Italian airports are well managed as far as technical efficiency is concerned").

8. **Descriptive statistics on double bootstrap** (see Table 5, pag.1049). The total number of observations (1000 observations) is dubious. Indeed, the authors use a dataset of 31 airports, over a 3 year time period. Using the double bootstrapped algorithm, the number of observations should be given by the number of airports times the numbers of years, replicated by the number of bootstrap fixed. Independently from the number of bootstrap replications set (2000 are suggested by Simar and Wilson, 2007 to have a better estimation), the number of observations should be a multiple of 93 (given by 31x3), that is inconsistent with

1000, as they report.

9. **Explanatory variables in the second stage** (see pag. 1049). The inclusion of WLU (i.e. sum of number of passengers and amount of cargo) in the explanation variables is dubious because it is not exogenous due to the fact number of passengers and amount of cargo are used as input variables in the first stage. A choice between input and environmental variables is requested in this analysis.

10. **Economies of scope** (see pag. 1049). They state: "North is a dummy variable which is one for airports belonging to north part of the country, the more developed region and zero otherwise. It aims to capture economies of scope in the activity." There is not clear evidence of relation between North regions and economies of scopes.

11. **Farrell distance measurement** (see Table 4 and expression 7 on pag.1048, table 5 on page 1049 and expressions 4, 5 on pag. 1045). The Debreu-Farrell output measure of efficiency θ is, by costruction, ≥ 1. It means increasing values of θ are less inefficiency. In Table 4 they are expressed by the inverse values. In the second stage of the analysis, it is not clear if the authors use the efficiency scores (according to expression 7 on page 1048, i.e. values less than 1) or their inverses (according to expressions 4,5 on page 1045, as done by the Simar and Wilson, 2007). This point is important because, depending on it, there could be different interpretation of the sign of the parameters to estimates. Indeed, if they use efficiency score greater than 1, the parameters estimated in table 5 require the opposite interpretation provided. Indeed, an environmental variable with a positive sign will have a negative impact on efficiency. On the other hand, if they use efficiency score less than 1, they do not respect the algorithm, that is built on that way to avoid working on two bounds (0 and 1) instead of only one.

12. **Bias correction** (see pag. 1040). They state: "The empirical estimates of efficiency are upwardly biased (Simar and Wilson 2007)"; but they do not correct it, although a bootstrap procedure has been pro-

posed to estimate the bias of efficiency scores and to obtain confidence intervals (e.g. see for details Simar and Wilson (1998), 1998, 2000a, 2008).

13. **References** (see pag.1040). They state: "Overall, (Simar and Wilson 2007) propose a procedure to deal with these challenges, based on a double bootstrap that enables consistent inference within models explaining efficiency scores while simultaneously producing standard errors and confident intervals for these efficiency scores. For example, an alternative bootstrap procedure adopted by Xue and Harker (1999) has been shown to be inconsistent by Simar and Wilson (1999a)". I point out that Simar and Wilson (1999a) shows the inconsistence of the bootstrap procedure used by Ferrier and Hirschberg (1997) and not about Xue and Harker (1999).

These points constitute a set of issues I have met in the paper by Barros and Dieke, 2008. In the remaining of this chapter, I try to provide a more accurate picture of the Italian airport sector and, at the same time, a more reliable estimation of the technical efficiency. I overcome the main statistical issues, sources of erroneous results but neglected by these authors, providing a more structure assessment for the Italian airport industry.

Curi et al. (2008) estimates the efficiency of 19 Italian airports during the period 2000-2004 but they assume variable return to scale (VRS) technology and made no attempt at statistical inference.

3.3 The Italian airport industry

Since 1987, significant policy developments have affected the European airport industry, enforcing a set of liberalization and privatization measures. The Community's airport industry has undergone fundamental organizational changes that have reflected the reassessment of the government's role played in the airport sector and the aim to enhance managerial incentives in private enterprises and to sever the link between managers and politicians (Gönenęt al. 2001).

In Italy, the airport reform process has been very slow to move along and difficult to implement as it involves three different actors. The State, as owner of lands and infrastructures, the management companies, both public and private, and the control organism, ENAC . Moreover, the existence of special laws and different concession agreements have been sources of heterogeneity in the airport governance forms. Indeed, since the mid-1950s, only some airport management companies as those of Genova (GOA), Milano Linate (LIN), Milano Malpensa (MXP), Roma Ciampino (CIA), Roma Fiumicino (FCO) and Torino (TRN) are in charge for the provision of all airport's services (airside and landside), through special laws . They have been collecting all revenues derived from all airport operations and services and are also responsible for the infrastructural development. This form of concession agreement, known as "Total" (**T**)[1], assigns to the management companies the right to use and manage the airport land for a period of 40 years. In 1997, the Italian law by decree n. 17 (March, 25th 1997) has extended the possibility to all commercial airports to obtain "Total" concession. Other forms of concession agreements are represented by the "Partial" (**P**)[2], "Provisional partial" (**PP**)[3] and "Direct" (D)[4]. In the P agreement the management company provides services for aircraft (taxiways, apron areas, fire fighting, etc), passenger and freight (security cleaning, etc.). The company is responsible for non flight airport infrastructures (aerostation, car-parking, etc) and receives revenues from passenger handling charges. The remaining infrastructures are managed by the State which derives revenues from all the remaining aeronautical charges. The PP agreement usually precedes the P and differs by the fact that the State receives all the aeronautical revenues. Finally, in the D agreement all the activities are managed by the State. Moreover, starting from 1999, some airports have obtained a **T** concession of three years as trial by ENAC. So far, only Napoli received a **T** concession after three years of trial in 2002.

The most important changes on the handling services liberalization have

[1] In Italian, "Totale".
[2] In Italian, "Parziale".
[3] In Italian, "Parziale precario".
[4] In Italian, "Diretta".

been driven by the Italian law n.351/95 and European directive 96/67/CE. The former has allowed airport management companies to exploit the possibility, but not the duty, to give in outsourcing handling services to external companies. On the other hand, the latter has enforced Italian law since January, 1st 2001. From that time on, the airports whose annual traffic is not less than 3 million passengers or 75,000 tonnes of freight or whose traffic has been not less than 2 million passenger movements or 75,000 tonnes of freight during the six-month period before April, the 1st or October, the 1st of the previous year, have had to open their handling services to the competition. This implies a restriction of the liberalization of handling services to only the main airports, excluding the secondary airports.

Lastly, the other issue is the increasing spread of low cost carrier phenomenon. It has constituted a large growth opportunity for small airports by means of the increase in passengers' movement by and to them. Totally, the entire system has undergone important changes which have partially damped the strong Italian polarized structure in the two systems of Roma and Milano (Bernardi 1983). Indeed, since the end of 1970s, more than 50% of the passenger traffic was absorbed by them. After the liberalization process, this percentage was held constant although the increase in the traffic demand, proving that the increase in the passenger demand has been absorbed by the other Italian secondary airports (Ferrario 2006).

Turning to the composition of the sector, the Italian airport industry is constituted of 101 airports; among them only 45 contribute to the amount of generated traffic and relative commercial activities (E.N.A.C. 2001–2007). Our sample includes up to 16 airports, shown in Table 3.1, and covers on average 89.9%, 95.6% and 83.6% of the total number of passengers, cargos and movements registered in Italy from 2000 to 2004. It does not include those airports devoted to the regional and commercial aviation, characterized by less than $150,000$ passenger movements. Following the airport classification based on traffic volume, the analyzed set contains 11 airports with more then $1,500,000$ passenger movements with a cover rate of traffic equal to 95.9%, 97.8% and 93.3% by and to Italy. The remaining airports are the so called "regional airports" in which operate many low cost companies.

The impact of the Italian government policies on capital composition

Table 3.1: List of selected Airports and their characteristics. Year 2004.

Airport name	IATA code	Company	Ownership	Agreement	ROI (%)	NAR (%)	Class
Roma Ciampino	CIA	ADR SpA	PRM	T			M
Roma Fiumicino	FCO	ADR SpA	PRM	T	15.6	45.7	H
Milano Linate	LIN	SEA SpA	PUM	T			H
Milano Malpensa	MXP	SEA SpA	PUM	T	7.8	34.9	H
Bergamo Orio	BGY[a]	SACBO SpA	PUM	T	7.1	17	H
Bologna Borgo Panigale	BLQ	SAB SpA	PUM	P[b]	8.9	35.4	H
Catania Fontanarossa	CTA	SAC SpA	PRM	P	7.9	30	H
Napoli Capodichino	NAP	GESAC SpA	PRM	T[c]	6.9	28.4	H
Palermo Punta Raisi	PMO	GESAP SpA	PUM	P	6	26.1	H
Pisa San Giusto	PSA	SAT SpA	PUM	P	neg.	23.1	H
Torino Caselle	TRN	SAGAT SpA	PUM	T	1.3	44.4	H
Venezia Tessera	VCE	SAVE SpA	PRM	T	5.8	20.6	H
Verona Villafranca	VRN	Aeroporto V.Catullo SpA	PUM	PP	neg.	24.4	H
Alghero Fertilia	AHO	SOGEAAL SpA	PUM	PP	7.3	22.5	M
Ancona Falconara	AOI	AERDORICA SpA	PUM	PP	9.2	33.4	M
Genova Sestri	GOA	Aeroporto di Genova SpA	PUM	T	11.7	24.5	M
Lamezia Terme	SUF	SACAL SpA	PUM	PP	6.8	31.8	M
Pescara P. Liberi	PSR	SAGA SpA	PUM	PP	neg.	24	M

PRM=Private Majority; PUM=Public Majority. T=Totale; P=parziale; PP=parziale precario. ROI= return on investment. NAR= non aeronautical revenues. H: more than 1.5 million of passengers; M: less than 1.5 million of passengers.

[a] SEA SpA, Milano airport management company, holds 49% of SACBO SpA.
[b] SAB SpA obtains 40-year Total concession in 2005.
[c] GESAC SpA obtains 40-year Total concession in 2003.

of the airports management companies is summarized in Table 3.1. Most of Italian airports are privatized and few of them are characterized by a private majority. Comparing the operating efficiency, expressed by the ROI index, to the capital composition (Table 3.1), it is evident the absence of any systematic tendency between high values of ROI and the type of ownership structure: private vs public. The unique evidence is shown by the Airports of Roma, managed by a company with private majority, if compared with those of Milano, managed by a company with public majority. However, airports, characterized by less than 1.5 million of passengers, show scarce capacity to generate returns on the invested capital. As shown in Table 3.2, the Italian airport infrastructure is characterized by a peculiar structure, that distinguishes it from the rest of European airports (OECD 2001). It is constituted by a high number of small airports wide spread over the country, different in nature and volume of served traffic, business and governance structure. Indeed, some airports serve mostly international traffic, such as CIA, FCO, MPX and BGY whereas others serve mostly domestic passengers (e.g. LIN, NAP, PMO, TRN, see Table 3.2). Moreover, some airports face high fluctuation in served traffic, caused by seasonality in passengers' demand, high ratio between maximum and minimum value of WLUs. Inside each group, both the volume and growth rate of traffic served is very different: the volume of traffic ranges from 15 million passengers for MPX to 3 million passengers for BGY in 2004, while the growth rate faces a steady increase owing to the air-transport services liberalization process (see Table 3.2).

In particular, CIA has shown an average increase of 40% while BGY 50% in the international passengers. The two hubs, Roma Fiumicino and Milano Malpensa have shown, respectively, 3.11% and −0.04% growth rates. As far as the domestic traffic, there have been small variations in the entire Italian system, expect for Milano Malpensa (−10.4%) and Roma Ciampino (−32.7%), pointing out their orientation towards international traffic. Looking at the revenues composition, it can be noticed as the non aeronautical revenues represent a significant portion of total airport revenues. Generally speaking, the polarized structure of the entire Italian system persists over the considered period but, at the same time, smaller airports are absorbing

Table 3.2: List of selected Airports and their characteristics. Year 2004.

			Traffic composition (average 2000-2004)					Traffic Evolution (2000-2004)		
Airports	**IATA code**	**WLU**[a]	**Passengers (%)**	**Cargos (%)**	**Movements (%)**	**Nat/Int passenger**	**Max/Min WLU**	**WLU**	**Nat. passengers (%)**	**Int. passengers (%)**
Roma Ciam.	CIA	1,561,635	1.6	2.4	2.8	0.917	1.49	1.42	0.21	3.11
Roma Fium.	FCO	28,145,135	30.4	22.7	24.6	0.006	2.62	32.66	-32.67	40.41
Total			**31.9**	**25.1**	**27.4**					
Milano Linate	LIN	7,992,568	8.9	3.2	9.1	0.294	1.75	-1.55	-10.39	-0.04
Milano Mal.	MXP	21,934,638	21.4	41.7	19.1	2.488	1.74	10.33	11.27	9.07
Total			**30.4**	**44.9**	**28.2**					
Bergamo O. S.	BGY	3,089,581	2.2	14.2	3.5	0.219	1.92	23.33	3.76	50.16
Bologna B. P..	BLQ	3,620,933	3.9	3.1	4.6	0.49	1.88	-1.94	-4.44	-4.03
Catania Font.	CTA	4,493,185	5.1	1.4	4.3	3.784	2.36	6.45	8.05	1.95
Napoli Cap.	NAP	4,407,464	5	1.1	5.2	1.572	2.02	6.45	8.05	1.95
Palermo P. R.	PMO	3,541,719	4	0.7	3.6	6.463	2.2	3.94	2.64	14.41
Pisa S. G.	PSA	1,769,875	1.9	1.4	2.4	0.455	2.31	12.6	-4.54	24.44
Torino Cas.	TRN	3,054,068	3.3	2.2	5	1.224	1.34	2.34	4.71	1.08
Venezia Tes.	VCE	4,928,555	5.5	2.3	5.9	0.549	1.79	9.49	8.78	10.18
Verona Vill.	VRN	2,471,202	2.7	1.4	3.2	0.589	2.71	4.45	0.34	6.53
Total			**33.6**	**27.7**	**37.7**					
Alghero Fer.	AHO	823,492	0.9	0.2	0.9	2.555	2.84	10.37	1.06	42.58
Ancona Fal.	AOI	534,661	0.6	0.7	1.6	0.93	1.64	5.08	-3.86	12.76
Genova Sestri	GOA	1,108,591	1.2	0.8	2.3	1.486	1.45	0.34	1.88	-1.6
Lamezia T.	SUF	1,000,569	1.1	0.3	1	4.353	2.8	12.8	17.64	1.25
Pescara P. L.	PSR	263,589	0.3	0.3	0.8	0.52	2.48	28.29	3.45	118.65
Total			**4.1**	**2.3**	**6.7**					
Total Sample			**100**	**100**	**100**					

Nat=National; Int=International.

[a]Work Load Unit (WLU) is a commonly used output measure in the aviation industry. It is defined as one passenger or 100 kg of cargos.

the increase in volume of traffic, outlining a new way of making business and supporting the regional development.

3.4 The analytical framework

So far, few studies have focused on the productivity and efficiency of Italian airports since they have boasted of benefits of exercising monopoly and being a public utility, owned by a management focused only on core business. The need to measure, monitor and benchmark the performance of airports is risen with the airport economic regulation that has promoted a truly dynamic environment, characterized by privatization, commercialization, rapid growth of traffic, airline market deregulation and alliances. Strategically speaking, the pressure to be more operational competitive and productive has increased to attract air carrier operations since the freedom of airlines to move their base of operations (Ashford 1994). Indeed, it is well recognized that the possibility to create the "lock-in" of the air carries is a critical strategic issue that determines the long viability of airports; in turn, the "lock-in" may be determinated by the efficiency of airports (Sarkis 2000).

Contemporaneously, the airports have been moving to more complex business model focused on the diversification: the business related to the traditional activity, called aeronautical business, focuses on transportation of both passengers and goods while the new business, called non-aeronautical business, focuses on the commercial activities (as parking, hotels, shops,..), that allows exploiting the complementary demand between aeronautical services and commercial services (Oum et al. 2004). Figures B.1 and B.2 show a graphical process model, developed using the standard IDEF0[5], of entire Italian airport system at macro level. They depict:

- the different forms of airports' businesses;
- the different demands to be served ;
- the resources needed to get each activity worked;
- the regulation to which each activity is submitted.

[5] www.idef.com.

The performance analysis is evaluated in terms of technical efficiency since it is the most crucial indicator to keep a check on to be more competitive and productive increasing. The managerial evaluation is done focusing on:

- the meaningful actions of the management to monitor and improve aspects of their own operational performance by reference to, and learning from, other organizations (Francis et al. 2002);
- comparing a set of different airports to improve their competitive position through the identification and adaptation of best practise (Graham, 1999, 2001).

From an analytical point of view, departing from the previous studies, the DEA estimator of technical efficiency is used in a sophisticated and robust approach, which takes into account the statistical inference (Simar and Wilson 2000b). From a managerial point of view, technical efficiency scores are evaluated using two different models:

I Physical Model that expresses technical efficiency as function of airports characteristics variables, following Sarkis (2000);

II Revenue Model that expresses technical efficiency as function of economic variables, following Fernandes and Pacheco (2003).

The first model emphasizes the level of the exploitation of resources employed due to the ability of managing the operational processes and airport capacity, while the second one, the exploitation of the business diversification strategy due to the ability of capitalizing the advantages from the new reformed system. The results obtained by the previous analysis methodology are jointly evaluated by means of a scatter plot matrix (Fernandes and Pacheco 2003), to give operative support to both managers and policy makers in future strategy developments of the Italian sector.

3.4.1 The analytical methodology

In this section, the analytical methodology is discussed in regard to the industrial sector analyzed. The technical efficiency analysis is modelled using the efficiency measurement defined in section 1.2, as well as the advanced developments proposed by Simar and Wilson (1998) and discussed in section 1.3, which allow obtaining more accurate measures for the problem of efficiency measurement. The approach used here aims to identify the economic problem of production related to the Italian airport industry, convert it into a statistical model and, finally, interpret the statistical results in managerial standpoints.

Starting from Gillen and Lall (1997) that presented their pioneristic work on the investigation of airports efficiency of US market, a huge economic literature has grown following the traditional approach that consists in point estimation of the efficiency, output orientation in the distance measurement from the estimated frontier, returns to scale defined as function of the research objectives or locally tested by means of comparisons between the two forms, constant return to scale (CRS) or variable return to scale (VRS). However, the above approaches neglect the statistical properties of the non parametric estimators that, in turn, depend on the properties of the process which generate the original dataset. Indeed, they dealt with estimates of the efficiency from DEA model without taking into account the uncertainty due to the sampling variation. So far, in air transport field the efficiency analysis has been carried out by employing both parametric (e.g. stochastic frontiers) and non parametric Techniques (e.g. index numbers). Parametric techniques (e.g. Pels et al., 2003) requires the functional specification of the underlying production frontier and have the limit of the single output. The index number (e.g. Oum et al., 2006), instead, need the knowledge of the input and output prices. For the above reasons DEA method is mostly employed. In fact, Parker (1999) applied DEA to study the relative performance of British Airport Authority, before and after privatization, Sarkis (2000) continued the examination of the productivity of US airports. Adler and Berechman (2001) used DEA to measure the quality of airports from point of view of air carriers, using principal component analysis to reduce the dimensionality of the space of inputs and outputs. Martìn and Romàn (2001) applied DEA to evaluate the performance of Spanish airports. Pels et al. (2001) made the analysis for a set of European airports. Abbott and Wu (2002) investigated the efficiency and productivity of 12 Australian airports using DEA. Fernandes and Pacheco (2003) used DEA to analyze the efficiency of Brazilian airports taking into consideration two different dimensions: financial and physical. Pels et al. (2003) studied the contribution of the airline inefficiency (low load factor) to the European airports inefficiency in terms of passenger movements. Lin and Hong (2006) used DEA to assess the operational performance of 20 major airports around the world.

In this chapter, the overall productivity performance of the Italian airport industry is considered, explicitly taking into account the diverse nature of the airport operation and market environment, using a more robust and accurate methodology. This methodology allow to analysis the sensitivity of the efficiency measures to the sampling variation, providing confidence intervals and correction for the bias inherent in the DEA procedure. Deeply, I am able to purify the effects due to the analyzed process from those inducted by sampling variation on the efficiency estimates. Hence, non parametric frontier techniques, based on a statistical inference approach (Simar and Wilson, 2000, 2002, 2006), are used to measure the technical efficiency. This approach consists in performing a smoothed homogeneneous bootstrap procedure to implement statistical inference for the efficiency point estimates and obtain the relative confidence intervals (see Section 1.3).

I assume an output orientation model to align the management strategy to the criterion of technical efficiency measurement. It assures to take into account the objectives set by the management of exploiting the facilities to satisfy the steady growth demand in aviation market (Martìn and Romàn 2001). The efficiency indexes are derived using the Shephard (1970) output distance function (equation (1.5)).

In our case, the sample is composed by 16 observations and I propose two production models (see Section 3.5): in the first model, the production process is described in a six dimensional-space (three inputs and three outputs) while in the second one, I have five dimensions (three inputs and two outputs). Thereby, to preserve the speedy of the convergence rate and avoid additional noise to the estimation, I aggregate the input and output vectors. So, for both models two proxy factors, which best summarize the information hold by all input and output variables, are computed reducing the dimensional space from six (or five) to two (i.e. one input and one output). Due the high level of correlation among the variables[6], the procedure proposed by Daraio and Simar (2007a) and showed in Section 1.2.9 is applied and the two proxy factors are computed[7].

Moreover, attention has been devoted to the technological frontier. Indeed, I test the hypothesis of Global Returns to Scale -Constant (CRS), Non Increase (NIRS) or Variable (VRS)- using a formal statistical test, proposed by Simar and Wilson (2002) and showed in Section 1.3.1.

I use FEAR package Wilson (2007) for R software to compute DEA estimates. The results throughout this paper are obtained from 5000 bootstrap iterations. I employ the Cross-Validation method for the choice of the bandwidth and the results appear robust with respect to variations[8].

3.5 Data

To estimate the output distance functions and, hence, the efficiency scores, three sources are used: balance sheet of each airport, Traffic Data of Assaeroporti, and Annual Statistics from E.N.A.C. (2001–2007). The criterion for selecting the strategical variables requires considering the new nature of the airports, described by Figures B.1 and B.2. The Physical Model aims to measure Technical Efficiency by capturing the effects of operations strategy, regards the airside activity[9].

Labour, number of runways and apron dimension are chosen as input variables while number of movements, number of passengers and amount of cargos as output variables. The labour variable is measured by the number of employees who work directly for an airport (Oum et al., 2003, 2006). The number of runways variable is used to provide a better estimation of the airport dimension than the runway length should gives since the disappearance

[6] Correlations between the variables is always greater than 80%. See Tab.B.3-B.4.

[7] They are reported in Tab.B.5-B.6.

[8] I check the robustness of the results setting the bandwidth h at 0.5 and 1.5 times the previous value.

[9] The analysis is restricted to the airside activity since the lack of data of strategical variables regarding the landside. The number of gates and/or terminal should be good strategical variables to measure the technical efficiency of the landside activity, but here it is not included due to the lack of complete data across the panel.

of the distinction between national and international runways. It is simply measured by the sum of total of runways. Finally, the apron dimension, expressed in square meters, is assumed as a proxi to measure the operational and service aspects of the airside: it is a part of the airport intended to aircraft operations (manoeuvring, refuelling, servicing, maintenance, parking and movement of aircrafts), passengers and cargo service (loading and unloading). On the other hand, the number of movements variable includes both takes-off and landings (E.N.A.C., 2001–2007), the number of passenger movements is measured by the sum of passengers arriving or departing via commercial airplane and of passengers stopping temporarily at a designed airport (Sarkis and Talluri, 2004). The amount of cargos is included because it is becoming increasingly important for many Italian airports and it is expressed in tons. Differently, the Revenue Model aims to measure the Technical Efficiency by capturing the effects of the diversification business strategy, regarding both airside and landside activities.

Labour cost, other costs and airport size are taken as input variables while aeronautical and non-aeronautical revenues as output variables. For most airports, input data are not accounted separately following the classification aeronautical and non aeronautical service; therefore, as input variables I use aggregate data. The labour cost variable is measured as the cost of labour, taken from the annual balance sheet. Following Oum et al. (2006), the "other cost" variable is chosen to measure all the expenses not directly related to capital and personnel and reflects also the expenses on outsourcing activities of the airports. This variable allows taking into account the effects of the new adopted strategy with respect to outsourcing activities on productivity performance. From the output side, I use the revenues as output variables. For all airports, revenues are separately accounted for the two businesses. Inclusion of non aeronautical services output removes bias in efficiency estimates, otherwise underestimated in those airports with more proactive managers focused on exploiting the revenue generation opportunities from non aviation business. Indeed, non aviation revenue for some airports generate high portion of their total revenues (e.g. CIA_FCO with 45.7% and GOA with 44.4%, see Table 3.1). It represents the revenue given by concessions, parking and rental space to airline, car rental agencies and

Table 3.3: Summary statistics of Physical Model.

Year	2000		2001		2002		2003		2004	
	Mean	Std.dev	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Inputs										
Employees	851.40	1,728.90	807.90	1,716.30	590.50	1,019.20	482.3	669.60	485.60	665.00
Number of runways	1.7	1.2	1.8	1.2	1.8	1.2	1.7	1.2	1.7	1.2
Apron size	226,335.0	346,847.6	254,272.5	434,505.2	278,613.8	434,215.9	279,482.5	433,944.6	282,310.0	432,310.0
Outputs										
Number of movements	72,680.9	98,349.5	72,722.2	101,856.5	72,255.8	98,010.9	76,465.1	102,914.2	76,977.2	107,065.0
Number of passengers	5,22,862.9	8,587,084.6	5,075,243.1	8,279,386.1	5,156,305.8	8,186,346.5	5,645,693.4	8,579,348.1	5,993,878.6	9,179,570.2
Amount of cargo	48,146.5	92,160.1	48,877.7	96,224.3	49,228.8	96,625.0	52,633.4	103,742.9	52,485,8.0	104,329.3

Table 3.4: Summary statistics of Revenue Model.

Year	2000		2001		2002		2003		2004	
	Mean	Std.dev	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Inputs										
Airport size	429.2	504.1	427.5	512.5	428	512.3	427.4	512.9	427.5	512.9
Labor cost	308,518.20	611,549.40	287,014.90	580,769.30	224,339.20	396,396.40	185,242.90	271,341.30	180,251.80	260,684.10
Soft Costs	278,007.20	494,875.50	272,512.70	443,289.70	262,318.80	415,446.40	263,748.90	392,693.00	272,872.80	385,827.90
Outputs										
Aeronautical Revenue	539,295.30	967,761.70	504,210.10	908,988.00	430,355.90	709,244.40	433,182.80	660,754.40	444,690.00	681,017.40
Non aeronautical revenue	272,409.80	571,699.80	262,841.20	523,052.80	275,175.90	541,089.60	276,375.40	510,674.20	289,133.30	530,623.30

other concessionaire (Gillen and Hinsch, 2001).

It is worth to highlight that the management companies, respectively of Rome Ciampino and Fiumicino airport and Milano Linate and Malpensa airport do not provide for the managed airport separated balance sheet. Thus, I consider Ciampino and Fiumicino (CIA_FCO) as well as Linate and Malpensa (LIN_MPX) as a single airport. Table 3.3 and 3.4 report descriptive statistics on the employed variables of each model.

3.6 Estimation and analysis

3.6.1 Preliminary results

The analytical methodology suggests the reduction of dimensional space for the efficiency analysis, aggregating the input and output variables (Tables B.1 and B.2, Appendix B) for each model in each year. Such a strategy can be pursued, since the variables present high and persistent correlation value (Tables B.3 and B.4). Hence, the factors F^{inp} and F^{out} are computed, using the parameters α_k and β_k reported in Tables B.5 and B.6.

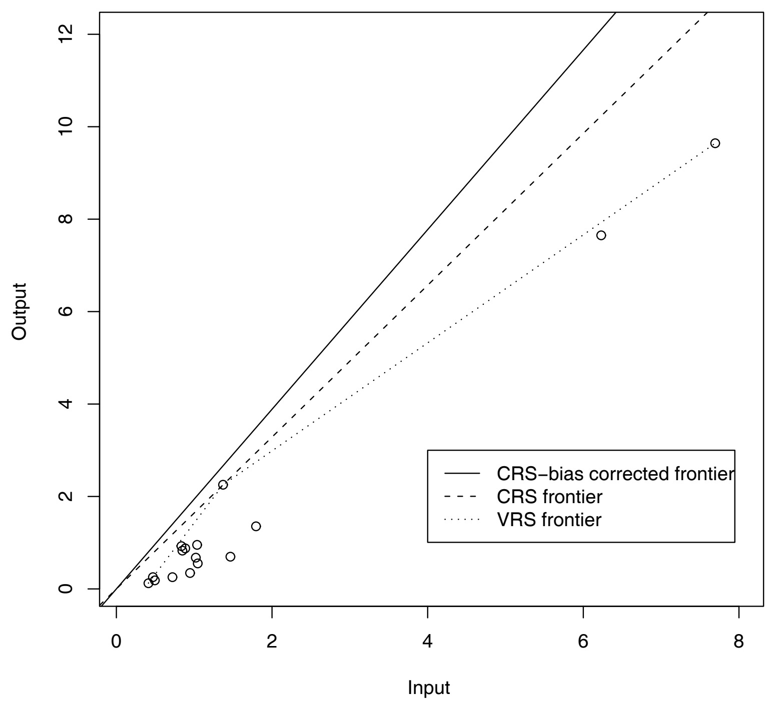
Next, I investigate Returns to Scale in airport process, using F^{inp} and F^{out} as input and output variables, respectively. I test the null hypothesis of Globally Constant Returns to Scale (GCRS) in the technology versus the alternative hypothesis of Globally Variable Returns to Scale (GVRS). I use the statistics described in equation 1.30 and 5000 bootstrap replications. I fall to reject the null hypothesis of constant returns to scale at 5% level for each statistics (Table B.7). They point out that the airports of our sample work at the maximum average productivity and the sources of inefficiency are attributable only to the management policy and not to the deficiency of the scale.

3.6.2 A look to the estimate frontiers

When we have only one input and one output, it is easy to plot the observations and the estimate frontiers. In Fig. 3.1-3.2 the estimate frontiers of both models are showed. The solid line is the bias-corrected CRS frontier and the dashed line is the CRS frontier. It is possible to note that the non bias-corrected frontier is downer than bias corrected frontier. Further, the

VRS frontier is reported: note that this is very close to CRS frontier.

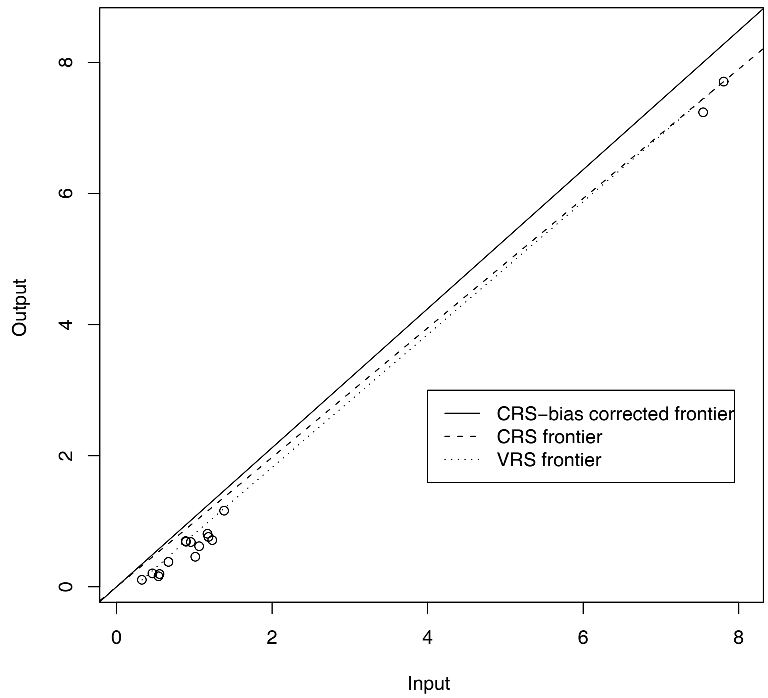
Figure 3.1: Estimate frontiers for "Physical Model", 2004.



3.6.3 Efficiency and Sensitivity results

The output distance estimates, and hence the efficiency scores, are performed from the two models using F^{inp} and F^{out} and assuming a CRS technology. Tables B.8-B.12, and B.13-B.17 report the computed estimated over the period 2000-2004, respectively, for the Physical and Revenue Model. Columns from 2 to 6 give, respectively, the original DEA efficiency estimates, the corresponding bias corrected efficiency estimates, the bias estimates, the estimated standard deviations across bootstrap replications, the μ ratio. The remaining columns contain estimated lower and upper bounds for confidence intervals at 5% confindence level. As shown by μ ratio, the bias is substantial and should not be neglected. Hence, I correct all the point estimates

Figure 3.2: Estimate frontiers for “Revenue Model”, 2004.



according to the relation given by (1.25) and I carry out the analysis taking into account the new unbiased estimates. Indeed, important insights are provided considering the stochastic nature of the estimation problem. Firstly, DEA efficiency scores overestimate the real efficiency, being biased upwards (Table 3.5 and 3.6). Secondly, the difference in the efficiency within the sample might be no statistically significant. For instance, let's focus on the Revenue Model for the CIA_FCO and LIN_MXP 2004. CIA_FCO is 100% efficient while LIN_MXP is efficient at a level of 97.2%. They differ in point estimate of 2.8%. This percentage difference decrease with the bias-corrected measure (column 3, Table B.17). The main result is the that this difference is not statically significant since the overlapping of their confidence intervals to a large degree.

Meaningful industrial considerations are stated looking at the geometric

Table 3.5: Physical Model: Descriptive statistics of the original and bias-corrected efficiency scores.

Mean	2000	2001	2002	2003	2004	*Overall*
Original	0.500	0.503	0.453	0.411	0.417	0.455
Bias Corrected	0.449	0.450	0.390	0.345	0.353	0.395

Table 3.6: Revenue Model: Descriptive statistics of the original and bias-corrected efficiency scores.

Mean	2000	2001	2002	2003	2004	*Overall*
Original	0.547	0.512	0.553	0.612	0.593	0.562
Bias Corrected	0.509	0.467	0.510	0.575	0.552	0.521

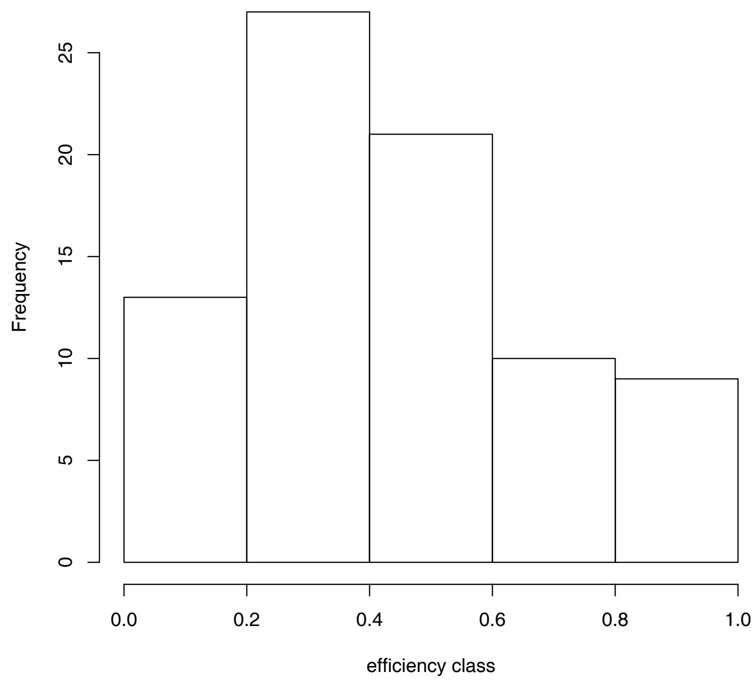
mean efficiency scores. The two models exhibit different tendency of the bias-corrected estimates on average. In the Physical Model, the overall mean is 0.395 while the Revenue Model is 0.521, proving that Italian airport system is quite inefficient from both perspective, but certainly more competitive from a revenue perspective.

Moreover, looking at the frequency distributions of the bootstrapped efficiency estimates over the all period (Figure 3.3 and 3.4), most airports seem to cluster around levels of efficiency of around 0.4 (22 observations on 80) for the Physical Model and around 0.7 (23 observations on 80) for the Revenue Model. The most striking finding is that physical performance differs from the revenue one, showing a more concentrate distribution of efficiency close to 0. Such diversity on performance can be potentially might stem from two considerations.

From an operational point of view, the Italian airport industry still shows a backward management of the airside capacity, encumbering it to increase efficiency and quality of airport processes. From a financial point of view, the benefits of governance reform stem from the application of a commercial view to the entire airport enterprise, even if the reform governance does not attain from cost reduction or increased capital investment.

Looking at the impact of the concession agreement, (Tab. 3.7), the

Figure 3.3: Frequency distribution of bias corrected efficiency scores (Physical Model).

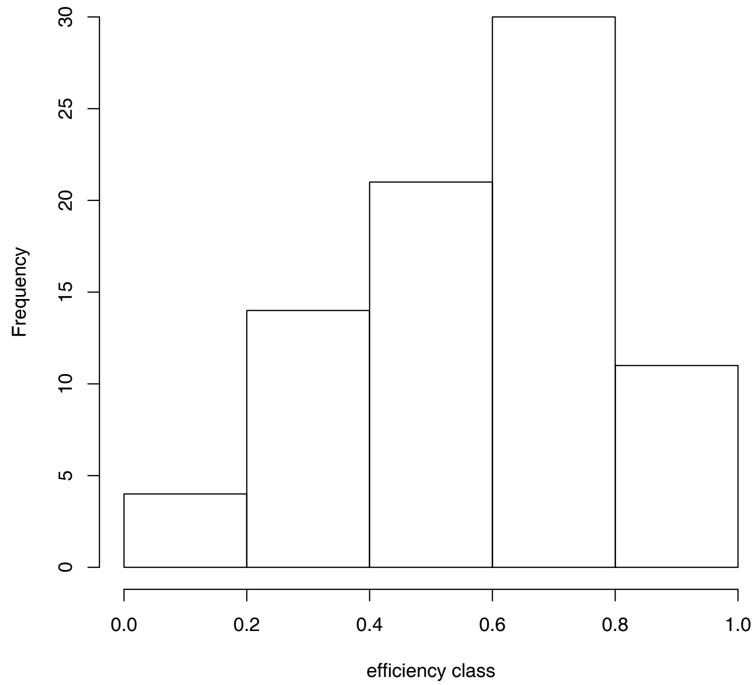


airports with T concession show better result for both models on average. In fact, it can be noticed that more restrictive is the concession agreement form less is the airport efficiency. For the Physical Model differences between T and P concession are slightly.

Table 3.7: Geometric means of bias-corrected efficiency scores by concession agreements and models.

	Total (T)	Partial (P)	Provisional Partial (PP)
Physical Model	0.514	0.451	0.247
Revenue Model	0.716	0.576	0.314

Figure 3.4: Frequency distribution of bias corrected efficiency scores (Revenue Model).



Useful insights for operational and financial managers are provided by the rankings, based on the bootstrapped efficiency scores, depicted by Tables 3.8 and 3.9.

They allow identifying stable benchmarks for improving the poorly performing airports and providing good managerial implications. Indeed, it has been proven that airports relatively straightforward in improvement direction are those with stable benchmarks Sarkis and Talluri (2004). The tables show stationary rankings for most airports for both models. Few airports change drastically their positions over time. In the Physical Model, CTA gets worse ranking passing from fourth to seventh position in 2002 but preserving it stable over the last years. LIN_MPX, instead, shows a decrease in ranking in 2001, followed by a great retrieval, levelling off in second position

Table 3.8: Airport ranking (Physical Model).

Airport code	2000	2001	2002	2003	2004
AHO	13	13	14	15	13
AOI	10	11	11	10	10
BGY	1	1	1	1	1
BLQ	3	5	6	5	6
CIA_FCO	4	3	3	4	3
CTA	5	4	7	7	7
GOA	15	14	13	13	14
LIN_MXP	7	9	5	2	2
NAP	2	2	2	3	4
PMO	11	10	10	12	12
PSA	12	12	12	11	11
PSR	16	15	15	16	16
SUF	14	16	16	14	15
TRN	6	6	4	6	5
VCE	9	8	9	8	8
VRN	8	7	8	9	9

Table 3.9: Airport ranking (Revenue Model).

Airport code	2000	2001	2002	2003	2004
AHO	15	15	16	16	16
AOI	10	12	13	13	13
BGY	7	10	11	9	8
BLQ	2	2	3	4	6
CIA_FCO	1	1	1	1	1
CTA	12	11	9	10	9
GOA	9	4	7	8	11
LIN_MXP	3	3	2	2	2
NAP	4	7	4	5	4
PMO	8	8	8	7	7
PSA	13	13	12	12	12
PSR	16	16	15	15	15
SUF	14	14	14	14	14
TRN	6	6	5	6	5
VCE	5	5	6	3	3
VRN	11	9	10	11	10

over the last years. In the Revenue Model, GOA ranks the fourth position in 2001 and then gets worse till achieving the eleventh position while NAP undergoes a downturn in 2001, resuming its position over the remains years.

On the other hand, some airports have not changed over the five-year period: they are BGY for the Physical Model and CIA_FCO and SUF for the Revenue Model. Both BGY and CIA_FCO result at the top of the ranking for the whole period.

To identify the cluster of best performers, I refine these results evaluating the statistical differences among the bootstrapped efficiency estimate through the overlapping of their confidence intervals. In the Physical Model, BGY is certainly the best performer if I evaluate the bootstrapped efficiency scores.

Turning to the inference analysis, its confidence intervals range from a minimum lower bound equal to 0.734 (in 2003) to the upper bound, constant over the 5 periods, equal to 0.996. This implies that BGY does not reach the maximum level of efficiency (equal to 1) and gets worst over the five years since the wider bootstrapped range towards decreasing values of lower bound. Moreover, its performance is quite not statistical different from BLQ and NAP in 2000 and BLQ and NAP in 2002. For the last years, BGY appears to be the best significant performer in the cluster. In the Revenue Model, CIA_FCO is distinctly the best performer if I look at the point corrected efficiency scores. Turning to the inference analysis, its confidence intervals range from a minimum lower bound equal to 0.811 (in 2001) to the upper bound, equal to 0.998. The width of the confidence intervals is constant. This highlights that BGY tends to reach very high values of the efficiency scores. Oppositely to the insights given by the point estimates, BGY performance is statistically similar to the performance gained by LIN_MPX in 2003 and 2004 since the huge overlapping of their confidence intervals. Thereby they constitute the revenue benchmark.

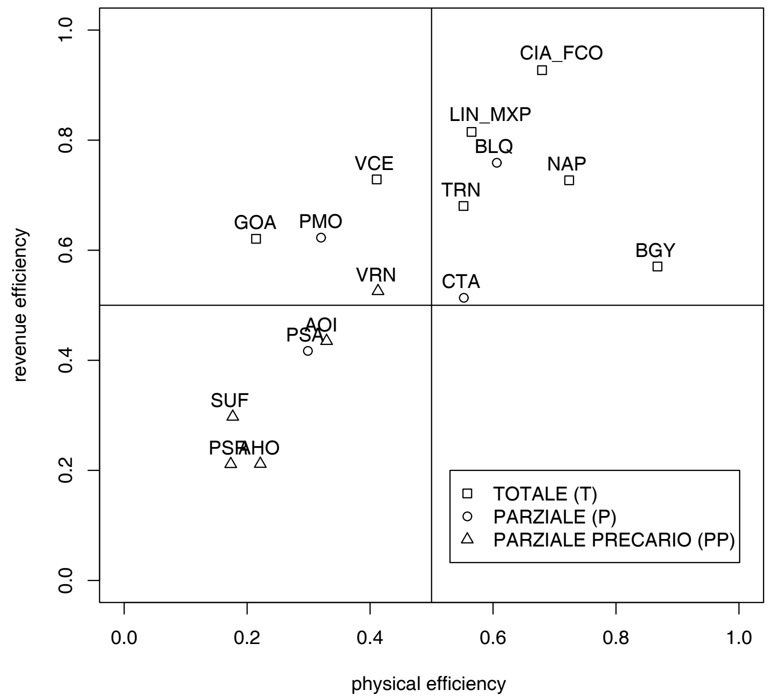
Fig. B.3 and B.4 depict the boxplots of the bootstrapped efficiency scores over the all period. For the Physical Model, it is worth noting the fact that most airports get worse their efficiency since the shift of their confident intervals downwards. Moreover, some airports among them (CTA, NAP, VCE and VRN) vary drastically the range of their confidence intervals. Only LIN_MPX improves its efficiency, denoted by an upward shift o f the confidence intervals while BGY appears to hold the efficiency stationary. The worse performers (AHO, AOI, GOA, PMO, PSR, PSA) show less variability of their efficiencies due to narrower confidence intervals. The boxplot related to the Revenue Model depicts a different industrial scenario of efficiency evolution. For most airports, the confidence intervals shift upwards regard to the year before. AOI and CTA lose in efficiency while CIA_FCO appears to hold stationary its range of efficiency variation. Moreover, it is clear that the variation of the efficiency scores among airports is less than that from the Physical Model since the narrower confidence intervals. It assures more accuracy to the analysis. It is evident that the two Italian Hubs are the best benchmarks in the diversification strategies. To check the robustness of the results with the respect to the choice of bandwidth in the bootstrap algorithm described Section 1.3, the analysis on the same data is repeated setting the bandwidth h first at 0.5 times the value chosen by the cross-validation procedure, then to 1.5 times the cross-validated bandwidth. The results reveal that the bootstrap procedure is very robust with respect to choices of the bandwidth parameter used in the kernel density estimator, since the decrease or increase in h has negligible effect on the estimated confidence interval for each DMU in the sample.

3.6.4 Strategical Analysis

The Italian airport system is moving toward a very complex context characterized by a progressive realization of the privatization process. This trend is offering new paradigm of business that aims to replace the old, non profit, public service model of infrastructure management with a new commercial model. This turning to private sector has got as result partnerships between public owners of airports and private management firms as result. Under the new commercial model, management is expected to run the enterprise to profit, maximizing all possible revenue sources, subject to regulatory constraints and customers' needs to satisfy. This enterprise approach to airport management allows conducting a strategical analysis of airport competitive arena. The statistical results obtained by the application of the analytical methodology are jointly analyzed by means of a scatter plot matrix Fernandes and Pacheco (2003) of the geometric mean over the period 2000-2004 (Figure 3.5).

The bi-dimensional visualization of the space jointly generated using the

Figure 3.5: Airport efficiency matrix.



two bootstrapped efficiency estimates (Physical and Revenue) allows the positioning of Italian airports within the four quadrants. This may helps to analysis how Physical and Revenue efficiencies affect the airport unit and to delineate possible local and global strategies for, respectively, management and political decision makers.

The first quadrant contains the "HH" airports. They represent the airport class able to guarantee log-run opportunities for both growth and profitability for the entire Italian airport system. They are efficient from a revenue point of view but operate with little inefficiency in the process management. Thus, they boast leadership positions inside the competitive arena but, at the same time, need for continuous investments and further spending to defend their dominant positions and maintain their growth. This airport class is composed by BGY, BLQ, CIA_FCO, CTA, LIN_MPX, NAP and

TRN. In particular, BGY could be considered as benchmark for airports devoted to taking off/landing of low cost carries. It is becoming, together with CIA, one of the most important Italian scalo, whose developments are due to particularly favourable geographic position, being centrally located in a highly industrialized area and close to a tourist area. CIA_FCO could be taken as private majority owned benchmark as well as LIN_MXP, as public majority owned. They appear to reach efficiency levels not statistical different in the last years. Instead, NAP could be considered as benchmark for the management efficiency. In fact, it was the first airport in Italy to undergo privatization, managed by GE.S.A.C. The airport operator company was privatized in 1997 with the acquisition of the majority of shares by BAA, a world leader in the field of airport management. In March 2003 GE.S.A.C. assumed total management of Naples International Airport with a 40 year license. The presence of BLQ in the first quadrant is attributable to the effort employed to pass the evaluating and inspection process for obtaining the forty-year complete concession by ENAC. This need has led the company to carry out some activities for improving all the system (both airside and landside). Instead, TRN has been completely renovated since it has followed modernization and requalification processes, launched in the spring of 2004, both to measure up to the challenges of the Olympic Winter Games in 2006 and the future traffic needs.

The second quadrant contains the "HL" airports (GOA, PMO, VCE and VRN); they are the most profitable airports in the Italian airport portfolio, therefore, they can be milked for money. They need an improvement in the management of their operational facilities to maintain their strong position for as long as possible. In fact, most of them have supported huge investments to upgrade infrastructure and do not still have optimized their use.

The third quadrant contains the "LL" airports (AHO, AOI, PSA, PSR and SUF); they are consumer resources with, at best case, marginal profitability. They are be affected by both seasonality and low volume of air traffic (Table 3.2) that do not allow to exploit their capacity. Moreover, high investments have been done to obtain certifications from ENAC with low return to investment in the short period. PSR has shown low ROI values due to the high investments in infrastructures although it has faced a steady increase of the traffic given by the so called "Rynair Effect", started since 2001. Thus, a good strategy is the retrenchment both in physical and revenue efficiency, for example, boosting the attractiveness to new air carriers and well managing the demand.

The fourth quadrant contains the "LH" airports and, fortunately, any airport is positioned, since this category offers low returns on high investments done. Looking at this Table jointly with Table 3.1, it is possible to note that the "HH" and "HL" airports are those classified in Table 3.1 with more than 1,500,000 passengers, with the exception of GOA. This indicate that, in the airport sector, the capacity of exploitation of efficiency is correlated both to the dimension of passengers' and carriers' demand both to the capacity to manage the seasonality of air transport services. Each quadrant shows different strategical implications depending on the objectives set by the management and policy makers but it is extremely important to search a balanced airport portfolio to achieve high level of competitiveness both in international and national scenario.

3.7 Conclusion

This chapter presents new evidence on the technical efficiency of the Italian airport industry, after the privatization and liberalization processes over the period 2000-2004. It is the first study to examine technical efficiency of the current Italian airport industry thought on a robust non parametric approach based on bootstrap method (Simar and Wilson 1998, 2000a, 2002) for the frontier estimation. Like previous studies, I treated the efficiency measures using the Data Envelopment Analysis (DEA) estimators but, unlike them, I account for the statistical nature of the estimators, avoiding any sources of misleading.

Since the peculiarity of the Italian airport infrastructure and the new competitive environment, I handle the technical efficiency measure and evaluation problems in a statistical setting where important issues are addressed and suggest some global strategical insights for both managers and policy makers, evaluating two different models: Physical and Revenue. I address the important economic issue of identifying of the underlying airport technology by means statistics for testing hypothesis regarding returns to scale of the technology, based on a bootstrap procedure. Moreover, I provide a sensitivity analysis efficiency by means of confidence intervals. Since the curse of dimensionality due to the nature of the economic problems (small number of airports and high number of input and output variables). Firstly, I find strong evidence of Globally Costant Returns to Scale for each year. Secondly, the Italian airports are statistically more efficient from a financial point of view and shows gains in efficiency in the Revenue model and losses in Physical Model, both statistically significant. It should be attributed to the different nature of each airport; for instance, difference in traffic demand, position and governance reforms. The analysis points out some relevant aspects of the entire airport system:

- the possibility to achieve high level in technical efficiency scores also for the regional airports, as exhibited by BGY, through serving low cost carries, although its proximity to the airport system of Milano;

- the room to increase high level in technical efficiency for airports managed by both a full private corporations, as NAP, and a private majority ownership corporations , as CTA, CIA_FCO and VCE.

The best Italian performers are identified following the sensitivity analysis of the technical efficiencies for both Models. From an operational point of view, BGY is the best significant performer for all period. It results not statically different from NAP and BLQ in 2000 and from NAP and CIA_FCO in 2002. From a financial point of view, CIA_FCO and LIN_MPX constitute the benchmark. By means of a bi-dimensional visualization, three airport classes are identified and high level of heterogeneity of Italian airport portfolio is remarked. The matrix exhibits the following positioning:

- BGY, BLQ, CIA_FCO, LIN_MXP, NAP and TRN are in dominant position but need investments to defend it in future scenario;

- CTA, GOA, PMO, VCE and VRN are in comfortable position in relation of the group since they should improve their operation management without need of immediate investments;

- AHO, AOI, PSA, PSR and SUF are in worst position and they need a revitalization program.

The bi-dimensional analysis points out the path to be followed by airport managers and political decision makers to create a balanced portfolio.

Chapter 4

Italian hospital efficiency

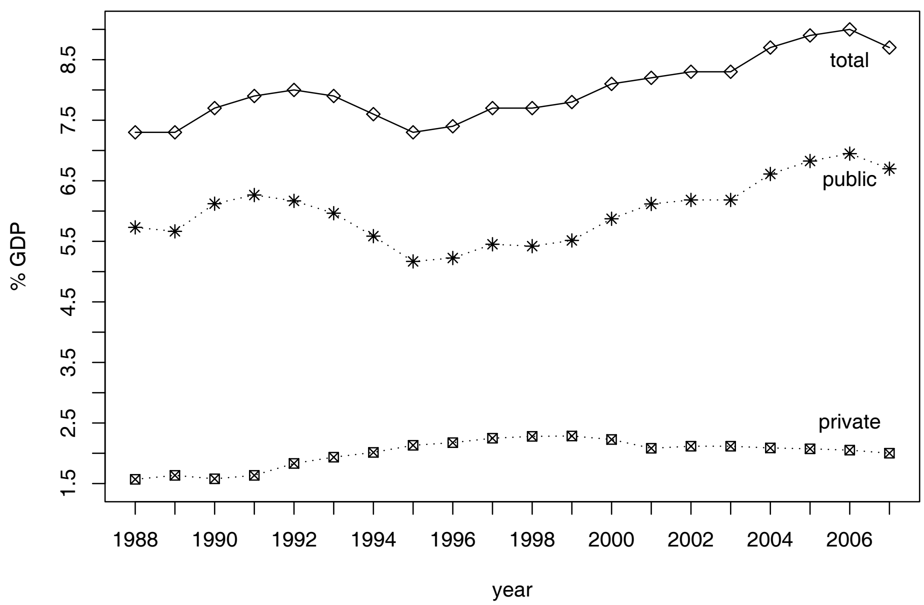
4.1 Introduction

Over the last thirty years, the health systems of many industrial countries have undergone significant reforms aimed at reducing cost in the provision of health care services. Among European countries, Italy in particular has experienced wide-ranging changes in its health-care sector as the Italian government has attempted to reduce the negative impact of the health-care expenditure on its budget deficit and public debt. In part, the Maastricht criteria on deficit and debt of European countries acceding to European monetary union in the year 2000 has motivated attempts to reduce costs in Italy's health-care system. Figure 4.1 shows how health-care expenditures as a percentage of gross domestic product (GDP) have varied over 1988–2007. In 2005, public health expenditure totaled 95.1 billion euros; 40.6 billion euros of those expenditures were for inpatient care ISTAT (2005). Despite attempts to reduce public expenditure, public health-care expenditure in Italy increased at a faster rate than GDP from 1998 to 2007, due perhaps in part to low annual GDP growth during this period.

Only 15 percent of Italian citizens purchase private health insurance, primarily to cover expenses related to ambulatory specialist care and private hospital care for obstetrics and minor surgery (France et al., 2005); the vast majority depend exclusively on public health insurance to cover health-care expenses[1]. Consequently, any successful effort to reduce costs of health-care

[1]This situation is not unlike that in the U.S.; see Wilson and Carey (2004) for additional discussion.

Figure 4.1: Health-care Expenditure as Percentage of GDP, 1988-2007. Source: OECD.



provision are likely to involve hospitals. This chapter examines the hospital sector of the Italian health-care system in order to (i) examine the effects of previous cost-cutting measures on hospital performance, and (ii) to assess the potential for further reductions in expenditures by improving efficiency among hospitals.

Only a few papers have examined the efficiency of Italian hospitals. Cellini et al. (2000) used non-parametric data envelopment analysis (DEA) estimators to examine technical efficiency among Italian hospitals operating in 1996; they do not found clear evidence of systematic differences between private and public hospitals in terms of their technical efficiencies[2]. Sicil-

[2]Cellini et al. (2000) attempted to explain technical inefficiency by regressing DEA efficiency estimates on various environmental variables in a second-stage, ordinary least-squares (OLS) regression. As discussed by Simar and Wilson (2007), the classical inference methods used by Cellini et al. in their second-stage regression is invalid due to correlation among the DEA estimates that are used as the endogenous variable; moreover, the use

iani (2006) examined efficiency among 17 Italian hospitals from 1996 to 1999, comparing efficiency estimates obtained from nonparametric DEA estimators and parametric, stochastic frontier estimators. Such comparisons, however, are misguided since the underlying assumptions required for statistical consistency of these two estimators are quite different. In particular, under typical assumptions where parametric, stochastic frontier estimators are used, DEA estimators are inconsistent[3]. Barbetta et al. (2007) used both parametric and non-parametric techniques to estimate technical efficiency of Italian hospitals for the period 1995–2000. They evaluate the introduction of a prospective payment system based on diagnostic related groups and found a decline in technical efficiency over the period they examined. Barbetta et al. attributed this decline to policies aimed at reducing hospitalization rates; since hospital capacity is relatively inflexible in the short-run, a reduction in hospital use would be reflected by excess capacity in the short-run.

This chapter employs some recently-developed non-parametric estimation methods to analyze technical efficiency and how efficiency has changed over time among Italian hospitals. In addition, I investigate changes in productivity and other features of the Italian hospital industry. I use the newly-developed, non-parametric, unconditional hyperbolic α-quantile estimator introduced by Wheelock and Wilson (2008a). This estimator has several advantages over the traditional DEA estimator that has been widely used. In particular, the new efficiency estimator is robust with respect to outliers and asymptotically normal. In addition, the new estimator converges at the classical parametric rate root-n, unlike the DEA estimator which suffers from the well-known curse-of-dimensionality. The unconditional hyperbolic α-quantile estimator has been used to examine productivity change among U.S commercial banks by Wheelock and Wilson (2008b), but so far has not been used in a health-care setting.

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of OLS is inappropriate in the context of the statistical model presented by Simar and Wilson (2007).

[3]See Section 1.2.1 for details on the statistical properties and underlying assumption required by DEA estimators.

4.2 The Italian Hospital Industry

France et al. (2005) provide a detailed overview of the Italian health-care system. They observe that the *Servizio Sanitario Nazionale* (SSN), or national health service, is required by law to provide equal access to primary care. However, they also observe that lower income groups face barriers to specialist care. In addition, there are large and growing differences in regional health service organization and provision which complicate the uniform provision of comprehensive care.

Decision-making and administration in the Italian health-care system are carried out at three levels: (i) the State (i.e., federal government); (ii) the 21 *Regioni*[4]; and (iii) local organizations, which are responsible for provision of health-care services. The local organizations were known as *Unitá Sanitarie Locali* (USLs), until 1992, when legislation to reform the health-care system changed these organizations to *Aziende Sanitarie Locali* (ASLs)[5].

The SSN was created in 1978 along the lines of the British National Health Service[6]. The system was designed to provide health-care services to all Italian citizens[7]. The State determines *livelli essenziali di assistenza* (LEAs), or essential levels of care to be provided to all residents; the State in turn provides funding to the *Regioni*, which have responsibility for administration of publicly funded health-care within their geographic domains. The *Regioni* vary a great deal in terms of their demographic characteristics, wealth levels, and health-care expenditures. Table 4.1 gives some statistics on health-care expenditures in each ofthe *Regioni*.

Looking at the demography structures and the wealth, it is clear the gap among the more economic development area (*Nord* and *Centro*) and the remaining one (*Mezzogiorno*); deficit in health expenditure is accumulated

[4]The Italian constitution of 1948 defines twenty Regions. However, for INHS Trentino Alto Adige is divided into two parts: Bolzano and Trento. Consequently, we refer to 21 Regions throughout the remainder of this chapter.

[5]To avoid potential confusion, I retain the Italian names of organizations in Italy. USL is sometimes translated as "local health-care authority", which is close to "local health-care enterprise", the translation sometime used for ASL. Other translations are perhaps also possible.

[6]See France et al. (2005) and Del Vecchio (2003) for detailed descriptions of the SSN and its evolution.

[7]Since 2002, coverage is also provided to non-citizens who are legal residents in Italy.

Table 4.1: The Italian *Servizio Sanitario Nazionale*, 2005

	Patients	Total Health Expenditure (millions €)	Expenditure (€)	Surplus or Deficit (millions €)
North:				
Piemonte	736,864	7,105	1,638.62	1
Valle D'Aosta	19,748	225	1,823.00	−14
Lombardia	1,952,154	14,269	1,512.48	−14
Bolzano	103,239	995	2,073.53	28
Trento	77,928	803	1,605.96	−2
Veneto	839,261	7,265	1,539.48	−114
Friuli Venezia Giulia	201,044	1,927	1,597.18	27
Liguria	389,725	2,969	1,854.21	−253
Emilia Romagna	802,808	6,790	1,628.51	−16
Central:				
Toscana	651,480	5,743	1,591.27	−15
Umbria	170,745	1,379	1,597.16	−8
Marche	267,047	2,304	1,512.01	−18
Lazio	1,352,636	10,387	1,964.49	−1,733
South:				
Abruzzo	348,147	2,182	1,675.51	−241
Molise	78,577	650	2,022.21	−139
Campania	1,233,964	9,603	1,658.56	−1,788
Puglia	804,069	6,103	1,499.57	−412
Basilicata	107,227	901	1,513.48	−43
Calabria	389,005	2,972	1,480.93	−79
Sicilia	1,230,508	7,924	1,580.01	−574
Sardegna	358,316	2,662	1,610.54	−317
North	5,122,771	42,348	1,593.85	−358
Central	2,441,908	19,813	1,755.90	−1,774
South	4,549,813	32,997	1,589.93	−3,593
TOTAL	12,114,492	95,158	1,623.66	−5,725

in the less economic development area.

Delivery of health-care services is performed by the ASLs, which are responsible for varying hospital and community services in geographical areas typically containing about 300,000 persons. France et al. (2005) note that in 2003, publicly funded hospital care was provided in 1,308 facilities; of these, 59 percent were publicly owned and accounted for 86.3 percent of total hospital discharges. France et al. also note that 79 percent of public hospitals were managed directly by ASLs, while another group of 96 large hospitals (including teaching hospitals) operate as quasi-independent public enterprises known as *Aziende Ospedaliere* (AOs). Only about 2.9 percent of hospitals in Italy operate as non-profit organizations (NPs); most of these are owned by the Catholic Church. In 2002, 41 percent of all hospitals in Italy operated as for-profit organizations; these hospitals treated 13.7 percent of inpatient cases and accounted for 13.8 percent of hospital beds in Italy (Sistema Informativo Sanitario, 2005).

Reforms were enacted in 1992 by law #502/1992 in an attempt to contain costs. Through law #502/1992, the State gave the *Regioni* more responsibility than they had previously for organizing health-care provision. In addition, law #502/1992 imposed managerial principles on the ASLs[8].

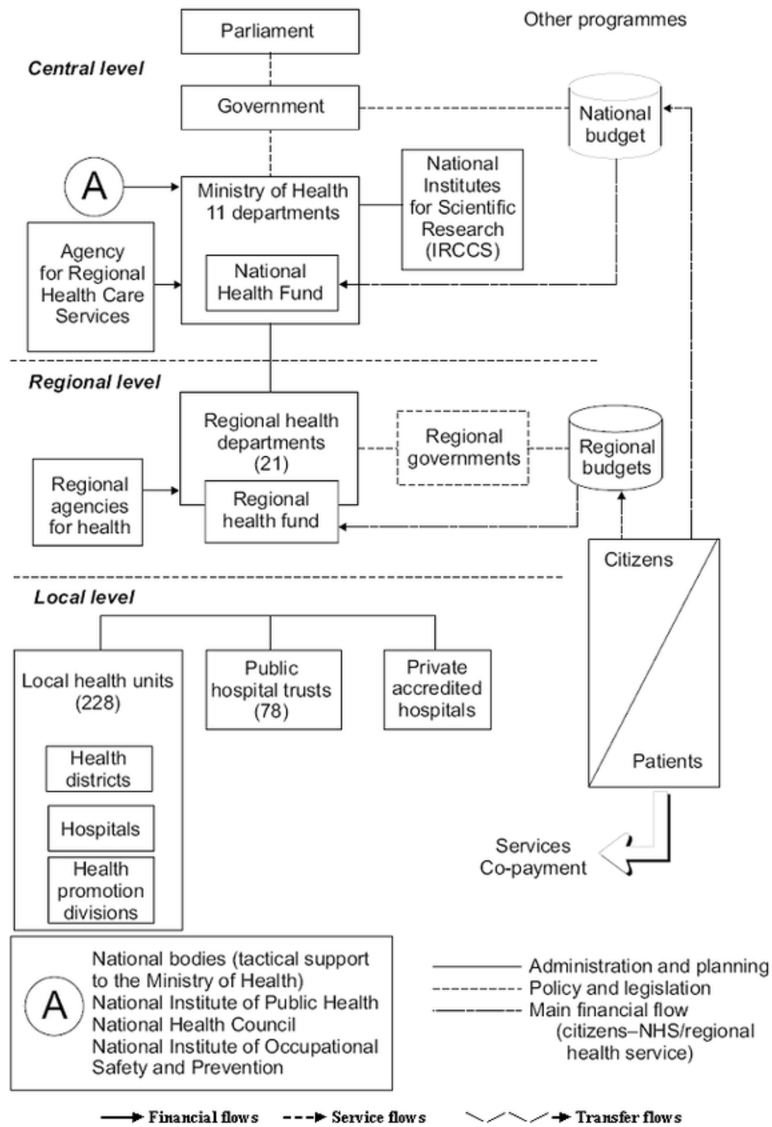
Figure 4.2 gives a schematic overview of the system. The *Regioni* are responsible for organization, administration and management of funds collected from a regional tax (specifically, the *Imposta Regionale sulle Attivita' Produttive*).

The organizational units that physically provide health-care services are the ASLs, AOs and private hospital and ambulatory care organization accredited for provision of the LEA services. Hospitals operated by an ASL do not have independent corporate governance; rather, they are directly managed by the ASL. In order to distinguish these hospitals from the AOs mentioned earlier, I will refer to hospitals operated by an ASL as *Ospedali a Gestione Diretta* (OGDs) throughout.

Unlike the OGDs, AOs have a corporate structure and are not directly controlled by an ASL. Instead, they report to the governmental authority of the region in which they are located. Legislation by the State (laws #502/1992 and #229/1999) has determined the managerial structure of

[8]Prior to enactment of law #502/1992, there were 659 USLs, which as noted earlier were transformed and consolidated into ASLs. By year 2000, there were 197 ASLs operating in Italy. Consolidation of activities in a smaller number of ASLs likely enabled the *Regioni* to exploit economies of scale by eliminating duplicated administrative tasks among the USLs.

Figure 4.2: Italian Health Care System. Source: Health Care Systems in Transition: Italy, 2001. European Observatory on Health Care Systems.



the AOs. AOs have a corporate structure with a general manager who is appointed by the governor of the Region in which the AO is located. In the typical AO organizational chart, an administrative director, a clinical director, and clinical directorates report to the general manager. Lega (2008) discusses the tradeoffs inherent in this system under the current political environment. Lega argues that the AOs should have clear objectives, and that AOs' general managers require support both within and from outside the hospitals (e.g., to avoid conflicts with leading physicians), and they should not be replaced too frequently[9].

The increased autonomy given to the *Regioni* has led a wide variety of organizational structures and practices for the provision of the health care. For example, the region Abruzzo has developed along the lines of the ASL-centered model, where the ASL receives financial support from *la Regione* on a capitation basis, and negotiates services with accredited public and private providers. In Abruzzo, hospitals remain connected to ASLs; similarly, Marche and Umbria have both reduced the number of AOs operating within their boundaries in recent years. Other *Regioni* have taken a different approach by focusing on the hospitals themselves; for example, Lombardia has given more autonomy to its hospitals, and has the largest number of AOs among the 21 *Regioni.* Despite the differences that have been allowed to develop across the *Regioni,* the State retains substantial control over the health-care system in Italy; for example, the State mandates that any hospital utilizing less than 75 percent of its beds be closed.

Hansmann (1980) suggests that the incentives created by payment systems may have a larger impact on hospital managers' behavior than differences in forms of ownership (e.g., AOs versus OGDs) or corporate structure. The Italian payment system is characterized by a variety of forms that deriving from decentralization and from regional responsibility. Prior to 1992, hospitals' budgets were based on historical cost, but this system has been replaced; hospitals are today reimbursed according to a prospective payment scheme based on Diagnosis Related Groups (DRGs). The new system defines three cost groups, depending on the nature of care that is required for treatment: (i) acute inpatient days; (ii) out-patient visits; and (iii) long-term care. Each of the *Regioni* was given wide latitude in implementing a DRG-based reimbursement scheme, with the result that there is now substantial variation over the 21 *Regioni.* Barbetta et al. (2007) discuss the introduction of this system in Italy but they do not look at the differences

[9] Carbone and Lecci (2006) show that general mangers of AOs have an average tenure as manager of 3.8 years.

between the *Regioni*.

The reforms of the 1990s were made with the idea of leaving the individual *Regioni* free to design their own reimbursement systems within broad guidelines, and to make each of the *Regioni* responsible for controlling healthcare costs within their territories. Hence each Region was, in principle, able to design a system suitable to the particular conditions (e.g., age distribution, urban versus rural, etc.) being faced. Differences among the systems adopted by the *Regioni* can be discussed in terms of three dimensions, as was done by Centro Studi Assobiomedica (2005) and Carbone et al. (2006):

- the specific DRG system that was adopted;
- predominant structure of hospitals within each Region (i.e. AO versus OGD); and
- methods used to monitor and control budgets and operations.

Use of the DRG tables varies across the *Regioni*. All regions reimburse hospitals according to DRG classifications, but regional governments are free to set reimbursement rates for each DRG category. Three different approaches are used among the *Regioni*:

- the "national system," where regions adopt reimbursement rates set at the national level, perhaps with changes for a small number of specific DRGs or perhaps with adjustments to reflect peculiarities across types of hospitals;
- the "weight system" (*metodo dei pesi*), where regions use the coefficients from the original, national DRG tables, but calculate a different (lower) average cost for DRGs;
- the "analytic system," where regions define new reimbursement rates using their own cost analyses.

Regions using the national system adopt reimbursement rates set at the national level, but in some cases reimburse more for a few specific DRGs. In addition, regions have discretion to update the DRG reimbursement rates to reflect the rate of overall price inflation. In the weight system, regions set standard costs of production, but maintain the weights or coefficients in the original DRG tables set at the national level. Consequently, these regions modify average reimbursement rates for patients, but maintain proportions listed in the DRG tables. Regions using the analytic system reimburse hospitals independently of the DRG tables set at the national level. Typically, these regions use analyses of hospital costs in their own territory to create their own reimbursement system.

With regard to the predominant structure of hospitals within a Region, regions may increase or reduce specific reimbursement rates depending on the type of hospital that supplies a given service. Typically, reimbursement rates paid to AOs are higher than those paid to OGDs. This difference is due to the greater complexity and specialization of AOs versus OGDs. Differences in reimbursement rates may also reflect the presence of emergency treatment units or units for specialized treatment in hospitals.

Methods to monitor and control budget and operations concerns the creation or use of mechanisms to prevent over-payment for hospital services. Cantú and Jommi (2002) discuss the risk of an increase in numbers of operations in a system where reimbursements are directly connected to supplied services. Regions may set limits on the number of operations performed in a hospital or for a specific DRG; if a hospital reaches the limit, the corresponding reimbursement rates are reduced. ASLs in a decentralized system) or the *Regioni* (in a centralized system) set the limits and monitor services provided by hospitals.

By now, the *Regioni* have had several years to adapt and modify their systems in response to reforms in the Italian health-care sector. In addition, the Ministry of Health has collected a large amount of data that permits investigation of differences in these responses, performance, etc. across the *Regioni*. Given the substantial variation over the *Regioni* in their response to heath-care reform, it is important for policy-makers at both national and local levels to understand how these responses have translated into performance.

4.3 The Data

Data on Italian public hospitals in 2001 and 2005 were obtained from the Italian Ministry of Health[10]. In in 2001, there were 777 public hospitals providing services to patients in dataset; in 2005, there were 669 public hospitals in dataset. After eliminating observations with missing values, the data I use for estimation include 660 observations for 2001 and 575 observations for 2005.

Table 4.2 shows, for each of the *Regioni*, the numbers of hospitals in each of the four management types represented in our sample for 2001 and 2005: *Aziende Ospedaliere* (AOs), teaching hospitals (THs), non-profit hospitals (NPs), and *Ospedali a Gestione Diretta* (OGDs)[11].

Our specification of inputs and outputs for hospitals is roughly consistent with specifications that have been used in other hospital studies (e.g., see Ancarani et al., 2008; Barbetta et al., 2007; Burgess and Wilson, 1996; Chang et al., 2004; Grosskopf and Valdmanis, 1993 and Grosskopf et al., 2004). In particular, I specify five inputs (physicians, nurses, other employees, outpatient beds, and inpatient beds) and four outputs (number of inpatients, number of outpatients, long-term days, and number of surgical procedures). All inputs and outputs are physical quantities; no reliable price data are available.

The physician input is measured in terms of the number of salaried physicians in each hospital[12]. Similarly, the nursing input is measured by the number of salaried employees working as nurses; other employees are measured as the total number of employees in a hospital, minus numbers of doctors and nurses. Outpatient beds consist of the number of beds for outpatients, while inpatient beds are the number of beds available for treatment of

[10]See http://www.ministerosalute.it/.

[11]Legislation 132/1968 classified some hospitals managed by religious bodies as public hospitals; these hospitals comprise the non-profit hospitals listed in Table 4.2.

[12]In Italy, the *Regioni* have responsibility for remuneration of physicians. Physicians working in hospitals typically receive their salaries from the ASL, AO, or OGD which employs them. This differs somewhat from the situation in the U.S. , where most doctors have a private practice together with loose associations with one or more hospitals where they are permitted to treat patients, but are not typically employees of a hospital (with the exception of physicians working in hospitals operated by the U.S. Department of Veterans Affairs).

Table 4.2: Distribution of Hospital Types over *Regioni*

	2001				2005			
Region	AO	TH	NP	OGD	AO	TH	NP	OGD
North:								
Piemonte	7	1	8	23	8	0	2	20
Valle D'Aosta	0	0	0	1	0	0	0	1
Lombardia	27	16	6	18	29	17	5	1
Bolzano	0	0	0	6	0	0	0	7
Trento	0	0	1	8	0	0	1	6
Veneto	2	0	8	56	2	1	9	23
Friuli Venezia Giulia	3	3	0	11	3	2	0	8
Liguria	3	2	2	15	3	2	2	10
Emilia Romagna	5	1	0	29	5	1	0	20
Central:								
Toscana	4	3	0	28	4	3	1	30
Umbria	2	0	0	7	2	0	0	8
Marche	4	1	0	27	2	1	0	23
Lazio	3	8	7	44	4	10	9	40
South:								
Abruzzo	0	0	0	19	0	0	0	20
Molise	0	1	0	3	0	1	0	6
Campania	8	3	1	37	8	4	3	43
Puglia	6	4	1	46	2	3	2	27
Basilicata	1	0	0	6	2	0	0	6
Calabria	4	0	0	27	4	1	0	26
Sicilia	17	4	0	47	15	4	0	43
Sardegna	1	2	0	22	1	3	0	26
North	47	23	25	167	50	23	19	96
Central	13	12	7	106	12	14	10	101
South	37	14	2	207	32	16	5	197
TOTAL	97	49	34	480	94	53	34	394

inpatients. The number of beds provides a proxy measure for capital, which is otherwise difficult to measure; using beds as a proxy for capital is typical in hospital studies. Separating the bed counts into inpatient and outpatient

Table 4.3: Summary statistics for Inputs and Outputs

	Min	Mean	Median	Max	Std. Dev.
2001 (660 obs.):					
doctors	3.0	143.7	82.0	1501.0	170.2
nurses	8.0	352.0	199.0	2726.0	412.1
other employees	2.0	313.2	154.5	2985.0	410.0
acute beds	1.0	30.1	16.0	269.0	37.6
long-term beds	19.0	305.4	180.0	2310.0	333.3
inpatients	200.5	11470.5	6516.1	91589.4	13349.3
outpatients	1.0	1447.2	789.5	27681.0	2033.1
patient days	868.9	86183.2	44928.9	695155.5	109439.3
operations	15.4	21184.8	11552.9	227128.8	27390.3
2005 (575 obs.):					
doctors	2.0	174.3	104.0	1297.0	189.7
nurses	11.0	387.8	228.0	2872.0	423.0
other employees	1.0	365.3	184.0	3878.0	469.4
acute beds	1.0	37.6	24.0	271.0	41.0
long-term beds	6.0	308.0	200.0	1822.0	309.2
inpatients	169.5	11694.9	7130.5	72711.4	12644.8
outpatients	2.0	1462.0	838.0	44124.0	2420.9
patient days	1447.3	88619.6	50575.6	611537.8	102320.5
operations	3.9	12394.2	6380.7	121550.6	16791.3

categories captures, as far as possible, how hospital managers allocate scarce capital across patients receiving different types of treatment. As discussed earlier in Section 4.2, several regions have included favorable reimbursement rates for treatment of outpatients in an attempt to encourage hospitals to provide more treatment on an outpatient-basis than was previously done.

Output quantities are adjusted by multiplying numbers of inpatients, long-term days and surgical procedures by a hospital case-mix index (CMI) in order to weight output quantities by the severity of the illness treated, or intensity of treatment received. This approach has become standard in the hospital literature; see Grosskopf and Valdmanis (1993) for additional discussion. Table 4.3 gives summary statistics for the input and output quantities for both 2001 and 2005. As in the U.S., the difference in size among Italian hospitals is large, with sizes ranging from 20 to more than 2,000 beds. The distribution of size in both 2001 and 2005 is skewed to the right; i.e., there are relatively large numbers of small hospitals compared to numbers of very large hospitals.

Our choice of the non-parametric, unconditional, hyperbolic α-quantile estimator is motivated in part by the summary statistics in Table 4.3. With highly skewed data, as in our application, parametric specification of translog production or cost functions is problematic. Analyzing U.S. hospital data, Wilson and Carey (2004) found that a translog cost function was trivially rejected by the data[13]. The risk of mis-specifying the response function is avoided by fully non-parametric estimation, but, as noted earlier, DEA and FDH estimators incur the dreaded curse of dimensionality. Our specification of inputs and outputs involves $p + q = 9$ dimensions, resulting in a convergence rate of $n^{-2/(p+q+1)} = n^{-1/5}$ for DEA estimators of efficiency[14]. This is the same convergence rate as that achieved by the Nadarya-Watson kernel estimator and by local-linear estimators in bivariate regression problems (Li and Racine 2007). Although there are several hundred observations in each year, these numbers are likely to small to avoid substantial estimation error if the DEA estimator is used. In addition, DEA estimators are sensitive to outliers. By contrast, the non-parametric, unconditional, hyperbolic α-quantile estimator converges at the classical parametric rate of $n^{-1/2}$, and is robust with respect to outliers.

4.4 Estimation Results

Using α-quantile estimators requires choosing a value for α to define the quantile to be used for benchmarking efficiency, productivity, etc. I initially

[13]A number of studies have discussed mis-specification issues when the translog functional form is used with data displaying wide variation in size of institutions. For Monte Carlo evidence, see Guilkey et al. (1983) and Chalfant and Gallant (1985). For evidence involving consumer demand, see Cooper and McLaren (1996) and Banks et al. (1997). For evidence involving banks, see McAllister and McManus (1993), Mitchell and Onvural (1996), and Wheelock and Wilson (2001). The distribution of bank sizes in the U.S. is similar to the distribution of hospital size in Italy, in that the distribution is characterized by right-skewness.

[14]See Section 1.2.8 for details.

computed contemporaneous efficiency estimates using (1.39) for each hospital in 2001 and 2005 for each $\alpha \in \{0.9,\ 0.925,\ 0.95,\ 0.975,\ 0.99\}$, and compared the efficiency estimates within each year across the five values of α. Figure C.1 shows, for 2005, scatter plots of the contemporaneous efficiency estimates for each of the five values of α plotted against each other. The estimates fall mostly along a 45-degree line in each panel of Figure C.1, indicating that there is little qualitative difference in the choice of α over the range 0.9 to 0.99. Results for 2001 were similar. In addition, I computed estimates of productivity, efficiency, and technology change using the same five values of α, and found no qualitative differences among the results corresponding to the different values of α (see Table 4.4). Consequently, in the remainder of this section I focus on results obtained with $\alpha = 0.95$.

Table 4.4: Malmquist index and decomposition for Italian hospitals. Hyperbolic estimates, 2001-2005.

	$\alpha = 0.9$	$\alpha = 0.95$	$\alpha = 0.97$	$\alpha = 0.99$
Productivity change	1.189	1.183	1.174	1.157
Efficiency change	0.972	0.984	0.982	1.005
Technology change	1.223	1.202	1.195	1.151

For each hospital appearing in our sample for both 2001 and 2005, I computed estimates of the indices defined in (1.41), (1.42), and (1.43), and then used a naive bootstrap (based on resampling from the empirical distributions of input/output vectors in each year) to estimate confidence intervals for the hospital-specific productivity, efficiency change, and technology change indices defined above in Section 1.4.2. For each hospital, I then examine whether the estimated confidence intervals each index lie strictly below 1 (indicating an improvement), include 1 (indicating no statistically significant change), or strictly above 1 (indicating a decrease or worsening).

Table 4.5 shows results for changes in productivity, efficiency, and technology for the northern, central, and southern regions of Italy, as well as for the country as a whole. The results indicate that a majority of hospitals in Italy declined in terms of productivity over 2001–2005, although some hospitals showed improvement in productivity. In total, about 82 percent of

Table 4.5: Numbers of Hospitals Experiencing Changes in Productivity, Efficiency, and Technology, by Region, 2001-2005 (α=0.95)

	Productivity Change	Efficiency Change	Technology Change
North			
decline	117	28	125
no change	15	78	24
improvement	17	43	0
Central			
decline	92	16	105
no change	10	55	13
improvement	16	47	0
South			
decline	171	57	178
no change	7	83	20
improvement	20	58	0
Total			
decline	380	101	408
no change	32	216	57
improvement	53	148	0

Italian hospitals became less productive over the period of our sample, while about 11 percent became more productive. About 78 percent of hospitals in both the northern and central regions became less productive, while about 86 percent of hospitals in the southern regions became less productive.

The results in Table 4.5 also indicate that changes in efficiency among Italian hospitals over 2001–2005 were more modest than the changes in productivity; across the entire country, about 46 percent of hospitals in our sample had no significant change in efficiency. Among hospitals that experienced a statistically significant change in efficiency, about 60 percent showed an improvement in efficiency. Significant improvements outnumber significant declines in efficiency in the northern and central regions, and are roughly even in the southern regions of Italy.

The fourth column of Table 4.5 gives results for changes in technology,

Table 4.6: Numbers of Hospitals Experiencing Changes in Productivity, Efficiency, and Technology, by Hospital Type, 2001-2005 (α=0.95)

	Productivity Change	Efficiency Change	Technology Change
	AO		
decline	73	27	60
no change	10	49	26
improvement	3	10	0
	TH		
decline	32	5	38
no change	4	19	4
improvement	6	18	0
	NP		
decline	21	4	24
no change	2	12	1
improvement	2	9	0
	OGD		
decline	254	65	286
no change	57	157	26
improvement	42	111	0

i.e., shifts in the α-quantile. For the majority of hospitals, the results indicate that the α-quantile shifted downward or inward during 2001–2005; there are no hospitals with a significant improvement, or upward shift of the α-quantile. Conceivably, the full frontier $\mathcal{P}^{t\partial}$ could remain fixed, and the α-quantile could change over time if there was a change in the distribution of efficiency over time. However, a two-sample Kolmogorov-Smirnov test fails to reject the null hypothesis of identical distributions for efficiencies in 2001 and 2005 (the p-value of the test is 0.1343). Moreover, the apparent downward shift in technology is consistent with the other results in Table 4.5; in particular, most hospitals experienced a decline in productivity, meaning that the used more input to produce less output in 2005 as opposed to 2001. At the same time, many hospitals had no significant change in efficiency, and improvements in efficiency were almost evenly balanced by declines in efficiency. This suggests that the technology, as well as the α-quantile, shifted downward, and hospitals roughly matched this shift, leaving efficiency largely unchanged, but resulting in a decline in productivity.

Figures C.2–C.4 give further insight into the changes among Italian hospitals over 2001–2005. In Figure C.2, bootstrap estimates of confidence intervals for the productivity index defined in (1.41) are divided among the northern, central, and southern regions, sorted by their lower bounds, and then plotted in three panels to give an idea of the distribution and magnitudes of the changes in productivity both within regions and across regions. Once again, results for the northern and central regions are similar, but in the southern regions, many of the declines in productivity (indicated by confidence intervals lying entirely above the horizontal line at one on the vertical axis) are larger in magnitude than any declines found in the northern and southern regions.

Figures C.3 and C.4 show similar plots of estimated confidence intervals for efficiency change and technology change, respectively. Figure C.4 reveals that the changes in technology are similar across all regions, but in Figure C.3, it is apparent that hospitals in the southern regions in many cases experienced larger declines in efficiency than in the other regions, consistent with the larger decline in productivity in the southern regions as seen if Figure C.2. Thus, while the change in technology was similar over regions, many hospitals in the southern regions experienced exceptionally large declines in efficiency, resulting in corresponding large declines in productivity over 2001–2005.

Analogous to Table 4.5, Table 4.6 displays numbers of hospitals that experienced significant changes in productivity, efficiency, and technology for the four hospital types represented in our sample. In addition, Figures C.5–C.7 show estimated confidence intervals for changes in productivity, efficiency, and technology by hospital type. The results reveal that changes in technology were broadly similar across hospital types. In addition, changes in productivity and efficiency appear broadly similar across AO, TH, and NP hospitals. However, many OGD hospitals experience substantially larger declines in productivity and efficiency than did hospitals in the other three groups. This is consistent with the distribution of hospital types over the

Regioni shown in Table 4.2; the southern regions have the largest proportion of OGD hospitals.

Finally, Figures C.8–C.10 show estimated confidence intervals for changes in productivity, efficiency, and technology as measured by the indices defined in (1.41)–(1.43) by region and hospital type. As in previous Figures, the estimated confidence intervals in each panel are sorted by their lower bounds. There are relatively few teaching and non-profit hospitals in the southern regions. However, among AO as well as OGD hospitals, Figures C.8 and C.9 show that the largest declines in productivity and efficiency among hospitals in the southern regions are larger in magnitude than the declines in productivity and efficiency among AO and OGD hospitals in the northern and central regions. In other words, these results suggest that the apparent poor performance of hospitals in the southern regions are not merely a consequence of the fact that relatively more OGD hospitals are located in the south than in the northern and central regions; i.e., both AO and OGD hospitals in the south experienced substantial declines in productivity and efficiency. On the other hand, with regard to changes in technology, Figure C.10 confirms the earlier observations; i.e., technology seems to have declined similarly across both hospital types as well as regions.

Conclusions

This thesis showed several methods to measure the productivity and the efficiency. Its aim was to present these methods and to show how these can be used in several industry sectors. In particular, I presented an application of the *Tornqvist* index numbers to measure the total factor productivity of Alitalia, the main Italian airline (Chapter 2); a study of Italian airport sector with the use of bootstrapped-dea (Chapter 3); and an investigation of the efficiency of public Italian hospitals using a hyperbolic, α-quantile estimator (Chapter 4).

The *Tornqvist* index numbers (Section 1.5) are commmon in the study of productivity and they have a great variety of applications. Their drawback concers the required data, given that they require information on price and quantity for each input and output.

In the studies of efficiency, the DEA (Section 1.2) is become a very common methodology. DEA is a nonparametric tecnique and its large use is due to potential simplicity, given that no specification on the functional form of frontier. Althought its large use due to potential simplicity, its statistical properties and its basic assumptions are not often considered and this is source of mistake (Section 1.2.1). In the last years, the statistical properties of DEA were investigated (Section 1.2.8) and now we can use the boostrap to do inference on efficiency estimates (Section 1.3).

Further, recently, a "family" of nonparametric estimators was developed: the partial frontiers (Section 1.4). Their aim is to overcome to two main problems of DEA estimator: the curse of dimesionality and the sensitive to outliers. Indeed, the partial frontiers do not envelop all data point and are more robust to outlier and gain a rate of convergence equal to root-n.

The applications show how to apply these methods and discuss the economic implication of the results. The empirical evidence shows as the Alitalia productivity slowdown has been caused by the company failure to follow a supply-oriented strategy once expanded its inputs. Company privatization and consolidation of domestic market seems the only solution.

In the Italian airport industry, the analysis highlights a very diversified airports portfolio, characterized by constant return to scale technology and heterogeneous benchmarks. Looking at the political implications, the empirical evidences show as the institutional changes, which have deeply modified the governance structures of the Italian airports, have generated increase in efficiency. However, this improvement manly relies on the non core airports business activities. Thus, while Italian airport management companies have taken the opportunity of the new business they are still working on improving efficiency of the core activities, a crucial aspect of the entire system since its huge impact on the air transport service and consumers.

In the study of public Italian hospital sector, we find evidence of decreased productivity over the sample period, as well as declines in production possibilities (i.e., technology); the poor performance appears especially pronounced in the southern regions of Italy.

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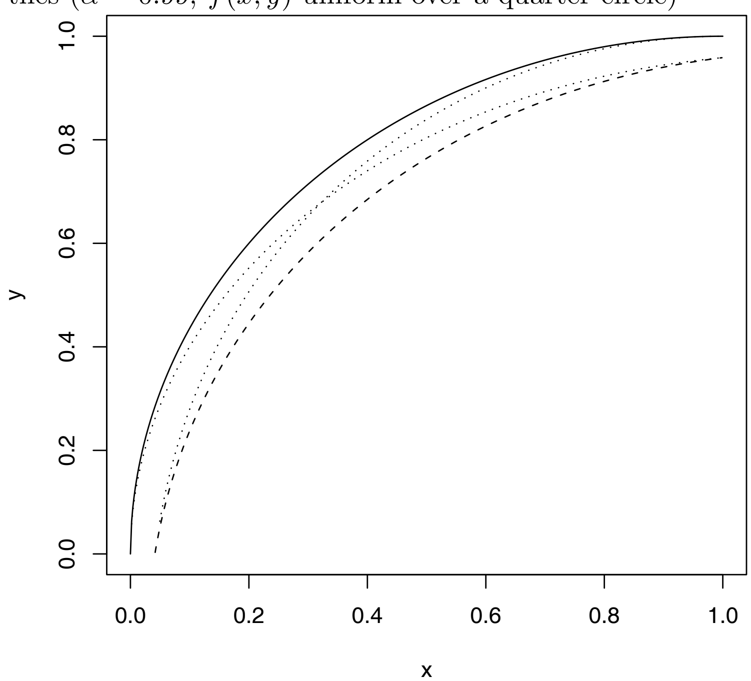
Appendix A

Figure A.1: Conditional Input, Conditional Output, and Hyperbolic Quantiles ($\alpha = 0.99$; $f(x, y)$ uniform over a quarter-circle)



NOTE: The solid curve shows the frontier $\mathcal{P}^{\partial}$. The dashed curve illustrates the hyperbolic α quantile $\mathcal{P}^{\partial}_{\alpha}$. The two dotted curves show conditional α-quantiles; the steeper of the two is the input conditional α-quantile, while the less-steeply sloped dotted curve corresponds to the output conditional α-quantile.

Appendix B

Table B.1: Definition of Inputs and Output (Physical Model)

Variable code	*Type of variable*	*Description*
In1	Input 1	Number of employees
In2	Input 2	Number of runways
In3	Input 3	Apron area
Ou1	Output 1	Number of passengers
Ou2	Output 2	Amount of cargos
Ou3	Output 3	Number of movements

Table B.2: Definition of Inputs and Output (Revenue Model)

Variable code	*Type of variable*	*Description*
In1	Input 1	Labor costs
In2	Input 2	Soft Costs
In3	Input 3	Airport size
Ou1	Output 1	Aeronautical Revenue
Ou2	Output 2	Non aeronautical Revenue

Table B.3: Correlation matrices (Physical Model)

2000	In1	In2	In3	Ou1	Ou2	Ou3
In1	1					
In2	0.821	1				
In3	0.973	0.863	1			
Ou1	0.933	0.916	0.952	1		
Ou2	0.96	0.878	0.965	0.931	1	
Ou3	0.942	0.909	0.961	0.996	0.945	1

2001	In1	In2	In3	Ou1	Ou2	Ou3
In1	1					
In2	0.73	1				
In3	0.983	0.8	1			
Ou1	0.868	0.898	0.923	1		
Ou2	0.953	0.831	0.978	0.914	1	
Ou3	0.902	0.877	0.95	0.994	0.941	1

2002	In1	In2	In3	Ou1	Ou2	Ou3
In1	1					
In2	0.831	1				
In3	0.985	0.812	1			
Ou1	0.944	0.901	0.923	1		
Ou2	0.961	0.82	0.958	0.89	1	
Ou3	0.953	0.885	0.941	0.996	0.909	1

2003	In1	In2	In3	Ou1	Ou2	Ou3
In1	1					
In2	0.942	1				
In3	0.911	0.831	1			
Ou1	0.992	0.931	0.921	1		
Ou2	0.876	0.816	0.954	0.876	1	
Ou3	0.989	0.926	0.933	0.997	0.89	1

2004	In1	In2	In3	Ou1	Ou2	Ou3
In1	1					
In2	0.947	1				
In3	0.919	0.831	1			
Ou1	0.991	0.937	0.911	1		
Ou2	0.89	0.824	0.954	0.87	1	
Ou3	0.988	0.931	0.928	0.997	0.886	1

Table B.4: Correlation matrices (Revenue Model)

2000	In1	In2	In3	Ou1	Ou2
In1	1				
In2	0.9019	1			
In3	0.9354	0.9829	1		
Ou1	0.9969	0.924	0.9482	1	
Ou2	0.8764	0.9967	0.9772	0.8987	1

2001	In1	In2	In3	Ou1	Ou2
In1	1				
In2	0.9019	1			
In3	0.9354	0.9829	1		
Ou1	0.9969	0.924	0.9482	1	
Ou2	0.8764	0.9967	0.9772	0.8987	1

2002	In1	In2	In3	Ou1	Ou2
In1	1				
In2	0.9499	1			
In3	0.9277	0.9843	1		
Ou1	0.9825	0.9902	0.9736	1	
Ou2	0.9237	0.9947	0.989	0.9764	1

2003	In1	In2	In3	Ou1	Ou2
In1	1				
In2	0.9932	1			
In3	0.9822	0.9846	1		
Ou1	0.9976	0.9958	0.9871	1	
Ou2	0.9913	0.9979	0.9875	0.9932	1

2004	In1	In2	In3	Ou1	Ou2
In1	1				
In2	0.9938	1			
In3	0.9812	0.9818	1		
Ou1	0.9963	0.9966	0.9874	1	
Ou2	0.9902	0.9955	0.9888	0.9933	1

Table B.5: Input and Output Factors (Physical Model).

	2000	2001	2002	2003	2004
α_1	0.726	0.724	0.681	-0.62	0.618
α_2	0.35	0.310	0.368	-0.423	0.426
α_3	0.592	0.616	0.634	-0.661	0.661
β_1	0.577	0.565	-0.562	0.551	0.548
β_2	0.641	0.647	-0.653	0.661	0.658
β_3	0.506	0.512	-0.508	0.510	0.516

Table B.6: Input and Output Factors (Revenue Model).

	2000	2001	2002	2003	2004
α_1	-0.653	-0.673	-0.638	0.598	0.602
α_2	-0.604	-0.577	-0.594	0.605	0.594
α_3	-0.457	-0.464	-0.49	0.526	0.534
β_1	0.659	0.677	0.658	0.656	0.659
β_2	0.752	0.736	0.753	0.755	0.752

Table B.7: Tests of Return to Scale: p-values (H_0: technology is globally CRS; $H1$: technology is VRS).

p-value	2000	2001	2002	2003	2004
Physical model	0.456	0.279	0.331	0.231	0.244
Revenue Model	0.12	0.072	0.077	0.085	0.078

Table B.8: Original and bias-corrected DEA estimates, Physical model; $h_{cv} = 0.692$, Year 2000.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.288	0.259	0.029	0.028	1.047	0.228	0.287
AOI	0.442	0.397	0.045	0.043	1.048	0.35	0.44
BGY	1.000	0.899	0.101	0.097	1.046	0.792	0.997
BLQ	0.927	0.833	0.094	0.09	1.047	0.734	0.924
CTA	0.778	0.699	0.079	0.075	1.046	0.616	0.776
GOA	0.226	0.203	0.023	0.022	1.047	0.179	0.225
SUF	0.255	0.229	0.026	0.025	1.046	0.202	0.255
LIN_MXP	0.599	0.539	0.061	0.058	1.047	0.475	0.598
NAP	0.929	0.835	0.094	0.09	1.047	0.736	0.927
PMO	0.437	0.393	0.044	0.042	1.048	0.346	0.436
PSR	0.208	0.187	0.021	0.02	1.05	0.165	0.207
PSA	0.357	0.321	0.036	0.035	1.047	0.283	0.356
CIA_FCO	0.796	0.715	0.081	0.077	1.047	0.63	0.793
TRN	0.608	0.546	0.062	0.059	1.047	0.481	0.606
VCE	0.551	0.495	0.056	0.053	1.047	0.436	0.549
VRN	0.591	0.531	0.060	0.057	1.047	0.468	0.59
Mean	0.500	0.449					
Dev. Std.	0.264	0.237					

Table B.9: Original and bias-corrected DEA estimates, Physical model; $h_{cv} = 0.776$, Year 2001.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.302	0.27	0.032	0.03	1.067	0.238	0.301
AOI	0.434	0.388	0.046	0.043	1.067	0.342	0.433
BGY	1.000	0.894	0.106	0.099	1.066	0.788	0.997
BLQ	0.771	0.689	0.082	0.077	1.067	0.608	0.769
CTA	0.789	0.705	0.084	0.078	1.067	0.621	0.786
GOA	0.29	0.259	0.031	0.029	1.068	0.228	0.289
SUF	0.173	0.155	0.018	0.017	1.072	0.136	0.173
LIN_MXP	0.551	0.492	0.058	0.055	1.068	0.434	0.549
NAP	0.996	0.89	0.106	0.099	1.067	0.785	0.993
PMO	0.451	0.403	0.048	0.045	1.068	0.355	0.45
PSR	0.203	0.181	0.022	0.020	1.07	0.16	0.202
PSA	0.404	0.361	0.043	0.04	1.068	0.318	0.403
CIA_FCO	0.913	0.816	0.097	0.091	1.067	0.719	0.91
TRN	0.668	0.597	0.071	0.066	1.066	0.526	0.666
VCE	0.556	0.497	0.059	0.055	1.067	0.438	0.555
VRN	0.61	0.546	0.065	0.061	1.067	0.481	0.608
Mean	0.503	0.45					
Dev. Std.	0.269	0.241					

Table B.10: Original and bias-corrected DEA estimates, Physical model; $h_{cv} = 1.124$, Year 2002.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.266	0.229	0.037	0.035	1.054	0.2	0.265
AOI	0.400	0.345	0.055	0.053	1.053	0.300	0.398
BGY	1.000	0.862	0.138	0.131	1.052	0.751	0.996
BLQ	0.627	0.541	0.087	0.082	1.053	0.471	0.625
CTA	0.570	0.491	0.079	0.075	1.052	0.428	0.568
GOA	0.269	0.232	0.037	0.035	1.054	0.202	0.268
SUF	0.166	0.143	0.023	0.022	1.052	0.125	0.165
LIN_MXP	0.633	0.545	0.087	0.083	1.053	0.475	0.630
NAP	0.918	0.791	0.127	0.12	1.052	0.689	0.914
PMO	0.401	0.346	0.055	0.053	1.053	0.301	0.400
PSR	0.231	0.199	0.032	0.03	1.054	0.173	0.230
PSA	0.340	0.293	0.047	0.045	1.053	0.255	0.338
CIA_FCO	0.792	0.682	0.109	0.104	1.052	0.594	0.788
TRN	0.730	0.629	0.101	0.096	1.052	0.548	0.727
VCE	0.406	0.350	0.056	0.053	1.053	0.305	0.405
VRN	0.428	0.369	0.059	0.056	1.052	0.322	0.426
Mean	0.453	0.390					
Dev.Std.	0.252	0.217					

Table B.11: Original and bias-corrected DEA estimates, Physical model; $h_{cv} = 1.234$, Year 2003.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.209	0.175	0.034	0.032	1.065	0.154	0.208
AOI	0.316	0.265	0.051	0.048	1.064	0.232	0.315
BGY	1.000	0.838	0.162	0.152	1.063	0.734	0.996
BLQ	0.623	0.522	0.101	0.095	1.064	0.457	0.620
CTA	0.537	0.45	0.087	0.082	1.063	0.394	0.535
GOA	0.236	0.197	0.038	0.036	1.064	0.173	0.235
SUF	0.225	0.188	0.037	0.034	1.066	0.165	0.224
LIN_MXP	0.738	0.618	0.12	0.112	1.063	0.541	0.734
NAP	0.71	0.595	0.115	0.108	1.063	0.521	0.707
PMO	0.299	0.251	0.049	0.046	1.064	0.22	0.298
PSR	0.177	0.149	0.029	0.027	1.063	0.130	0.177
PSA	0.311	0.261	0.050	0.047	1.063	0.228	0.310
CIA_FCO	0.689	0.577	0.112	0.105	1.063	0.505	0.686
TRN	0.585	0.49	0.095	0.089	1.063	0.429	0.582
VCE	0.418	0.35	0.068	0.064	1.064	0.306	0.416
VRN	0.391	0.328	0.063	0.060	1.064	0.287	0.389
Mean	0.411	0.345					
Dev. Std.	0.239	0.200					

Table B.12: Original and bias-corrected DEA estimates, Physical model; $h_{cv} = 1.151$, Year 2004.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.225	0.19	0.035	0.034	1.032	0.166	0.224
AOI	0.325	0.275	0.05	0.049	1.031	0.24	0.324
BGY	1.000	0.846	0.154	0.150	1.03	0.738	0.996
BLQ	0.598	0.505	0.092	0.090	1.031	0.441	0.595
CTA	0.56	0.474	0.087	0.084	1.031	0.414	0.558
GOA	0.223	0.189	0.035	0.033	1.033	0.165	0.222
SUF	0.213	0.180	0.033	0.032	1.031	0.157	0.212
LIN_MXP	0.763	0.645	0.118	0.114	1.031	0.563	0.760
NAP	0.672	0.568	0.104	0.101	1.031	0.496	0.669
PMO	0.289	0.244	0.045	0.043	1.032	0.213	0.287
PSR	0.185	0.156	0.029	0.028	1.031	0.137	0.184
PSA	0.319	0.270	0.049	0.048	1.032	0.236	0.318
CIA_FCO	0.747	0.632	0.115	0.112	1.031	0.552	0.744
TRN	0.603	0.510	0.093	0.090	1.031	0.445	0.60
VCE	0.459	0.388	0.071	0.069	1.032	0.339	0.457
VRN	0.405	0.342	0.063	0.061	1.032	0.299	0.403
Mean	0.417	0.353					
Dev. Std.	0.242	0.204					

Table B.13: Original and bias-corrected DEA estimates, Revenue model; $h_{cv} = 0.499$, Year 2000.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.175	0.162	0.012	0.012	1.046	0.146	0.174
AOI	0.652	0.607	0.045	0.043	1.043	0.545	0.650
BGY	0.708	0.659	0.049	0.047	1.043	0.591	0.707
BLQ	0.927	0.863	0.064	0.061	1.043	0.774	0.925
CTA	0.466	0.434	0.032	0.031	1.044	0.389	0.465
GOA	0.673	0.627	0.047	0.045	1.044	0.563	0.672
SUF	0.290	0.270	0.020	0.019	1.046	0.243	0.290
LIN_MXP	0.864	0.805	0.060	0.057	1.043	0.722	0.863
NAP	0.843	0.785	0.058	0.056	1.044	0.704	0.841
PMO	0.684	0.637	0.047	0.045	1.045	0.571	0.683
PSR	0.139	0.13	0.010	0.009	1.043	0.116	0.139
PSA	0.432	0.402	0.030	0.029	1.044	0.361	0.431
CIA_FCO	1.000	0.931	0.069	0.066	1.043	0.836	0.998
TRN	0.708	0.659	0.049	0.047	1.044	0.592	0.707
VCE	0.785	0.730	0.054	0.052	1.043	0.655	0.783
VRN	0.571	0.532	0.039	0.038	1.043	0.477	0.570
Mean	0.547	0.509					
Dev. Std.	0.258	0.240					

Table B.14: Original and bias-corrected DEA estimates, Revenue model; $h_{cv} = 0.626$, Year 2001.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.168	0.153	0.015	0.014	1.041	0.136	0.168
AOI	0.462	0.422	0.040	0.038	1.038	0.374	0.461
BGY	0.548	0.500	0.047	0.046	1.038	0.444	0.547
BLQ	0.808	0.738	0.07	0.067	1.038	0.655	0.806
CTA	0.514	0.47	0.044	0.043	1.037	0.417	0.513
GOA	0.747	0.683	0.065	0.062	1.038	0.606	0.746
SUF	0.276	0.252	0.024	0.023	1.038	0.224	0.275
LIN_MXP	0.766	0.700	0.066	0.064	1.037	0.621	0.764
NAP	0.709	0.648	0.061	0.059	1.039	0.575	0.707
PMO	0.619	0.566	0.054	0.052	1.037	0.502	0.618
PSR	0.144	0.132	0.012	0.012	1.039	0.117	0.144
PSA	0.425	0.388	0.037	0.035	1.039	0.345	0.424
CIA_FCO	1.000	0.914	0.086	0.083	1.037	0.811	0.998
TRN	0.714	0.652	0.062	0.06	1.038	0.579	0.713
VCE	0.746	0.681	0.065	0.062	1.038	0.605	0.744
VRN	0.551	0.503	0.048	0.046	1.038	0.447	0.550
Mean	0.512	0.467					
Dev. Std.	0.238	0.218					

Table B.15: Original and bias-corrected DEA estimates, Revenue model; $h_{cv} = 0.553$, Year 2002.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.271	0.249	0.021	0.020	1.074	0.223	0.270
AOI	0.404	0.372	0.032	0.030	1.071	0.332	0.403
BGY	0.525	0.484	0.041	0.039	1.070	0.432	0.524
BLQ	0.792	0.729	0.062	0.058	1.069	0.651	0.790
CTA	0.596	0.549	0.047	0.044	1.069	0.49	0.595
GOA	0.674	0.621	0.053	0.050	1.070	0.554	0.673
SUF	0.311	0.287	0.025	0.023	1.072	0.256	0.311
LIN_MXP	0.822	0.757	0.065	0.061	1.070	0.676	0.820
NAP	0.763	0.703	0.060	0.056	1.069	0.628	0.761
PMO	0.646	0.595	0.051	0.048	1.071	0.532	0.645
PSR	0.285	0.262	0.023	0.021	1.071	0.234	0.284
PSA	0.450	0.414	0.036	0.033	1.071	0.37	0.449
CIA_FCO	1.000	0.921	0.079	0.074	1.069	0.822	0.998
TRN	0.706	0.65	0.056	0.052	1.07	0.581	0.705
VCE	0.696	0.641	0.055	0.051	1.07	0.573	0.695
VRN	0.529	0.487	0.042	0.039	1.071	0.435	0.528
Mean	0.553	0.51					
Dev. Std.	0.21	0.194					

Table B.16: Original and bias-corrected DEA estimates, Revenue model; $h_{cv} = 0.432$, Year 2003.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.267	0.25	0.016	0.016	1.038	0.227	0.266
AOI	0.418	0.393	0.026	0.025	1.037	0.355	0.417
BGY	0.667	0.626	0.041	0.039	1.034	0.567	0.666
BLQ	0.853	0.801	0.052	0.050	1.033	0.725	0.852
CTA	0.619	0.581	0.038	0.036	1.035	0.526	0.618
GOA	0.686	0.644	0.042	0.040	1.035	0.583	0.684
SUF	0.385	0.361	0.023	0.023	1.035	0.327	0.384
LIN_MXP	0.992	0.931	0.06	0.058	1.035	0.843	0.990
NAP	0.821	0.771	0.05	0.048	1.034	0.698	0.82
PMO	0.715	0.672	0.044	0.042	1.034	0.608	0.714
PSR	0.335	0.314	0.02	0.02	1.034	0.285	0.334
PSA	0.485	0.455	0.03	0.029	1.034	0.412	0.484
CIA_FCO	1.000	0.939	0.061	0.059	1.033	0.85	0.999
TRN	0.764	0.717	0.047	0.045	1.035	0.649	0.763
VCE	0.868	0.815	0.053	0.051	1.033	0.737	0.866
VRN	0.601	0.565	0.037	0.035	1.034	0.511	0.601
Mean	0.612	0.575					
Dev. Std.	0.228	0.214					

Table B.17: Original and bias-corrected DEA estimates, Revenue model; $h_{cv} = 0.518$, Year 2004.

Airport Code	Eff. Scores	Eff. Bias-Corrected Scores	Bias	Std	μ	LB	UB
AHO	0.297	0.276	0.02	0.020	1.046	0.247	0.296
AOI	0.447	0.416	0.031	0.030	1.045	0.372	0.446
BGY	0.650	0.605	0.045	0.043	1.044	0.542	0.649
BLQ	0.726	0.676	0.05	0.048	1.044	0.605	0.725
CTA	0.59	0.55	0.041	0.039	1.043	0.492	0.589
GOA	0.578	0.538	0.040	0.038	1.044	0.481	0.577
SUF	0.355	0.330	0.024	0.023	1.044	0.296	0.354
LIN_MXP	0.972	0.905	0.067	0.064	1.042	0.810	0.970
NAP	0.792	0.737	0.055	0.052	1.043	0.660	0.790
PMO	0.700	0.651	0.048	0.046	1.043	0.583	0.698
PSR	0.322	0.299	0.022	0.021	1.043	0.268	0.321
PSA	0.459	0.428	0.032	0.030	1.045	0.383	0.458
CIA_FCO	1.000	0.931	0.069	0.066	1.042	0.833	0.998
TRN	0.782	0.728	0.054	0.052	1.043	0.651	0.780
VCE	0.850	0.791	0.059	0.056	1.044	0.708	0.848
VRN	0.585	0.545	0.04	0.039	1.042	0.487	0.584
Mean	0.593	0.552					
Dev. Std.	0.219	0.204					

Figure B.1: The Italian airport system : AO level

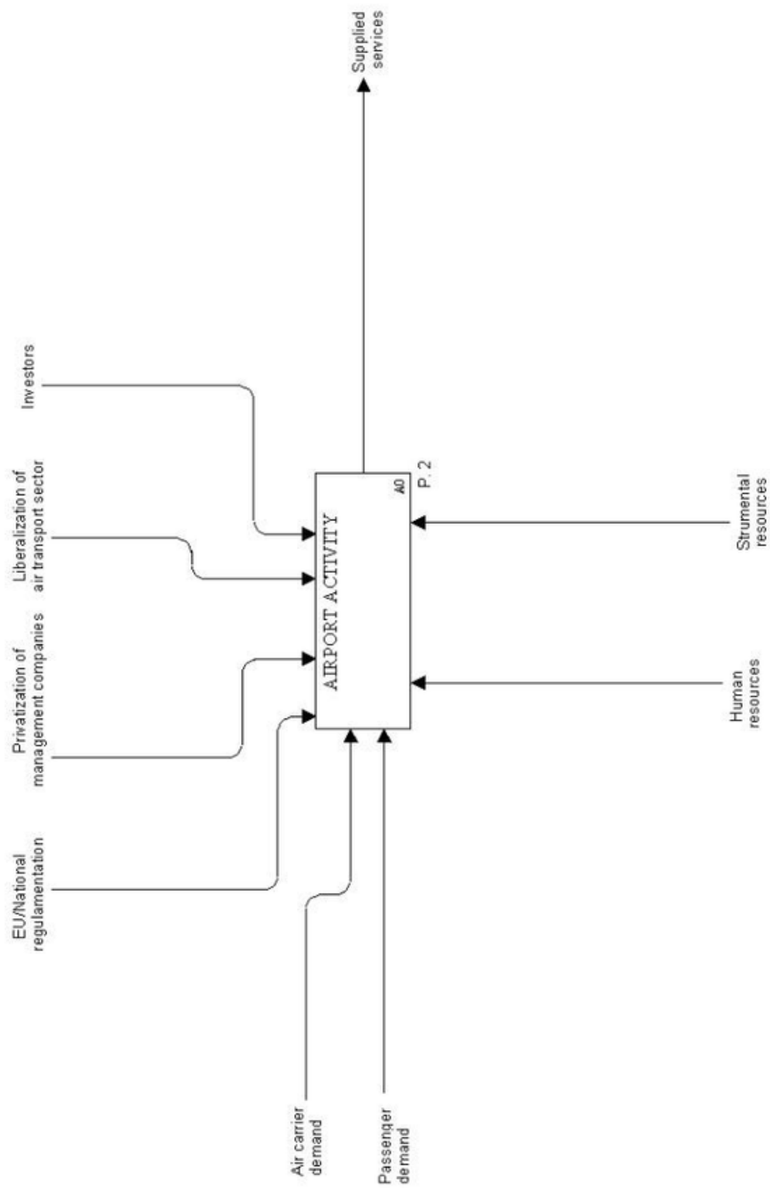


Figure B.2: The Italian airport system : A1 and A2 level

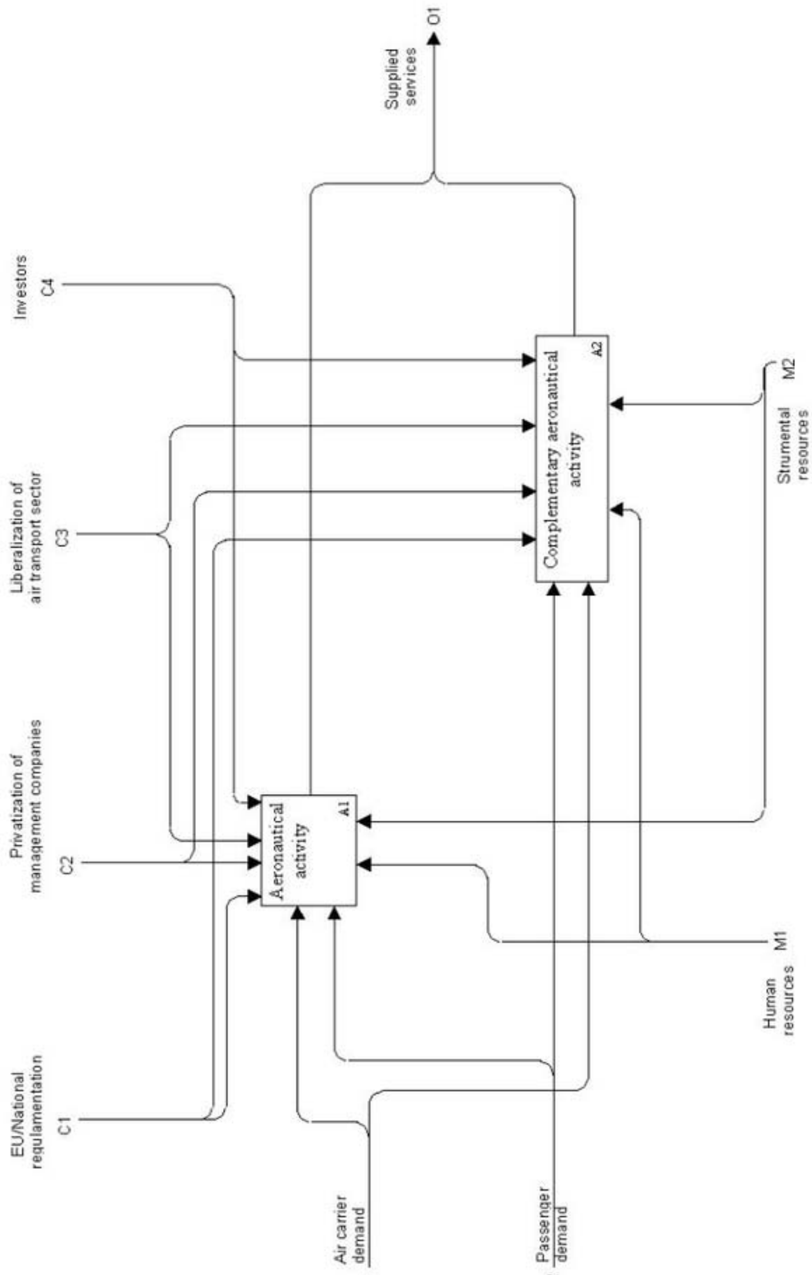


Figure B.3: Boxplot of the Bootstrapped Efficiency Scores (Physical Model).

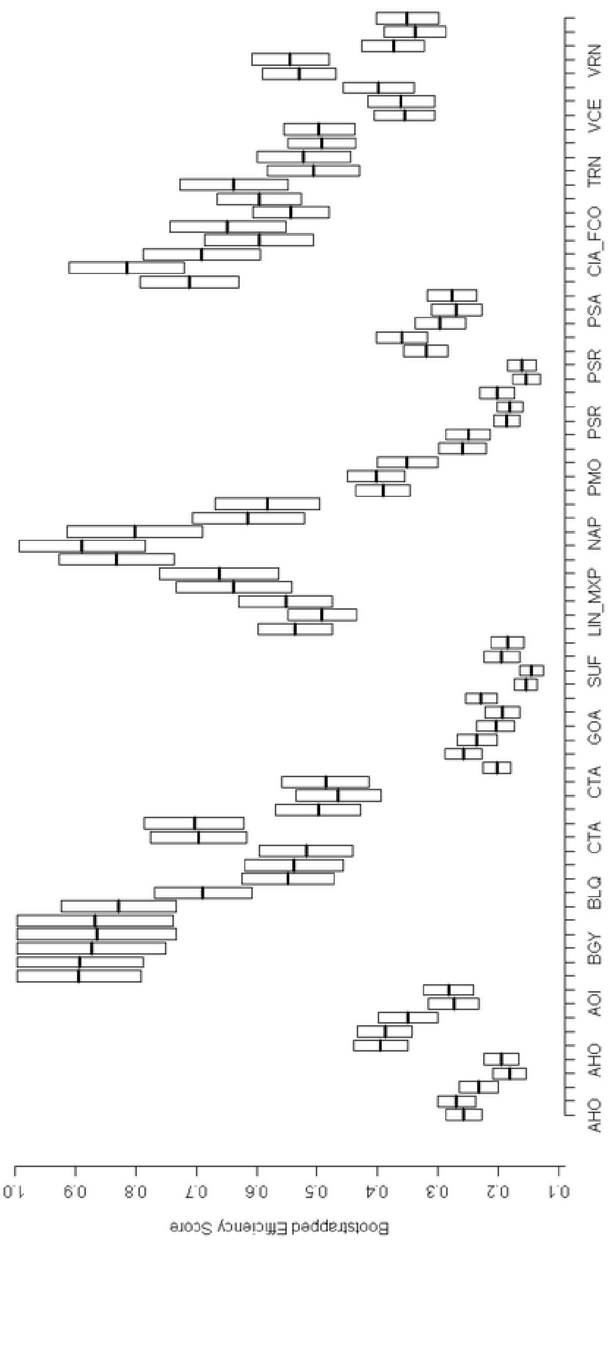
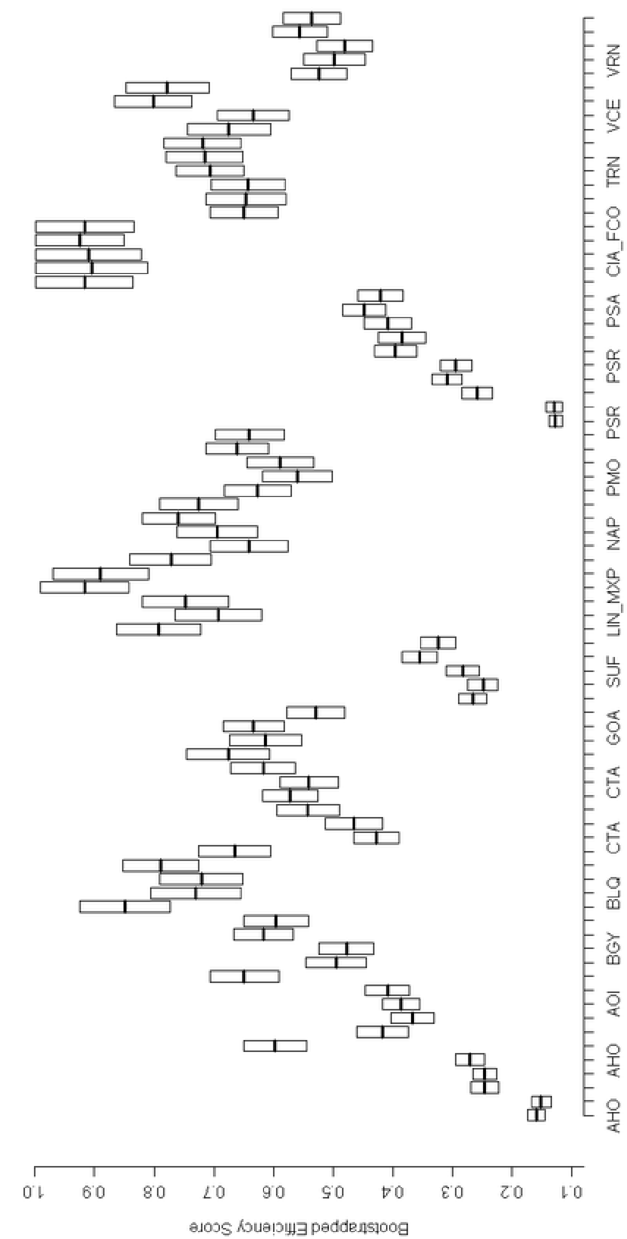


Figure B.4: Boxplot of the Bootstrapped Efficiency Scores (Revenue Model).



Appendix C

Table C.1: Malmquist index and decomposition by region. 2001-2005, $\alpha = 0.99$.

REGION	n obs	Productivity change	Efficiency change	Technology change
ABRUZZO	19	1.241	1.065	1.165
BASILICATA	7	1.447	1.221	1.185
BOLZANO	6	1.307	1.114	1.173
CALABRIA	26	1.251	1.073	1.165
CAMPANIA	45	1.210	1.050	1.153
EMILIA ROMAGNA	25	1.092	0.959	1.139
FRIULI	12	1.219	1.029	1.184
LAZIO	57	1.071	0.940	1.139
LIGURIA	16	1.019	0.933	1.093
LOMBARDIA	46	1.129	0.973	1.160
MARCHE	24	1.099	0.939	1.170
MOLISE	3	1.946	1.633	1.192
PIEMONTE	25	1.037	0.962	1.078
PUGLIA	12	1.179	0.974	1.210
SARDEGNA	24	1.142	0.996	1.146
SICILIA	62	1.222	1.042	1.172
TOSCANA	30	1.180	1.017	1.161
TRENTO	6	1.173	1.075	1.091
UMBRIA	7	1.168	1.119	1.044
VALLE AOSTA	1	1.106	1.039	1.065
VENETO	12	1.062	0.903	1.176
NORD	149	1.104	0.973	1.135
CENTRO	118	1.109	0.969	1.145
MEZZOGIORNO	198	1.228	1.053	1.166
ITALY	465	1.157	1.005	1.151

Table C.2: Number of hospitals with improvement, no change and decline of productivity, efficiency change and technology change by region. $\alpha = 0.99$.

	Productivity change			Efficiency change			Technology change		
Region	improvement $M < 1$	no change $M = 1$	decline $M > 1$	improvement $M < 1$	no change $M = 1$	decline $M > 1$	improvement $M < 1$	no change $M = 1$	decline $M > 1$
North:									
Piemonte	8	5	12	10	11	4	0	13	12
Valle D'Aosta	0	0	1	0	1	0	0	0	1
Lombardia	1	10	35	7	33	6	0	26	70
Bolzano	0	0	6	0	4	2	0	4	2
Trento	0	1	5	0	6	0	0	2	4
Veneto	2	2	8	3	9	0	0	4	8
Friuli	0	1	11	2	9	1	0	2	10
Liguria	3	0	13	4	9	3	0	7	9
Emilia Romagna	3	7	15	9	15	1	0	8	17
Central:									
Toscana	0	5	25	12	13	5	0	7	23
Umbria	0	1	6	0	2	5	0	7	0
Marche	3	7	14	6	17	1	0	9	15
Lazio	10	5	42	18	36	3	0	21	36
South:									
Abruzzo	1	3	15	1	14	4	0	6	13
Molise	0	0	3	0	1	2	0	1	2
Campania	7	1	37	13	21	11	0	17	28
Puglia	2	1	9	3	7	2	0	2	10
Basilicata	0	0	7	1	3	3	0	2	5
Calabria	1	3	22	5	17	4	0	12	14
Sicilia	6	4	52	10	40	12	0	15	47
Sardegna	3	3	18	6	16	2	0	12	12
North	17	26	106	35	97	17	0	66	83
Central	13	18	87	36	68	14	0	44	74
South	20	15	163	39	119	40	0	67	131
TOTAL	50	59	356	110	284	71	0	177	288

Figure C.1: Comparison of Efficiency Estimates for Various Values of α (2005)

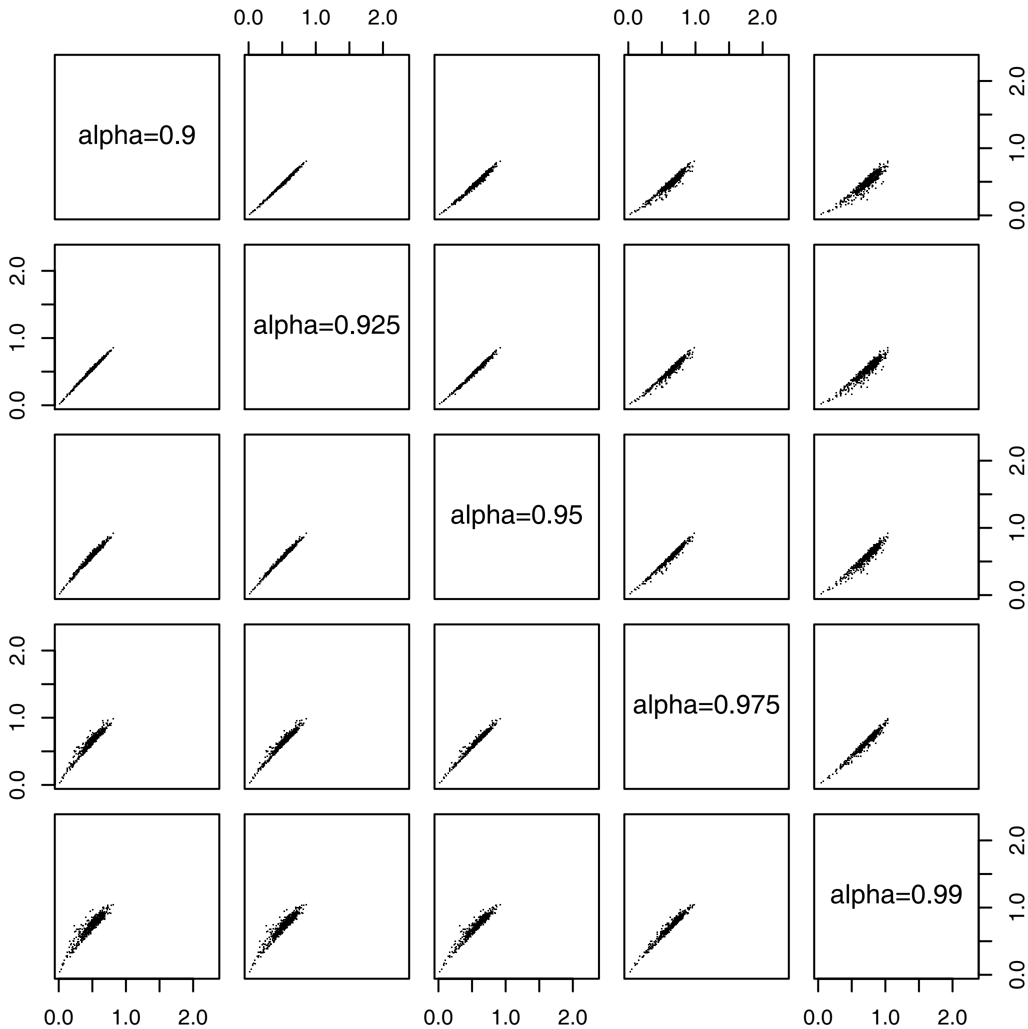


Figure C.2: Estimated Productivity Change, 2001–2005, by Region ($\alpha = 0.95$)

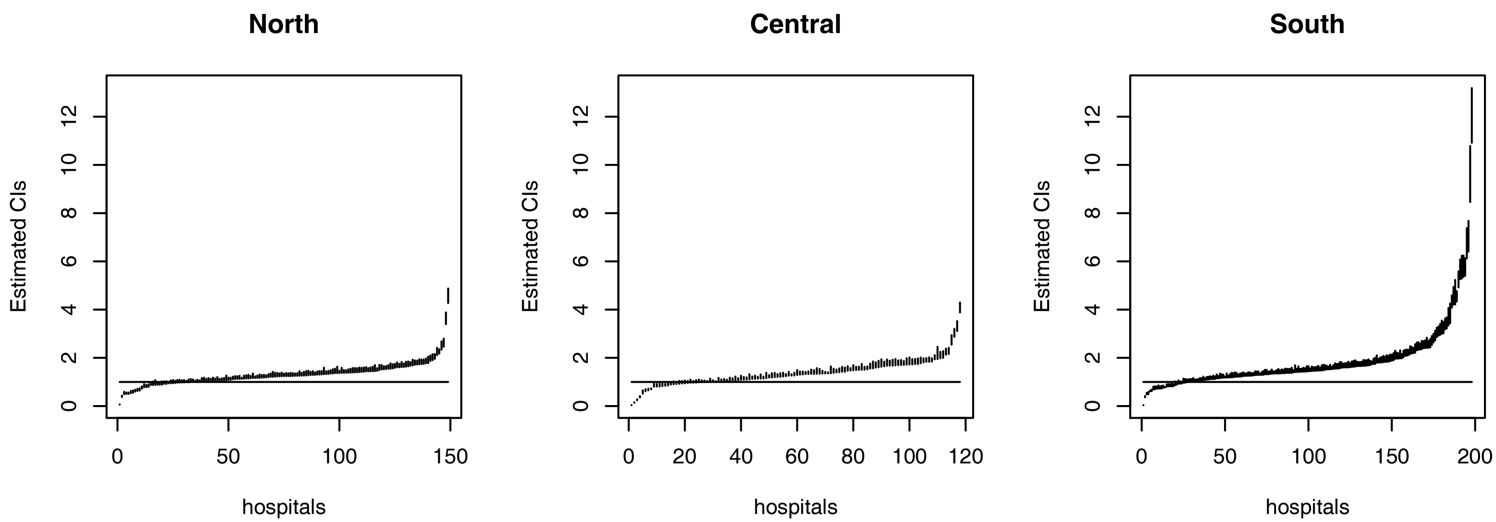


Figure C.3: Estimated Efficiency Change, 2001–2005, by Region ($\alpha = 0.95$)

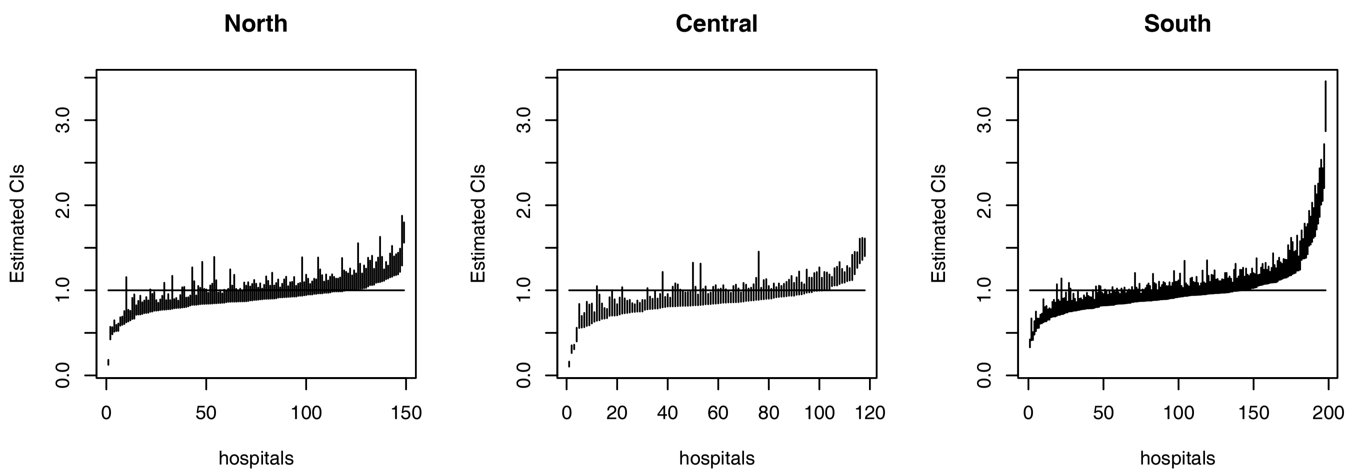


Figure C.4: Estimated Technology Change, 2001–2005, by Region ($\alpha = 0.95$)

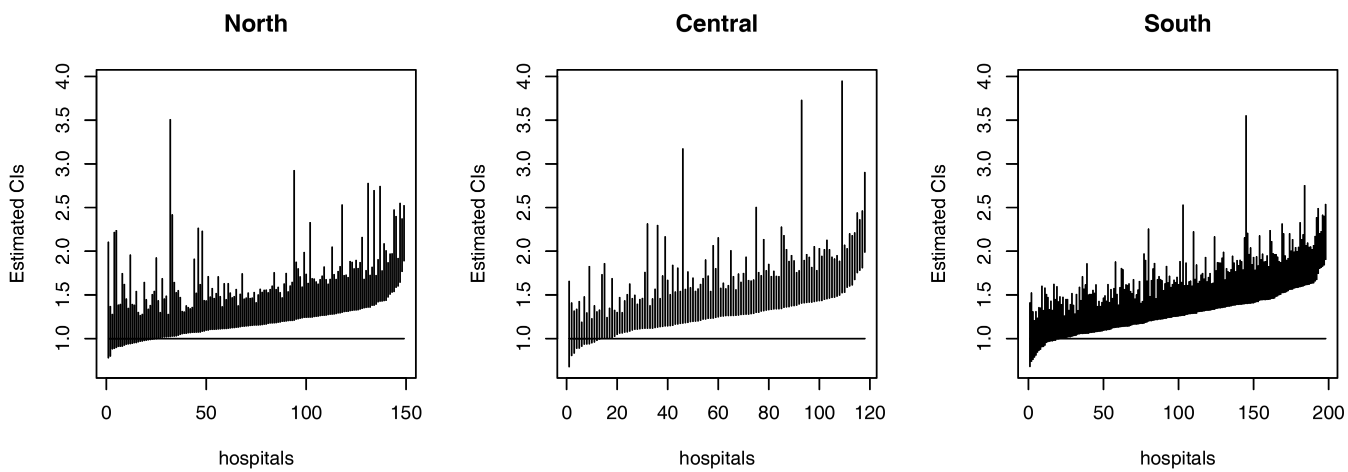


Figure C.5: Estimated Productivity Change, 2001–2005, by Hospital Type ($\alpha = 0.95$)

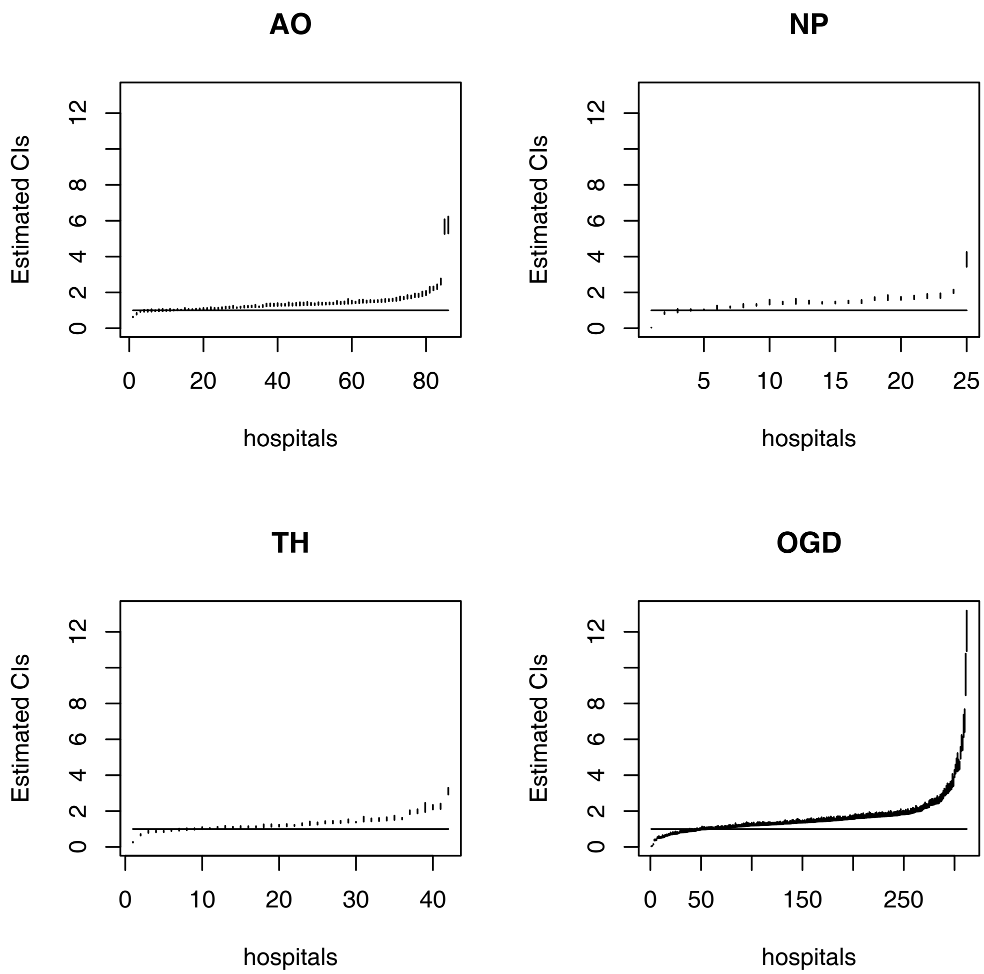


Figure C.6: Estimated Efficiency Change, 2001–2005, by Hospital Type ($\alpha = 0.95$)

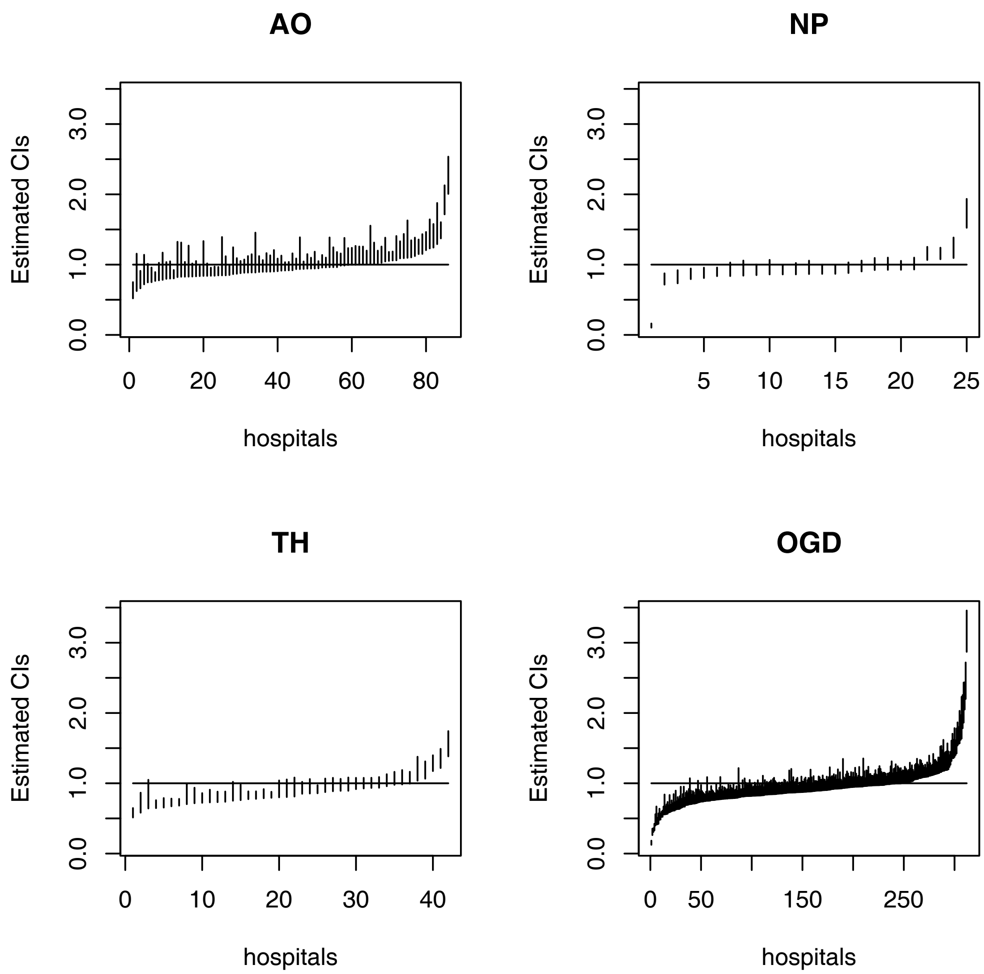


Figure C.7: Estimated Technology Change, 2001–2005, by Hospital Type ($\alpha = 0.95$)

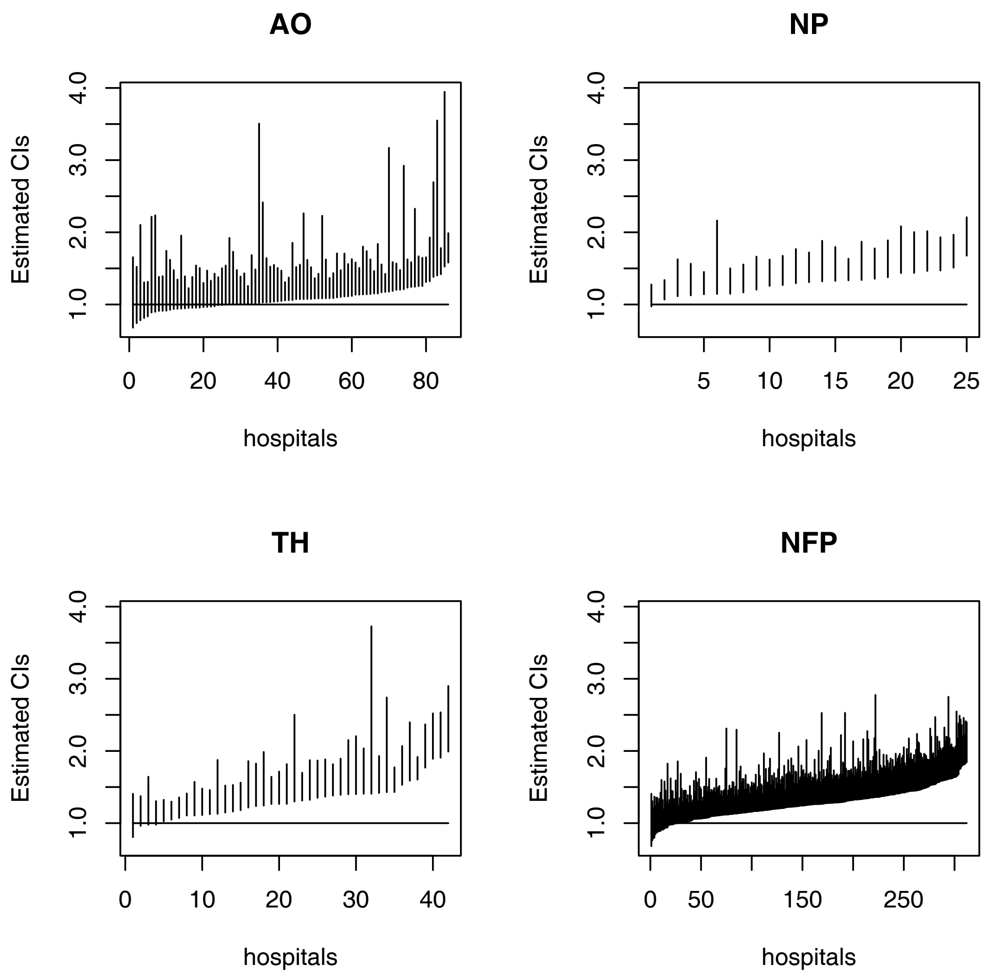


Figure C.8: Estimated Productivity Change, 2001–2005, by Type and Region ($\alpha = 0.95$)

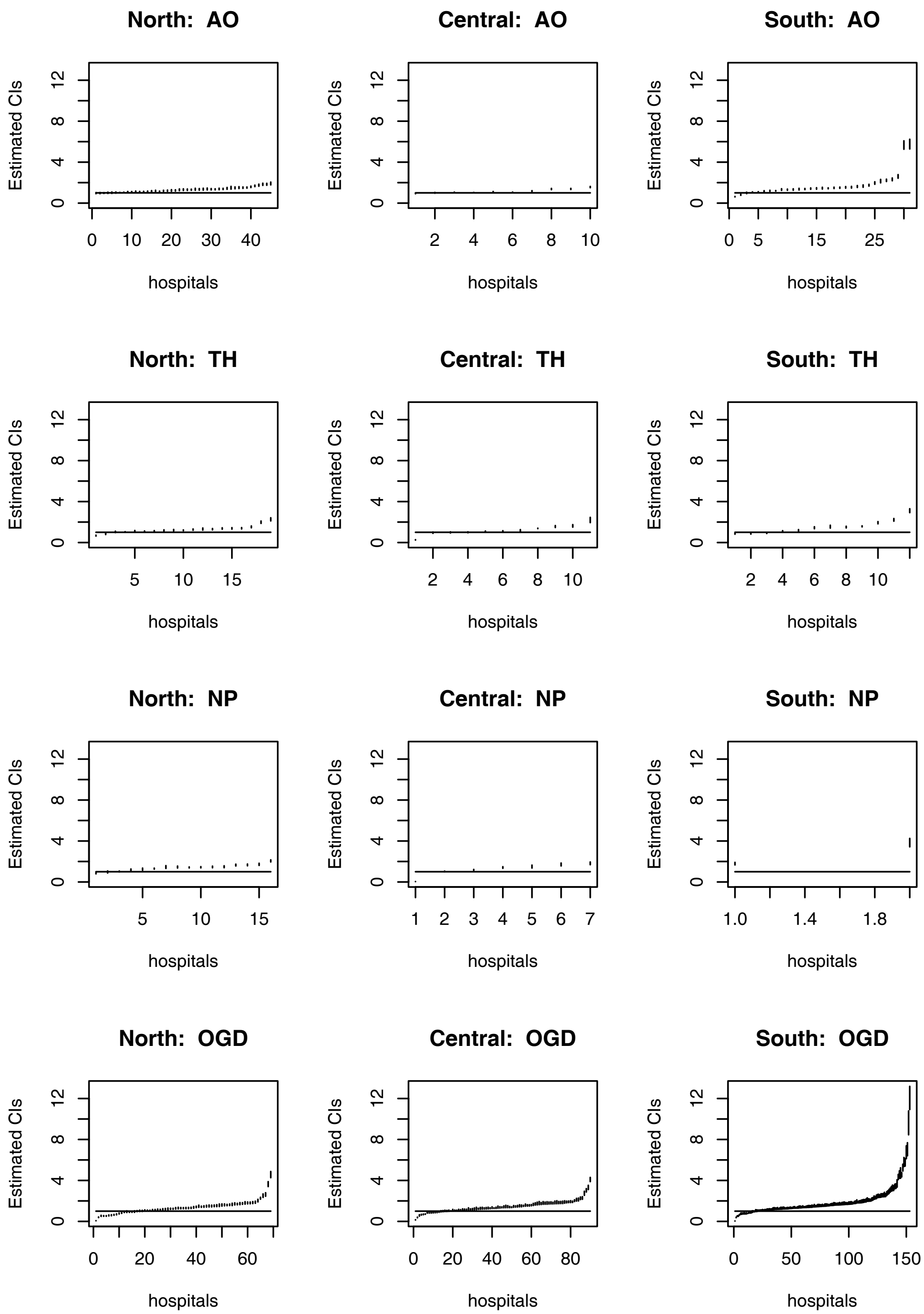


Figure C.9: Estimated Efficiency Change, 2001–2005, by Type and Region ($\alpha = 0.95$)

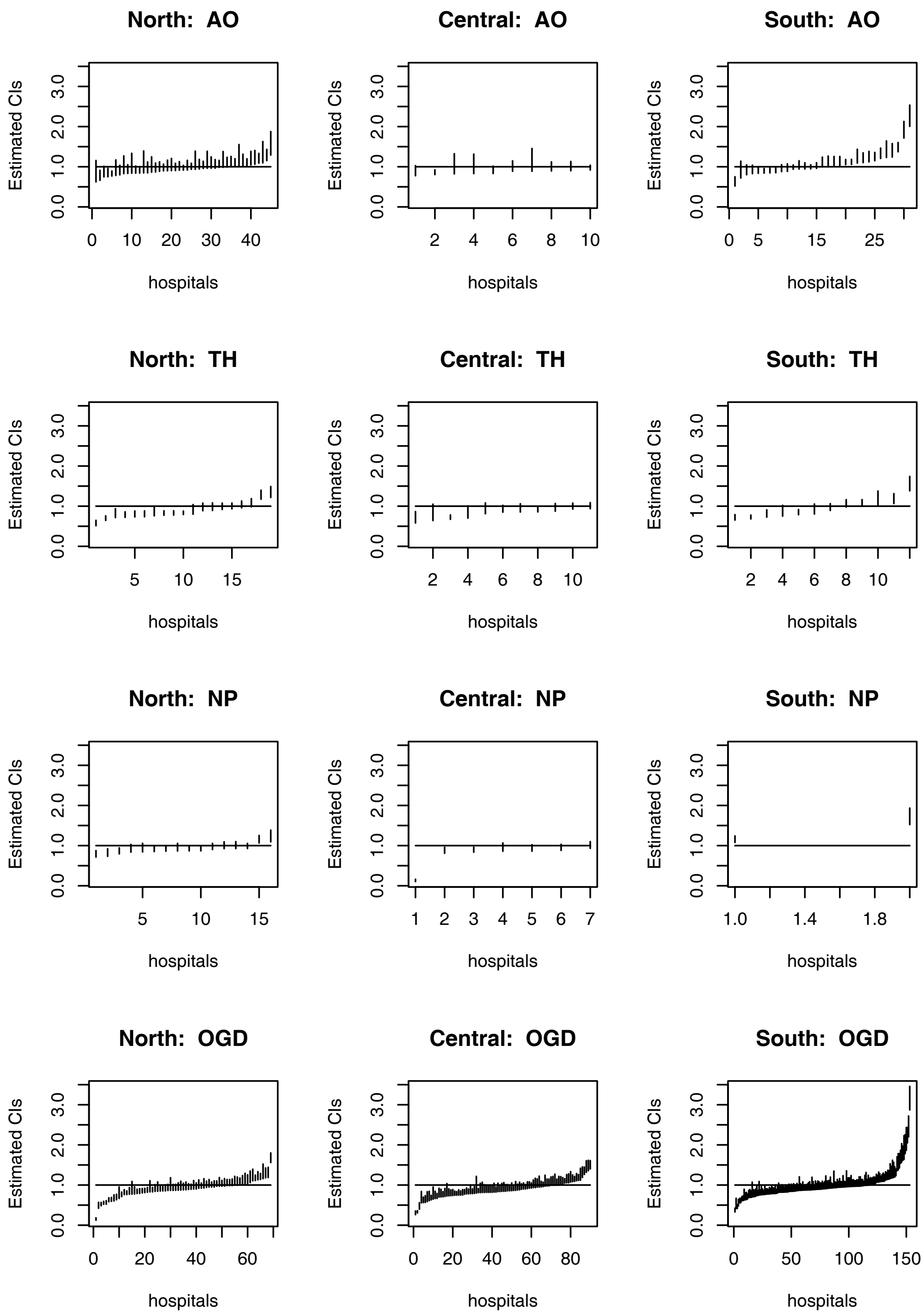
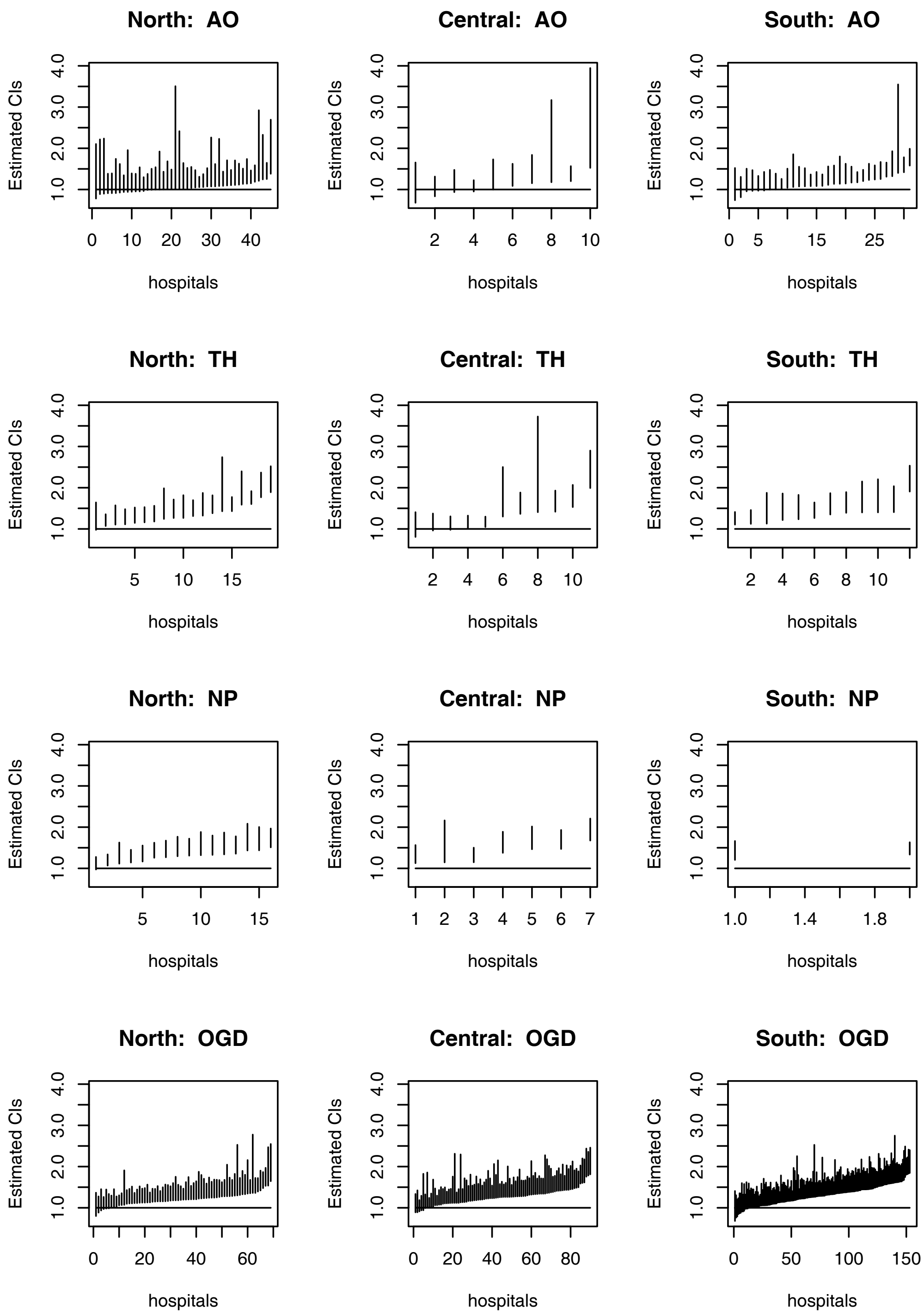


Figure C.10: Estimated Technology Change, 2001–2005, by Type and Region ($\alpha = 0.95$)



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