Data Envelopment Analysis and Performance Management

Edited by:
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Emrouznejad Ali and Victor Podinovski (2004) ***Data Envelopment Analysis and Performance Management***, Warwick Print, Coventry, UK, ISBN: 0 902683 73 X

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AND
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4th International Symposium of DEA
5th-6th September 2004
Aston Business School
Aston University
UK

www.DEAzone.com/DEA2004
First print, September 2004

ISBN: 0 902683 73 X

PREFACE

Data Envelopment Analysis (DEA) is a recognised modern approach to the assessment of performance of organisations and their functional units. DEA spans the boundaries of several academic areas including management science, operational research, economics and mathematics. The theoretical development of DEA has been driven and supported by numerous applications in various areas, including industry, agriculture and public sector.

A testament to the continuing success of DEA is this volume comprising some of the papers presented at the 4th International Symposium of DEA, held at the University of Aston in Birmingham, UK. The 4th Symposium continued the successful series of previous DEA events: Wernigerode (Germany, 1998), Brisbane (Australia, 2000) and Moscow (Russia, 2002).

Overall, more than 190 papers have been submitted from all continents, to be presented at the Symposium. On behalf of the Organising Committee, we wish to thank all authors for their valuable contribution to this international event.

Ali Emrouznejad
Victor Podinovski
Editors
September, 2004

TABLE OF CONTENTS

In the alphabetic order of titles

A CONSTANT SUM OF OUTPUTS DEA MODEL FOR OLYMPIC GAMES TARGET SETTING

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ABSTRACT

In principle, Data Envelopment Analysis (DEA) tries to find an individual measure of the efficiency and the corresponding input and output targets for each DMU. However, in certain problems, the total sum of outputs must be shared among the processing units. In these situations, the targets calculated by the conventional DEA models for each DMU are not realistic, since they assume that every unit can improve its outputs as much as the technology permits, not taking into account that the total sum of outputs is fixed a priori. This is what happens in Olympic Games: the total number of medals is fixed for each metal. In this paper, a linear programming DEA model, named Constant Sum of Outputs model (CSO), is proposed to provide both target output levels and performance scores for every DMU, when the above situation arises. We have applied it to the case of Sidney 2000 Olympic Games, and compared the results with existing alternative models.

INTRODUCTION

Data Envelopment Analysis is a well known family of mathematical programming tools for assessing the relative efficiency of a set of comparable processing units (a.k.a. Decision Making Units, DMUs). For an extensive description of this technique, the reader is referred to existing papers and textbooks on the subject[1,2,3].

In Lozano et al (2002)[4] a VRS, AR weighted-constrained[5] DEA model was presented for measuring the performance of nations at summer Olympic Games. Recently, Lins et al (2003)[6] has proposed another DEA model called Zero Sum Gain (ZSG-DEA) which incorporates the fact that the total sum of medals that can be won by the participants is in principle constant. Unfortunately, their model is non linear, which makes it difficult to solve. In addition, it cannot provide useful targets since they solve the ZSG model independently for each participant so that, in the end, the sum of the number of medals in their projections is not equal to the total number of medals available.

In this paper we propose a new DEA model called Constant Sum of Outputs (CSO-DEA) which takes into account such scenario with the advantage that the resulting model is a linear program. First, the efficiency of the units is assessed using the model in Lozano et al (2002) and then the CSO-DEA model is solved.

In section 2 the Constant Sum of Outputs DEA model (CSO-DEA model) is introduced. In section 3 a single input two outputs (XYY) case is presented to illustrate through a simple example the efficiency scores and targets provided by the proposed model. In section 4, we present the results given by the model applied to Sidney 2000 Olympic Game making a comparison between the CSO model and both ZSG DEA and VRS AR models to test if the rankings provided by these models are similar. Finally, in section 5 we summarize the results and draw some conclusions.

CONSTANT SUM OF OUTPUTS (CSO) DEA MODEL

In this section we present the Constant Sum of Outputs DEA model. The model introduced addresses those situations in which the performance of all units are submitted to a fixed amount of certain outputs. We present the general formulation, not the specific non-discretionary inputs, weight-constrained scenario that corresponds to the Olympic Games case.

Let:

n number of DMUs

j,r=1,...,n indexes for DMUs

i=1,...,m index for inputs

k=1,..,p index for outputs

x_{ij} amount of input i consumed by DMU j

y_{kj} amount of output k produced by DMU j

γ_r radial increase/decrease of outputs for DMU_r.

γ_r^{BCC} radial increase of outputs for DMUr provided by the BCC-OUTPUT model.

s_{ir} slack in the amount of input i for DMU_r

t_{kr} slack in the amount of output k for DMU_r

$(\lambda_{1r}, \lambda_{2r},..., \lambda_{nr})$ vector of variables for projecting DMU_r

The proposed model has two steps. First, the conventional (BCC[2] for example) DEA model is solved. Since that model does not take into account that total outputs must be fixed, a second step is needed.

The second step has two phases. The first one is:

(Phase I)

$$\text{Max} \quad \min_r \left\{ \frac{\gamma_r}{\gamma_r^{BCCO}} \right\}$$

s.t.

$$\sum_{j=1}^{n} \lambda_{jr} x_{ij} \le x_{ir} \qquad \forall i, \forall r$$

$$\sum_{j=1}^{n} \lambda_{jr} y_{kj} \ge \gamma_r y_{kr} \qquad \forall k, \forall r$$

$$\sum_{r=1}^{n} \sum_{j=1}^{n} \lambda_{jr} y_{kj} = \sum_{r=1}^{n} y_{kr} \qquad \forall k$$

$$\sum_{j=1}^{n} \lambda_{jr} = 1 \qquad \forall r \quad (*)$$

$$\gamma_r \ge 1 \quad \forall r : \gamma_r^{BCCO} > 1$$

$$\lambda_{jr} \ge 0 \quad \gamma_r \text{ free}$$

This is an LP with n^2+n variables and m n + p (n+1) + n constrains. The first set of constraints establishes that the inputs provided by the model for each DMU must not decrease. With the following pAn constraints, the model searches for a solution in which for each DMUr all its outputs are radially expanded by the amount given by variable γ_r. The following p constraints keep the total sum of each output constant in the solution provided by the model. The last set of constraints, signaled with an asterisk, should be only considered for VRS problems.

Because of the constraints that keep the total sum of outputs constant, the increase of the outputs of a DMU will be only possible to the detriment of others DMUs that will have to decrease their outputs. For those DMUs γ_r will be lower than unity. On the contrary, γ_r>1, if DMU r is to augment its outputs. The optimal values of the variables γ_r will be chosen so as to maximize the minimum of the γ_r/γ_r^{BCC} ratios, i.e. the model tries to maximize the extent to which all units achieve the radial output expansion predicted by the conventional DEA model. Using this max min expression in the objective function, we dissuade the model from assigning a very high radial output expansion to the most inefficient units and a very high radial output reduction of outputs to the efficient ones, looking for a more balanced projection.

Let γ^*_r be the value of variable γ_r in the solution of the above model. As usual in DEA, a second slack-optimizing phase needs to be performed:

(Phase II)

$$\text{Max} \quad \sum_{r=1}^{n} \sum_{i=1}^{m} s_{ir}$$

s.t.

$$\sum_{j=1}^{n} \lambda_{jr} x_{ij} = x_{ir} - s_{ir} \qquad \forall i, \forall r$$

$$\sum_{j=1}^{n} \lambda_{jr} y_{kj} \ge \gamma_r^* y_{kr} \qquad \forall k, \forall r$$

$$\sum_{r=1}^{n} \sum_{j=1}^{n} \lambda_{jr} y_{kj} = \sum_{r=1}^{n} y_{kr} \qquad \forall k$$

$$\sum_{j=1}^{n} \lambda_{jr} = 1 \qquad \forall r \quad (*)$$

$$\lambda_{jr} \ge 0 \quad s_{ir} \ge 0 \quad t_{kr} \ge 0$$

This is an LP with m n + p (n+1) constraints (plus n in case of VRS) and n^2 + m n + p n variables. This model offers the opportunity for the DMUs to reduce their inputs as much as possible compatible with their radial output expansion/reduction obtained in the first phase.

After phase II, the total amount of input 'i' consumed by DMUr can be computed as:

$$\hat{x}_{ir} = \sum_{j=1}^{n} \lambda^*_{jr} x_{ij}$$

and the total amount of output 'k' produced by DMU_r is:

$$\hat{y}_{kr} = \sum_{j=1}^{n} \lambda^*_{jr} y_{kj}$$

Note that the model has projected in a joint manner all the DMUs but not onto the efficient frontier. This is not possible since the amount of outputs is fixed and, therefore, the inefficient units can improve their level of outputs (coming closer to the frontier) only because the efficient units reduce them (moving away from the frontier).

AN XYY ILLUSTRATION

In this section we present a single input - two outputs case with seven DMUs to analyze the results provided by the above model. To portray the data and the solution graphically, we have considered a constant and equal value of input for every DMU.

Tables 1, 2 and 3 show the data, and the results given by both the traditional BCC-O and the proposed CSO-DEA models.

Table 1. Data

	DATA		
DMU	x	y1	y2
1	1	1	8
2	1	2	7
3	1	3	5
4	1	4	2
5	1	1.5	6
6	1	2	4
7	1	2.5	2
TOTAL	7	16	34

Table 2. BCC-O targets and efficiency

	BCC-O SOLUTION			
DMU	x	y1	y2	γ^{BCCO}
1	1	1	8	1
2	1	2	7	1
3	1	3	5	1
4	1	4	2	1
5	1	1.8	7.2	1.20
6	1	2.8	5.5	1.38
7	1	3.7	2.9	1.47
TOTAL	7	18.2	37.6	---

Table 3. CSO targets and efficiency

	CSO SOLUTION				
DMU	x	y1	y2	γ^*	γ^*/γ^{BCCO}
1	1	1.0	8.0	0.99	0.99
2	1	1.7	6.1	0.87	0.87
3	1	2.6	4.3	0.87	0.87
4	1	3.5	2.0	0.87	0.87
5	1	1.6	6.3	1.04	0.87
6	1	2.4	4.8	1.20	0.87
7	1	3.2	2.6	1.28	0.87
TOTAL	7	16	34	---	---

Note that, the BCC-O model increases as much as possible the output level of each DMU, and consequently, the total sum of each output is greater than in the initial situation (i.e. from 16 to 18,2 for y1; and from 34 to 37,6 for y2). The last column of Table 2 shows the radial amplification (γ^{BCCO}) obtained for each DMU. On the other hand, we can observe from Table 3 that the total amount of each output remains constant in the CSO-DEA solution. This is possible since the efficient DMUs reduce some of their outputs so that inefficient units could improve theirs.

In Table 3 it can be seen that the max min character of the objective function of Phase I model leads to almost uniform values for the ratio γ/γ^{BCCO}.

Since the amount of input for every DMU is constant (equal to one), it is possible to draw a bi-dimensional graphic (Figure 1) in where the results from tables 1 and 3 can be represented. The black circles represent the DMUs at the initial situation, and the gray ones are the targets provided by the CSO-DEA model. The BCC-O solution is shown in Figure 2.

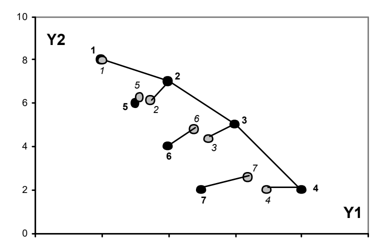

Figure 1. XYY illustration of CSO projections.

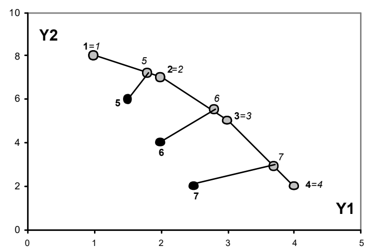

Figure 2. XYY illustration of BCC-O projections.

We can appreciate that in the proposed CSO approach the DMUs tends to move to a specific area (a line in this case) of the VRS production possibility set where the sum of each output remains constant and, in addition, the value of the objective function is maximum. Note that the units are not necessarily projected onto the (technical) efficient frontier as in the BCC-O case. On the contrary, most units that were efficient are projected by the CSO-DEA model onto inefficient operating points with less amount of outputs. This may seem awkward. To understand why that can happen one must consider that the observed good performance of efficient units has been obtained because of the poor performance of the inefficient units so that when the latter is set to improve, the former is sure to worsen. The model takes a neutral, system-wide view looking for a fair projection that is more realistic that expecting inefficient units to increase their outputs and efficient units to keep theirs.

CSO DEA MODEL APPLIED TO SIDNEY 2000 OLYMPIC GAMES

In this section we show the results provided by the CSO-DEA model in the Olympic Games case and we compare them with both the VRS, AR-weighted constrained DEA model proposed by Lozano et al.[4] and the Zero Sum Gain ZSG-DEA model by Lins et al.[6] Let:

NC: number of DMUs (countries)

j, r: index of countries

GNP_j: Gross National Product of country j

P_j: population of country j

NG_j: number of Gold medals won by country j

NS_j: number of Silver medals won by country j

NB_j: number of Bronze medals won by country j

It is essential to incorporate weight constraints in the model due to the value of the different metals (i.e. gold medals are more valuable than silver medals and bronze medals). With this aim we use the following parameters:

α: minimum number of silver medals that are equivalent to one gold metal

β: minimum number of bronze medals that are equivalent to one silver metal

The CSO - DEA model is:

(Phase I)

$$\text{Max} \quad \min_{r} \left\{ \frac{\gamma_r}{\gamma_r^{VRS-AR}} \right\}$$

s.t.

$$\sum_{j=1}^{NC} \lambda_{jr} \cdot GNP_j \le GNP_r \qquad \forall r$$

$$\sum_{j=1}^{NC} \lambda_{jr} \cdot P_j \le P_r \qquad \forall r$$

$$\sum_{j=1}^{NC} \lambda_{jr} \cdot NG_j \ge \gamma_r \cdot NG_r + {}^{r}_{NG,NS} \qquad \forall r$$

$$\sum_{j=1}^{NC} \lambda_{jr} \cdot NS_j \ge \gamma_r \cdot NS_r - \alpha \cdot {}^{r}_{NG,NS} + {}^{r}_{NS,NB} \qquad \forall r$$

$$\sum_{j=1}^{NC} \lambda_{jr} \cdot NB_j \ge \gamma_r \cdot NB_r - \beta \cdot {}^{r}_{NS,NB} \qquad \forall r$$

$$\sum_{r=1}^{NC} \sum_{j=1}^{NC} \lambda_{jr} NG_j = \sum_{r=1}^{NC} NG_r$$

$$\sum_{r=1}^{NC} \sum_{j=1}^{NC} \lambda_{jr} NS_j = \sum_{r=1}^{NC} NS_r$$

$$\sum_{r=1}^{NC} \sum_{j=1}^{NC} \lambda_{jr} NB_j = \sum_{r=1}^{NC} NB_r$$

$$\sum_{j=1}^{NC} \lambda_{jr} = 1$$

$$\gamma_r \ge 1 \qquad \forall r : \gamma_r^{VRS-AR} > 1$$

$$\lambda_{jr},\ {}^{r}_{NG,NS},\ {}^{r}_{NS,NB} \ge 0 \qquad \gamma_r \text{ free}$$

Note that the third, fourth and fifth set of constraints are affected by ${}^{r}_{NG,NS}$ and ${}^{r}_{NS,NB}$, the dual variables corresponding to the gold vs. silver and silver vs. bronze weight constraints for each DMU r.

In order to compare this model with the ZGS model, we have considered the same values of α and β used in Lins et al., i.e.

$$\alpha = \frac{0.5814}{0.2437} \quad ; \quad \beta = \frac{0.2437}{0.1749}$$

Since the two inputs are non discretionary, there is no need in this case to carry out phase II.

Table A in the appendix shows the actual number of medals won by the participants. Note that the number is not exactly equal for gold, silver and bronze due to ties.

Table 4 shows the targets and the efficiency obtained by the weighted VRS-AR model. Note that these projections are unrealistic. This is so because it is assumed that all inefficient countries will increase their outputs and efficient ones will keep theirs, which would require an inordinate total number of medals.

Table 4. VRS-AR projection for Sidney00

Country	Gold	Silver	*Bronze*	$\gamma^{VRS\text{-}AR}$
Algeria	14.0	17.0	26.0	4.11
Arabia Saudi	6.4	9.3	7.1	13.73
Argentina	5.3	5.0	12.4	8.60
Armenia	15.3	20.2	17.2	1.00
Australia	0.0	0.0	1.0	1.00
Austria	16.0	25.0	17.0	4.10
Azerbaijan	8.2	8.2	5.0	1.80
Bahamas	3.6	3.6	3.0	1.00
Barbados	1.0	1.0	0.0	1.00
Belgium	0.0	0.0	1.0	3.67
Brazil	3.0	3.0	11.0	4.71
Bulgaria	3.0	3.0	11.0	1.52
Byelorussia	32.4	27.8	28.3	1.00
Cameroon	8.0	8.0	5.2	11.04
Canada	11.0	11.0	7.0	2.29
Chile	16.3	24.2	18.3	12.19
China	5.4	6.4	12.2	1.16
Colombia	32.6	27.8	28.4	15.85
Costa Rica	15.9	15.6	12.2	2.50
Croatia	15.9	24.5	17.5	4.48
Cuba	19.0	25.3	19.1	1.00
Czech Rep	1.2	0.7	5.0	3.02
Denmark	4.5	4.3	4.5	2.37
Estonia	11.0	11.0	7.0	1.00
Ethiopia	4.8	7.0	4.3	1.79
Finland	5.2	5.1	3.2	2.70
France	2.4	2.0	1.7	1.62
Georgia	17.6	24.5	19.1	1.00
Germany	39.0	25.0	33.0	1.00
Greece	1.0	0.0	2.0	2.41
Hungary	7.2	7.2	5.4	1.26
India	5.4	5.4	3.1	28.06
Indonesia	21.0	25.9	20.4	8.37
Iran	0.0	0.0	6.0	5.70
Ireland	10.3	12.9	8.4	15.19
Island	14.0	19.6	13.1	1.01
Israel	10.1	10.1	6.4	7.00
Italy	32.1	28.0	28.1	1.58
Jamaica	13.6	12.2	16.6	1.14
Japan	17.1	15.9	13.1	4.90
Kazakhstan	4.2	5.1	2.9	3.56
Kenya	0.0	0.0	1.0	3.80
Kuwait*	1.8	1.4	6.9	3.00
Kyrgyzstan	20.7	25.8	20.7	1.14
Latvia	1.4	1.1	3.4	1.88
Lithuania	29.4	27.5	26.2	1.42
Macedonia	11.8	11.7	7.8	2.25
Mexico	9.8	9.8	7.6	7.88
Moldavia	0.0	0.2	1.1	1.00
Morocco	0.9	0.1	3.0	2.92
Mozambique	1.9	1.9	1.9	3.09
Netherlands	2.8	2.1	4.2	1.18
New Zealand	0.0	0.1	2.3	1.67
Nigeria	4.2	4.0	11.7	14.37
North Korea	25.6	26.7	23.7	5.86
Norway	0.0	1.0	1.0	1.04
Poland	3.1	3.2	2.7	2.69
Portugal	12.9	12.5	8.9	5.50
Qatar	4.2	3.8	3.1	2.00
Rumania	1.7	1.0	5.0	1.00
Russia	15.9	17.1	13.0	1.00
Slovak Rep	3.0	3.0	11.0	3.31
Slovenia	1.0	0.0	2.0	1.18
South Africa	21.0	25.9	20.4	5.16
South Korea	6.7	7.4	9.0	1.76
Country	**Gold**	**Silver**	***Bronze***	$\gamma^{VRS\text{-}AR}$
Spain	11.0	6.0	9.0	3.81
Sri Lanka	32.0	28.0	28.0	9.00
Sweden	7.0	7.0	9.0	2.14
Switzerland	11.1	11.4	15.5	2.96
Taiwan	8.6	10.8	6.9	3.96
Thailand	6.4	9.6	6.1	8.51
Trinidad	13.2	11.8	17.0	2.00
Turkey	13.1	19.4	15.8	6.58
Ukraine	1.0	0.0	2.0	1.22
United Kingdom	19.7	20.0	16.7	1.91
Uruguay	6.3	5.9	12.2	11.26
USA	3.3	3.3	2.0	1.00
Uzbekistan	5.1	5.1	10.3	5.15
Vietnam	12.3	12.0	8.3	41.06
Yugoslavia	1.0	1.0	1.0	7.63
TOTAL	**784.5**	**826.2**	**820.6**	---

Table 5 shows the number of medals of each metal that the CSO-DEA model assigns as targets to each nation as well as the value of γ, and the $\gamma/\gamma^{VRS\text{-}AR}$ ratio.

Table 5. CSO-DEA projection for Sidney00

Country	Gold	Silver	*Bronze*	γ	$\gamma/\gamma^{VRS\text{-}AR}$
Algeria	1.7	1.7	5.2	1.74	0.42
Arabia Saudi	1.0	3.4	5.8	5.82	0.42
Argentina	1.2	4.3	7.3	3.65	0.42
Armenia	0.0	0.0	1.0	0.42	0.42
Australia	6.8	10.6	7.2	0.42	0.42
Austria	3.5	1.7	0.5	1.74	0.42
Azerbaijan	2.0	0.0	1.0	1.00	0.55
Bahamas	0.4	0.4	0.6	0.42	0.42
Barbados	0.0	0.0	1.0	0.42	0.42
Belgium	0.1	3.6	3.5	1.56	0.42

Brazil	3.5	4.4	10.9	2.00	0.42
Bulgaria	5.0	6.0	2.0	1.00	0.66
Byelorussia	1.3	1.3	4.7	0.42	0.42
Cameroon	4.7	2.4	3.1	4.68	0.42
Canada	3.0	3.0	8.0	1.00	0.44
Chile	0.0	0.0	5.2	5.17	0.42
China	28.0	16.0	15.0	1.00	0.86
Colombia	6.7	4.2	2.5	6.73	0.42
Costa Rica	0.0	0.0	2.1	1.06	0.42
Croatia	1.9	0.0	1.9	1.90	0.42
Cuba	4.7	4.7	3.0	0.42	0.42
Czech Rep	2.6	3.8	3.8	1.28	0.42
Denmark	2.0	3.0	1.0	1.01	0.42
Estonia	0.4	0.0	0.8	0.42	0.42
Ethiopia	4.0	1.0	3.0	1.00	0.56
Finland	2.3	1.1	1.1	1.14	0.42
France	13.0	14.0	11.0	1.00	0.62
Georgia	0.0	0.0	2.5	0.42	0.42
Germany	5.9	7.2	11.0	0.42	0.42
Greece	4.1	6.1	3.1	1.02	0.42
Hungary	8.0	6.0	3.0	1.00	0.79
India	0.0	5.1	4.7	11.90	0.42
Indonesia	4.2	9.0	7.1	3.55	0.42
Iran	7.3	4.6	2.8	2.42	0.42
Ireland	2.4	0.7	0.1	6.44	0.42
Island	0.0	0.0	1.0	1.00	0.99
Israel	0.0	0.0	3.0	2.97	0.42
Italy	13.0	9.0	11.6	1.00	0.63
Jamaica	0.0	4.0	3.0	1.00	0.88
Country	**Gold**	**Silver**	***Bronze***	γ	$\gamma/\gamma^{VRS\text{-}AR}$
Japan	12.8	10.9	10.4	2.08	0.42
Kazakhstan	4.8	5.4	1.5	1.51	0.42
Kenya	3.2	4.8	3.2	1.61	0.42
Kuwait*	0.0	0.0	1.3	1.27	0.42
Kyrgyzstan	0.0	0.0	1.0	1.00	0.88
Latvia	1.0	1.0	1.0	1.00	0.53
Lithuania	2.0	0.0	3.0	1.00	0.70
Macedonia	0.0	0.0	1.0	1.00	0.44
Mexico	3.7	5.8	10.0	3.34	0.42
Moldavia	0.0	0.4	1.0	0.42	0.42
Morocco	0.1	0.9	4.9	1.24	0.42
Mozambique	1.3	0.0	0.4	1.31	0.42
Netherlands	12.0	9.0	4.0	1.00	0.85
New Zealand	1.0	0.4	2.4	1.00	0.60
Nigeria	5.6	5.0	1.5	6.10	0.42
North Korea	0.3	4.6	3.6	2.48	0.42
Norway	4.0	3.0	3.0	1.00	0.96
Poland	6.8	5.7	3.4	1.14	0.42
Portugal	0.0	0.4	4.2	2.33	0.42
Qatar	0.0	0.0	1.0	1.00	0.50
Rumania	4.7	3.6	2.4	0.42	0.43
Russia	13.6	11.9	11.9	0.42	0.42
Slovak Rep	1.8	3.2	1.4	1.40	0.42
Slovenia	2.0	0.0	0.0	1.00	0.85
South Africa	0.7	2.7	6.6	2.19	0.42
South Korea	8.0	9.0	11.0	1.00	0.57
Spain	4.9	4.9	8.0	1.62	0.42
Sri Lanka	0.0	0.0	3.8	3.82	0.42
Sweden	4.0	5.0	3.0	1.00	0.47
Switzerland	2.9	3.5	2.5	1.26	0.42
Taiwan	0.0	4.0	3.5	1.68	0.42
Thailand	3.6	3.4	2.5	3.61	0.42
Trinidad	0.0	1.0	1.0	1.00	0.50
Turkey	8.4	5.5	3.1	2.79	0.42
Ukraine	3.0	10.0	10.0	1.00	0.82
United Kingdom	11.0	10.0	7.0	1.00	0.52
Uruguay	1.9	0.2	0.0	4.78	0.42
USA	16.5	10.6	14.0	0.42	0.42
Uzbekistan	2.2	2.2	4.4	2.19	0.42
Vietnam	5.1	5.2	1.5	17.42	0.42
Yugoslavia	3.2	3.2	3.2	3.24	0.42
TOTAL	**301**	**299**	**328**	**---**	**---**

Note that this time the total number of medals is the same as in the original DMUs. In the fifth column of table 5 (i.e. γ), we can see that the CSO model assigns the minimum radial amplification (γ=0.42) to the VRS-AR efficient countries. It is not surprising since they have to contribute to the improvement of the inefficient ones, decreasing their outputs as much as possible.

Note also that the ratios $\gamma/\gamma^{VRS\text{-}AR}$ have a minimum of 0.42 and a maximum of 0.96. This means that the proposed approach projects the units expecting of all of them to reach a certain performance level measured from their theoretical maximum potential. Finally, note that there is a tendency for the CSO-DEA model to decrease the amount of each metal for those VRS-AR efficient countries (e.g. Germany, Australia or USA) and increase them for inefficient ones (e.g. South Africa, UK or Croatia). But not always the behavior is the same for all metal types, (e.g. Switzerland increases the number of gold and bronze medals, but decreases the number of silver medals).

Also, using γ values in the fifth column of table 5, we can establish a ranking of nations according to the proposed approach. At this point, it is interesting to compare the ranking that other models (i.e. VRS-O by Lozano et al.[4] and ZSG model by Lins et al.[6]) give for this problem. We have computed Spearman's Rank-order Correlation coefficient (ρ). The test has been applied to the rankings given by CSO versus ZSG; CSO versus VRS-AR; and VRS-AR versus ZSG models.

From Table 6 we can deduce that the null hypothesis that each of these pair of rankings do not correspond to the same population is rejected since the absolute value of the obtained ρ is much greater than the critical ρ (for n=80 and with a significance level α=0.05, the critical ρ is 0.22). As expected, in all three cases the sign of Spearman's correlation is positive. We can conclude the three methods provide very similar rankings. This does not mean that, as previously shown, they give the same targets. In this respect, the CSO-DEA targets are more realistic than the VRS-AR or ZSG targets. In addition, the CSO-DEA model is simpler than the non-linear ZSG-DEA approach.

Table 6. Value of Spearman's correlation

CSO / VRS-AR	CSO / ZSG	ZSG / VRS-AR
0.986527	0.804688	0.801014

SUMMARY AND CONCLUSIONS

This paper has presented a new simple DEA-based tool to assess the performance of the nations in the Olympic Games, incorporating a set of constraints that keep constant the total number of medals of each type. This approach is more realistic than our previous approach[4]. In addition, not only is it simpler than the method proposed by Lins et al.[6] but it provides useful targets whose sum of outputs is kept constant, something their approach does not provide.

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APPENDICES

Table A. Medals obtained by each participant in Sidney00

Country	Gold	Silver	*Bronze*
Algeria	1	1	3
Arabia Saudi	0	1	1
Argentina	0	2	2
Armenia	0	0	1
Australia	16	25	17
Austria	2	1	0
Azerbaijan	2	0	1
Bahamas	1	1	0
Barbados	0	0	1
Belgium	0	2	3
Brazil	0	6	6
Bulgaria	5	6	2
Byelorussia	3	3	11
Cameroon	1	0	0
Canada	3	3	8
Chile	0	0	1
China	28	16	15
Colombia	1	0	0
Costa Rica	0	0	2
Croatia	1	0	1
Cuba	11	11	7
Czech Rep	2	3	3
Country	Gold	Silver	*Bronze*
Denmark	2	3	1
Estonia	1	0	2
Ethiopia	4	1	3
Finland	2	1	1
France	13	14	11
Georgia	0	0	6
Germany	14	17	26
Greece	4	6	3
Hungary	8	6	3
India	0	0	1
Indonesia	1	3	2
Iran	3	0	1
Ireland	0	1	0
Island	0	0	1
Israel	0	0	1
Italy	13	8	13
Jamaica	0	4	3
Japan	5	8	5
Kazakhstan	3	4	0
Kenya	2	3	2
Kuwait*	0	0	1
Kyrgyzstan	0	0	1
Latvia	1	1	1
Lithuania	2	0	3
Macedonia	0	0	1
Mexico	1	2	3
Moldavia	0	1	1
Morocco	0	1	4
Mozambique	1	0	0
Netherlands	12	9	4
New Zealand	1	0	3
Nigeria	0	3	0
North Korea	0	1	3
Norway	4	3	3
Poland	6	5	3
Portugal	0	0	2
Qatar	0	0	1
Rumania	11	6	9
Russia	32	28	28
Slovak Rep	1	3	1
Slovenia	2	0	0
South Africa	0	2	3
South Korea	8	9	11
Spain	3	3	5
Sri Lanka	0	0	1
Sweden	4	5	3
Switzerland	1	6	2
Taiwan	0	1	4
Thailand	1	0	2
Trinidad	0	1	1
Turkey	3	0	1
Ukraine	3	10	10
United Kingdom	11	10	7
Uruguay	0	1	0
USA	39	25	33
Uzbekistan	1	1	2
Vietnam	0	1	0
Yugoslavia	1	1	1
TOTAL	**301**	**299**	**328**

A DEA ANALYSIS OF BANK PERFORMANCE IN MALAYSIA

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ABSTRACT

The banking sector in Malaysia had a severe experience during the Asian financial crisis and after the year 2000 the domestic banks had to merge amongst themselves. This study seeks to measure and break down the technical efficiency of the commercial banks prior to the consolidation. It then compares the relative performance between the domestic and foreign banks and identifies the characteristics of the so-called efficient banks. To measure the technical efficiency, two basic models of the DEA were used under the assumptions of the constant returns to scale and the variable returns to scale. The study found that the average pure technical efficiency score is 93%. The main source of overall inefficiency was caused by scale problem. By ownership, foreign banks were found to have higher efficiency level, followed by the state-owned banks and the private banks. The differences in the efficiency scores are all statistically significant except between the state-owned banks and the foreign banks. Finally, the study found that the efficient banks are significantly characterised by higher profitability rate and larger size of assets.

INTRODUCTION

The performance of the financial institutions is crucial for the well being of the whole economy and it has attracted the attention of many researchers. At present, most of the studies focus on the developed economies, like Drake and Hall (2003), Cavallo and Rossi (2002), Elyasiani and Rezvanian (2002), Maudos et al (2002), Drake (2001) Altunbas and Molyneux (1996) and Molyneux and Forbes (1993). The developing and Far East countries have not been left untouched, though – they are examined in studies such as those by Rezvanian and Mehdian (2002), Hardy and di Patti (2001), Karim (2001), Hashim (2001), Edwards (1999), Laevan (1999), Katib and Matthews (1999), Chu and Lim (1998), Bhattacharyya et al (1997) and Fukuyama (1995). However, the number of the studies related to this region is not as many as those done in the developed countries. Berger and Humphrey (1997) surveyed 130 studies that have employed frontier analysis in 21 countries. Of these studies, only 8 were done in the developing and Asian countries (including 2 in Japan). Studies on US financial institutions were the most common, accounting for 66 out of 116 single country studies. In the case of Malaysia, this study is driven by the significance presence of the foreign banks, the heavy reliance on the banking sector as main source of funds and the growing stiff competition from the globalisation of the financial system.

This study aims is to investigate the performance of the commercial banks in Malaysia. To achieve this objective, firstly, we measure and break down the efficiency of the commercial banks by using two basic models of the Data Envelopment Analysis. The scope of efficiency is however limited to the technical aspect only. Any discussion on the cost efficiency is beyond the scope of this paper. We then compare the efficiency scores across the banks based on their ownership (private, state and foreign ownership). The idea here is to determine whether or not the different types of different ownership are related to efficiency. Finally, we seek to identify the main characteristics of the so-called efficient or inefficient banks. Amongst others, the characteristics cover the rates of return, market power, market size and asset quality.

BANKING INDUSTRY IN MALAYSIA

The banking system in Malaysia started in 1959 with the establishment of the Central Bank or Bank Negara Malaysia. By the end of that year, there were already 26 commercial banks but only 8 were Malaysian. The foreigners owned the rest. This reflected the dominance of overseas banks (mainly British), which specialised in foreign exchange business, the finance of foreign trade and of the development of rubber plantations and tin mines. Since the early 1960s , the main priority of the Central Bank was to develop a truly Malaysian-oriented banking system. This led to expansion of the domestic banking network and reorientation of operation of the foreign banks toward meeting and catering for domestic needs. By 1990, the number of domestic banks increased to 22. It increased further to 23 in 1994. However, since 1997, the number of domestic banks had been declining, due to major consolidation amongst them. By the end of 2001, there were only 10 domestic banks, of relatively larger size. It is believed that the merged banks are now more well-capitalised to meet future calls for capital expenditure, as well as being able to undertake higher levels of risks as a result of wider business activities. The merger exercise has also led to the closure of 187 bank branches, relocation of bank branches and staff redundancy. It was estimated that 4240 staff left the banking industry. On the other hand, the number of foreign banks had declined to 14 by 1994. It was reduced further to 13 by the end of 2003. 2 foreign banks had merged in 2002.

EFFICIENCY: MEANING AND MEASUREMENT

Economically, efficiency refers to the relationship between scarce factor inputs and output of goods and services. This relationship can be seen and evaluated in term of either physical output or cost. If we plan to identify and determine the best possible (optimal) combination of inputs to produce a given level of output in physical term, then we are talking about technological or technical efficiency. With regard to technical inefficiency, it is caused by the failure to achieve the best possible output levels and / or usage of an excessive amount of inputs. On the other hand, if we want to determine the optimal combination of inputs that will minimise the cost of producing a given level of output, then we are talking about economic efficiency or cost efficiency. This kind of efficiency requires the availability of input prices like the price of labour and capital. According to Drake and Hall (2003), in the absence of accurate data on input prices, performance analysis should be focused on technical efficiency.

Farrell (1957) tried to measure the efficiency of a firm in the single input-output case. This involved the measurement of technical and allocative efficiency and the derivation of the efficient production function. In the case of the efficient production function, he suggested the use of either a non-parametric piecewise linear convex frontier or a parametric function such as the Cobb-Douglas form. Farrell's idea was later picked up and extended by Charnes et al (1978). They proposed a model that can generalise the single input-output ratio of efficiency of a single decision making unit in a multiple input-output setting. The technical efficiency is measured as ratio of virtual output produced to virtual input used. Their work later became popularly known as the CCR model (after their names) which latterly generated the birth of the Data Envelopment Analysis (DEA). The main assumption in their model is that the firms are assumed to experience constant returns to scale. The model was later extended by Banker et al (1984) under the assumption of variable returns to scale. This study used both models under the assumptions of constant and variable returns to scale.

BANK INPUT AND OUTPUT

The choice of bank inputs and outputs remain an issue for debate. This is due to different perceptions on the ideal function of the bank, the differences in the focus of study and the types of data available. Siems and Barr (1998) outlined key considerations in choosing appropriate inputs and outputs of the bank. Both must reflect their importance and contribution in attracting deposits and making loans and advances. There are two main approaches that can be used to determine what constitutes bank input and output. In the intermediation approach, the selection is based on the bank's assets and liabilities. Bank assets represent inputs and liabilities for outputs. For Berger and Mester (1997), bank inputs are purchased funds, core deposits and labour. Outputs are consumer loans, business loans and securities. Rezvanian and Mehdian (2002) apply the same method. Inputs are borrowed funds (time deposits and other borrowed funds) and other inputs (labour and capital). Outputs are total loans, securities and other earning assets. Cavallo and Rossi (2002) also treat labour, capital and deposits as bank inputs. In contrast, the production approach considers the bank as a producer just like producers in the product market. Inputs, therefore, are physical entities such as labour and capital. In relation to the deposit, its proponents argue that all deposits should be treated as output since they are associated with liquidity, safekeeping and are involved in generating value added.

In this study, the selection of input and output was based on the intermediate approach. Inputs are the number of employees (LAB), fixed assets (FA) and total deposits (TD). TD is made up of demand deposit, saving deposit and fixed deposit. In the first place, we use bank deposit as either input or output. The result showed that regardless of its position, this factor did not have a significant influence over the efficiency measure. It turned out that the difference was only 2%. This result conforms to what had been found by Favero and Papi, 1995. In contrast, Katib and Matthews (1999) used total deposit as bank output in their study of banking performance in Malaysia. Our outputs are overdrafts (ODR), term loans (TERM), other earning assets (OEA), net interest income (NRY) and other operating income (OOY). The OOY variable was selected to reflect the growing contribution of non-interest income to banks' total income. In 1999, OOY of the banks in the sample on average stood at 11.38%. The inclusion of this variable is in line with the works of Maudos and Pastor (2003), Yildirim (2002) and Siems and Barr (1998).

This study covered a period between 1994 until 2000. We chose 1994 because from this year, all foreign banks, which had been locally incorporated, are now required by the BAFIA (1989) to publish their annual financial statement. We excluded observations after 2000 because all domestic banks had become new entities after the merger. Except for LAB, other variables are in real value (1994 = 100). The total number of bank-year observations is 193. From one year to another, the number of observations varied due to unavailability of data and merger activities. The main sources of the data are Bankscope and ABM Bankers Directory

DEA MODELS AND RESULTS

Let say that there are *n* DMUs (banks), each producing *s* different outputs using *r* different inputs. The efficiency ratio is measured as;

$$E_l = \frac{\sum_{i=1}^{s} u_i y_{il}}{\sum_{j=1}^{r} v_j x_{jl}} \qquad \text{Equation 1}$$

where
E_l = relative efficiency of the DMU
s = number of outputs produced by the DMU
r = number of inputs employed by the DMU
y_i = the i th output produced by the DMU
x_j = the j th input employed by the DMU
u_i = s x 1 vector of output weights and
v_j = r x 1 vector of input weights..
i runs from 1 to *s* and *j* runs from 1 to *r*.

Rewritten in the form of fractional programming and then transformed into a linear programming as done by Charnes et al. (1978), we have

$$\max E_l = \sum_{i=1}^{s} u_i y_{il} \qquad \text{Equation 2}$$

subject to

$$\sum_{j=1}^{r} v_j x_{jl} = 1$$

$$\sum_{i=1}^{s} u_i y_{im} - \sum_{j=1}^{r} v_j x_{jm} \leq 0,\ m = 1,\ldots\ldots,n.$$

u_i, v_j ≥ 0. u and v are small but positive quantities. The first constraint (? $v_j x_{jl}$ = 1) guarantees that it is possible to move from a linear programming to a fractional programming as well as from a fractional programming to a linear programming (Bowlin, 2002). Equation 2 is constructed under the assumption of constant returns to scale.

However, the CCR model shown by Equation 2 is only appropriate when all decision making units (DMUs) are running at an optimal scale, and this requires the DMUs to operate at the flat portion of the long run average cost (LRAC) curve. In practice, some factors may prevent a DMU from operating at optimal scale, such as financial and legal constraints, imperfect information etc. Coelli (1996) highlighted that the use of the CRS specification when some of the DMUs are not running at optimal scale will result in measures of technical efficiency which are mixed up with scale efficiency. To overcome this problem, Banker et al (1984) suggested their model (known as the BCR model). It improved the CCR model by introducing a variable that represents the returns to scale. The BCR model allows a calculation of technical efficiency that is free from the scale efficiency effects.

In the BCR model, the primal formulation is written as;

$$Maximise\ E_l = \sum_{i=1}^{s} u_i y_{il} - c_l \qquad \text{Equation 3}$$

subject to;

$$\sum_{j=1}^{r} v_j x_{jl} = 1$$

$$\sum_{i=1}^{s} u_i y_{im} - \sum_{j=1}^{r} v_j x_{jm} - c_l < 0,\ m = 1,\ldots\ldots\ldots,N.$$

The parameter c_l is unconstrained in sign. It indicates the various possibilities of returns to scale. $c_l > 0$ means increasing returns to scale and $c_l = 0$ implies constant returns to scale. Finally, $c_l < 0$ implies decreasing returns to scale. This model forms a convex hull of intersecting planes which envelop the data points more tightly than the CRS model. Therefore, it enables technical efficiency scores to be greater than or equal to those obtained under the CRS model.

The process of estimating individual efficiency measures was done by using the Warwick Windows DEA Version 1.02. Overall technical efficiency (OTE) and pure technical efficiency (PTE) are calculated directly by the CCR (CRS) and BCR (VRS) models respectively. Scale efficiency (SE) on the other hand is given by OTE/PTE.

Efficiency Scores

Under the assumption of VRS, we find that the average pure technical efficiency between 1994 and 2000 is 92.77%. This implies that the commercial banks could have produced, on average, the same amount of outputs with approximately 7.23% fewer resources than they actually employed. This finding is similar to what others have found in the literature. For example Yildirim (2002) found the average score is 96.06% for the Turkish banks. Favero and Papi (1995) meanwhile found the average efficiency score for Italian banks is 91%. Miller and Noulas (1996) found that the average efficiency score for the large banks in the United States is 96%. However, in another study using Malaysian commercial banks, Katib and Matthews (1999) found that the average efficiency score had declined between 1989 and 1995. The average score was 90 % in 1989 and 82% in 1995. The average score for the whole period was 86%. This shows that our average score of 92.77% is slightly higher than that obtained by Katib and Matthews (1999). Another study on Malaysian banks by Laevan (1999) found that the average efficiency score was only 70%.

Under the CRS assumption, as expected, the average efficiency score is around 73%. Graphically, under this assumption, the production frontier is a straight line. In contrast, the frontier under the VRS assumption is concave. Thus, the later can accommodate more efficient DMUs than the former. For scale efficiency, the average score is 78.4%. This implies that the actual scale of production has diverged from the most productive scale size by about 21.6%.

If PTE > SE, then inefficiency is caused by scale inefficiency. The results show that on average, the main source of inefficiency was caused by inappropriate scale operation. This implies that the banks have difficulty in finding an optimal combination between various inputs to produce the desired output. The result is in accordance with what had been found by Yildirim (2002) and Katib and Matthews (1999). However, it contradicts the findings of Drake and Hall (2003) and Miller and Noulas (1996). According to Drake and Hall (2003), the bulk of inefficiency of the Japanese banks is attributable to pure technical inefficiency rather than scale inefficiency. Meanwhile, Miller and Noulas (1996) found that pure technical inefficiency of large US banks is twice as great as scale inefficiency.

Efficiency Scores and Ownership

To compare the performance across various ownerships, the banks were categorised into three, foreign-owned banks, state-owned banks and private banks. The result shows that the foreign banks performance is superior to the local banks. For example, based on the average PTE, the foreign-owned banks have the highest efficiency score (98.2), followed by the state-owned banks (96.2%) and the private-owned banks (87.5). In 1995, a striking result is obtained where all the foreign banks have a perfect score of 100. This implies that all of them are located on the best-practice frontier. With regard to this comparison, we implemented the one-sample Kolmogorov-Smirnov test as shown by Siegel and Castellan (1988) to determine whether the difference in efficiency scores for 2 groups of banks is statistically significant. The results show that the differences in efficiency scores are all statistically significant except for the comparison between the state-owned banks and foreign banks. Our finding is slightly different from Yildirim (2002) who found the ranking as follows; first the state-owned banks (98.5%), followed by the foreign banks (96.63%) and the private banks (96.08%). His study was carried out done in Turkey involving commercial banks for the period between 1988 and 1999. Compared with his findings, it is obvious that the performance of private banks in Turkey is better than those performances in Malaysia. In contrast, Sathye (2001) found that the local banks are more efficient than the foreign banks. The scores are 90% and 71% for both local and foreign banks. However, he did not divide the local banks into private and state-owned banks. His study used Australian commercial banks in 1996.

Characteristics of Efficient Banks

In order to identify the characteristics of efficient banks, the banks were divided into 2 groups, efficient and inefficient banks. Then we employed test statistics for this group with regard to return on asset (ROA), market power (D/TD), bank size (A/TA) and asset quality (LLP/LN). The result shows that the efficiency is related to the selected indicators of financial performance. For example, the efficient banks have a higher rate of return (ROA) than the inefficient banks. The null hypothesis of equality of pure technical efficiency among group of banks with different ROAs was rejected. Yildirim (2002) found the same finding. This suggests that the efficient banks enjoy higher rates of profit as compared to the inefficient banks.

It also appears that the efficient bank is characterised by its size . Since the mean size of the efficient banks (4.1362) is larger than the mean size of the inefficient banks (2.8428), this suggests that efficient banks are relatively larger than the inefficient banks. However, our view is that this must be treated cautiously. The standard deviation tells us that there is substantial deviation in the asset size of the efficient banks i.e. the existence of both extremely large and small banks. This is similar with what had been found by Yildirim (2002).

The two banking groups also differ with respect to market power, but this is only significant at the 10% level. Market power, represented by the percentage of bank deposit to total deposit, refers to bank's ability to influence the market price (in this case, market interest rate). Our findings show that the efficient banks have stronger market power (the mean is 4.0301) as compared to the inefficient banks (the mean is 3.0062). But, again, the standard deviation of market power in the efficient banks is larger than those in the inefficient banks. Cautious interpretation is required here.

The last indicator is asset quality, shown by the percentage of loan loss provision to bank loans. We find that these two groups do not differ significantly with respect to this indicator.

CONCLUSION and DISCUSSION

The main aims of the study are to measure the technical efficiency of Malaysian banks using two basic models of the DEA. We then break down the composition of technical efficiency, compare the scores across the banks amd finally identify the characteristics of the so-called efficient banks. We found that the average score of pure technical efficiency is at par with the findings of other studies. It was also shown that the main source of inefficiency originated from inappropriate scale operation. In tern of the rankings, the study showed that the foreign banks are at the top, followed by the state-owned banks and the private banks. The study also shows that the efficient banks are closely associated with higher rate of returns and larger size.

The closed association between the efficient banks and the size of the asset seems to lay down some support for the merger policy pursued by the Malaysian authority. The finding implies that as the banks get larger in term of their size, their technical efficiency will improve. Hence justifying the consolidation policy. Another closed association is between the efficient banks and the rate of returns (profitability). This seems to suggest that being technically efficient is a pre-condition for profit maximisation. Using econometric approach, such claim can be proved by testing whether efficiency measure is one of the determinants of bank profit.

Our sample covers from 1994 until 2000 during which the banking system had undergone significant changes. One definite aspect of the changes is technological improvement. Since technology is assumingly embedded in the production function, such improvement will cause the production frontier to shift upward. In the literature, this is called a shift effect. At the same time, efficiency also improves through better utilisation of resources and this enables the bank to get closer to the frontier implying higher efficiency level. This movement towards the frontier is called a catching-up effect. (See Casu et al, 2004; Canhoto and Dermine, 2003 and Drake, 2001.) Because of the shift and catching-up effect, we should be cautious in comparing the efficiency scores from one year to another.

ACKNOWLEDGMENTS

I greatly thank my principal supervisor, Kent Matthews of Cardiff Business School, for his helpful comments and advice. I am also indebted to Gerry Makepeace for his editorial assistance in my original work.

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A MODEL FOR TEACHER QUALIFICATION POLICIES ASSESSMENT

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ABSTRACT

This paper presents the conceptual basis and the main results of the model for teacher qualification policies assessment developed in Bonilha (2002). That model uses the Data Envelopment Analysis approach to construct effectiveness frontiers that represents the short run and the long run equilibrium conditions and that identify effective and no-effective teachers. Statistics tests were used to verify and to control the school climate and the family environment influences on student's performance. The main focus of the model is to identify the most effective ways to improve teacher's performance.

INTRODUCTION

The relationship among production frontiers was used originally by Rhodes (1978) to compare the efficiency of schools that belonged and that didn't belong to the Program Follow-Through. Thanassoulis and Portela (2001) located the relationship among frontiers in a model with multilevel structure, with the purpose of evaluating the influence of the school and of the school type in the students' performance. In this paper the efficiency frontiers and their relationships are analyzed under the perspective of the economic comparative static theory and used in the evaluation of the qualification policies of the primary education teachers that teach Portuguese, Mathematics and Sciences simultaneously.

In that perspective the efficiency frontiers represent the equilibrium conditions in the short run, when at least an input is fixed, and the equilibrium conditions in the long run, when all the inputs are variable. The relationship between the equilibrium conditions in the short run and in the long run reveals the limits of the improvements in the qualification level that can be obtained with the available technologies of teacher qualification.

Conceptually, teacher qualification is the subjective dimension of teachers' professional preparation and the supportive work environment is its objective dimension. In the traditional educational policy approach, usually, these two dimensions have been treated separately but in the proposed model these two dimensions are considered in an integrated way.

Improving the teacher qualification level is the most effective way to improve the students' educational performance but the teacher qualification level is determined in an indirect way through inputs controlled by the educational system's managers. There is little consensus among educators on what are these inputs or how to measure them. Therefore the relevant inputs for the proposed model were selected in according with the reviewed literature and Brazilians data reports. Some of these inputs that determine the teacher qualification level are supposedly homogeneous and continuous and others are supposedly discrete. Consequently, the teacher qualification level is a function of the following variables that modify the teacher pedagogic practices applied at class room level: the teacher educational level, the participation in training courses, the teaching experience and the teaching professional licensing.

On the other hand the effective work conditions are determined by the school climate and by the family environment.

In the applied quantitative model, the teacher qualification level was represented by the following *proxies*: the teacher education level, hours in training courses, time of teaching exercise and par-time/full-time teacher. The teacher's wage and the family environment represented the school climate by the students' proportion whose parents have superior education.

The sources of the data were the students' and teachers' individual questionnaires that integrate the database ANALISASAEB that contains data referring to 1997 and were edited by the National

Institute of Educational Studies (INEP, 1999). The application database used 1068 student's questionnaires that accomplished exams in Portuguese, Mathematics and Sciences, and 117 teacher's questionnaires, among which 50 had secondary education level and 67 had superior education level. The data of the questionnaires were crossed to generate 117 classes of the 4th grade of primary education for the South Region of Brazil. The data are in Appendices.

THE CONCEPTUAL MODEL

The model was set up to reflect the guidelines adopted in the Brazilians teacher qualification policies. In that sense, the policy guidelines in the short run seek to offer training opportunities in specific areas that can be related to pedagogic practices or to subjects updating. These policy guidelines are characterized by courses with reduced classroom hours and with a limited number of subjects. The long run policies guidelines seek to improve the teacher education level. This political guideline has a great meaning in the Brazilian educational context since a significant proportion of the teachers don't have an education level compatible with the functions that they carry out in the poorest areas.

In accordance with these characteristics of the Brazilian teacher qualification policies, the assessment of the effectiveness of the short run policy guidelines is accomplished through efficiency frontiers that represent the short run equilibrium, when the teacher education level is considered constant. On the other hand, the evaluation of the effectiveness of the long run guidelines is accomplished through the efficiency frontier that is an envelope of the short run frontiers, in an analogy with the long run cost curve of the traditional microeconomic theory.

THE SHORT RUN APPLIED MODEL

The output-oriented BCC Model was used to construct the short run frontiers and Fischer's Exact Test to verify whether the teachers' teaching performance was partly influenced for the family environment.

The inputs and outputs of the BCC Model are:

Inputs

-ESC = level of the teacher's education;

-EXP = years of teaching experience;

-CAP = total hours in training courses;

-HAB = full-time/part-time teacher;

-SAL = the teacher's wage;

-FE = proportion of class students whose parents have superior education.

Given the output oriented DEA model, the distinction between discretionary and non-discretionary inputs doesn't have practical effects. On the other hand, the available data made it unfeasible to use the HAB and EXP variables. The variable FE (Family Environment) is a control variable.

Products

-CIE = class mean score in Sciences;

-MAT=class mean score in Mathematics;

-FOR=class mean score in Portuguese;

Two short run frontiers were constructed with the above indicated inputs and outputs: the Teachers with Secondary Education Frontier (F2G) with 50 observations and the Teachers with Superior Education Frontier (FSUP) with 67 observations. The long run envelope frontier was named Global Frontier (GF) and it was obtained from adjusted 117 observations.

The following DEA model results were used to analyze the effectiveness of the teacher qualification policies guidelines in the short run: the grouping of effective and no-effective teachers; the efficiency scores distribution; the input and output multipliers relationships; and the number of times that each effective teacher serves as reference for each no-effective teachers.

The grouping in effective and no-effective teachers is the basis for the identification of possible patterns in the distribution of the inputs that are supposed to determine the teacher qualification level.

The dispersion of the no-effective teachers scores in relation to the frontier was used to evaluate the teacher qualification policies contributions to the decrease of the gap among teacher performances.

The output multipliers relationships served as the basis to identify unbalances in the teaching practices. The inputs multipliers relationships, on the other hand, were used to identify unbalances between the available resources and the teacher's demands.

The number of times that each effective teacher was referred to by each no-effective teacher was used to identify the most relevant teachers in that context.

Finally, to verify the influence of the family environment on teachers' teaching performance the efficiency scores distribution was compared to the distribution of the variable (AF) that represents the proportion of students whose parents have superior education.

THE LONG RUN APPLIED MODEL

The Global Frontier (GF) represents the long run equilibrium, which is an envelope of the short run frontiers F2G and FSUP. This frontier was constructed with the application of the Additive Model to the data projected in the corresponding short run frontiers by Rhodes (1978) method.

In the long run the teachers' teaching performance is a function of the differences in their education levels. Global Frontier was built with the objective to identify performance differences between teachers with secondary education level and teachers with superior education level. It is assumed that the technology of teachers' formation is predominantly based on regular courses. This means that the implications of the use of new technologies in teacher formation need to be appraised.

It was also necessary to verify whether the teacher's teaching performance was influenced by exogenous factors. In order to do this, the Fischer Exact Test and the χ^2 Test were used to evaluate the influence of the public/private school type and the family environment on teachers' teaching performance.

THE RESULTS AND THE POLICY IMPLICATIONS

Relating to teacher's education level: the students' performance varies significantly because of the differences in this level. This result corroborates the principles of the Lei de Diretrizes e Bases (The Basic Brazilian Educational Law) that establishes as a minimum requirement for the teaching career the superior education level;

Relating to the training courses: its could reduce the discrepancies in the teaching performances of teachers with secondary education; the improvement of this performance also involves a reduction of the wage inequalities; the performance of this group is more sensitive to the influence of the teaching experience and of the family environment; the main deficiencies in teaching practices are concentrate in Portuguese and Science. Therefore, to improve the teaching performance of teachers with secondary education level and, at the same time, to minimize the differences among them it is necessary to establish differentiated strategies and to concentrate efforts in Portuguese and Science teaching.

On the other hand, teachers with superior education level show more homogeneous teaching performances; the improvement of this group's performance is less sensitive to wage inequalities; the teaching performance of this group is also less sensitive to the influence of family environment; the main deficiencies are in Math teaching. Therefore, in the short run, training teachers with superior education level is less expensive than training teachers whit secondary education level.

Relating to the school climate: the wage level is the main restricting factor to a higher performance of teachers with secondary education level; for this reason the policies that adopt the training strategy instead of regular education are ineffective.

Relating to the family environment: the students' educational performance is sensitive to it. The level of the parents' education has a double meaning in the Brazilian context: it indicates their appreciation of education and, at the same time, it is significantly associated with the income level. The last relation is stronger than the former and reflects itself in a higher performance of private schools student's as compared with public schools students.

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APPENDIX

Table 1. Order number, class code and variables values for classes of teacher with secondary education level.

Classes		Inputs				Outputs		
Order	T2G	FE	CAP	EXP	SAL	MAT	POR	CIE
2G1	41128401	0,00	100	3,0	420,00	124,72	125,27	126,65
2G2	41128402	0,00	100	3,0	420,00	197,69	160,66	135,86
2G3	41129301	0,00	160	3,0	180,00	211,58	175,03	188,66
2G4	41129501	0,00	100	8,0	180,00	217,31	150,75	180,10
2G5	41129601	0,00	70	13,0	180,00	171,99	127,21	119,66
2G6	41129701	0,00	30	13,0	180,00	161,28	139,05	158,29
2G7	41129801	0,00	50	13,0	180,00	174,91	97,95	157,90
2G8	41130001	0,00	50	0,5	180,00	155,76	105,76	102,82
2G9	42130703	0,00	10	8,0	620,00	179,43	141,39	190,54
2G10	42130801	0,00	0	13,0	300,00	164,13	185,14	178,27
2G11	42130802	0,00	0	8,0	620,00	201,26	128,65	206,32
2G12	42130902	0,00	160	3,0	300,00	216,20	154,12	201,67
2G13	42131102	0,00	0	18,0	300,00	163,99	153,04	139,49
2G14	42131703	0,00	0	8,0	420,00	203,61	154,89	189,60
2G15	42133402	0,00	70	13,0	180,00	176,85	171,38	174,25
2G16	42133801	0,00	30	18,0	420,00	141,06	121,99	147,64
2G17	43134101	0,00	0	18,0	620,00	167,22	152,46	167,41
2G18	43135701	0,00	0	8,0	620,00	172,24	171,60	179,23
2G19	43135803	0,00	0	27,0	300,00	135,06	130,45	170,06
2G20	43136401	0,00	100	18,0	620,00	132,54	104,34	115,49
2G21	41129202	0,03	30	18,0	620,00	184,31	165,95	194,86
2G22	42133602	0,03	210	13,0	1020,00	185,87	162,66	174,97
2G23	43134805	0,03	30	18,0	180,00	194,52	185,95	204,27
2G24	42131002	0,04	30	8,0	620,00	212,40	191,98	190,44
2G25	43134901	0,04	10	0,5	620,00	185,89	170,21	159,73
2G26	43135801	0,04	0	27,0	620,00	176,54	165,63	185,40
2G27	42130701	0,05	10	8,0	620,00	192,76	170,63	189,36
2G28	42133501	0,05	160	3,0	420,00	164,32	150,44	164,32
2G29	43134804	0,06	30	18,0	180,00	197,90	188,31	194,40
2G30	41128904	0,06	50	23,0	620,00	151,66	169,33	144,38
2G31	41129205	0,07	30	3,0	420,00	163,54	124,90	187,57
2G32	42130901	0,07	160	3,0	300,00	203,70	171,89	181,16
2G33	42133901	0,07	70	23,0	300,00	200,04	142,35	171,51
2G34	43136402	0,07	100	18,0	620,00	205,93	175,21	203,99
2G35	42131101	0,08	0	13,0	300,00	178,58	128,16	165,16
2G36	41128906	0,08	160	3,0	620,00	173,37	133,94	160,34
2G37	42131401	0,08	0	3,0	180,00	207,32	188,63	184,79
2G38	42131702	0,08	70	8,0	620,00	191,52	174,03	193,68
2G39	41128905	0,09	30	23,0	620,00	194,93	144,49	193,18
2G40	42133301	0,09	160	23,0	180,00	193,13	170,42	177,57
2G41	42130702	0,11	0	23,0	1020,00	195,25	141,93	200,95
2G42	41128901	0,12	100	18,0	620,00	201,53	146,35	167,29
2G43	43134302	0,12	50	13,0	620,00	170,45	201,79	173,62
2G44	42131403	0,14	0	8	420,00	216,47	159,43	181,54

Classes		Inputs				Outputs		
Order	T2G	FE	CAP	EXP	SAL	MAT	POR	CIE
2G45	42131003	0,15	160	3,0	620,00	181,29	181,68	194,23
2G46	43136301	0,15	0	23	620,00	196,46	151,55	195,03
2G47	42218201	0,16	0	8	1020,00	201,18	197,02	187,46
2G48	43134802	0,17	0	23,0	420,00	158,77	153,34	173,24
2G49	43220901	0,17	0	8,0	1020,00	215,20	188,47	185,92
2G50	42130803	0,18	30	8,0	620,00	158,83	156,90	176,10
2G51	41128903	0,18	70	13,0	1020,00	182,13	153,89	165,52
2G52	42218205	0,19	0	8,0	1020,00	189,40	197,75	175,40
2G53	42133302	0,20	30	18,0	300,00	203,70	188,15	199,85
2G54	42130602	0,23	0	0,5	300,00	151,86	164,86	171,21
2G55	42133303	0,26	160	18,0	300,00	205,24	186,19	200,02
2G56	42131001	0,27	0	8,0	620,00	185,36	194,05	175,23
2G57	43220904	0,28	160	23,0	420,00	224,34	153,66	172,09
2G58	41215603	0,43	30	8,0	1500,00	261,90	231,05	240,20
2G59	43134402	0,43	70	8,0	300,00	244,39	240,17	225,78
2G60	41215706	0,46	210	8,0	420,00	230,85	208,51	211,21
2G61	41128802	0,47	70	0,5	300,00	210,64	190,53	224,02
2G62	41215601	0,56	30	8,0	1500,00	244,75	243,71	243,76
2G63	41215701	0,62	70	18,0	620,00	238,87	233,58	220,87
2G64	43220806	0,62	210	8,0	420,00	247,54	241,76	211,06
2G65	42130502	0,63	70	8,0	1020,00	270,85	236,79	219,22
2G66	43220802	0,70	210	13,0	1020,00	229,56	188,78	215,57
2G67	42130503	0,73	0	23,0	620,00	263,90	252,40	236,74

Table 2. Order number, class code and variables values for classes of teacher with superior education level.

Classes		Inputs				Outputs		
Order	TSUP	FE	CAP	EXP	SAL	MAT	POR	CIE
SUP1	41129003	0,00	30	13,0	620,00	189,08	152,45	145,48
SUP2	41129204	0,00	10	18,0	1500,00	189,23	140,75	158,29
SUP3	42133603	0,00	210	18,0	620,00	192,72	192,46	200,49
SUP4	42133902	0,00	100	13,0	620,00	183,69	182,84	178,21
SUP5	43134001	0,00	0	18,0	620,00	230,49	174,05	209,71
SUP6	43135802	0,00	100	18,0	1020,00	178,17	144,61	160,91
SUP7	43136801	0,00	30	27,0	420,00	182,70	162,34	175,67
SUP8	41129201	0,03	10	8,0	1020,00	189,53	162,48	190,71
SUP9	41129203	0,03	10	8,0	1020,00	176,26	150,57	166,48
SUP10	42132801	0,03	30	3,0	620,00	217,25	190,96	175,70
SUP11	42132802	0,03	70	8,0	620,00	206,20	162,34	178,27
SUP12	41129002	0,03	30	8,0	420,00	184,72	166,70	170,55
SUP13	41129101	0,03	100	18,0	1500,00	170,71	169,45	185,60
SUP14	42131802	0,06	70	8,0	1020,00	209,07	176,15	204,25
SUP15	43134803	0,06	0	8,0	420,00	161,97	148,11	156,02
SUP16	42133201	0,06	30	18,0	420,00	202,81	159,35	185,23
SUP17	42133401	0,06	210	27,0	300,00	194,98	167,25	183,12
SUP18	42130601	0,07	0	13,0	1020,00	193,71	171,39	199,83
SUP19	42131501	0,07	210	13,0	180,00	185,28	162,55	165,32
Classes		Inputs				Outputs		
Order	TSUP	FE	CAP	EXP	SAL	MAT	POR	CIE

SUP20	42131701	0,07	210	13,0	300,00	201,38	142,87	197,23
SUP21	42132902	0,07	50	8,0	620,00	205,54	157,62	162,95
SUP22	43134801	0,07	30	8,0	420,00	181,32	155,04	189,14
SUP23	43135804	0,07	0	23,0	620,00	195,73	177,89	186,23
SUP24	43135602	0,07	50	18,0	620,00	160,30	157,90	190,23
SUP25	43135603	0,07	50	3,0	620,00	188,36	148,38	186,09
SUP26	43134806	0,08	0	8,0	300,00	170,51	159,39	200,53
SUP27	42133601	0,09	210	18,0	1020,00	213,86	178,42	212,15
SUP28	41129001	0,10	10	8,0	420,00	182,02	176,98	186,98
SUP29	42133403	0,11	30	8,0	620,00	191,21	189,83	201,48
SUP30	41128902	0,12	0	23,0	620,00	174,25	182,97	159,36
SUP31	42218202	0,12	160	23,0	180,00	197,83	195,73	174,09
SUP32	42218203	0,14	100	13,0	420,00	186,61	154,08	182,49
SUP33	41129004	0,15	0	8,0	620,00	199,73	200,66	186,29
SUP34	43135601	0,16	210	23,0	300,00	207,25	194,86	186,77
SUP35	42131402	0,16	70	8,0	620,00	192,65	231,47	204,76
SUP36	42133203	0,17	30	18,0	420,00	191,22	151,29	174,56
SUP37	41128703	0,20	10	13,0	620,00	239,01	220,33	239,65
SUP38	41128803	0,20	100	27,0	1500,00	218,23	187,83	200,51
SUP39	42218204	0,20	100	23,0	620,00	190,96	198,13	196,04
SUP40	41128702	0,26	100	27,0	1500,00	227,95	211,52	226,17
SUP41	41128801	0,28	10	27,0	620,00	211,64	229,69	188,69
SUP42	41215702	0,56	160	8,0	620,00	222,85	197,57	207,10
SUP43	41215705	0,58	210	8,0	620,00	216,65	252,65	198,74
SUP44	41215703	0,59	210	13,0	1020,00	245,99	214,46	204,70
SUP45	43220706	0,60	210	13,0	1500,00	246,14	225,78	220,74
SUP46	41215704	0,66	30	8,0	620,00	224,65	262,64	231,89
SUP47	41215602	0,73	100	13,0	1020,00	249,09	238,01	235,31
SUP48	43220701	0,78	30	18,0	1020,00	241,18	236,37	238,20
SUP49	42130501	0,80	210	8,0	1020,00	268,73	263,08	282,00
SUP50	41215604	0,91	100	13,0	1020,00	256,13	236,89	221,72

A NEW APPROACH TO DETERMINE EFFICIENT DMUS IN DEA MODELS WITH USING INVERSE OPTIMIZATION

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ABSTRACT:

This paper proposed a new approach for determining efficient DMUs in DEA Models with using inverse optimization and without solving any LPs. It is important to compare computational performance of solving the simultaneous linear equations with that of the LP, when computational issues and complexity analysis are at focus.

Keywords: *Data Envelopment Analysis (DEA), Decision Making Units (DMUs), Inverse Optimization.*

1. INTRODUCTION

The DEA model is a programming technique for the construction of a non-parametric, piecewise linear convex hull to the observed set of input and output data for discussions of methodology ([4]). DEA defines a linear segmentation to envelop the whole sample data, and uses radial expansion or concentration to measure the efficiency ([2]). This methodology, proposed initially by Charnes, Cooper and Rhodes and known as CCR model. An inverse optimization problem consists of inferring the values of the model parameters such as cost coefficient, right hand side vector, and the constraint matrix given the values of observable parameters (optimal decision variables) ([1]). Geophysical scientists were the first ones in studying inverse optimization problems. In the early few years, inverse optimization problems attracted many operation research specialists and different kind of inverse optimization problems have been studied by researchers.

In this paper based on inverse optimization under L_1 norm, a new approach to determine efficient DMUs in DEA models without solving any LPs is delivered.

Amin et al. ([3]) Proposed a polynomial-time algorithm for computing the non-Archimedean ε in DEA models, which there is no need to identify the specific value of ε in this paper.

2. A Necessary and Sufficient Condition of Efficient DMUs

Let **S** denote the set of feasible solutions for an optimization problem called as P, the relevant specified cost vector is **c**, and x^0 be a given feasible solution. The inverse optimization problem is to perturb the cost vector **c** to **d**, so that x^0 is an optimal solution of P with respect to **d** and $\|d-c\|_P$ is minimum, where $\|d-c\|_P$ is some selected L_P norm.

Consider the following linear programming:.

$$\begin{aligned} \text{Min} \quad & \sum_{j=1}^{n} c_j x_j \\ s.t. \quad & \sum_{j=1}^{n} a_{ij} x_j = b_i, \qquad i = 1, \dots, m \\ & x_j \ge 0, \qquad j = 1, 2, \dots, n \end{aligned}$$

Suppose that x^0 be a feasible solution. The corresponding inverse problem under L_1 norm is as follows ([1]):

$$\text{Min} \sum_{j=1}^{n} \left(\alpha_j + \beta_j\right)$$

s.t.

$$\begin{cases} \sum_{i=1}^{m} a_{ij}\pi_i - \alpha_j + \beta_j + \gamma_j = c_j, \ \forall j \in L \\ \sum_{i=1}^{m} a_{ij}\pi_i - \alpha_j + \beta_j \qquad = c_j, \ \forall j \in F \\ \alpha_j \geq 0, \ \beta_j \geq 0, \ j = 1, \ldots, n, \\ \gamma_j \geq 0, \forall j \in L, \pi_i \ free, i = 1, \ldots, m \end{cases}$$

Where,

$$L = \left\{j : x_j^0 = 0\right\}, \ F = \left\{j : 0 < x_j^0\right\}$$

In basic DEA Models, the k^{th} DMU is obviously efficient if and only if $\theta^* = 1$ and all the slack variables are equal to zero. Notice that for the k^{th} DMU the objective function in CCR and BCC model is $Z_k = \theta - \varepsilon(1s^i - 1s^o)$. Now consider the feasible solution $x^0 = \left(\theta, \lambda, s^i, s^o\right)$ with $\theta = 1, \lambda_k = 1, \lambda_j = 0$ for all $j = 1, \ldots, n$, $j \neq k$, $s^i = 0$ and $s^o = 0$ in the CCR model. The corresponding inverse linear program for the k^{th} DMU is as follow:

$$\text{Min} \sum_{j=1}^{m+n+s+1} (\alpha_j + \beta_j)$$

s.t.

$$\sum_{i=1}^{m+s} a_{ij}\pi_i - \alpha_j + \beta_j + \gamma_j = c_j \qquad \forall j \in L$$

$$\sum_{i=1}^{m+s} a_{ij}\pi_i - \alpha_j + \beta_j \qquad = c_j \ ; \ \forall j \in F$$

$$\alpha_j, \beta_j \geq o, \ \forall j = 1, \ldots, m+n+s+1,$$

$$\gamma_j \geq 0, \ \forall j \in L, \pi_i \ free$$

Where n is the number of DMUs, m and s are the number of inputs and outputs respectively, and

$$L = \{2, \ldots, k, k+2, \ldots, m+n+s+1\}, \ F = \{1, k+1\}$$

Notice that for each $j \in L$, $c_j \in \{0, -\varepsilon\}$ and for each $j \in F$, $c_j \in \{0, 1\}$. It is easy to see that If the optional value of the inverse problem equal to zero then x^0 also is optimal of CCR model. Now consider the following essential Theorem:

3. The Essential Theorem

Theorem: The k^{th} DMU is efficient if and only if the following simultaneous linear equations have a solution:

$$\begin{cases} \sum_{i=1}^{m+s} a_{ij}\pi_i + \gamma_j = c_j \qquad \forall j \in L \\ \sum_{i=1}^{m+s} a_{ij}\pi_i \qquad = c_j \qquad \forall j \in F \\ \gamma_j \geq 0, \ \forall j \in L, \pi_i \ free, i = 1, \ldots, m+s \end{cases}$$

Proof:

Sufficient Condition: Suppose that the above system have a solution, say $\left(\pi^0, \gamma^0\right)$ then by taking $\alpha_j^0 = \beta_j^0 = 0$ for each $j = 1, \ldots, m+n+s+1$, $(\pi^0, \gamma^0, \alpha^0, \beta^0)$ is an optimal solution of the inverse problem. Therefore x^0 is an optimal solution of CCR model, so the k^{th} DMU is efficient.

Necessary Condition: Conversely, suppose that the k^{th} DMU is efficient then x^0 is an optimal solution and the corresponding inverse LP have zero optimal solution value, that is $\alpha_j^* = \beta_j^* = 0$ for each $j = 1, \ldots, m+n+s+1$. So the constraint of inverse LP must have a solution when $\alpha_j = \beta_j = 0$ (for each j). The mentioned proof satisfied the necessary condition.¦

Notice that the only difference is $\sum_{i=1}^{m+s+1} a_{ij}\pi_i$ that appears instead of $\sum_{i=1}^{m+s} a_{ij}\pi_i$ in the equations and all other details are as the same, if the above Theorem is applied to BCC model.

4. Illustrated Example

Suppose on a given system there are two DMUs, two inputs and one output such as the following table:

DMU No.	I_1	I_1	O
1	2	5	1
2	2	6	1

Obviously with respect to the 1nd DMU the 2st one is inefficient. According to the essential Theorem, the 1nd DMU will be efficient if and only if the following linear equations have a solution:

$$\begin{cases} 2\pi_1 + 5\pi_2 = 1 \\ -2\pi_1 - 5\pi_2 + \pi_3 = 0 \\ -2\pi_1 - 6\pi_2 + \pi_3 + \gamma_3 = 0 \\ -\pi_1 + \gamma_4 = -\varepsilon \\ -\pi_2 + \gamma_5 = -\varepsilon \\ -\pi_3 + \gamma_6 = -\varepsilon \\ \gamma_3, \gamma_4, \gamma_5, \gamma_6 \geq 0, \pi_i \ free, i = 1,2,3 \end{cases}$$

Where ε is a positive parameter, by considering $\pi_2 = \frac{1}{6}$ (arbitrary), it concludes the solution

$$(\pi_1, \pi_2, \pi_3, \gamma_3, \gamma_4, \gamma_5, \gamma_6) = \left(\frac{1}{12}, \frac{1}{6}, 1, \frac{1}{6}, \frac{1}{12} - \varepsilon, \frac{1}{6} - \varepsilon, 1 - \varepsilon\right)$$

The corresponding linear equations for the 2st DMU is as follows:

$$\begin{cases} -2\pi_1 - 5\pi_2 + \pi_3 + \gamma_2 = 0 \\ -\pi_1 + \gamma_4 = -\varepsilon \\ -\pi_2 + \gamma_5 = -\varepsilon \\ -\pi_3 + \gamma_6 = -\varepsilon \\ 2\pi_1 + 6\pi_2 = 1 \\ -2\pi_1 - 6\pi_2 + \pi_3 = 0 \\ \gamma_2, \gamma_4, \gamma_5, \gamma_6 \geq 0, \pi_i \ free, i = 1,2,3 \end{cases}$$

Subtracting the 6th equation from the 1st one implies that $\pi_2 + \gamma_2 = 0$, which implies that $\pi_2 \leq 0$, and so $\gamma_5 = -\varepsilon + \pi_2 \leq -\varepsilon < 0$, that contradicts to $\gamma_5 \geq 0$. Then the above equations have no solutions and therefore DMU2 is inefficient.

5. Conclusion

Determining the most efficient DMUs in data envelopment analysis models requires solving the relevant linear programs. In this paper we showed that by using the inverse optimization technique there is no need to solve any mathematical programs such as linear program. By constructing a few simple simultaneous linear equations efficient DMUs will be determined easily. A necessary and sufficient condition proofed this hypothesis that the k^{th} DMU is efficient if and only if the relevant mentioned linear equations set has a solution. Our proposed approach is important to compare computational performance, when computational issues and complexity analysis are at focus.

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A MULTI-CRITERIA APPROACH TO TECHNOLOGICAL PROGRESS, EFFICIENCY CHANGE, AND PRODUCTIVITY GROWTH IN GLOBAL TELECOMMUNICATIONS

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ABSTRACT

This paper examines total factor productivity, efficiency change, and technological progress in 39 samples of global telecommunications during the period 1989 to 1998. The approach uses DEA-type Malmquist productivity index to determine the differences of telecommunications performance between countries or regions. We partitioned our data sets into four regional groupings; namely: Africa, Asia-Pacific, the Americas, and Europe. Empirical results suggest that Europe has obtained the highest productivity growth in telecommunications infrastructure, followed closely by the Americas and Asia Pacific. We indicate that technological progress is highly correlated with the increased TFP growth in these regions rather than efficiency changes. We also found that Africa shows a greater potential for telecommunications productivity growth as evidenced by positive changes both in efficiency and technology. However, we found that general TFP growth across the whole sample of countries has declined, owing mostly to low innovation rather than increased efficiency. This empirical result has policy implications of investing more on advanced technology to boost technological capability of the telecommunications sector in the world and introducing market reforms such as competition.

INTRODUCTION

Telecommunication is rapidly changing the way people communicate with each other and organizations conduct businesses around the world. Among policymakers, telecommunications may be viewed as a strategic resource. A well-developed telecommunication infrastructure attracts investments, because the cost of doing business is reduced significantly in such environment.

Telecommunications may also cause firms to be more productive and perform at lower cost (Read and Youtie (1996, p.12)). From an economic perspective, the role of telecommunications in development can be considered an important factor of production (Williams (1991)). It is more likely that increased use of telecommunications in business may substitute for labor and capital inputs. The convergence, moreover, of telecommunications with computers, fax, and Internet can be responsible for efficiencies in the growing complexity of the production process.

The identification of drivers of productivity growth and examination of efficiency changes form a significant part of government policy reforms on telecommunications performance against international best practice. The measurement of efficiency and productivity growth is widely applied to several industries around the world. The most widely cited approach in the empirical literature is the data envelopment analysis (DEA). This approach was first applied by Charnes *et al.* (1978) for measuring efficiency for not-for-profit organizations in U.S. programs, using constant returns to scale (CRS) model. Banker, Charnes, and Cooper (1984) proposed the variable returns to scale (VRS) model. Consequently, after Charnes *et al.*'s (1978) work, DEA was widely used by many scholars to measure efficiency and productivity. DEA, for instance, is commonly applied to measuring bank efficiency (Rebelo *et al*. (2000), Tser and Tsai (2000), Drake and Howcroft (2002), and Isik and Kabir Hassan (2003)).

DEA method was also useful in calculating efficiency scores in various industries such as transportation, hospitals/health, and manufacturing, as well as in education and service sectors (Odeck (1999), Chirikos and Sear (2000), Mahadevan (2002, 2002a) Illueca and Lafuente (2003), Boussofiane *et al*. (1991), Abott and Doucouliagos (2002), and Galagedera and Silvapulle (2002). However, as to date, there is a dearth of literature on telecommunications productivity using DEA approach, except studies of Madden and Savage (1999, 2001), Koski and Majumdar (2000) and Calabrese *et al*. (2002)).

This study investigates the telecommunication technological progress, efficiency changes, and productivity growth in 39 countries that represent four regions in the world for the period 1989-1998, using DEA-Malmquist indices. Three major research questions raised in this paper are (1) What are the main drivers of telecommunications productivity growth in global telecommunications? (2) Which countries are best performers? and (3) Which regions are showing greater potentials for increased productivity?

METHODOLOGY AND SAMPLE

A Multicriteria Approach

DEA is a "non-parametric programming method used for assessing the efficiency of decision-making units, where the presence of incommensurate inputs and outputs makes the measurement of overall efficiency difficult" (Boussofiane *et al*. (1997, p.127)). There are two most striking advantages of DEA for our own purposes over other econometric models. First, DEA allows the correlation of inefficiency with inputs (Gong and Sickles (1992)). Second, it obtains no standard measurement error or statistical noise, which contributes to accuracy of results (Mahadevan (2002)). Therefore, no statistical tests can be used as typical of the parametric approach. This can be viewed as either the advantage or disadvantage of using DEA.

This approach is an ideal measure for broad measurement of efficiency based on input and output quantities beyond simple items in the growth accounting model. Sequences of the linear programming solution for each of the firms in the sample construct a piece-wise frontier over the data points where the frontier represents an efficient technology. DEA allows measurement of efficiency without having to specify in advance either the form of production function or the weights for inputs and outputs used (Coelli (1996)). That is, DEA is a generalization of total factor productivity methods and thus flexible. DEA comes from its property to envelop all points on or below a production frontier line (Cooper *et al.* (2000)). It is a measure of productivity growth, technical progress, and efficiency change, using the Malmquist index.

The Malmquist productivity index is an indicator of productivity (Malmquist (1953)). This index allows us to break down productivity over time into two drivers: efficiency change (catching-up effect) and technological progress (innovation). The Malmquist index represents total factor productivity that is a product of two *geometric means* either input-oriented or output oriented. Thus, DEA can deal either with *input-orientated* or *output-orientated* efficiency measure for any entity (Coelli *et al. (*1998, pp.135-140)).

The Malmquist index measures the total factor productivity change (TFPCH) between two data points over time by calculating the ratio of data-point distances relative to a common technology. Fare *et al*. (1994) determined the components of distance function of the Malmquist index, using a non-parametric programming method. The technical change or innovation is defined as how much the world frontier shifts at each country's (or firm's) observed input mix. The output-orientated Malmquist productivity change index between period *t* and *t+1* is illustrated following Fare *et al*. (1994, p. 71), as follows:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t}(x^t, y^t)} \mathrm{X} \left[\frac{D_0^{t}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \; \frac{D_0^{t}(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right]^{1/2} \tag{1}$$

Equation 1 presents Malmquist productivity index (m_0), which measures the TFP change over the production point (x_{t+1}, y_{t+1}) and the production point (x_t, y_t), as a ratio of the distance of each point relative to a common technology. This index uses period *t* (observation) technology and period *t+1* technology. TFP growth is the geometric mean of two output-based Malmquist-TFP indices from period *t* to period *t+1*. A TFP value greater than one indicates positive growth from period *t* to period *t+1*. Farell (1957) defined this positive growth as efficient firms operating on the production frontier. Thus, inefficient production units are those operating below the production frontier with a TFP value lesser than one indicating a decrease in TFP growth or performance relative to the previous year.

An econometric approach cannot handle panel data. The DEA-Malmquist approach uses panel data to estimate changes in TFP. DEA method constructs a non-parametric envelopment frontier over the data points in all observations that either lie on or below the production frontier. The envelopment frontier exhibits the closeness (efficiency change or catching-up) of a firm to the frontier. The amount of shifts each firm has in its input mix in the frontier is "technical change". TFP is broken down into technical efficiency and technological progress to show the "changes and shifts" as shown below (Fare *et al*. (1994, p.71)):

Technical Efficiency Change =

$$\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t}(x^{t}, y^{t})} \qquad (2)$$

Technical Change =

$$\left[\frac{D_0^{t}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})}\;\frac{D_0^{t}(x^{t}, y^{t})}{D_0^{t+1}(x^{t}, y^{t})}\right]^{1/2}$$

(3)

The technical efficiency change (Equation 2) measures the change in efficiency between period *t* and *t+1*; whilst, the technical change (Equation 3) captures the shift in a frontier technology. A value greater than one derived for both indices indicates a growth in productivity. Moreover, when *Mo > 1*, this reflects improvement; *Mo < 1, declines in* productive performance, and no improvement when *Mo = 1*.

From the frontier (reference technology) in period *t*, constant returns to scale (CRS) may be relaxed to assume variable returns to scale (VRS); that is, increasing, constant or decreasing returns to scale. Fare *et al.* (1994) used an enhanced decomposition of the Malmquist index to decompose technical efficiency change (EFFCH) under CRS into two components, namely: pure efficiency change (PECH) and scale change (SECH). The PECH can be calculated under the VRS. SECH represents changes in divergence between VRS and CRS technology. Technical change (TECHCH) is measured under the CRS. The enhanced decomposition of Fare *et al*. (1994) is presented as:

$$m_0(y_{t+1}, x_{t+1}, y_t, x_t) = \text{TECHCH x PECH x SECH} \qquad (4)$$

Where: EFFCH = PECH x SECH.

Thus, the Malmquist TFP growth (TFPCH) can be decomposed and re-written as:

TFP Growth =Technical Efficiency Change (EFFCH) X Technological Change (TECHCH) (5)

The Malmquist decomposition helps us to determine the sources of a firm's efficiency and inefficiency. The index is derived using the computer program called Data Envelopment Analysis Program (DEAP) Version 2.1, which is designed by Coelli (1996).

DATA AND SAMPLE

Data for inputs and outputs from 1989 to 1998 were taken from the *ITU Yearbook of Statistics-Telecommunication Services Chronological Time Series 1989-1998*, published by the International Telecommunications Union (ITU). The two inputs used were capital investment and number of employees. Data for outputs were total telecom services revenue, total fixed line, international outgoing telecom minutes, and teledensity. There were 39 sample countries in the four regional groupings distributed as follows: 5 in Africa, 13 in the Asia-Pacific, 7 in the Americas, and 14 in Europe. The completeness of data sets over time period led to unbalanced sample sizes. TFP growth and its decompositions were calculated for each regional grouping, each country, and for the total sample as a whole.

EMPIRICAL RESULTS

The Malmquist productivity index shows the results for efficiency, technological, and TFP changes for countries in Africa, Asia-Pacific, the Americas, and Europe against the standard of international best practice.

Africa

In Africa, five countries in the sample showed a remarkable decline in TFP growth due to technological regress. For the five African countries, technical changes have jointly led to a decline in productivity of 151.4 percent per year. The technological regress has not been offset by the positive efficiency growth observed, especially in Algeria (1.032), Morocco (1.091), and South Africa (1.043). Declines in technical efficiency change and technological progress pulled down the TFP growth in Senegal (33.9 percent annually) and Zambia (41.2 percent annually). In aggregate, the average TFP growth has a decline of 146.8 percent per year. This implies that to achieve the 100 percent level of productivity growth, African countries needs more improvements to attain the international best practice standard, as follows: 24 percent (Algeria), 17.8 percent (Morocco), 33 percent (South Africa), 32.1 percent (Senegal), and 39.9 percent (Zambia).

Asia-Pacific

In the Asia-Pacific group, the Philippines has shown a surprisingly positive TFP growth (1.041). The main drivers for its positive TFP growth are improved efficiency (1.014) and technological progress (1.026). This was perhaps due to the injection of market reforms, wherein, the telecommunications industry allowed full competition in the market in 1992. China has the lowest TFP growth of 0.389 and needs a 61 percent improvement to achieve the international best practice. This is not surprising because China's telecommunications market is still closed to foreign competition, and privatization seems to be farfetched.

Surprisingly, Singapore has obtained the 2nd to the lowest TFP growth (0.514) (next to China). This implies that Singapore still needs a 48.6 percent improvement to achieve the 100 percent productivity growth. This new result affirms the finding of Mahadevan (2002a) that Singapore's service sector suffered from a decreased TFP growth, wherein, the information technology sector obtained a negative growth. Tan and Virabhak (1998) proved that TFP growth in Singapore's service sector was about zero (0) percent. These findings are interesting considering that Singapore is a well-known for its high technology and was the first newly-industrialized country (NIC) to attain the advanced developing status by OECD in 1996 (Mahadevan (2002)). Singapore's government, which does not allow competition in its telecommunications market, owns about 92.8 percent of Singtel.

Countries like Australia, Japan, Hong Kong, Korea, Malaysia, and New Zealand have TFP growth below one. Low catching-up effect and technological regress contributed both to the decrease in their productivity growth between 12 to 61 percent per year. Positive efficiency growth was seen in Singapore, Taiwan, Fiji, Myanmar, and Macau; but poor technological progress led to the decline in their TFP growth between 2 and 49 percent per year. Though these countries underwent privatization reforms (others just recently), the government still holds more than 50 percent stake in ownership shares, except New Zealand (0 percent after privatization). Most Asia-Pacific countries have the statist orientation (except the Philippines), which perhaps explains government intervention in the utility sector that results in inefficiency in most cases.

Americas

In the Americas, Peru, the United States, and Uruguay obtained the highest productivity growth or more than one. This positive TFP growth is attributed to increased technological progress over time rather than catching-up effect. Positive catching-up effect was seen in Canada but inadequate to pull its TFP growth upward because of very low technological progress. Canada needs a 21.3 percent improvement to reach the expected productive performance. A deteriorating efficiency growth and technological progress are the main drivers of poor productivity growth seen in Honduras and Mexico. The decline in TFP growth was 17.2 percent per year in Mexico and 9.5 percent in Honduras.

Europe

In Europe, there were five countries that showed a negative catching-up effect or efficiency growth over time as follows: -1.7 percent (Germany), -7.1 percent (Iceland), -6.1 percent (Luxembourg), -8.7 percent (Malta), and –0.7 percent (Romania). However, the increased innovation (technological progress) has offset a decrease in efficiency growth that led to positive improvements in their TFP growth. Both positive catching-up effect and high technological progress have led to increased TFP growth as evident in cases of Greece, Poland, Spain, Switzerland, and Turkey. These results suggest that these countries were able to maximize their telecommunication outputs despite limited inputs (EFFCH), and they demonstrated an ability to use optimal inputs given the production technology (TECHCH). Thus, all European countries in our sample have shown increased TFP growth.

FULL SAMPLE OF COUNTRIES

Taking the whole sample of countries, the average TFP growth is below one (0.961). This implies the need for 3.9 percent improvement to achieve 100 percent productive performance. Though both are below one, it seems that the potential driver of TFP growth is catching-up effect (0.991) rather than innovation (0.970). Innovation shows a decrease of 3 percent over the decade, compared to 0.9 percent for catch-up.

In our 39 sample of countries, the top five performers with the highest productivity growth rates per year are from Europe: Spain (107 percent), Turkey (106.8 percent), Poland (103 percent), Romania (86 percent), and Switzerland (72 percent). Privatization reforms were introduced in Spain more than a decade ago. Perhaps these reforms have helped in boosting that country's productivity growth. On the other hand, the five poor performers with the lowest productivity growth rates per year are China (-61 percent), Singapore (-48.6 percent), Zambia (-39.9 percent), South Africa (-33 percent), and Senegal (–32.9 percent). In China, telecommunications remains under 100 percent state ownership; and Singapore's telecommunications industry is still government-majority owned. In African countries, no market reforms have been introduced yet, except recently in South Africa. Though South Africa embraced privatization reforms in 1997, the government still owns a 70 percent share in its telecommunications industry.

REGIONAL PERFORMANCE

Data sets were partitioned into four regional groupings, and their Malmquist productivity performances were compared. We obtained more interesting results when each country's productive performance was taken against the standard of international best practice in the whole sample. In this way, we can determine which region is performing better. The first regional group to be examined is Africa. Our results show that TFP growth in Africa region suggests a positive improvement, with an index growth of 1.003. This positive growth is due more to technological change (1.003). Our result indicates that five African countries in the sample were able to acquire and adapt new technology over time; this is an encouraging result. The catching-up effect has obtained a constant average of one.

The Asia-Pacific group, like the other three regions in our sample, has also shown a positive TFP growth (1.033). Technological progress is the main driver of its productivity growth. The technical efficiency change (0.998) shows a decline of 0.2 percent growth per year, which is lower, compared with the Americas group (2.4 percent). Like the Americas, catching-up effect in Asia Pacific group has not dragged down its productivity growth. In this case, technological progress is more correlated with a TFP growth. This is perhaps due the fast technological changes observed among NICs (e.g., Hong Kong, Malaysia, Taiwan, Singapore, South Korea) as well as advanced economies (e.g., Japan, Australia, and New Zealand) in our sample. These results are not surprising because, according to some observers, in the 1990s the Asia Pacific region emerged as the "economic powerhouse of the 21st century (ITU, 2000). So goes the prediction that the world's power balance is shifting to Asia-Pacific, and the Information and Communications (ICT) sector in this region signifies this shift of power (*Ibid*.). As mentioned previously, Asia-Pacific obtained 33 percent in regional shares of fixed telephone lines (next to Europe's 34 percent) as of January 1, 2000 (*Ibid.,* p.3). The region is projected to increase to 46 percent shares in 2010 (*Ibid*.). The positive technological progress in the Asia-Pacific region may be attributed also to its strikingly fast-growing mobile market, which is projected to account for half of the world's market by 2010 (*Ibid*.). Hence, the positive TFP performance implies that Asia Pacific countries recognize that a well-developed telecommunication infrastructure attracts investments.

In the Americas, TFP growth also exhibits an increased performance, having obtained an index of 1.040. Technological change is the main driver for the increased productivity growth, but the catching-up effect shows a declining growth as evidenced by its index growth of 0.976. This suggests inefficient performance over time. Though technical efficiency decline was observed, this did not pull down the region's TFP growth. The decline was offset by the positive growth of technological progress (1.066). Thus, innovation is positively correlated with the TFP growth, with about seven percent growth per year.

In the Europe group, the TFP growth indicates increasing improvement over time, which is shown in its positive growth of 1.293. Technological progress, with a score of 1.313, is the main contributing factor to an increased productivity. This improved innovation is expected since most countries in the Europe group are all highly industrialized economies, with well-developed and advanced telecommunications infrastructure. Europe's efficiency growth requires 1.5 percent improvement to achieve 100 percent efficiency.

In the four regional groupings, TFP growth shows its highest improvement in Europe (1.293), followed closely by the Americas (1.040), Asia-Pacific (1.033), and Africa (1.003). A closer examination of each region shows that efficiency growth in the Americas, Asia-Pacific, and Europe needs further improvements or more catching up to achieve 100 percent efficiency. Africa seems to have positive catching-up effect and technological progress that have jointly led to improved productivity.

CONCLUSIONS

Many governments in the world have made significant market reforms in their telecommunications market to attract investments and improve the efficient delivery of telecommunications services. Assessment of its efficiency and productivity is paramount in the policy reform programs for each government. Thus, our study contributes to the existing productivity measurement of the telecommunications sector in the panel or across a sample of countries to assess the productive performance against the standard of the international best practice.

We indicate that technological progress is more highly correlated with the increased TFP growth in regions of Asia-Pacific, the Americas, and Europe than with efficiency changes. We also found that Africa shows a greater potential for telecommunications productivity growth as evidenced by positive changes both in efficiency and technology. However, we found that general TFP growth across the whole sample of countries has declined, owing mostly to low innovation rather than increased efficiency. This empirical result has important policy implications: More capital should be invested in advanced technology to boost the technological capability of the telecommunications sector throughout the world, and there is a need for introducing market reforms such as competition.

ACKNOWLEDGMENTS

The authors would like to acknowledge the Graduate School of the University of Santo. Tomas, Manila, Philippines for the financial support provided for this research. Tim Coelli provided the DEAP (2.1) Computer Software for empirical analysis. Special thanks are expressed to Lyle Brown and Exequiel Cabanda for their technical assistance. Any remaining errors in this paper are the responsibility of the authors alone.

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A SIMULATION-BASED ADAPTIVE POLICY FRAMEWORK TO STUDY THE EFFECTS OF POLICY CYCLES ON THE EFFICIENCY FRONTIER DYNAMIC

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ABSTRACT

This research conceptualises a tool for studying the effects of asynchronous policy cycles on the dynamics of the efficiency frontier, considering learning and imprecision. The model integrates data envelopment analysis, Malmquist Productivity Index, and process learning into a discrete-dynamic stochastic simulation framework. It analyses an entire system of decision making units that act independently to improve production quality and efficiency, but their actions have global effects on the efficiency frontier. Policies adapt to changes in the system's state and their effects are dynamic and uncertain due to process learning and imprecision. This model produces no normative solutions. We demonstrate its functionality with an example and argue that this approach can improve the utility of DEA for supporting decision-making.

INTRODUCTION

Efficiency dynamics are generally explained by changes in efficiency and by technical changes, which may be induced by policies or may occur autonomously. This work conceptualizes a tool that integrates data envelopment analysis (DEA), Malmquist productivity indices (MPI), and process learning (PL) in a discrete-dynamic stochastic simulation framework for studying the dynamics of the efficiency frontier as it responds to asynchronous policies, which are based upon variations in production efficiency and process quality. We model a class of decision-making problems where there are K decision making units (DMUs) that, while producing similar outputs and using similar inputs, differ in various other ways: (a) process quality and learning, (b) management culture, and (c) resources. The DMUs act independently to control process quality and efficiency, but their actions have global effects in that they determine changes, both shifts and composition, on the efficiency frontier over time. Thus, convergence toward the efficiency frontier is dynamic and uncertain. A DMU is unable to fully internalise the effects of the competition's policies on the efficiency frontier over time when formulating its own policies. The best it can do is to adapt.

The adaptive policy decision model simulates the policy decision process for each DMU. Policies adapt to changes in output, process quality, and productivity each period, depending on the management and other constraints, and their effects are dynamic due to PL and imprecision. PL, autonomous or induced, determines the rate at which improvement in quality and efficiency may be achieved over time whereas imprecision limits the ability of the DMU to control variability in the inputs-outputs and external effects.

We employ Färe et al. (1992)'s extension of the MPI model to compute the efficiency dynamics each period. MPI is defined as the geometric mean of ratios of distance functions which are evaluated using DEA. For each DMU, the relation between PL and the efficiency frontier dynamics is established using process desirability functions which are based on the work of Derringer and Suich (1980). The process quality is defined in term of the desirability functions with the advantage that policies can be targeted to a specific output or process. The process quality is characterized by the output quality and the process learning rate.

To the best of our knowledge, there is no existing work employing DEA or MPI that follows our approach. The model have been developed employing C++, MySQL, and cplex (an alternative to the cplex is currently being considered due to accessibility). An example demonstrates the functionality and practicality of this modeling approach. It shows that while policies may be relatively irresponsive to variations in the system state, the efficiency frontier exhibits considerable dynamics, which may be better explained by process learning.

We argue that this integrated modelling approach can improve the utility of DEA/MPI for supporting decision-making in real world application both in public and private sector operations. The goal is to provide a tool with flexibility for studying the relationship between the policy decision-making process and efficiency dynamics, considering imprecision. The model analyses the entire system of DMUs, but it produces non-normative solutions.

The next section will explain DEA and MPI techniques and elaborate further the rationale for our research. Section 3 is devoted to a formal description of the conceptual model, including explanation of the design variables, the adaptive policy model, and the model architecture. In section 4 some evidence of the functionality and capacity of the model will be provided. Concluding remarks and future considerations can be found in section 5.

DEA/MPI and research considerations

The DEA literature is very extensive so we will not review it here. Readers are directed to Cooper, Lawrence, and Thrall (2000) for a comprehensive treatment of DEA. It suffices to note that since the CCR model first appeared in 1978, DEA has received wide acceptability, particularly in its application to education, transportation, health care, and banking (Thanassoulis and Dustan (1994), Colbert et al. (2000), Vargas and Bricker (2001), Fukuyama and Weber (2002), Adler and Golany (2001), Wagner, Shimshak, and Novak (2003), Golany and Storbeck (1999), Emel et al. (2003), Yeh (1996)). Numerous extensions and refinements to the DEA model have also been introduced to address important caveats or application-specific requirements (Boussofiance, Dyson, and Thanassoulis (1991), Cooper, Thompson, and Thrall (1996), Cooper, Lawrence, and Tone (2000). Despite the advances and extensions, the usability of DEA for policy decision remains a hot topic. Two particular issues are the workability of the policy options produced by DEA and the dynamics of the efficiency. This work deals specifically with these issues.

DEA, developed by Charnes, Cooper and Rhodes (1978), produces a binary rating of the DMUs' efficiency based on a vector $\mathbf{Y}$ of outputs and a vector $\mathbf{X}$ of inputs. Mathematically, the efficiency of a DMU k is determined by solving M1, where $0 \le e_{[k]} \le 1$ is an efficiency measure. The weights v_j and w_i are the decision variables chosen optimally by the DMU k in order to maximize its efficiency score, with the constraint that, using the same weights, no other DMU in the system can have an efficiency score e greater than one (100%). M1 is the CCR (1978) ratio model for a CRS technology. DMU k is efficient if $e^*_{[k]}=1$ and there exists at least one optimal set of weights (v^*, w^*), with $v^*>0$ and $w^*>0$. Otherwise, DMU k is CCR-inefficient $e^*_{[k]}<1$ (Cooper, Lawrence, and Thrall, 2000)

For each inefficient DMU, the reference set $\mathbf{R}=\{(\hat{\mathbf{x}},\hat{\mathbf{y}}) / \hat{\mathbf{x}}=e^*\mathbf{x}, \hat{\mathbf{y}}=1/e^*\mathbf{y}, e^*<1\}$ represents technically feasible efficient input-output policies. Projecting its inputs-outputs mix to $(\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k) \in \mathbf{R}$, DMU k will converge to that coordinate on the frontier without altering the positions of the efficient DMUs defining that particular facet in the frontier nor the positions of inefficient DMUs in the cone formed by the reference set (Cooper, Lawrence, and Thrall , 2000).

$$Max\, e_{[k]} = \sum_{j=1}^{m} v_j y_{k,j}^t; \quad \forall k$$

$$st.$$

$$\sum_{i=1}^{n} \omega_i x_{k,i}^t = 1; \qquad [\text{M}1]$$

$$\sum_{j=1}^{m} v_j y_{k,j}^t - \sum_{i=1}^{n} \omega_i x_{k,i}^t <= 0; \quad k = 1,...K$$

$$v_j, \omega_i >= 0; i = 1,...n, j = 1,...m$$

In practice, however, the workability of the policy options and efficiency dynamics will affects the transition of an inefficient DMU to a facet on the efficiency frontier. In most production systems adjustments to the inputs and outputs, both quantity and quality, generally require time, resources and management's commitment. Improvement in productivity and quality is dynamic due to process learning and imprecision. With no cooperation, a DMU cannot perfectly internalise the effects of global competition on the frontier. These effects affect both the composition and location of the efficiency frontier over time. Hence, even if changing the inputs-outputs mix to $(\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k) \in \mathbf{R}$ be possible, convergence to the frontier is uncertain and multiple policy changes may be needed to achieve a desired target. A goal for developing this model is to provide a tool with flexibility for studying the relationship between the policy decision-making process and efficiency dynamics, considering imprecision.

Efficiency dynamics can be computed employing Färe et al. (1992) extension of Caves, Christensen and Diewert (1982)'s MPI. The authors define MPI as the geometric mean of the efficiency change index $\nabla E^{t-1,t}$ and a technical change index $\nabla T^{t-1,t}$ (eq.1), which are specified as ratios of distance functions. Färe and Grosskopf (1996) employ output distance functions to define the indexes and compute these functions using DEA. We follow this approach. DMU k shows efficiency and productive frontier progress at *period t* if $\pi_k^t > 1$, $\nabla E_k^{t-1,t} \geq 1$ and $\nabla T_k^{t-1,t} \geq 1$ with at least one strict inequality.

$$\pi_k^t = \nabla E_k^{t-1,t} \ . \ \nabla T_k^{t-1,t} \qquad \text{[eq.1]}$$

$$\pi_k^t = \frac{D_k^t(x^t, y^t)}{D_k^{t-1}(x^{t-1}, y^{t-1})} \left[\frac{D_k^{t-1}(x^t, y^t)}{D_k^t(x^t, y^t)} \frac{D_k^{t-1}(x^{t-1}, y^{t-1})}{D^t(x^{t-1}, y^{t-1})} \right]^{1/2} \qquad \text{[eq.2]}$$

The output-oriented distance function $D^t(x^t, y^t) = \inf\{\theta \mid (x^t, y^t/\theta) \in \mathbf{F}^{\mathbf{t}}\}$ for the period t technology $\mathbf{F}^{\mathbf{t}}$ measures the maximal feasible radial increase of vector of output $\mathbf{y}^t$ given the vector of input $\mathbf{x}^t$, where $\theta = 1$ if $e^*_{[k]} = 1$, $v^* \geq 0$ and $w^* \geq 0$ with at least one strict equality. Thus, the output oriented Ferrell efficiency equal θ^{-1}. Single period $D^t(x^t, y^t)$ and mixed periods $D^{t-1}(x^t, y^t)$ distance functions can be computed using M1. This method is computational intensive and requires $\mathbf{X} > \mathbf{0}$ and $\mathbf{Y} > \mathbf{0}$.

Conceptual model description

This section presents a description of the variables, the adaptive policy model, and the model architecture.

The design variables

DMU k has a single production process that uses a vector $\mathbf{V} = (\mathbf{X} \geq 0, \Theta \geq 0)$ of inputs of dimension $(n+h)$ to produce a vector $\mathbf{Y} \geq 0$ of outputs of dimension (m) each period. The matrix $(\mathbf{V}, \mathbf{Y})$ represents quality levels; however, the quality of $\mathbf{X}$ is not perfectly controllable at entrance. The production of $\mathbf{Y}$ follows a piecewise and stochastic Cobb-Douglas technology (eq.3)

$$\mathbf{Y}_k^t = A_k \prod \Theta_k^{\rho, t-1} \mathbf{X}_k^{\omega, t} \pm v \qquad \text{[eq.3]}$$

$$0 < \omega < 1, \ 0 < \rho < 1$$

$$0 < v = D(\alpha, \beta) < 1$$

$$k = 1, \ldots K$$

where A_k is a positive constant and may be considered an indicator of the state of the technology, ω is a positive fraction, and ρ is another positive fraction which may or may not be equal to $1-\omega$. ω and ρ are the marginal contributions of Θ_k^{t-1} and $\mathbf{X}_k^t$ to $\mathbf{Y}_k^t$. Θ_k^{t-1} is the process quality at the start of *period t* (eq.6). Finally, v is a stochastic disturbance with mean $\mu_v \geq 0$ and standard deviation σ_v which parameters may differ among the DMUs.

The stochastic process $\{\mathbf{Y}_k^t, t \geq 0\}$ with finite state space $\hat{Q}_k = \{(Q_k^{-*}, Q_k^{+*})\} \subset Q$ describes the state of the output for DMU k at *period t*, where $Q = \{Q^-, \ldots Q^+\}$, $Q_k^{-*} \geq Q^-$ and $Q_k^{+*} \leq Q^+$ are the lower-upper quality targets for $\mathbf{Y}_k^t$, and $Q_k^{+*} \leq (\mathbf{Y})_k^t \leq Q_k^+$ is possible. $t \geq 0$ indicates the production period. $\mathbf{Y}_k^t$ can also be controlled setting levels for λ_k, and σ_v. For example, decreasing σ_v and increasing λ_k DMU k can increase $\mathbf{Y}_k^t$.

For each output y_{kj} the process desirability function φ_{kj} is specified as in eq.4, where $0 \leq \varphi_{kj} \leq 1$ measures the process capability (quality). φ_{kj} is a generalization of Harrington (1965)'s desirability function proposed by

$$\phi_{kj} = \begin{cases} 0 & y_{kj} \leq Q_k^{-*} \\ \left[\dfrac{y_{kj} - Q_k^{-*}}{Q_k^{+*} - Q_k^{-*}} \right]^{\lambda_{kj}} & Q_k^{-*} \leq y_{kj} \leq Q_k^{+*}; \ \lambda \geq 0 \\ 1 & y_{kj} \geq Q_k^{+*} \end{cases} \qquad \text{[eq.4]}$$

Derringer and Suich (1980). Using φ_{kj}, policies can be targeted to a specific output or process by specifying limits for y_{kj} and λ_{kj}. For example, DMU k may set λ_{kj} high to rapidly increase y_{kj} above Q_k^{-*}. The overall process desirability Φ_k is the geometric mean of the φ_{kj} (eq.5). Φ_k is also defined in the zero-one interval: $\Phi_k \in [0,1]$. It is zero if any of the individual processes is undesirable (i.e., $y_{kj} \le Q_S^{-*}$) and one if all processes are 100% desirable (i.e., y_{kj} Q_S^{-*}). This condition requires all processes to be in control for the overall process quality Φ_k to be desirable. To ensure strictly positive values, we define the overall process quality Θ as an affined transformation of Φ_k (eq.6). If $\Theta_{kj} \le \vartheta$ the quality is undesirable and it is 100% desirable if $\Theta = 1$. This approach establishes the relationship between PL and the efficiency frontier through the output $\mathbf{Y}$.

DMU k publishes $\mathbf{X}$ and $\mathbf{Y}$ each period to be compared against its peers in term of its performance. It then uses the results of the evaluation to design improvement policies.

$$\Phi_k = \left(\prod_{j=1}^{m} \phi_{kj} \right)^{1/R} \qquad \text{[eq.5]}$$

$$\Theta_k = \left\{ (\vartheta + 1/\eta\, \Phi_k) \; \Phi_k \ge 0, \vartheta > 0 \right. \qquad \text{[eq.6]}$$

$$(0 < \Theta \le 1]$$

$$k = 1, \cdots K\,; \; j = 1, \cdots m$$

Adaptive policy decision model

The adaptive policy decision model simulates the dynamics of the policy decision process for each DMU. Policies decisions are independent and adaptive, and their effects are dynamic and imprecise, which result in asynchronous policy cycles. The policy cycle r is the average time between sequential policy decisions and can be interpreted as a measure of the responsiveness of the DMU to changes in the state. The higher the value of r the less responsive the DMU is to variations in the state. Two underlying assumptions are: (a) policy decisions require management commitment and resources; (b) policy outcomes are imprecise and dynamic.

The stochastic process $\{s_t, t \ge 0\}$ with finite state space $S = \{s_i / s_i = (e_k^t, \pi_k^t, \Theta_k^t); i,t \ge 0\}$ where $e_k^t = h$, $\pi_k^t = f$, $\Theta_k^t = l$ are possible outcomes as indicated below (Figure 1), and defines the state at *period t* for DMU k. Each period, the new state for DMU k will be identical to the previous state, except that it specifies a different level for at least one of the performance measures. Thus, an event only has to change a part of the system current state in order to change the entire system state.

The transition probabilities from state s_i at *period t* to state s_j at *period t*+1 p_{ij} are not specified. We consider the conditional probability that DMU k changes or modifies its policy the next period after observing $(e_k^t, \pi_k^t, \Theta_k^t)$ at *period t* given the current policy and its effective cycle $pc_k^t = c, 0 \le c \ge r$, $\Pr(./.)$. This probability is zero if $c = 0$ and it increases as $c \to r$; however, the shape of the distribution may vary among the DMUs. We specify a set of rules to determine $\Pr(./.)$ and the choice of policy. For DMU k: *First* determine the mean improvement $\mu_I^t = \sum E_s^t / M, s = 1, \ldots M$, where the E_s^t is the differences between the n periods moving averages for e_k^t, π_k^t, Θ_k^t and the observed values for these measures at *period t*. *Second* evaluate the current policy state and then determine $\Pr(./.)$ if $\mu_I \ge 0$ or $\mu_I < 0$. *Third,* determine the policy choice.

$$h = \begin{cases} 0 & \text{if } e < 1\,(\textit{inefficient}) \\ 1 & \text{if } e = 1\,(\textit{efficient}) \end{cases} \qquad f \begin{cases} -1 & \textit{if}\ \pi < 1\,(\textit{decrease}) \\ 0 & \textit{if}\ \pi = 1\,(\textit{efficient}) \\ 1 & \textit{if}\ \pi > 1\,(\textit{increase}) \end{cases} \quad \text{eq.3. 1}$$

$$l = \begin{cases} 0 & \textit{if}\ \Theta \le 0.5\,(\textit{undesirable}) \\ 1 & \textit{if}\ \Theta > 0.5\,(\textit{desirable}) \end{cases}$$

Figure 1. Definitions for h, f, and *l*

At any period, DMU k may choose to increase λ_{kj}, reduce σ_v, and/or to set $\{Q_k^{-*}, Q_k^{+*}\}$ to improve Θ_k and $\mathbf{Y}_k$ with the condition that if DMU k is inefficient $Q_k^{+*} \le 1/e_k^t \mathbf{Y}_k^t$. The DMU may also choose to do nothing (no change in policy).

Model architecture

The top level architecture for the integrated technology is shown in Figure 2. This model includes four modules: inputs-outputs simulation, efficiency and productivity evaluation, policy decision simulation, and data management. Following initialization the model first determine $(\mathbf{V}, \mathbf{Y})$ then e, ΔE, ΔT, and π are computed. Next, the policy decision process is simulated and the process advances one period. The execution advances sequentially until reaching the end of the simulation period. Data management functions as a bi-directional buffer to each module using a "retrieve/insert" procedure. Data are retrieved to begin an operation and the results are inserted at the end of the operation. This procedure improves memory management.

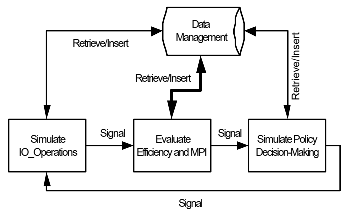

Figure 2 Technology Integration: Top Level System Architecture

The model has been developed using C++, MySQL, and cplex. An alternative to the cplex is currently being considered due to accessibility. Following we present an example.

Example Results

This example tests the current functionality of the model. The results are only preliminaries. We are reprogramming one of module due to lack of access to the cplex. Then we'll conduct more testing. The example includes 20 DMUs, 3 inputs (x1, x2, Θ), and 3 outputs (y1,y2,y3). For each DMU $\mathbf{X}$ is draw from the uniform distribution in [0,1], the output $\mathbf{Y}$ is a stochastic process with finite state space $Q=\{(0.60,0.90)\}$, and the process quality Θ_k^t is computed as indicated above. The Cobb-Douglas' parameters are $A=1$, $\rho\in[0.4,0.6]$, and $\omega\in[0.4,0.6]$. The random disturbance υ is draw from a beta distribution $\beta(\alpha_1,\alpha_2)$, where $\alpha_1>0$ and $\alpha_2>0$. Finally λ is draw from the interval [4.0, 6.0]. The simulation runs for four periods (SP=4). Each DMU has the policy options indicated above each period.

Table 1, we list means productivity growth results for the production periods. These numbers are derived from the original solution of the MPI by subtracting one. Considering Table 1, it is clear that the overall productivity grew remarkably in t1/t2, but it did not improve as significantly in t2/t3 compared to t1/t2 and third t3/t4. The results by DMU indicate productivity improvements in 10 out of 20 DMUs in t1/t2 and improvements in 12 out of 20 in the following two periods. Within periods most improvements in productivity are modest (less than one). Over time, all DMUs experience significant fluctuations in productivity, which result in small overall means for most DMUs (see Table 2)

The efficiency change index increases continuously over the periods whereas the technical change index decreases sharply in t2/t3 and increases in t3/t4. Overall, in t1/t2 the main improvement in productivity comes from technical change and in t3/t4 efficiency change contributes more to the realized improvement (Table 1). By DMU the results show that technical improvement occurred in 13 out of 20 DMUs in t1/t2 with significant increase in only 3 of the DMUs. Efficiency improvement occurred in 11 out of 20 DMUs in t2/t3 and 4 DMUs experienced no change over the period. In t3/t4, efficiency and technical improvements occurred in 9 of DMUs, but efficiency change has the strongest effect. There was marked technical regress in t2/t3 and t3/t4 with 11 of the 20 DMUs showing decrease. On average most DMUs observed only modest improvement on both indexes over the 4 periods (Table 2).

System Performance			
Means	t1-t 2	t2 - t3	t3 - t4
Malmquist	0.6377	0.2293	0.5334
Efficiency change	-0.0184	0.2249	0.3754
Technical change	0.5909	-0.0235	0.1288
Efficiency score	0.7822	0.7522	0.8603

Table 1. Overall means

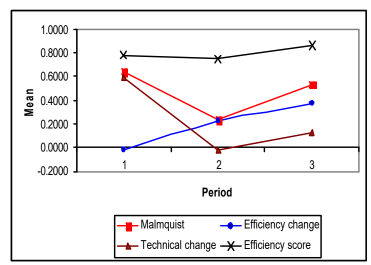

Figure 3. Overall means

The composition of the efficiency frontier varies over the periods. The number of efficient DMUs decreased in t2 and increased in the following periods relatively to t1; however, no DMU is consistently efficient each period and only two of the DMUs are consistently inefficient each period. Thus, for each DMU the overall mean efficiency is less than 1.00 (Table 2).

No DMU changed policies during the period, indicating that changes in the system' state were likely due to autonomous learning and random effects that with the initial conditions, the current policy cycle may be longer than 4 periods for all DMUs. Without changing policy 5 of 20 DMUs moved gradually and consistently to the efficiency frontier over the 4 periods. These DMUs show continuous improvement on the efficiency change index each period and modest variation on the technical change index each period.

The results clearly demonstrate the functionality of the model at its current stage of development. For the example's conditions, policies appear non-responsive to variations in performance while the frontier experiences significant dynamics.

Mean Efficiency and Productivity Growth				
DMU_ID	EffChange	TechChange	Productivity	Efficiency
1	0.0103	-0.0182	-0.0493	0.9597
2	0.0324	0.2381	0.2802	0.9333
3	0.0132	0.3805	0.2366	0.9675
4	0.0951	0.2293	0.5626	0.8911
5	0.0504	0.2309	0.4775	0.9672
6	0.2567	0.0599	0.1783	0.6702
7	0.1295	0.1301	0.4431	0.7694
8	-0.0298	1.2634	0.4078	0.9776
9	0.0197	0.4416	0.0677	0.9157
10	0.0741	0.1271	0.1397	0.9306
11	0.0236	-0.1344	0.2367	0.8064
12	0.2385	-0.3558	0.0029	0.6292
13	0.3991	-0.0486	0.2406	0.7897
14	0.1155	0.0186	-0.4346	0.8344
15	0.6490	0.3560	1.2758	0.5186
16	0.2862	0.0474	0.4061	0.5765
17	0.0891	0.1815	0.3675	0.7811
18	1.0344	1.0601	0.8616	0.7438
19	0.2953	0.2422	2.4142	0.4884
20	0.0973	0.1920	1.2206	0.8966
AVERAGE	0.1940	0.2321	0.4668	0.8023

Table 2. Mean productivity and efficiency for the DMU over 4 periods

CONCLUSIONS AND IMPLICATIONS FOR THE FUTURE

This work leverages the advantages of DEA, MPI, simulation, and PL for modeling complex production systems. We propose an integrated simulation framework for studying the dynamics of the efficiency frontier as it responds to asynchronous policies which are based upon variations on performance. Policy decisions adapt to changes in the system's state, depending on the management culture, process learning, and the policy cycle. Thus, the workability of the input-output policy options produced by DEA is limited at any period. The model analyses the entire system of DMUs; however, it is not intended to produce normative policies or solutions.

The DMU cannot control variability in the inputs quality nor can it internalise the effects of the competition's policies on the efficiency frontier. These effects are dynamics affecting both, the composition and position of the efficiency frontier over time. Thus, the DMU's position with respect to the efficiency frontier is uncertain at any period.

The functionality of the model is demonstrated using a simple example. The efficiency frontier shows significant dynamics over the 4 period simulated; however, policy decisions were irresponsive to variations in the system's state. Learning and random effects are likely explanations for the changes.

We argue that this approach can improve the utility of DEA for supporting decision-making in real world application both in public and private sector operations. Future works involve completion of the model development, further testing, and applying it to real world systems. Extending the model to a distributed simulation framework to better resemble the independent operations of the real systems is another plan for the future.

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ACKNOWLEDGMENTS

The author is grateful to Dennis Bricker for several helpful discussions.

A NEW ALGORITHM FOR RANKING EFFICIENT DECISION MAKING UNITS IN DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Basic data envelopment analysis (DEA) models evaluate the relative efficiency of DMUs but do not allow ranking of the efficient units themselves. This fact is the main weakness of basic DEA models. One way to rank efficient DMUs is to modify basic DEA models. One of them has been formulated by Andersen and Petersen [1,2] but it can be unstable when one of the DMUs has a relatively small value for some of its inputs. This paper proposes a new ranking algorithm that can be used for ranking efficient DMUs by DEA method and removes the foregoing difficulty.

Keywords: *Data envelopment analysis (DEA), Efficiency, Ranking*

1. INTRODUCTION

Charnes et al [4] first introduced data envelopment analysis (DEA) as a new methodology for measuring relative efficiency. Not only has the theoretical development of DEA been quite remarkable, its use in practice has been expanded to address many public and private sector issues.

While basic DEA models have many desirable features that have contributed to their rapid adoption by practitioners, there remain some weaknesses with the original models. For example, all efficient Decision Making Units (DMUs) have the same efficiency scores equal to one in both the CCR model developed by Charnes et al [4] and in the BCC model developed by Banker et al [3]. Therefore, it is impossible to rank or differentiate the efficient DMUs with the CCR and BCC models. However, the ability to rank or differentiate the efficient DMUs is of both theoretical and practical importance. Theoretically, the inability to differentiate the efficient units creates a spiked distribution at efficiency scores of one. This poses analytic difficulties to any post-DEA statistical inference analysis. In practice, further differentiation among efficient DMUs is also desirable and even necessary in many cases.

Why is it important to provide a full ranking of the whole set? There are several reasons. First, since DEA efficiency scores are basically a measurement for relative efficiency, one of the desirable results is essentially the position of each DMU compared to its peers. To provide a full ranking of the whole set is the only way to fulfill such a need. Second, with the full ranking of the whole set, further statistical inferences of the ranks are made possible, which will provide insights into the question we are ultimately interested in: what are those factors that significantly influence a DMU's efficiency?

To overcome this weakness, Andersen and Petersen [2] presented the Modified DEA (MDEA) method. The core idea of MDEA is to exclude the DMU under evaluation from the reference set and therefore, the efficient DMUs will, in general, have different efficiency scores. The infeasibility problem with MDEA model was first noticed in thrall [17]. In Zhu [19], it was shown in the constant returns to scale (CRS) MDEA models that the infeasibility occurs if and only if there is a zero in the data.

In this paper, a new ranking algorithm is proposed that can be used for ranking efficient DMUs. This algorithm removes the foegoing difficulty related to Andersen-Petersen's model.

The rest of the present paper is organized as follows. Section 2 presents the proposed algorithm. Section 3 presents an illustrative example. The main conclusions of the present paper are summarized in section 4.

2. RANKING EFFICIENT DMUS BY NEW ALGORITHM

In order to rank efficient DMUs in the CCR input oriented model by new algorithm the following steps should be done:

1. Determining the efficiency scores of DMUs by using DEA method.
2. Identifying the efficient MUs (DMUs with efficiency scores equal to one)
3. Determining virtual optimum DMU.

It should be mentioned that the inputs and outputs of virtual optimum DMU are the best inputs and outputs of efficient DMUs. On the other hand, for each input the minimum amount of it regarding efficient DMUs are selected and for each output the maximum amount of it regarding efficient DMUs are selected.

4. Solving a linear program model for efficient DMUs and virtual optimum DMU.

In this case, the virtual optimum DMU will be the only Pareto Efficient DMU that will have the efficiency score equal to one and it's slacks equal to zero. Therefore, the other DMUs, that were determined as efficient DMUs in stage b of this algorithm, will be ranked relative to this DMU.

3. ILLUSTRATIVE EXAMPLE

In this section, we use one example in order to explain how this algorithm can be used for a full ranking. Through this example, we show how a full ranking is obtained by this algorithm and the results will be compared with the results of Andersen and Petersen's model.

3.1. Example

In this example, we are going to consider the case that one of the inputs of one DMU is equal to zero.

We have two inputs and one output with constant returns assumption. The amounts of inputs and outputs are shown in table 1.

Table 1: Amounts of inputs and outputs in the example

DMUs	Input		Out put
	1	2	
1	0	2	4
2	1	1	5
3	2	1.5	8
4	3	2	8
5	4	3	10

The results of the CCR model, Andersen-Petersen's model and the new algorithm are shown in table 2.

Table 2: Results

DMUs	Efficiency		
	The CCR-Model	Anderson-Petersen's Model	The New Algorithm
1	1	Infeasible	0.25
2	1	1.11	0.62
3	1	1.06	0.66

As it can be seen, Andersen-Petersen's model for evaluation of DMU_1 leads to an infeasible problem because its first input is zero. This difficulty can be removed by the new algorithm.

4. CONCLUSION

In this paper, we have introduced a new algorithm for ranking efficient DMUs. Andersen-Petersen's model may lead to infeasible cases when some of the inputs are small. The new algorithm removes this difficulty.

By using this algorithm we can rank the whole DMU set and with the full ranking, further statistical analysis of the efficiency ranks of the DMUs and other Post – DEA analysis based on ranks are made possible.

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AN ANALYSIS OF THE RELEVANCE OF OFF-BALANCE SHEET ITEMS IN EXPLAINING PRODUCTIVITY CHANGE IN EUROPEAN BANKING

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ABSTRACT

The 1990s have witnessed a significant growth in bank income generated through non-traditional activities especially for large EU universal institutions. Using the non-parametric Malmquist methodology this paper analyses the importance of the inclusion of off-balance sheet (OBS) business in the definition of bank output when estimating total factor productivity change indexes. The analysis is then extended to the decomposition of total factor productivity change into technical efficiency and technological change. The results reinforce the prevalent view in the recent literature, indicating that the exclusion of non-traditional activities leads to a misspecification of banks output. In particular, the inclusion of OBS items results in an increase in estimated productivity levels for all countries under study. However, the impact seems to be the biggest on technological change rather than efficiency change. Overall, results suggest that despite the uneven distribution of OBS between countries and among different institutions in the same country, these non-traditional activities are increasingly important and failure to account for them would lead to biased conclusions.

1. INTRODUCTION

European deregulation and the introduction of the single market for financial services, together with technological advances, have all played a role in shaping EU banking markets during the 1990s. In recent years, banks have responded to the challenges posed by the new operating environment by developing new products and by creating new forms of intermediation and other fee-based activities. As a result, the traditional business of financing loans by issuing deposits has declined in favour of a significant growth in activities that are not typically captured on banks' balance sheets (Boyd and Gertler, 1994; Siems and Clark, 1997; Rogers and Sinkey, 1999).

The changing nature of bank activities has recently received growing attention from researchers. However, whereas a large number studies, using both econometric and non-parametric models, have examined banks' cost and profit efficiency and productivity change, only a few have explicitly accounted for off-balance-sheet (OBS) business like lines of credit, loan commitments, securitisation and derivatives. Recent studies (see for example, Rogers, 1998; Stiroh, 2000; Clark and Siems, 2002) have argued that omitting OBS in the estimation of bank cost and profit efficiency may result in a misspecification of bank output and lead to incorrect conclusions. However, less is known on the effect that the increase in non-traditional activities has on banks' productivity levels. This paper aims to bridge this gap in the literature by investigating the relevance of the inclusion of OBS business on productivity change in five European banking markets over 1994-2000.

In particular, using the non-parametric Malmquist methodology this paper investigates the impact of the inclusion of OBS items in the definition of banks output when estimating of total factor productivity change indexes. The analysis is then extended to the decomposition of total factor productivity change into technical efficiency and technological change to assess the impact of the inclusion of OBS items on the main components of productivity growth.

The results reinforce the prevalent view in the recent bank efficiency literature, indicating that the exclusion of non-traditional activities leads to a misspecification of banks output. In particular, the inclusion of OBS items results in an increase in estimated productivity levels for all countries under study. However, the impact seems to be the biggest on technological change rather than efficiency change. Overall, results suggest that despite the uneven distribution of OBS activities between the countries under study and among different banking institutions in the same country, omitting non-traditional activities in the definition of bank output understates productivity levels and may lead to biased conclusions.

2. METHODOLOGY AND DATA

In the context of this study, total factor productivity (TFP) measures changes in total output relative to inputs and the concept derives from the ideas of Malmquist (1953)[1] and the distance function approach[2]. The Malmquist TFP index is the most commonly used measure of productivity change.[3] It measures TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. For more details on the methodology see Casu et al. (2004). Our data set is primarily drawn from BankScope and includes annual information for a balanced panel of over 2000 European banks between 1994 and 2000. The sample comprises only large banks (total assets > Euro 450 million) from the largest European banking markets: France (357 banks), Germany (518 banks), Italy (413 banks), Spain (448 banks) and United Kingdom (350 banks).

The approach to output definition used in this study is a variation of the *intermediation approach* (Sealey and Lindley, 1977). Specifically, the input vector used in this study are proxies for cost of labour (personnel expenses); the cost of deposits (interest expenses) and the cost of capital (total operating expenses) The output variables capture both the traditional lending activity of banks (total loans) and the growing non-lending activities (securities). In addition, we also include the nominal value of banks' off-balance sheet items as a third output.

3. RESULTS

The importance of including OBS activities in the output definition to estimate banks TFP change is examined in two ways. The first approach examines the correlation between TFP estimates obtained with and without OBS at country level and tests for differences between mean TFP estimates when the OBS measure is first excluded and then included from the analysis. Then ranking differences are investigated to identify the impact of the inclusion/exclusion of OBS items on individual institutions in each country.

Following Färe et al. (1994) the Malmquist (output-oriented) TFP change index has been calculated. A value of the index greater than one indicates positive TFP growth while a value less than one indicates TFP decline over the period. Productivity change is then decomposed into *Technological Change* (TC), and *Technical Efficiency Change* (TEC), where TFP = TC x TEC. An improvement in TC is considered as a shift in the best practice frontier, whereas an improvement in TEC is the "catch up" term.

Productivity change estimates are summarised below. The annual entries in each column in Table 1 are geometric means of results for individual banks and the period results reported in the last row for each country are geometric means of the annual geometric means.

From Table 1 it is possible to note that, when the estimations are carried out without the inclusion of OBS items in the banks output specification, the TFP index for the French and

[1] Important developments in this field have been introduced, among others, by the work of Diewert (1976, 1978, 1981), Caves et al. (1982a and 1982b) and Färe et al. (1985, 1994).
[2] Shephard's (1970) distance functions have guided much of the development in efficiency and productivity analysis. In a multi-input multi-output framework, an output distance function is defined as the reciprocal of the maximum proportional expansion of the output vector, given inputs. An input distance function is defined as the reciprocal of the maximum proportional contraction of the input vector, given outputs.
[3] For a literature survey on the subject, see Grosskopf (1993) and Färe et al. (1997). Also, Ray and Desli (1997) discuss the conceptual framework and Mukherjee et al. (2001) derive the geometric decomposition for a generalised Malmquist index.

German banking sectors shows a slight decrease over the 1994-00 period (-1.6% and -2.8% respectively). The results relative to both banking systems suggest deterioration in the performance of best practice banks, as indicated by Technological Change indices smaller that unity. An interesting feature is the catching up with best practice institutions (efficiency change of +4.5%) for German banks, whereas French banks seem to display deterioration also in the cost efficiency levels.

The results relative to the Italian and UK banking sectors show an improvement in the TFP index with an overall increase in productivity of about 6.9% and 1.2% respectively. This productivity growth seems to have been brought about by both a positive technological change (+3.5%) and increase in efficiency (+3.3) in the Italian banking system, whereas TFP growth in the UK seem to be mainly explained by positive technological change rather then by improvements in efficiency. On the contrary, the improvement in technological change in the Spanish banking sector (+1.9) was not enough to contrast a decrease in productive efficiency (-2%) over the period, therefore resulting in an almost constant rate of productivity change.

When OBS items are added to the definition of banking output, a different picture seems to emerge. Overall, there seems to be TFP growth for all countries under analysis, with a particularly important change in direction of the index in the case of Spanish banks, which now indicates TFP growth of +9.5%. The introduction of OBS items in the definition of bank output seems to have impacted the most on technological change, which increased with respect to the previous estimation for most countries in the sample (for example, for Spanish banks technological change increased from +1.9 without OBS to +9.2 with OBS; in France it increased from -0.7% to +3.1%). These results can be justified by the assumption that those banks that are "shifting the frontier" are more likely to have a substantial OBS portfolio and would have been penalised the most if such output had not been included in the analysis.

To test the statistical significance of such differences, Table 2 presents the results of a series of t-test of the null hypothesis that the mean estimated productivity changes, and its components, are the same whether OBS activities are included or excluded from the output specification.

The results shown in Table 2 indicate that the null hypothesis of no difference in estimated productivity change, or in its components, can be rejected in 11 of 15 instances. Furthermore, in the case of the UK, where the null hypothesis could be accepted in all instances, that is there is not a statistically significant difference between the two groups, the power of the test is below the desired level and therefore such results should be interpreted with caution. In all cases where the null hypothesis can be rejected, the estimated mean productivity change increases when OBS are included in the output specification, thus reinforcing the view prevalent in the recent literature that the exclusion of OBS items leads to underestimation of productivity levels. However, when analysing the components of productivity change, whereas in all instances mean technological change increases when OBS are included as an output variable, in three cases efficiency change results deteriorate.

Table 3 shows the results of the Mann-Whitney rank sum test, which reinforces the evidence presented in Table 2.

Again, the null hypothesis that the differences in the median values between the groups are greater than we would expect by chance is rejected in 10 of 15 instances. A closer analysis of the impact of OBS items points to country differences. Correlation analyses of individual bank's TFP index with and without the introduction of OBS in the output specification are positive and statistically significant at the 0.01 level for all countries with the exception of the UK[4]. From these results is possible to infer that for UK banks OBS activities are relatively more important than in Italy and Germany. Indeed, this reflects the different magnitude and trend of the OBS/Total Asset (OBS/TA) ratios for the whole banking sector. For example, in the year 2000, the ratio OBS/TA was around 35% in the UK and 13% in Italy[5]. However, while in the UK

[4] It is to note that data on OBS items for UK banks were available on for 6 institutions, namely HSBC, Barclays Bank, Clydesdale Bank, Abbey National, NatWest and the Royal Bank of Scotland.

[5] Specifically, according to ECB (2000 and 2003) the OBS/Total Assets ratio for the whole banking sectors in the year 1994 (2000) was: 28.31 (29.76) in France, 14.54 (13.46) in Germany, 24.91 (13.46) in Italy, 5.65 (9.66) in Spain and 32.53 (34.2) in the UK.

the ratio shows a constantly increasing trend over the 1994-00 period; it sharply decreased in Italy, where banks have been concentrating mainly on asset management as a non traditional source of income.

To consider the impact of omitting OBS items on individual institutions, we analyse the ranking differences, that is how much an institution betters (or worsen) its rank position under the two output specifications. The results are illustrated in Figure 1.

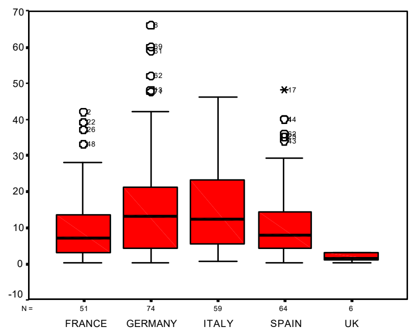

Figure 1: Absolute Ranking Differences

Italian and German banks are displaying the biggest changes in ranking between the two models. This indicates that, whereas on average the TFP growth of Italian and German banks is not greatly affected by OBS items, for a number of institutions the results change dramatically. These findings are in line with the structure of the relative banking sectors: the Italian and German banking systems are indeed the least concentrated within the countries in our sample (the 5-firm concentration ratio (CR-5) is equal to 23 and 20 respectively) with a handful of big universal institutions competing globally and a high number of small sized banks which are still concentrated on traditional lending business.

Overall, results suggest that despite the uneven distribution of OBS between countries and among different institutions in the same country, these non-traditional activities are increasingly important and failure to account for them would lead to biased conclusions.

5. CONCLUSION

Banks' responses to the changing nature of the operating environment have resulted in changes in the structure of their financial accounts and are mainly reflected in the increase of OBS activities. Using the non-parametric Malmquist methodology this paper attempts to investigate to what extent the inclusion of OBS items in the output definition of banks affect the estimated total factor productivity change indexes. The inclusion of OBS items seems to impact the most on technological change rather than efficiency change. This indicates that banks that are "shifting the frontier" are more likely to have a substantial OBS portfolio and would have been penalised the most if such output had not been included in the analysis. Overall, the results suggest that despite the uneven distribution of OBS activities between the countries under study and among different banking institutions in the same country, omitting non-traditional activities in the definition of bank output understates productivity levels and may lead to biased conclusions.

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Table 1: Malmquist Index Decomposition (Summary of Annual Means)[a,b]

		WITHOUT OBS			WITH OBS		
		EFFICIENCY CHANGE	TECHNOLOGICAL CHANGE	TOTAL FACTOR PRODUCTIVITY CHANGE	EFFICIENCY CHANGE	TECHNOLOGICAL CHANGE	TOTAL FACTOR PRODUCTIVITY CHANGE
FRANCE	1994/95	1.044	0.934	0.975	1.076	0.903	0.972
	1995/96	0.943	1.014	0.956	0.938	1.155	1.084
	1996/97	1.042	0.923	0.961	0.944	1.090	1.028
	1997/98	0.931	1.054	0.981	1.010	0.989	0.999
	1998/99	1.037	0.957	0.993	0.935	1.162	1.086
	1999/00	0.955	1.086	1.038	1.030	0.921	0.949
Mean	**1994/00**	**0.991**	**0.993**	**0.984**	**0.987**	**1.031**	**1.018**
GERMANY	1994/95	0.952	0.970	0.923	1.045	0.919	0.960
	1995/96	1.089	0.914	0.995	1.027	1.040	1.068
	1996/97	0.793	1.186	0.940	1.019	1.017	1.036
	1997/98	1.111	0.849	0.943	1.033	0.949	0.980
	1998/99	1.341	0.787	1.055	1.005	1.067	1.073
	1999/00	1.064	0.926	0.985	0.982	0.947	0.930
Mean	**1994/00**	**1.045**	**0.931**	**0.972**	**1.018**	**0.988**	**1.006**
ITALY	1994/95	0.961	1.005	0.965	0.982	0.965	0.948
	1995/96	1.088	0.890	0.968	0.995	1.042	1.037
	1996/97	1.173	0.901	1.057	1.025	1.144	1.173
	1997/98	0.954	1.198	1.142	0.987	1.211	1.195
	1998/99	1.042	1.103	1.149	0.968	1.320	1.278
	1999/00	0.995	1.158	1.152	0.954	0.992	0.947
Mean	**1994/00**	**1.033**	**1.035**	**1.069**	**0.985**	**1.105**	**1.089**
SPAIN	1994/95	0.925	1.009	0.933	1.040	0.928	0.965
	1995/96	1.035	0.981	1.015	1.009	1.064	1.074
	1996/97	1.080	0.988	1.067	0.884	1.408	1.244
	1997/98	0.915	1.060	0.970	1.100	1.064	1.170
	1998/99	1.010	1.027	1.037	0.993	1.226	1.217
	1999/00	0.931	1.049	0.976	1.003	0.934	0.937
Mean	**1994/00**	**0.980**	**1.019**	**0.999**	**1.003**	**1.092**	**1.095**
UK	1994/95	1.016	0.949	0.965	1.087	0.878	0.954
	1995/96	0.972	1.126	1.095	0.985	1.073	1.057
	1996/97	0.963	1.011	0.973	0.961	1.072	1.029
	1997/98	1.040	0.869	0.904	1.045	0.929	0.971
	1998/99	1.023	1.175	1.202	0.965	1.071	1.033
	1999/00	0.978	0.976	0.955	1.046	0.972	1.017
Mean	**1994/00**	**0.998**	**1.012**	**1.011**	**1.014**	**0.996**	**1.010**

[a] Note: A number <1 indicates decline; a number >1 indicates growth.

[b] TEC × TC = TFP

Table 2: t-test for Differences between measures of Malmquist TFP

		EFFICIENCY CHANGE	TECHNOLOGICAL CHANGE	TOTAL FACTOR PRODUCTIVITY CHANGE
FRANCE	without OBS	0.993	0.994	0.988
	with OBS	0.988	1.032	1.020
	mean	0.005	-0.038	-0.032
	t-Statistic	0.559	-6.171	-0.303
	Sig. (two-tailed)	0.578	0.000	0.004
GERMANY	without OBS	1.047	0.933	0.977
	with OBS	1.018	0.990	1.009
	mean	0.028	-0.578	-0.315
	t-Statistic	-18.340	-5.310	5.768
	Sig. (two-tailed)	0.000	0.000	0.000
ITALY	without OBS	1.034	1.036	1.071
	with OBS	0.986	1.106	0.089
	mean	0.049	-0.070	-0.184
	t-Statistic	-16.841	-2.396	-1.997
	Sig. (two-tailed)	0.000	0.000	0.020
SPAIN	without OBS	0.984	1.020	1.004
	with OBS	1.003	1.093	1.096
	mean	-0.019	-0.072	-0.920
	t-Statistic	-15.721	-8.835	-2.261
	Sig. (two-tailed)	0.050	0.000	0.000
UK	without OBS	0.099	0.990	0.977
	with OBS	1.014	0.997	1.011
	mean	-0.027	-0.007	-0.338
	t-Statistic	-2.261	-0.409	-1.503
	Sig. (two-tailed)	0.073	0.700	0.193

Table 3: Mann-Whitney Rank Sum Test

		EFFICIENCY CHANGE	**TECHNOLOGICAL CHANGE**	**TOTAL FACTOR PRODUCTIVITY CHANGE**
FRANCE	without OBS	0.996	1.003	0.99
	with OBS	0.994	1.036	1.022
	H_o	*Accepted*	*Rejected*	*Rejected*
	t-Statistic	2661	1858	2230
	P-value	0.820	<0.001	0.008
GERMANY	without OBS	1.044	0.933	0.982
	with OBS	1.024	0.998	1.023
	H_o	*Rejected*	*Rejected*	*Rejected*
	t-Statistic	6502	3104	4553
	P-value	<0.001	<0.001	<0.001
ITALY	without OBS	1.035	1.033	1.075
	with OBS	0.99	1.107	1.09

	Ho	*Rejected*	*Rejected*	*Accepted*
	t-Statistic	4615	1845	3183
	P-value	<0.001	<0.001	0.078
SPAIN	without OBS	0.977	1.017	0.99
	with OBS	1	1.1	1.099
	Ho	*Rejected*	*Rejected*	*Rejected*
	t-Statistic	3547	2664	2789
	P-value	0.006	<0.001	<0.001
UK	without OBS	0.994	1.008	0.992
	with OBS	1.004	0.997	1.014
	Ho	*Accepted*	*Accepted*	*Accepted*
	t-Statistic	27	38	34
	P-value	0.065	0.937	0.485
	P-value	0.065	0.937	0.485

Table 4: Correlation Analysis

		EFFICIENCY CHANGE	TECHNOLOGICAL CHANGE	TOTAL FACTOR PRODUCTIVITY CHANGE
FRANCE	Pearson	0.298*	0.553**	0.535**
	Spearman's rho	0.352*	0.335*	0.499**
GERMANY	Pearson	0.210	0.867**	0.813**
	Spearman's rho	0.281*	0.014	0.426**
ITALY	Pearson	0.320	-0.253	0.366**
	Spearman's rho	0.032	0.110	0.309*
SPAIN	Pearson	0.606**	0.751**	0.623**
	Spearman's rho	0.485**	0.695**	0.626**
UK	Pearson	0.056	0.733	0.607
	Spearman's rho	-0.059	0.429	0.429

*,** indicates significant at the 0.05 and 0.01 level respectivel

AN EFFICIENCY ANALYSIS OF RUSSIAN BANKS

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ABSTRACT

This work uses the stochastic econometric frontier approach to investigate the efficiency of Russian banks. We are applying stochastic frontier techniques to data of banking system in Russia for selecting an appropriate model specification and comparing the results of estimating with existing researches for world banking systems. We pay special attention to specification of the stochastic frontier model. Models with Cobb-Douglas, translog and Fourier-Flexible functional forms of production frontier and different forms of inefficiency distributions (half-normal, truncated normal) are compared. The estimation of frontier parameters and bank-specific inefficiency values makes with utilization of panel data of items of bank's balance sheets (deposits and loans values and structure) and another indexes of bank's activity (branch structure, employed staff characteristics). The model is estimated with assumption of time-varying inefficiency. Estimated values of bank's inefficiency and corresponding efficiency ranking are compared with bank reliability ratings given by experts and high correlation values are found. Also in this work we examine the dynamics of bank's inefficiencies during considered time interval (2000-2003). Finally, we analyze influences of factors, included into model specification, to bank efficiency and draw some conclusions about strengths and weaknesses of Russian bank.

INTRODUCTION

This researching is based on the application of the stochastic econometric frontier approach to investigate the efficiency of Russian banks. We are applying stochastic frontier techniques to data of banking system in Russia for selecting an appropriate model specification and comparing the results of estimating with existing researches for world banking systems.

There are three characteristics of bank efficiency that have an influence on its measurement:

1. multiple-factor nature of efficiency. In practice it's impossible to describe efficiency of bank activity quite precisely using only one aggregate index. The efficiency can be described through the set of indexes, some of which can't be present by numbers;
2. relativity nature of efficiency. The most interesting part for analysts is measurement bank's efficiency with regards to other banks and it's own potential;
3. stochastic nature of efficiency. The estimation of bank's efficiency measured in one moment can deviate from its true value as affected by random factors.

The main goal of our researching is to estimate Russian bank's efficiency on the basis of stochastic frontier. The efficiency is examined as relative, stochastic index that aggregate quality of internal bank activity and random influence of external factors. The Stochastic Frontier Analysis (SFA) is used for estimation of efficiency level.

On the basis of the model constructed in our work we tried to defined factors, which have an influence on efficiency level and evaluated the power on this influence. Bank size indexes, bank organization structure, structure of bank assets play the main role to define bank's efficiency and was included into the model as explanation variables.

We concentrate the special attention on the result's robustness for different model specifications and sets of parameters.

We carry out the efficiency analysis using panel data. It allows us to estimate the dynamics of Russian bank efficiency during last years and give possibility to separate the efficiency by the reason of it's appearing (technical and allocative).

REVIEW OF LITERATURE

At present time there are several methods of construction the efficiency frontier. Our researching is based on the using of Stochastic Frontier Analysis.

SFA originated in 1977 with two papers, published nearly simultaneously by two independent teams of researchers - Aigner, Lovell, and Schmidt (1977) and Meeusen, and van den Broeck (1977). In both investigations the researchers used the production function as frontier and proposed the composite type of error term. According to these models the error term is the sum of two stochastic values – normal distributed component and non-negative component that shows the inefficiency. Aigner, Lovell, and Schmidt examined the exponential and half-normal distributions of inefficiencies, later Greene (1990) examined model with gamma-distributed inefficiencies.

Johdrow et al. (1982) developed the method of estimation of individual values of inefficiencies for each firm included into analysis. This research allows next researcher to use these values in further works in own researching goals.

The important part of the modern SFA-method is the possibility of it's application to panel data analysis. Schmidt and Sickles (1984) show three main problems of basic stochastic frontier analysis which can be resolved by using panel data (with special estimation methods):

Method of maximum likelihood estimation demands the definition of strong distribution form of both error term component. This is very strong limitation, especially because the results of efficiency estimation don't very firmness with variation of distribution forms.

Maximum likelihood estimator demands the strictly independence of explanation variables.

The Johdrow method gives inconsistent estimates of individual inefficiencies on simple cross-sectional data.

Besides these problems resolving the using of panel data allows to monitor dynamic of efficiency estimates in time. Kumbhakar, Lovell (2000) and Greene (2002) examine the extensions of SFA models for panel data in details. Both works contains analysis of – with fixed and random effects and with time-variant and time-invariant inefficiency.

Berger and Humphey (1997) show the main advantages of SFA-analysis - the possibility of separating (inside model specification) the inefficiency into two components – the internal inefficiency of bank process organisation and the inefficiency determinates by external random circumstances. The alternative methods of efficiency frontier construction (Data Envelopment Analysis and it's modifications) don't take into consideration the stochastic nature of efficiency.

The key concept of SFA-analysis is X-inefficiency. This conception was developed in 1966 by Leibenstein, which noted that firms usually works not on the limit of its possibilities, by the set of reasons. X-inefficiency defines the possibilities of bank to minimise costs and maximise revenues on the basis of more regular using and allocation of resources. In the most of analysis the X-inefficiency described as composition of two types of inefficiencies. The first type, technical inefficiency, defines the possibility of bank to reduce the resource using and save the same level of outputs (input-orientation) or to increase output values with invariable costs (output-orientation). The second component of X-inefficiency is allocative inefficiency, which shows the possibility of increasing outputs by changing the proportion of used resources.

Besides the development of SFA-analysis theory during last years there are many practical applications of SFA-analysis, and many of them are dealing with researching bank sector of economy. In 1997 Berger and Humphey published the analysis of more than 130 researching of banking systems in different countries, based on construction of efficiency frontiers. The majority of analysed researching was published from 1992 to 1997 that shows the increasing necessity of this kind of analysis.

In their researching Berger and Humphey analysed the results of efficiency estimation for 21 countries, more than half of which concentrate on USA banking system. During last decades many countries reorganised their economics, made it closer to market economy, and many new frontier analyses carried out on the banking system of these countries. On the base of SFA-analysis was investigated the efficiency of banking system in Turkey (Kasman (2002)), Hong Kong (Kwan (2001)), Croatia (Kraft, Hofler, Payne (2002)), Kuwait (Limam (2001)), Estonia (Jones, Mygind, Sinani (2003)).

First of all for construction SFA model we need to define the set of factors and variables that serve as input and outputs of system and also define the goal of system activity. There are two main approaches for analysis of financial organization (Freixas, Rochet (1997)):

– Production approach. In this case bank is examined as organization, which "produce" transactions with clients. These transactions are given credits, received deposits, the number of serviced obligations and other operations.

– Intermediation approach (Allen, and Santomero (1996)). By this approach bank realizes the intermediation between agents, which have spare assets and agents, which have possibilities of its profitable investments.

By virtue of chosen approach researchers mark out the set of input and output parameters – indexes of capital structure, bank size, organization form of bank. Also additional parameters are included into the model very often. Usually these parameters depend on the direction of analysis. For example, it can be ownership of the bank, time of bank functioning, level of modern technologies using.

THE METHODOLOGY

Stochastic frontier analysis based on probabilistic approach to constructing of efficiency frontier. The mathematical formalisation of stochastic frontier model can be presented as (Aigner, Lovell, and Schmidt):

$$y = g(X, ß) + e,$$

$$e = v - u,$$

$$u \sim N^{+}(\mu, \sigma_u^2), \quad v \sim N(0, \sigma_v^2),$$

where y –output parameter, X – vector of input parameters, g – production function, β - vector of unknown coefficients, ε - error term.

The model describes the dependence output parameters (y) from the set of input parameters (X). The dependence is defined by production function (g). The choice of production function type is very critical moment of model specification. We need to choose very flexible form of function, which don't include too many parameters at the same time. Usual researchers use modifications of next three functional forms:

Cobb-Douglas production function

Translog function

Fourier-Flexible functional form (combination of standard translog with Fourier trigonometric terms).

In our research we compared some models with different production functions and found out the considerable dependence of the estimated parameters on functional form. This result is obtained in other researches of banking efficiency based on stochastic frontier analysis.

The main feature of stochastic frontier model is the form of its error term ε. In contrast to standard linear regression the error term consists of two components. The first component (v) – normal identically distributed variate with zero mean; characterised the random efficiency frontier fluctuations. The second component (u) – non-negative variate is described the deviation the bank from the frontier, shows inefficiency. The deviation of bank efficiency from its own optimal value can be described by influence of random factors, which don't included into efficiency frontier definition.

The distributive law of u can be chosen arbitrarily (subject to its non-negative values). Usually researchers use the next distribution laws:

(a) half-normal, $u \sim N^{+}(0, \sigma_u^2)$;

(b) truncated normal, $u \sim N^{+}(\mu, \sigma_u^2)$;

(c) exponential, $u \sim \theta e^{-\theta u}$.

The estimates of presented distributions parameters are calculated using values of additional factors.

On the base of comparing of different distribution functions we chose the frontier model with truncated normal distribution of u. For determination of that distribution we need to estimate two parameters – mean and standard deviation. The mean describes the power of influence of all factors, which don't, included into frontier definition and nevertheless have an affect on bank efficiency. The estimates of mean and standard deviation can be accounted together with other unknown model parameters (Battese and Coelli (1997) method).

So we have the specification of regression model which error term is the combination of two stochastic components with certain frequency functions. It is enough for estimation of unknown parameters of model using, for example, maximum likelihood estimator or generalised least square method.

Actually, to construct stochastic frontier model we need to separate all factors, affected on efficiency of bank activity, into two groups – described the frontier (X) and influenced on bank's deviation from this frontier (Z).

DATA

The main source of information for our research was Information Centre "Rating" reports, which contain the list of 100 largest Russian banks with the main indexes of their activity. The information is enlarged every six months, so we have the unbalanced panel with seven time points (January 2000 – July 2003) with data of 160 banks.

On the base of available data we defined the list factors included into SFA-model:

Output:

y – balance sheet profit;

Inputs:

X_1 – deposited funds (both from citizens and companies);

X_2 – bank's deposited funds;
X_3 – loans (RUB);
X_4 – loans (foreign currency);
X_5 – deposits in banks;
X_6 – funds on banking cards;
X_7 – deposits in government-paper;
X_8 – trust assets.

Additional parameters influenced on individual inefficiency:

Z_1 – own capital;
Z_2 – total assets;
Z_3 – manning level;
Z_4 – number of bank branches;
Z_5 – dummy, registered in Moscow;
Z_6 – dummy, registered in St. Petersburg.

ESTIMATION RESULTS

Consequently the SFA-model for panel data with Cobb-Douglass production function, truncated normal distribution of inefficiencies is given by equation below:

$$\ln y_{it} = ß_0 + \sum_{j=1}^{8} ß_j \ln X_{jit} + e_{it},$$

$$e_{it} = v_{it} - u_{it},$$

$$u_{it} \sim N^+(\prod_{j=1}^{6} \delta_j Z_{jit}, \sigma_u^2), \quad v \sim N(0, \sigma_v^2).$$

After estimation procedures we receive the next estimation of model parameters.

Table 1. The estimation results

	Coefficient	Standard error	t -ratio
Const	4.678***	0.541	8.641
$ß_1$	0.193***	0.032	6.002
$ß_2$	-0.015	0.016	-0.924
$ß_3$	0.060**	0.024	2.436
$ß_4$	0.137***	0.026	5.181
$ß_5$	0.123***	0.029	4.273
$ß_6$	-0.001	0.013	-0.092
$ß_7$	0.042***	0.010	4.158
$ß_8$	0.0002	0.010	0.020
Const	0.683***	0.171	3.988
d_1	$-5*10^{-8}$***	$-1*10^{-8}$	-5.097
d_2	$-1*10^{-8}$***	0.000	-6.316
d_3	-0.001***	$1.677*10^{-4}$	-8.920
d_4	0.0002***	$2.286*10^{-5}$	8.821
d_5	0.357***	0.116	3.060
d_6	0.041	0.516	0.080
sigma-squared	1.336***	0.077	17.269
?	0.031***	0.007	4.018

Log likelihood function =-1068.6661

***, **, * - significant at 1%, 5% ? 10% correspondingly

CONCLUSIONS

The basic hypothesis "SFA vs. OLS regression" was tested with ?-test using. The ?-level=0.031 is significantly different from zero that testify the advantage of SFA-model over standard regression with ordinary least square estimations.

The first group of parameters (X) describes the location of an efficiency frontier. Deposits (from persons and companies) (X_1), loans in roubles(X_3) and foreign currencies(X_4), holdings into other bank's assets (X_5) and into government-paper (X_7) have significant influence on efficiency frontier. These results show the main directions of Russian banks activity.

The influence of second group of factors (Z) is very interesting as the source of Russian banks inefficiency. All factors in this group, besides registration in St. Petersburg (Z_6), are significant with confidence level 99%.

The coefficients for values of own banks capital and total banks assets (d_1, d_2) show the influence of bank size to its efficiency. We found the significant positive return of scale, the bigger banks working more efficiently in average. This result can be described by availability of considerable resources for professional management staff hiring, possibilities of wider number of customer services.

The coefficient d_3=-0.001 shows that the amount of banking staff have the significant negative influence on bank efficiency. It can be ride on insufficient professional skills or excessive bureaucracy level, but for more well-founded conclusion we need to separate the staff into different groups, such as managerial staff, business executives, operating and maintenance staff.

Also we discovered the significant positive influence of the number of branches (Z_4). The bigger number of branches allows to improve the accessibility of bank services, make the service more adapted to real customer's needs, and also to increase the competition inside the bank.

The registration of the head office in Moscow (Z_5) surprisingly contributes for bank inefficiency. The only thing that can explain it is the huge concentration of the banks in Moscow (We have 435 banks registered in Moscow of total 700 sample size).

After the analysis of different factors we estimated the individual banks inefficiency values. The mean bank efficiency over the sample comes to 48,6%, but we have some top banks with efficiencies near 100%.

Usually the bank efficiency has a good correlation with other important characteristic, such as reliability and bankruptcy risk. We investigate the correlation between the estimated individual efficiencies and expert's level of reliability showed by IC "Rating" and found great positive dependence (the banks with highest level of reliability have relatively high values of efficiency).

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BENCHMARKING THE ECONOMIC PERFORMANCE OF PORTUGUESE WATER AND SEWERAGE SERVICES

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ABSTRACT

Benchmarking refers to the process of comparing the performance of an organization with a standard. The use of benchmarking is fundamental to the water and sewerage services (henceforth WSS) being, many times, the only tool available for the governments to control their performance. This document will apply one of the benchmarking techniques available, which is the data envelopment analysis (hereafter DEA). DEA is a frontier method based on linear programming techniques for assessing the organizations comparative efficiencies. For the last two decades, DEA has already been used in WSS sectors, in many countries, by different actors, with several objectives. This paper uses DEA benchmarking method to determine efficiency measures for a set of Portuguese WSS. It begins with a short introduction explaining the benchmarking concept and its classification in the WSS. Next, the document describes briefly the DEA method and depicts its weaknesses and strengths and its relevance in these sectors. DEA main studies developed in the WSS until now are also reviewed. Then, the DEA developed models for the Portuguese WSS are defined and computed and the observed outcomes are analysed. Some DEA problems that jeopardize its use in regulatory benchmarking are discussed. Finally, the conclusions are presented.

INTRODUCTION

Benchmarking can simply be defined as the process of measuring the performance of something and its comparison with a standard. In natural monopolies and where there is also a lot of asymmetric information, benchmarking is the key tool to encourage the organizations in their performance improvement. In the water and sewerage sectors, benchmarking has been classified into metric and process benchmarking [Kingdom *et al*. (1996)]. Metric benchmarking enables the water and sewerage services (WSS) to deal with internal performance over time and to compare it with that of peers. Process benchmarking involves, first, identifying specific work procedures to be improved through a step-by-step process mapping and, then, searching for the industry best practices that lead to superior performance. From the utilities point of view, we agree with this classification, but when benchmarking is applied by other stakeholders, such as regulators or financial agents, we prefer, like others [for example, Eggen *et al*. (2001) and Carrington, Coelli and Groom (2002)], to classify it into macro or micro benchmarking or into top down or bottom up benchmarking, respectively. Macro or top down benchmarking is based on processes of analysis and on results modelling at a high aggregation level, while micro or bottom up benchmarking focuses on the analysis of the different activities and practices per se. Commonly, the first group of methods computes efficiency and productivity global measures and it is often used by regulators to obtain information about the organizations performance and its nature and to establish broad targets. The second group is employed, above all, by the business (utilities) in order to identify areas or activities of improvement, generally in the first stage of performance indicators calculation for a diagnosis and, subsequently, for a decision making process.

Macro benchmarking methods can be further classified into frontier or non-frontier methods, whether or not they admit that the organizations (WSS) are technically efficient. A WSS is said to be technically efficient if it operates on the frontier, that is, if it represents the maximum output attainable from each input level or vice-versa (minimum input from each level of output). The frontier and non-frontier methods can also be sorted into parametric and non-parametric according to the econometric estimation of parametric functions. Data envelopment analysis (DEA) is deemed a frontier non-parametric technique. Lovell (1993) and Coelli, Prasada and Battese (1998) are two noteworthy references in the introduction of these techniques.

In this article, DEA benchmarking technique is analysed and applied to the Portuguese WSS in the practitioner's view. This study appears in Portugal in a period when the WSS economic regulation, as well as their privatization, is under discussion. The high levels of inefficiency shown and the existing market structure suggest the use of some kind of incentive regulation. The issue under discussion is whether to adopt a light-handed regulation, as sunshine regulation (that consists only in publicizing performance) or a tighter form of regulation, such as yardstick competition (e. g. price cap regulation with factor X established through benchmarking techniques). In both situations, the DEA use is a real hypothesis. After this introduction, this document describes briefly the DEA technique, stressing its weaknesses and strengths. The following section consists in a DEA studies review carried out in the water and sewerage sectors. Then, the models are applied to the Portuguese WSS and the main results are depicted. Subsequently, some relevant questions related to the DEA use as a benchmarking tool in the WSS are discussed.

DATA ENVELOPMENT ANALYSIS

DEA is a method based on linear programming to evaluate the productive efficiency of homogeneous units, such as WSS. DEA builds the non-parametric frontier formed by the union of a group of linear segments (piece-wise surface) which include the WSS. The relative efficiency measuring is done through the comparison of the analysed WSS efficiency with that of the other WSS which remain in that frontier. From these WSS, the ones that use similar inputs and outputs combinations are taken as benchmark and simultaneously are the target of the WSS being analysed (peer group). The relative efficiency is determined by giving similar weights to the inputs and outputs of the WSS, in order to maximize the quotient of the inputs and outputs weighted average sum, subject to the constraint that any other WSS of similar characteristics can reach an efficiency level higher than one to the same set of weights.

DEA Models

The generic DEA model, called CCR, was developed in 1978 by Charnes, Cooper and Rhodes (1978), assuming constant returns to scale (CRS) and strong disposability of inputs (and outputs). The CCR model fell upon Farrell's work (1957) using the mathematical programming knowledge of Charnes and Cooper (1962). In 1984, this model was extended to account for variable returns to scale (VRS) by Banker, Charnes and Cooper (1984), originating the model known as BCC. The BCC model deems the VRS by adding a convexity constraint ensuring that an inefficient WSS is only compared against WSS of similar size. If we compute a CRS and a VRS DEA we may obtain a scale efficiency (SE) measure for each WSS. Hence, CRS technical efficiency measure can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE). CCR and BCC models, although the most used, are only a small part of the DEA models. Other models, as multiplicative models and additive models, despite being more complex to calculate, have nicer properties.

DEA Strengths and Weaknesses

DEA application is a non-parametric approach used to measure the WSS relative efficiency. Its main feature, with effects both at its strengths and weaknesses, is related with the fact that DEA does not prescribe an underlying functional form for the efficient frontier and it does not give specific values *ab initio* to the weights. DEA technique is said to be empirically based, in opposition to the parametric and statistical approaches to measure the efficiency. There are many benefits in the DEA use, such as: a) the identification of a group of efficient WSS to each inefficient WSS with a similar combination of inputs and outputs; b) the ability to deal easily with multiple inputs and outputs; c) the best practices adoption as comparison elements instead of the average values; d) the non-assumption of a functional form for the frontier or for the inefficiency term; e) the decomposition of efficiency into several components.

However, this technique (DEA) has some shortcomings, such as the fact that it is very sensitive to the outliers, it is very demanding concerning the required information and it does not allow the associated error measurement, neither to test statistically the results nor the specified models. In DEA, the explanatory factors analysis is also more complex, depending on the existing correlation degree reliability. From the operational point of view, the lack of statistical results makes its practical use to be difficult. For example, it is very tough for a regulator to take a decision with direct consequences in the companies financial health and in the consumers budget, given that the change of an input, sometimes only in the units (e. g. capital in quantities or in monetary units) has important consequences in efficiency values. The same happens with the sampling change (number of WSS) or with a production technology (e. g. CRS and VRS), which can be very difficult to compute. Even though several studies try to provide statistical properties (e. g. consistency, unbiasedness and robustness) and enforce the role of statistical inference in DEA analysis, such as Banker (1996), Grosskopf (1996) and Simar and Wilson (2000), for example, the state of the art in this domain is still in infancy. Even more attention should be given to this subject in the future. This paper will present some comments resulting from the difficulties faced.

DEA USE IN THE WATER AND SEWERAGE SECTORS

DEA studies have been gaining a growing interest since the 80s in the most different sectors and production areas with diverse aims. The situation is alike in the utilities sector. Although most of the published studies refer to the energy and telecommunication sectors, there is also a rising interest about this issue in the water and sewerage sectors. The latter, traditionally managed by the public sector, historically have not shown much concern with their efficiency and productivity. This circumstance has been progressively changing in the past two decades, owing to a stronger participation of the private sector, more demanding environmental and service quality requirements, and the strictness inflicted by globalization, regarding the macroeconomic policies and the services of general economic interest management. The DEA use in these sectors can aim at different ends, such as:

- Identification of the better managed and more innovative WSS (best practices), which can be taken as reference peers;
- Creation of a competitive environment between the WSS in their sector, or even outside it, although they act in the form of natural monopoly;
- Establishing the key element in economic regulation when regulatory methods are based in incentive regulation (e. g yardstick competition);
- Analysis of the sector market structure, concerning the companies size, ownership (e. g. private versus public) and organization (e. g. verticalisation and horizontalisation).

From 1985 to the beginning of 2004 about 30 applications of DEA to the WSS took place in the world. Marques (2004) reviews in detail the 22 known studies. The objectives of the studies are distinct, but the most important is the WSS performance measurement with regulatory aims. The main actors are either academics or the regulatory authorities. The models comprise 9 countries, namely the USA, Australia, UK, Denmark, Holland, Japan, Italy, Mexico and Brazil. From the case-studies, 7 out of 22 deal with water supply, sewerage and sewage treatment services altogether and 9, 3 and 3 separately with water supply, sewerage and sewage treatment services, respectively. The 22 studies mentioned correspond to 33 distinct models. Almost all these models are input minimising oriented. Only 2 of the studies are non-oriented models. Regardless of the units, the studies include 23 inputs, 22 outputs and 20 different explanatory factors. The most adopted inputs are the no. of employees, the OPEX, the energy and the mains length. The leading outputs are the revenue (delivered) water volume, the no. of customers and the mains length, whereas the most common explanatory factors are the water sources (or the water treatment), the revenue water volume for different uses (e. g. domestic and industrial) and the population density (or customers density).

DATA, MODEL SPECIFICATION AND RESULTS

Data

The data used in this research consists in the information collected near 70 Portuguese WSS. The number of these WSS in Portugal is over 300, but the study covers, nevertheless, around 64 % of the Portuguese population, approximately 6.5 million inhabitants. The remaining WSS are all of reduced size and they manage the water supply and sewerage together with other activities and do not have separate account. The year considered to gauge the efficiency was 2001. The information used here was gathered directly from the WSS activities and account annual reports. In some cases, it was necessary to make enquiries to collect more information and, in other situations, to have appointments with the staff responsible for the reports so as to clear up some doubts.

Model Specification

The models variables choice took into account the WSS particular characteristics, the references, the experts' opinion, the available data and the study aims. In DEA the models should, as much as possible, include the aspects that better characterize the production, that is, the consumed resources and the output produced. Besides, a second stage of analysis can exist in DEA, which considers the operational environment (explanatory factors) where the production process takes place. Sometimes, it is not very clear whether to classify the variables into inputs, outputs or explanatory factors. The variables should be measurable and consistent among WSS. The models followed an input minimising orientation basis. The WSS should satisfy not only all the customers needs, but also the tight demand side management policies, therefore, the option for another orientation or model was groundless. Another aspect carefully thought was the variables specification in quantities or monetary units.

The different models adopted comprise, altogether, six inputs and three outputs. The inputs include the total cost (TC), the OPEX, the CAPEX, the mains length, the no. of employees and the others OPEX (OPEX minus labour cost - OOPEX). Except the mains length, measured in km, and the no. of employees, all the other inputs are measured in monetary units. The outputs encompass the revenue water volume, the customers number and the mains length. All the outputs are measured in quantities, particularly, in cubic metres, in customers number and in kilometres number. Table 1 outlines the models applied and table 2 shows the statistical characteristics of the variables included in the models.

Results

Table 3 represents the TE and its components average values, as well as the efficiencies weighted values by the revenue water volume, the number of efficient WSS and the technical efficiency *minima* values. Computations were done using a GAMS code.

Table 1 – Preferred models specification

Models	M1	M2	M3	M4	M5
Inputs					
TC	X				
OPEX		X	X		
CAPEX		X			
M. length			X		
Staff				X	X
OOPEX				X	X
Outputs					
Volume	X	X	X	X	X
Costumers	X	X	X	X	X
M. length					X

Table 2 – Variables statistical features

	Mean	St. dev	Min	Max
Inputs				
TC (10^4 €)	619	1303	24	10290
OPEX (10^4 €)	488	944	20	7033
CAPEX (10^4 €)	131	387	4	3258
Mains length (km)	539	356	87	1669
Staff (no.)	117	151	9	935
OOPEX (10^4 €)	283	528	8	3649
Outputs				
Volume (10^4 m^3)	576	908	31	6371
Costumers (10^3 no.)	40.6	52.1	3.7	331.4
Mains length (km)	539	356	87	1669
Explan. Factors				
Groundwater (%)	35.2	35.6	0.0	100
Domestic vol. (%)	67.7	9.3	44.4	92.3
CD (no/km $^{-1}$)	67.5	42.7	14.5	198.6
Water losses (%)	34.5	10.1	16.2	66.8
ISW (l inh.$^{-1}$ day^{-1})	165	63	63	394

CD - customers density; ISW – inhabitant supplied water

Table 3 – Results of WSS DEA models

Models	M1	M2	M3	M4	M5
TE*	0.624	0.665	0.694	0.720	0.735
PTE*	0.680	0.734	0.769	0.812	0.827
SE*	0.918	0.906	0.902	0.887	0.889
TE**	0.590	0.641	0.811	0.705	0.708
PTE**	0.792	0.838	0.855	0.888	0.898
SE **	0.745	0.765	0.948	0.794	0.788
SE (no.)	2	5	8	8	11
PTE (no.)	7	10	15	22	15
Min (SE)	0.335	0.340	0.510	0.614	0.535
Min(PTE)	0.281	0.376	0.278	0.475	0.481

* arithmetic mean; ** weighted by volume

RESULTS ANALYSIS

The Portuguese WSS inefficiency levels to the year 2001 were meaningful, oscillating between an average TE of 0.624 for model 1 and of 0.735 for model 5. All the models took the PTE value as the key factor as the TE source, exactly the part that can be controlled by the WSS managers. The SE presents relevant and similar values to all the models, respectively, between 8 and 11 %. The biggest WSS are generally penalised by the SE, showing decreasing returns to scale (DRS). Taking model 1 as example, in Portugal, the WSS present the ability to improve the average TE in 37.6 %, from which 8.2 % corresponds to SE earnings and 32.0 % to the PTE improvement. This means that, on average, each WSS can reduce 37.6 % the input total cost, while producing the same quantity of outputs. From the 70 WSS, to CRS, 60 have slacks regarding one of the outputs, that is, consuming the same resources they can produce a larger quantity of one of the outputs. In model 1, on average, the output produced volume has a slack of 278 280 m^3 and the other output customers number a slack of 1015. From the 70 WSS, 54 present DRS, 14 IRS (increasing returns to scale) and 2 CRS. If one considers the revenue water volume of each WSS, the TE value is less, due to the SE penalisation of the larger WSS. Table 4 represents the slacks calculated according to the double-stage method, assuming VRS to the inputs and the outputs. In brackets there are the inputs and outputs numbers with slacks for each variable and by model. For example, taking the WSS 3, table 5 shows the present values of the inputs and of its targets, including and excluding the slacks by model, as well as their peers. This table provides remarkable evidence about the DEA technique potentialities as a benchmarking tool, identifying not only the possible savings of this WSS (radial and not radial) but also the reference peers that can be taken has benchmark to this WSS.

Table 4 – Inputs and outputs slacks average

V / M	M1	M2	M3	M4	M5
TC					
OPEX					
CAPEX		51.7 (15)			
Mains length			9.9 (7)		
Staff				3.1 (8)	3.0 (3)
OOPEX				64.7 (6)	36.3 (5)
Water volume	278 (40)	234 (28)	201 (34)	74 (13)	58 (12)
Costum.	1015 (20)	982 (20)	624 (11)	244 (8)	397 (12)
Mains length					64.1 (31)

Table 5 – WSS 3 Targets without/ with slacks ( )

V	Value	M1	M2	M3	M4	M5
TC (10^3 €)	24330	18044				
OPEX (10^3 €)	20750		15720	16150		
CAPEX (10^3 €)	3580		2710 (2330)			
Mains length (km)	1210			9420		
Staff (no.)	5590				461 (364)	481 (347)
OOPEX (10^3€)	12240				10100	10530
Peers	-	1; 2; 12	1; 12	2; 5; 11; 12	2; 11; 46	1; 2; 11

A comparison of the models results was made using the Spearman and the Pearson coefficients. All the correlation coefficients are statistically significant to a level of 1 %. Major correlations occur between models 1 and 2 and between models 4 and 5, as expected. The study also tested the impact of taking out each WSS peers in each model, having as basis the superefficiency value calculated according to Andersen and Petersen (1993) and the peer index developed by Togersen, Førsund and Kittelsen (1996). The superefficiency analysis, besides sorting out the efficient WSS, also enables to prove the consequences of possible outliers at the frontier. The peer index enables to identify the efficient WSS which are more often referent peers, that is, the ones that are more effective when the aim is the benchmarking use (through best practices identification). The models were also re-analysed taking some of the inputs as non-discretionary, in particular the input capital, represented by the CAPEX or by the mains length (models 2 and 3). This investigation was relevant, with an impact of more than 7 % in the TE average value.

DEA DISCUSSION RESULTS

The results presented above through DEA technique showed the potential features the use this tool might have in regulatory benchmarking. To publish these elements might have very positive effects in the market (sunshine regulation), since it makes the different stakeholders discuss the results. From another perspective, sunshine regulation creates competition among the WSS and at the same time embarrasses the WSS with poor performances. If a carrots and stick policy existed directed simultaneously to the best and worst performances, this mechanism could, in a first phase, be a form of successful regulation (or of government intervention) in these sectors.

However, DEA potentialities are unquestionably superior, despite some of the problems with the methodology that still need to be improved so as to be included in price regulation in a more or less straight way. The first problem regards the operational environment inclusion in DEA analysis. Among the several explanatory factors measurement processes discussed, for example, in Fried *et al*. (1999) and Pérez (2001), this study adopted the two-stage method, which used the Tobit model in a second stage to regress the values obtained by DEA in the first stage with the explanatory factors. The attained results, for example, for the VRS model 4 are presented in table 6. Although there is no significant explanatory factor at the 5 % level of significance, a likelihood ratio test does not enable the rejection of the hypothesis that all the coefficients in the model are zero.

Table 6 – Explanatory factors effect (model 4)

Explanatory factors	**Coef.**	**Error**	**T**
Groundwater (%)	-.058618	.198544	-0.30
Domestic vol. (%)	.119154	.333337	0.36
CD (no/km^2)	.000889	.000829	1.07
Water losses (%)	-.516625	.282160	-1.83
IWS (l inh.$^{-1}$ day^{-1})	.001048	.000568	1.84

CD - Customers density; IWS – inhabitants water supply

This methodology allows the explanatory factors presence in DEA study, but as Simar and Wilson (2002), for example, point up the results quality is problematic, once there is a correlation between these variables and the ones included in DEA first stage. However, the methodology suggested by those authors is also endowed with difficulties, at least in the empirical world.

A second question relates the DEA model specification. If there are five models presented here it is because some difficulties came up in its selection. Then, the option for one or another model can be particularly unkind to some WSS. As such, while a relatively consensual procedure does not yet exist, it is difficult to apply the DEA technique in the regulatory world beyond the "sunshine" perspective. Kittelsen (1998) developed the stepwise procedure which enables the DEA model selection through statistical hypothesis tests. However, this method relies on several principles that are difficult to fulfil and that influence the final conclusions. For example, the independence between variables and a WSS number of 100 to the sample are requirements difficult to obey. This study also employed this procedure, which allowed the selection of a model distinct from those presented (M1 to M5). It took the total cost and the water losses as inputs and the revenue water volume as outputs with a significance level of 5%. This model is perfectly reasonable in a practical point of view according to the water and sewerage sectors current performance in Portugal, given that the water losses is the main problem these sectors face at the moment (average near 40%) and the production cost (due to the recent creation of national company with that aim) is extremely high (sometimes higher than 50 % of the total cost). Nevertheless, this situation should be necessarily temporary and that will lessen the effect of the water losses when it reaches levels under 20 % (e. g. besides, there will always be a part of the water losses that will not be controllable by the WSS). From a theoretical point of view, the number of 70 WSS of the sample constrains this approach.

Finally, in order to obtain the statistical inference, a bootstrap methodology (re-sampling) was applied to the DEA estimators. The bootstrap allows the bias estimation and leads to the inference about the DEA results attained. The methodology follows the approach carried out by Simar and Wilson (1998), who use a smooth bootstrap algorithm based in a process of data generation, where the inputs are obtained through random deviation of the inputs efficient frontier. Table 7 depicts the results of the average values to each model (with a B times=1000) to the VRS technology. The bootstrap methodology enables the estimation of confidence intervals to each WSS, something extremely relevant.

Table 7 – Bootstrap results of different models

Model/Estimate	Mean	St. dev	Min	Max
M1 DEA	0.680	0.186	0.281	1.000
M1 bootstrap	0.612	0.155	0.267	0.935
M2 DEA	0.734	0.178	0.376	1.000
M2 bootstrap	0.608	0.135	0.337	0.919
M3 DEA	0.769	0.182	0.278	1.000
M3 bootstrap	0.688	0.147	0.269	0.963
M4 DEA	0.812	0.173	0.475	1.000
M4 bootstrap	0.710	0.136	0.427	0.913
M5 DEA	0.827	0.172	0.481	1.000
M5 bootstrap	0.709	0.128	0.441	0.907

Unfortunately, in spite of the recent improvements [*vide* Simar and Wilson (2004)], this methodology leads to some doubtful results or, at least, not very useful in the practical domain, mostly for the technically efficient WSS. Anyway, the bootstrap methodology, whose great advantage is to keep the same non-parametric orientation of DEA, enables the evaluation of the efficiency measures robustness obtained through DEA to the sample variations and the non-observable variables. When the re-sampling process is repeated B times, a particular imaginary frontier will be determined, corresponding to a specific group of peers (towards which the benchmarking of each WSS is done), which represents a particular level of non-observable or not considered variables.

CONCLUSIONS

This paper outlines a research in progress about the application of benchmarking through DEA to the Portuguese WSS. This non-theoretical study intends to put in evidence the DEA use strengths in these sectors, largely due to their particular characteristics. Some empirical results are presented, as well as some procedures of sensibility analysis. As it would be expected the potential earnings of technical efficiency, chiefly of pure technical efficiency, are meaningful. Finally, some practical problems in DEA use in regulatory benchmarking are briefly depicted and analysed.

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ACKNOWLEDGMENTS

The authors are grateful for a grant from the programme "Fundo de Apoio à Comunidade Científica (FACC)" of "Fundação para a Ciência e a Tecnologia (FCT)" from the Portuguese Government.

BENCHMARKING THE EFFICIENCY OF ELECTRIC COOPERATIVES IN THE PHILIPPINES

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ABSTRACT

This paper attempts to determine alternative methods of benchmarking the efficiency of electric cooperatives. Using a panel composed of 119 Philippine electric cooperatives from 1990 to 2002, a cost function is estimated to identify appropriate cost variables that will determine the frontier. It was found out that the main cost drivers are total sales, prices of labor and capital, distribution network, transmission capacity, actual billed customers, service area, demand structure, and system losses. Based on this specification, efficiency frontiers are computed using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The efficiency of each cooperative was then ranked and compared to check for consistency. The SFA reports that on the average, ECs are 34 percent away from the cost frontier while DEA estimates 42 percent. The panel data allowed for the calculation of Total Factor Productivity changes based on the Malmquist index. On the average, TFP increased by 1.7 percent from 1990 to 2002. The rankings and productivity values will prove to be useful for the energy regulator in determining efficiency targets. DEA and SFA are based on theoretically determined cost function which will lead to results that are more representative of the ECs actual performance.

INTRODUCTION

In this paper, the cost function for a panel of 119 Philippine electric distribution cooperatives (ECs) is estimated as a basis for efficiency benchmarking. With the passage of the Electric Power Industry Reform Act (EPIRA) in 2001, the Philippines is currently on the process of restructuring and privatizing its power industry. Despite the deregulation, however, ECs will still have a monopoly franchise to deliver electricity to residential consumers so that rate regulation by the regulatory commission is still necessary. Through benchmarking, the regulator can compare the costs of similar companies from which any one firm's attainable cost efficiency level can be inferred. With this, the dependence of price that ECs received on its own cost level would be broken. Benchmarking analysis can be used to set the informational basis for more effective regulation, as it reduces informational asymmetries between ECs and regulators regarding costs. Benchmarking exercises also make it possible to identify the scope for further efficiency improvements of each cooperative and to measure comparative improvement in their performance over time.

Traditional performance measurement system such as ratio analysis provides a very unbalanced picture of performance that can lead firm managers and regulators to miss important opportunities for improvement. The present study makes an important contribution by being the first study to consider multi-output and input distance functions in assessing the efficiency of rural electric cooperatives. It is also the first to apply two different methods of benchmarking efficiency to one data set and to estimate productivity gains of each cooperative from 1990 to 2002.

The paper is organized as follows: Section 2 outlines the estimation methods used in the study. Section 3 presents the results of SFA, DEA and Malmquist-DEA. The last section concludes and enumerates considerations for further studies.

ESTIMATION METHODS

Model Specification

Cost function rather than production function was estimated after considering the past studies and after analyzing the inherent qualities of the electricity industry. Since the cooperatives are under obligation to provide electricity at specified tariffs, the ECs maximize profit by minimizing the cost of delivering a certain level of electricity. Given that the Philippine regulator, the Energy Regulatory Board (ERC), evaluates the performance of regulated firms using operating costs, ECs' non-power cost was chosen as the cost variable.[1]

Having specified the function to be estimated, the input and output variables that should be included in the analysis were identified. The cost drivers chosen are based on the definition that the costs of operating a distribution system are the costs of building and maintaining the system of service lines, mains and transformers, and of measuring and billing electricity. The core output variable is specified to be total electricity delivered measured by total sales in KWh. The core input variable is identified to be total operating and maintenance expenditures, transformer capacity and length of distribution line, all of which are widely accepted in literature as required input variables. Environmental variables, such as service area and number of actual billed customers are included to account for geographical dispersion. Measurement of the effect of delivering energy at different voltages required by different customers is also needed, therefore the proportion of total energy delivered that is distributed to residential customers is included as an additional operating characteristic (Estache, Rossi and Ruzzier, 2004). Finally, system loss and maximum demand on the system measured by peak load are included as environmental input variables to account for technological differences among cooperatives in delivering electricity.

The data for all 119 cooperatives from 1990 to 2002 were obtained from the NEA database while land area was obtained from the Department of Environment and Natural Resources. The total operating and maintenance expenditure is expressed in real values (1994=100) using the CPI index for Fuel, Light and Water as published by the National Statistical Coordination Board.

EFFICIENCY ANALYSIS

Cost Function Estimation

The total operating and maintenance cost (TOM) is a function of output (S), input factor prices (P_i), distribution length (DL), transformer capacity (TC), and exogenous variables (Z_i),

$$TOM = f(S, P_i, DL, TC, Z_i). \quad (1)$$

In this essay, the most general functional form for electricity distribution in the Philippines is a Cobb-Douglas cost function:[2]

$$\ln TOM = \beta_0 + \beta_1 \ln S + \beta_2 \ln P_L + \beta_3 \ln P_K + \beta_4 \ln DL + \beta_5 \ln TC + u_i \quad (2)$$

where P_L and P_K are the prices of labor and capital, respectively.[3]

The cost function specified above does not include environmental variables. There are two approaches in their inclusion: (1) including them directly into the cost function as regressors, assuming that they influence the shape of the technology, and (2) accounting for their effect after the cost function estimation, assuming that they directly influence the degree of technical efficiency (Coelli, Perelman, and Romano, 1999). Following Estache, Rossi and Ruzzier (2004), the first approach was taken in this study in order to get efficiency measures that are net of environmental influences. Coelli, Perelman and Romano (1999) emphasized that the measurement of net efficiency is useful as it allows one to predict how companies would be

1 Non-power cost is composed of total operating and maintenance expenditure defined as the sum of distribution, consumer accounts, administrative and general expenses.

2 A translog production function was estimated , however, most of the coefficients turned out to be statistically insignificant.

3 P_L is obtained by dividing the actual administrative expenses over the number of employees while P_K is obtained by dividing distribution expenses over transformer capacity (Hattori, 2002).

ranked if they were able to operate in equivalent environments.

Adding the environmental variables, the function is specified as follows:

$$\ln TOM = \beta_0 + \beta_1 \ln S + \beta_2 \ln P_L + \beta_3 \ln P_K + \beta_4 \ln DL + \beta_5 \ln TC + \beta_6 \ln SA + \beta_7 \ln CUST + \beta_8 \ln DS + \beta_9 \ln SL + \beta_{10} \ln PL + u_i \quad (3)$$

where *SA* is service area, *CUST* is the number of actual billed customers, *DS* is the demand structure, *SL* is the system loss and *PL* is the peak load.

Following the methodology of Estache, Rossi, and Ruzzier (2004), the core cost function was estimated and the environmental variables were added into the model depending on their statistical significance. Peak load was dropped from the model due to an insignificant coefficient. Additional test the significance for the environmental variables was conducted using the log likelihood ratio test with the null hypothesis that $\beta_6 = \beta_7 = \beta_8 = \beta_9 = 0$. The null is strongly rejected by the data, suggesting that environmental variables cannot be omitted in the estimation of cost function in this sector.[4]

After correcting for heteroscedasticity, the following is the cost function estimated for an unbalanced panel of 119 firms using data from 1990 to 2002:

Table 1 Results of Panel Regression Using Total Cost

	Coefficient	Std. Err.	z-value
S	0.1646*	0.0087	18.9750
P_L	0.2087*	0.0071	29.2300
P_K	0.4429*	0.0082	53.8310
DL	0.4428*	0.0090	49.1170
TC	0.0718*	0.0081	8.9090
SA	0.0274*	0.0036	7.5810
CUST	0.2025*	0.0120	16.8320
DS	0.0321*	0.0084	3.8310
SL	0.0814*	0.0070	11.5520
Constant	-0.6412*	0.0662	-9.6810

NOTE: * significant at 0.01 level of significance.

To be able to check the consistency of these results, an average cost function was also estimated. Regression estimates are as follows:[5]

Table 2 Results of Panel Regression Using Average Cost

	Coefficient	Std. Err.	z-value
S	-0.9877*	0.0099	-99.516
P_L	0.3803*	0.0066	57.851
DL	0.6169*	0.0082	75.502
TC	0.0512*	0.0083	6.148
SA	0.0135*	0.0040	3.369
CUST	0.2182*	0.0152	14.385
DS	-0.0344*	0.0145	-2.365
SL	0.1433*	0.0084	17.096
Constant	0.4496*	0.0696	6.46

NOTE: * significant at 0.01 level of significance.

All parameter estimates are statistically significant with the expected signs. The total operating and maintenance cost is expected to increase given an increase in all its cost drivers. The average cost model gave negative output elasticity which implies that an increase in the production of output will decrease average cost. This confirms the presence of economies of scale, as what is expected from natural monopolies. An increase in service area and number of customers will positively affect average cost, however, an increase in the percentage of residential customers will decrease average cost. A possible explanation is that as more residential customers become connected to the network, all others held

[4] The χ^2 value obtained is 325.53, the test statistic of which indicates that it exceeds the 99th percentile for the corresponding χ^2 distribution.

[5] The average cost function estimated takes the form:

$$\ln \frac{AC}{P_K} = \beta_0 + \beta_1 \ln S + \beta_2 \ln \frac{P_L}{P_K} + \beta_3 \ln DL + \beta_4 \ln TC + \beta_5 \ln SA + \beta_6 \ln CUST + \beta_7 \ln DS + \beta_8 \ln SL + \beta_9 \ln PL + u_i$$

where *AC* is *TOM* divided by *S*. Since linear homogeneity in factor prices is imposed, the price of capital is specified to be the numeraire.

constant, there is a higher customer utilization of the network thereby bringing down cost.

Based on the cost function estimation, the functional form that SFA will assume and the validity of the variables that will be used are verified.

Stochastic Frontier Analysis Efficiency Estimates

Following the cost function estimation, the general functional form for the stochastic frontier among rural electric cooperatives in the Philippines is:

$$\ln TOM = \beta_0 + \beta_1 \ln S + \beta_2 \ln P_L + \beta_3 \ln P_K + \beta_4 \ln DL + \beta_5 \ln TC + \beta_6 \ln SA + \beta_7 \ln CUST + \beta_8 \ln DS + \beta_9 \ln SL + v_{it} + u_{it} \quad (4)$$

where v_{it} are independent and identically distributed random variables and u_{it} are non-negative random variables representing inefficiency. Table 3 shows the results of the econometric estimation.[6]

Table 3 Estimated Variable Parameters and Statistics for SFA

	Coefficient	Std. Err.	t-value
S	-0.9032*	0.1286	-7.0246
P_L	0.3207*	0.0200	16.0701
P_K	0.2212*	0.0107	20.7546
TC	0.3701*	0.0104	35.6650
DN	0.3716*	0.0124	29.8974
SA	-0.0005	0.0123	-0.0421
CUST	0.0855*	0.0080	10.6989
DS	0.0695*	0.0225	3.0854
SL	0.1539*	0.0227	6.7846
Constant	-0.0024	0.0100	-0.2376
σ^2	0.0219*	0.0029	7.6253
γ	0.7375*	0.0203	36.2640

NOTE: * significant at 0.01 level of significance.

All the variables are statistically significant except for service area. A one-sided generalized likelihood-ratio test for null hypothesis H_0: $\gamma=0$ was conducted to measure the significance of undertaking stochastic frontier estimation. If the null hypothesis is not rejected, the parameters can then be consistently estimated using ordinary least squares. The likelihood ratio test of the one-sided error, LR=-2{ln[L(H_0)]-ln[L(H_1)]}=99.8, exceeding the chi-square critical value, a=0.05, of 2.71. Thus, the null hypothesis is rejected and undertaking SFA for efficiency benchmarking is appropriate for the ECs. The yearly efficiency estimates based on these parameters is reported in Table 4.

SFA efficiency scores measure the distance an electric cooperative is operating away from its cost frontier. On the average, the 105 electric cooperatives are operating about 39.8 percent higher than the cost efficient frontier.

Table 4 SFA Cost Efficiency (Annual Means)

YEAR	SFA Efficiency
1990	1.4624
1991	1.4504
1992	1.4389
1993	1.4276
1994	1.4167
1995	1.4062
1996	1.3959
1997	1.3859
1998	1.3762
1999	1.3668
2000	1.3577
2001	1.3488
2002	1.3402
Mean	**1.3980**

Data Envelopment Analysis Efficiency Estimates

More important to the regulator is to be able to provide efficiency targets to the ECs. DEA results provide values for input reduction (in the case of input-oriented DEA) that can serve as guide to regulators in setting efficiency targets. DEA also identifies relevant peers for each cooperative that can serve as performance models as well as the economies of scale of each EC. This information will be useful for the regulator in benchmarking the performance of the ECs.

6 The SFA is estimated using the FRONTIER 4.1 program of Tim Coelli. The estimation assumed a half-normal distribution of the inefficiency term.

Since the data is a pooled cross section and time series, several possibilities arise within the computation of efficiency using DEA. According to Estache, Rossi, and Ruzzier (2004), three alternative approaches are possible. The first alternative would be to compute a frontier for each thirteen periods and to compare each of these cross-section results. This way, a frontier is constructed in each year and the efficiency of each firm is calculated relative to the frontier in each period. The second possibility is to treat the panel as a single cross-section (each firm in each period being considered as an independent observation), pooling all the 1365 observations together. With this approach, a single frontier is computed, and the relative efficiency of each firm in each period is calculated in reference to this single frontier. The last approach would be the window analysis approach proposed by Charnes et al. (1985). The problem with this approach, however, is that the choice of width for the windows poses an additional complication given that it is entirely ad hoc, and "currently determined by trial and error" (Charnes et al., 1994). In this essay, the first and second alternatives are undertaken. The second approach is used for the estimation of a Cost-DEA while the first approach is used to compare the efficiency ranking results with that of SFA.

The data obtained allows for the estimation of both Cost-DEA and Technical Efficiency DEA (TE-DEA). The estimation of Cost-DEA, however, does not allow for the inclusion of environmental input variables in the specification, making the results not comparable with SFA. Given this constraint, TE-DEA is then estimated to facilitate comparison between the two approaches. The estimates of Cost-DEA, however, are still presented since it allows for the disaggregation of technical, allocative and cost efficiencies.

The outputs specified in the computation of Cost-DEA are total electricity delivered, number of customers billed, service area covered and demand structure. Transformer capacity and number of employees are identified as input variables, while P_K and P_L account for their prices, respectively. [7]

[7] The envelopment form of the model is generally the preferred form to solve DEA and is the one utilized by the Data Envelopment Analysis Program (DEAP) by Tim Coelli (1996). The DEAP version 2.1 is used in this study.

Cost-DEA is estimated by pooling all the observations for each firm in 13 years into one single cross-section. This way, the results estimated will be robust. On the average, the electric cooperatives in the Philippines has a technical efficiency of 0.606, implying that the cooperatives could have delivered the same output using only 60.6 percent of its inputs. In terms of cost efficiency, had the cooperatives realigned their input mix, they could have been using only 57.7 percent of their costs. The annual means of Cost-DEA is presented in Table 5.

Table 5 DEA Efficiency Estimates (Annual Means)

YEAR	Technical Efficiency	Allocative Efficiency	Cost Efficiency
1990	0.536562	0.94839	0.511048
1991	0.564038	0.948971	0.536571
1992	0.549962	0.947343	0.521229
1993	0.561952	0.944781	0.529638
1994	0.560448	0.946952	0.529657
1995	0.592733	0.958105	0.566743
1996	0.60439	0.957124	0.577295
1997	0.612524	0.957429	0.584914
1998	0.632819	0.955924	0.603352
1999	0.639857	0.953429	0.608581
2000	0.657076	0.952048	0.624638
2001	0.663781	0.956819	0.634467
2002	0.70379	0.958029	0.67381
Mean	**0.606149**	**0.952719**	**0.577073**

Benchmarking of ECs

To be able to compare the two benchmarking methodology, the variables used have to be identical. Based on the original estimated cost function, variables were chosen to run TE-DEA and SFA for the year 2001.

It was found out that the rankings of DEA and SFA are similar only when outlier ECs are disregarded. Since one of the drawbacks of DEA is giving an efficient score of 1 to a firm who has no peer among the cohort, by using DEA and SFA simultaneously, the outlier firms can easily be identified. By removing those ECs which scored 1 from DEA but received low scores from SFA, a more comparable ranking can be obtained.

The National Electrification Administration (NEA), the agency in charge of monitoring EC performance, conducts its evaluation by cooperative classification and categorization. Cooperatives are classified based on their respective sizes as measured by circuit km of lines, total sales and residential connections. Based on these indicators, cooperatives are classified as extra large (EL), large (L), medium (M) and small (S). Categorization, on the other hand, deals with the compliance efficiency targets of NEA for the cooperatives. Cooperatives are categorized as A+, A, B, C, D, E, depending on the points they garner regarding the following indicators: amortization payment, system loss, collection efficiency, payments of purchased power, and non power cost. The ECs were also disaggregated according to NEA's classification to be able to minimize the problem of outlier firms. The results will also aid NEA in specifying appropriate efficiency targets for cooperatives operating on a particular classification. The efficiency ranking for 2001 per Cooperative Classification suggests that there is possible room for reduction in total operating cost and system losses, however, direct translation of DEA input target results as efficiency targets will not be appropriate. NEA has to evaluate the DEA results together with the partial productivity measures outlined in categorization assessments to be able to come up with more holistic efficiency targets.

Malmquist-DEA

Equally important to the regulator is information about the rate at which efficiency gains are be made. Accordingly, this paper examines historic rates of productivity change within the ECs. Total factor productivity changes are calculated for the period 1990 to 2002 using the Malmquist DEA.

The Malmquist TFP calculations are based upon DEA-like linear programs.[8] The input and output variables used in these calculations are the same as those used in the DEA technical efficiency calculations. The Malmquist annual TFP changes are presented in Table 6.

The overall technical efficiency change (shown in column 2) represents changes in technical efficiency (position relative to the frontier), and this is made up of pure technical efficiency change (column 4) and scale efficiency change (column 5). The technical change index number (column 3) indicates how far the frontier against which technical efficiency is assessed has moved (frontier shift). Overall TFP growth (column 6) is a combination of technical efficiency change (column 2) and frontier shift or technical change (column 3).

On the average, TFP increased by 1.7 percent from 1991 to 2002. Changes due to movements in the efficient frontier and technical efficiency improvement are equal. This indicates that the ECs at the frontier are driving efficiency improvements at the same rate that less efficient cooperatives are improving.

Table 6 Malmquist Annual TFP Index

YEAR	**TE ?**	**TECH ?**	**PURE TE ?**	**SCALE EFF ?**	**TFP ?**
1991	1.047	0.991	1.029	1.017	1.038
1992	0.97	1.03	0.966	1.004	1
1993	1.073	0.933	1.074	0.999	1.001
1994	1.002	1.034	0.996	1.005	1.035
1995	1.019	0.999	1.016	1.003	1.018
1996	1.009	0.978	1.009	1.001	0.987
1997	0.999	1.03	0.995	1.005	1.029
1998	0.996	0.998	0.997	0.998	0.994
1999	0.982	1.018	0.99	0.992	1
2000	1.003	1.029	1.003	1	1.032
2001	0.981	1.082	0.976	1.005	1.061
2002	1.025	0.991	1.026	0.999	1.016
Mean	**1.009**	**1.009**	**1.006**	**1.002**	**1.017**

On a yearly basis, 2001 posted the highest TFP improvement among all the years surveyed. TFP increased by 6.1 percent in 2001 primarily due to a frontier shift of 8.2 percent. This implies that ECs on the frontier were driving efficiency rate improvements. Conversely, TFP decreased by 1.3 percent in 1996.

CONCLUDING REMARKS

Alternatives ways of benchmarking the efficiency of electric cooperatives in the Philippines were estimated using SFA and

[8] For further reading, refer to Coelli, Rao and Battese (1998).

DEA. When used alongside the current NEA classification and categorization method of the agency, the efficiency targets will result to a more holistic and appropriate efficiency rankings and estimates. The fact that DEA and SFA are based on theoretically determined cost function will lead to results that are more representative of the ECs actual performance, rather than basing them on single ratios, which, when considered alongside other ratios will lead to results that are rather misleading.

Given that these methodologies are affected by the specification of variables, further examination of the effects of environmental variables is necessary. As suggested by Coelli, Rao and Battese (1998), a two-stage DEA which regresses the efficiency score obtained from DEA on environmental variables has the advantage of not having to make any prior assumptions on the direction of the influence of an environmental variable. Also, inputs such as transformer capacity and distribution lines cannot be easily altered in the short-run. Estimating DEA which accounts for these non-discretionary variables needs to be considered. On a per EC scale, the benchmarking exercise should be followed up by an independent examination of the extent of similarities and differences between inefficient firms and their peers.

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ACKNOWLEDGMENTS

The author acknowledges the help of her supervisor, Prof. Shigeki Kunieda. Thanks is also due to Mr. Hua Changchun and Ms. Sharon P. Pornillosa for their valuable comments and contributions.

CONSTRUCTING 'DATA ENVELOPMENT ANALYSIS' VIA PERFORMANCE MEASURES: A FIELD RESEARCH FROM MODIFYING THE BALANCE SCORECARD IN A PUBLIC TRAINING CENTER

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ABSTRACT

Rapid changes in life long training and performance measurement are posing serious challenges to the work environment of public sector managers. Meeting these challenges will require public sector managers, instructors and training programmes to undergo fundamental changes. Consequently, modern requirements seek ways through a framework to increase the value of taxpayers' money and provide accountability of decision makers' contribution.

The Balance Scorecard (BSC) integrates the latest performance measurement and control techniques with new realities of continuous improvement, strategy and organizational change. How public sector training management may use a modified BSC to stimulate, guide, and sustain such continuous improvement efforts is illustrated in the current study.

A field research of 14 directors of Decision Making Units with their civil servants trained in the state training center of the Hellenic Ministry of Economy and Finance, constructs the 'Data Envelopment Analysis' via performance measures on the modified BSC. This paper illustrates empirical evidence on the applicability and benefits to taxpayers of BSC by providing accountability for public sector training programmes spending. Finally, this study implements some selective Key Performance Indicators (KPIs), which should characterize an effective BSC for public training programmes, as well as those factors that affect its successful implementation.

INTRODUCTION

Management Accounting (MA) offers various alternative solutions of performance measurement. The initiative of performance measurement in life long training programmes attracts the attention of management accounting academics and practitioners alike. For Greek Public training centers such information has been neither available nor required, and a similar research, until recently, would have been difficult to persuade anyone of its usefulness or achievability.

MA entered in a new stage by the mid-90s, with focus on planning, control and waste reduction expanding to encompass a more strategic emphasis on the creation of firm value through the identification, performance measurement and management of the drivers of customer value, organizational innovation, and shareholder returns (*International Federation of Accountants*, 1998; *Ittner & Lacker,* 1998b, 2001).

A hallmark of this era is the introduction of a diverse set of 'new' MA techniques that include the development of balanced scorecards of leading and lagging indicators of economic success (e.g. *Kaplan & Norton*, 1996). The implementation of complex measurement systems is likely to be quite costly and even limited evidence on economic benefits of these systems is still scarce.

THE SELECTIVE ORGANISATION FOR FIELD RESEARCH

The selective organization that the following field research is based; is the public sector training center of the Hellenic (Greek) ministry of Economy and Finance. This training center provides life long education to all civil servants for its mother ministry (*SEYYO*, 2003). The organization in question has been selected for the following reasons. Firstly, it provides life-long education for the highest number of public servants (and more specifically for the first in rank ministry in Greece). Secondly the ministry whose servants are trained is responsible for planning economic policies and public finance, therefore more accustomed to economic applicability. Thirdly the training center supplies a wide array of training programmes, from issues relating to planning the state budgeting to methods and ways of collecting taxes. Fourthly, life-long training schools deliver many services and pursue varying goals. Therefore, the activities, which differentiate efficiency of outputs before and after training, should be described, so that the efficiency of the training programmes can be improved. Fifthly, life long training receives public funding from taxpayers and EU grants. Therefore, this is a way of describing the efficiency of resource allocation accountability. Thus, the selection of the case training center provides us with better insight into the consequences of life-long education, in various public sector departments design that have achieved efficiency improvement at a varying degree. It is obvious that departments have to cope with high levels of life-long training should be more competitive (*SEYYO*, 2003; *Vasilakis*, 2003). However, it has to be said that departmental changes (concerning policy and goals) are influenced from the central government's wish for change.

The operationalization of constructs may sometimes be determined or guided by the level at which data will be aggregated at the time of analysis (*Sekaran*, 1992). Not having done so in advance may mean that later data analysis cannot be appropriate for the study and therefore cannot be performed. The Training Center organizes a large number of training courses, seminars, workshops and lectures (*SEYYO*, 2003). It organised plenty of training programmes during 2001, 2002, 2003 upon which the field research was based. The training center used 46 civil servants and external instructors as university professors, ministerial managers, professionals and specialists from the private sector for running these training programmes. According to internal reviews and documents of training center the training activities that took place in the years of 2001, 2002, 2003 were considered highly satisfactory in turns of results and feedback received. Moreover, these training programmes covered partly the training ministerial needs of all 7 responsibility areas of the ministry: (Taxation, Customs Services, Public Finance Administration and Control, Repression of Economic Crime & Financial Fraud, Chemical Control of Foodstuffs, Public Finance, and Specialized Topics).

Another important factor for selecting the chosen organization is the number of customers-citizens for unit analysis. Government directories vary to a high degree depending on the number of citizens using their services. Because it is not necessary to limit this research to a specific category of directories, in-depth analysis took place at least in one responsibility area of the mother ministry (training organized by the Training Center).

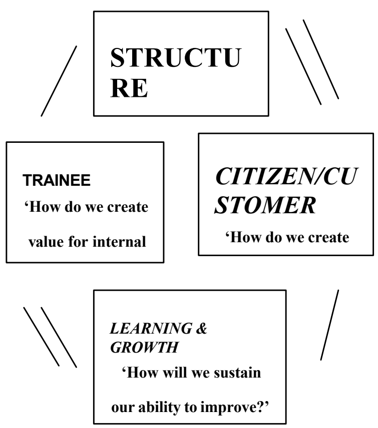
IMPLEMENTATION OF BSC IN A PUBLIC TRAINING CENTRE

Balanced Scorecard (BSC), popularized by *Kaplan & Norton* is a theoretical framework of translating an organisation's vision and strategy into groups of cause and effect linking performance drivers and outputs. The central theme of BSC is its focus on goal and collaborative determination of these goals and their measures. The aims of BSC combined with life-long training in Greece motivate the modification and applicability of this framework for the selective public training center. The content of BSC was mainly determined by newly established strategy documents and developed by the researcher with continuous feedback from the case organization (see the following figure). Such demonstrable cause-and-effect relationships provide a conceptual framework for selecting meaningful inputs and outputs for DEA (Data Envelopment Analysis).

For many years MA has developed implicit theories of BSC but the lack of explicitness has prevented MA from describing and testing these theories. As a consequence, before embarking on theory testing by field researches (see *Atkinson & Shaffir*, 1998; *Young*, 1999; *Dunk*, 2003), the researchers are obliged to modify and apply the theoretical framework with critical success factors of Key Performance Indicators (KPIs). BSC has the advantage of providing a comprehensive map of strategic outputs and outcomes for each Decision Making Unit (DMU), associating performance drivers and value propositions.

In this study two of the four BSC perspectives are softly modified 1) the structure perspective shift with financial and 2) trainee with internal process. The modification took place in order to apply BSC to DMUs. These are the ministry directories of the field research.

Figure: Modified Balanced Scorecard Framework applied in a public training center



The empirical testing of the modified BSC application took place by field research. MA provides information intended to influence the behaviour of individuals. Therefore, field research in MA invariably focuses on how people, either acting individually or in groups, react either to MA information, (such as cost or productivity data), or MA systems, (such as control or planning systems)[1].

THE MERGER OF BSC WITH DEA

Since 1966, *Zlatkovich et al* had stated, that the definition of accounting is the process of identifying, measuring and communicating economic information to permit informed judgments and decisions by users of the information. *Dean* (1997), observes that the above definition leaves plenty of room for the application of mathematical techniques within accounting. However, the practice of accounting limits itself to numbers, as opposed to equations and coordinate systems.

In order to materialize this evolvement, an attempt is made to bring together a measurement method, BSC and a liner programming method, DEA. *Charnes et al* (1978), states that DEA can be applied when an analyst intends to measure relative efficiency of comparable DMUs, which can be separate institutions, e.g. Ministry Directories.

Tomkins and Green (1988) have defined the conditions under which DEA is useful. 'If the technique yields additional insights and helps evaluators to sharpen their focus of enquiry and debate, DEA is useful'. If our evaluators are to be credible, they must be able to present reasoned methods for handling the multidimensional nature of the evaluation problem, which DEA highlights so well. Whether DEA is useful will depend to a large extent on the structure of the decision situation in which it is used – plausible number of variables, reliability of measurement, etc.

Borrowing Metrics from BSC

BSC generates a large quantity of data about operations. DEA can help focus MA's attention on areas of specific interest by enabling simultaneous multiple input /output /results /outcomes analysis. The choice of input, output, results, and outcomes variables for the DEA model is crucial. Results may vary according to the variables chosen. Two researchers may obtain different results depending on the choice of variables. Therefore,

[1] Atkinson & Shaffir (1998).

extreme care must be exercised in selecting the variables. Obviously, such a choice would depend on the objectives of the analysis.

While, the theoretical framework contents four perspectives, the design of questionnaire was structured in more simplistic way in order to be convenient to respondents. Each section contained items that asked responses on a 4 point Likert scale, followed by open-closed questions. For item, responses were sought relating to the time of the field research (December 2003) and three years previous (2001). Choice of the 3-year time span was based on extant finding that such a time window is needed to capture changes in organizational systems and practices (*Chenhall*, 1997).

There were four input, six output, and four results, five outcomes variables identified during the data collection stage (see tables 1, 2, 3, 4). Data on these variables were quantified and collected in 2003. The final variable chosen from among the initial identified set is based on the consideration of parity in the units of measurement of the variable and to ensure uniqueness in the representation.

Table1: Structure Perspective

No.	Key Performance Indicators
S1	Number of Trained employees
S2	Number of participating training programmes of your directory.
S3	Motivated Civil servants for training
S4	De-motivated Civil Servant for training

Table 2: Trainee Service' Perspective

No.	Key Performance Indicators
T1	Successfully completed aims
T2	Better reallocation of duties
T3	Cost reduction of directory processes
T4	Time saving of directory processes
T5	Productivity improvement of directory
T6	Modernisation of directory

Table 3: Customer / Citizen Perspective

No.	Key Performance Indicators
C1	Time reduction to citizens
C2	Citizen satisfaction improvement
C3	Cost reduction for citizens
C4	Financial authorities trusted by citizens

Table 4: Learning & Growth Perspective

No.	Key Performance Indicators
L1	Coverage of training needs
L2	Appropriate training needs identification
L3	Assimilate reduction of hired civil servants
L4	Improvement of working conditions
L5	Develop modern technology

DEA studies can take advantage of the many metrics used in BSC. Metrics should be quantifiable, complete and controllable (*Avkiran*, 2002). A qualitatively oriented approach to research contrasts with a positivist approach, which searches for cause through methods such as questionnaires and inventories that yield data amenable to statistical analysis. However, qualitative methodology is more than a set of data-gathering techniques; it is a way of approaching the empirical world (*Atkinson & Shaffir*, 1998).

DEA FOR DECISION MAKING UNITS

In DEA model identities the most efficient directories are identified and assigned a value (score) of unity to it while all other unities are attributed with a measure of inefficiency. These less efficient directories are assigned scores between zero and one and the more efficient are assigned scores between two and three. The structure perspective has input indicators that are assigned negative values. Thus DEA does not measure optimal efficiency of directories. Instead, it differentiates the least efficient directories from among the set of all directories.

DEA has gained more acceptability in recent years for evaluation and measurement of relative efficiency of any type of systems with an input and output, organisations, educational institutions, industrial organisations etc., have provided quality data. *Papadeas, Paggios and Vassilakis* (2002), applied DEA approach to measure the relative efficiency in starting education like in the case of Greek Universities.

In this paper DEA analysis approach of life-long education was carried out in three stages. At the first stage the model was considered to quantify the relative efficiency of directories in the form of each BSC's perspective. In the second stage the model considered the form of total weight of four BSC perspectives (total weight inputs by total weighted outputs, results, outcomes). In the third stage a DEA frontier is considered that consists with the best practice units (directories). Therefore, '*the main result is the relative efficiency of each unit measurement against the best-practice units similar to it*' (*Paradi*, 2002: p.19).

Results and Analysis

The intensive and time-consuming nature of field research invariably results in small sample sizes (*Dunk*, 2003). People with backgrounds in the scientific method, which focuses on theory confirmation, believe that field research is ill suited to theory testing (*Young*, 1999). Consequently, researchers such as *Yin* (1994) argue that it is more appropriate to use field research to develop respectable and believable working theories and then use other tools, such as archival research, surveys, or experiment to test these constructs. A questionnaire was design based on BSC methodology and according to field research organisation records; civil servants from 211 different Ministry's directories (DMUs) were trained during the year 2003. A sample of 20% could be considered as adequate and therefore 45 directories were selected as sample based on the amount of training. A survey of posted questionnaires to 45 directors of DMUs at the Hellenic Ministry of Finance & Economy took place. Finally, only 14 directors responded (31% of the sample).

Table 5: Structure Perspective Performance

Key Performance Indicators						
DMUs	***S1***	***S2***	***S3***	***S4***	***SUM***	***Rank***
1	0	4	1	-1	4,27	3
2	0	16	2	-1	17,36	11
3	1	8	3	0	11,62	9
4	1	17	2	-1	18,66	12
5	1	20	2	-1	22,02	13
6	0	11	2	-1	12,4	10
7	1	3	2	-1	4,5	4
8	2	32	1	-1	33,57	14
9	4	2	0	0	6	5
10	2	7	3	0	11,5	8
11	2	9	0	0	11	7
12	0	4	3	-1	6,31	6
13	1	3	1	-1	3,67	2
14	0	3	1	-2	2,41	1

Four selected structure (inputs) Key Performance Indicators are adjusted negatively only for the first perspective of BSC. The first input indicator (S1) contains the sum of total number of trainees for each DMU for 3 years (2001+2002+2003) divided by the number of civil servants in the directory in 2003. The second indicator (S2) contains the number of training programmes that the civil servants of the directory have participated in the last 3 years (2001+2002+2003). The third indicator (S3) illustrates positively the motivation for participating to training programmes of directory civil servants (none=0, few=1, enough= 2, many=3). The fourth indicator (S4) illustrates negatively the de-motivation for participating to training programmes of directory civil servants (none=0, few= -1, enough= -2, many= –3).

The results of the selective Key Performance Indicators from trainee' service, customer/ citizen and Learning & Growth perspective of BSC are illustrated as follows. The Key performance indicators were quantified from the answers of directors, as: none=0, few=1, enough= 2, many=3. Therefore, the ranks of DMUs depend on the sum of quantified descriptive Key Performance Indicators.

Table 6: Trainee' Service Performance

Key Performance Indicators								
DMUs	***T1***	***T2***	***T3***	***T4***	***T5***	***T6***	***Sum***	***Rank***
1	2	2	2	2	2	2	12	**5**
2	3	2	3	3	2	3	16	**1**
3	2	0	2	2	2	2	10	**11**
4	2	3	2	3	3	3	16	**1**
5	2	2	2	2	2	2	12	**5**
6	2	2	2	2	2	2	12	**5**
7	2	2	0	2	3	3	12	**5**
8	2	2	2	2	2	2	12	**5**
9	2	2	1	1	1	1	8	**13**
10	2	3	2	2	2	3	14	**3**
11	0	3	0	2	2	2	9	**12**
12	3	3	2	3	0	3	14	**3**
13	2	2	2	2	2	2	12	**5**
14	1	1	0	0	1	2	5	**14**

DEA has a long lead-time before any benefits are realised *(Paradi*, 2002). DEA can assist as a tool for sensitivity analysis and reduce the burden of interactive application of BSC(*Avkiran*, 2002).

For the implementation of DEA, the BSC framework and methodology was used, adopting the radial improvement model (balance of four perspectives), under constant returns to scale and uniform priorities. The implementation included different indicators of each perspective, involving the assessment of DMUs relative significance rates and was organized as follows.

Table 7: Customer / Citizen Performance

Key Performance Indicators						
DMUs	***C1***	***C2***	***C3***	***C4***	***SUM***	***Rank***
1	2	2	1	1	6	9
2	3	2	2	3	10	2
3	2	3	3	3	11	14
4	2	3	2	3	10	2
5	2	2	2	2	8	6
6	2	2	2	2	8	6
7	2	2	0	2	6	9
8	2	2	2	0	6	9
9	1	1	2	2	6	9
10	2	3	2	3	10	2
11	2	2	2	1	7	8
12	3	3	3	3	12	1
13	2	2	2	3	9	5
14	2	2	0	2	6	9

Table 8: Learning & Growth Performance

Key Performance Indicators							
DMUs	***L1***	***L2***	***L3***	***L4***	***L5***	*Sum*	***Rank***
1	1	1	1	2	2	7	**14**
2	2	2	3	0	3	10	**7**
3	2	2	3	2	2	11	**3**
4	3	2	2	3	2	12	**1**
5	3	2	2	2	2	11	**3**
6	2	2	2	2	2	10	**7**
7	3	2	0	2	2	9	**12**
8	3	2	2	2	2	11	**3**
9	2	2	2	2	2	10	**7**
10	2	2	2	3	2	11	**3**
11	2	2	1	2	2	9	**12**
12	2	1	3	3	3	12	**1**
13	2	2	3	1	2	10	**7**
14	2	2	2	2	2	10	**7**

Implementation of DEA

DEA allows each of the inputs/outputs to be measured in their respective units; i.e. the need for a common dominator such as money for all variables under consideration can be costed or converted into one unit of measurement – consider.

The merger of BSC with DEA enables relative performance measurement – benchmarking indicators along with a set of diagnostics for identifying problems and inefficiencies. These applied perspectives are 1^{stly} structure perspective, 2^{ndly} Trainee service perspective, 3^{rdly} citizen/ customer perspective, 4^{thly} learning and growth perspective.

Table 9: DMUs Relative Performance

BSC Perspectives' Ranks						**Final**
DMUs	**S**	**T**	**C**	**L**	**SUM**	**Rank**
1	3	5	9	14	7,75	**9**
2	11	1	2	7	5,25	**5**
3	9	11	14	3	9.25	**13**
4	12	1	2	1	4	**2**
5	13	5	6	3	6,75	**6**
6	10	5	6	7	7	**7**
7	4	5	9	12	7,5	**8**
8	14	5	9	3	7,75	**9**
9	5	13	9	7	8,5	**12**
10	8	3	2	3	4	**2**
11	7	12	8	12	9.75	**14**
12	6	3	1	1	2,75	**1**
13	2	5	5	7	4,75	**4**
14	1	14	9	7	7,75	**9**

The most inefficient directory (DMU No. 11) has a sum of 9,75 and divided by 2 makes 4,875. Therefore, we consider a frontier less than a sum 4,875 and they are the 4 best practices ranked DMUs. These four DMUs could create a frontier in order for the managers of the inefficient DMUs to use this application of the BSC modified framework as guidance for their improvements.

The final rank resulted from the sum of each four ranks of perspectives' ranks, and indicates the relative perfomance of each DMU. Therefore, the final rank illustrates each DMU with relative and balanced significance. This methodology could be considered as a useful tool for constructing DEA to each case public organisation.

CONCLUSIONS

BSC is a powerful MA tool that has evolved in response to the ineffectiveness of traditional cost accounting practices (*Kaplan & Norton* 2001, 2001a). BSC not only helps a public training centre to accurately measure its structure, trainee service, customer/citizen and learning & growth perspectives, but also provides the financial and non-financial information necessary to identify opportunities for the cost reductions and operating improvements of each unit.

Its seems clear that BSC is not a panacea for keeping a balance in attending the organisation's performance, but it has a lot to offer in improving the relationship of indicators' allocation to each perspective for actual usage of service and, consequently, also improving the efficiency of allocations (*Kaplan & Norton* 1996, 1996a, 1996b).

As *Avkiran* (2002) stated '*BSC plus DEA is an almost obvious marriage*'. Indeed, in its early years, linear programming (of which DEA is a variant) was sometimes referred to as activity analysis (*Dorfman, Samuelson & Solow,* 1958). The detail information on inputs, outputs, results and outcomes that BSC generates often at a high cost is directly applicable to the DEA algorithm that tries to establish whether individual units are getting the most output out of their given inputs for each individual perspective.

In the first stage of the analysis the merger of BSC and DEA provide a two-dimensional portrayal of a public training centre organisation across four adjusted perspectives and selective individual indicators. Therefore it illustrates the relative importance of a particular DMU by keeping the balance between four BSC perspectives.

In the second stage of the analysis, the relative efficiency score for every DMU is established of the peer BSC, getting an estimate of how much benefit is possible of each particular directory overall and in each particular perspective.

Finally, in the third stage of the analysis, 'the establishment of the efficient frontier consisting of the best performing DMUs, could be used as a guide to what to do for the DMU managers' (Paradi, 2002: p.32). Consequently, inefficient directories could use the guidance of the frontier for their improvements.

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ACKNOWLEDGMENTS

All acknowledgments for financial and technical support should go to University of Piraeus (Research Center and Department of Business Administration) and to (Hellenic) State Foundation of Scholarships.

CORPORATE FINANCIAL PERFORMANCE AND PRODUCTION EFFICIENCY: A STUDY ON INDONESIA'S PUBLIC AND PRIVATE SECTOR FIRMS

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ABSTRACT

This paper reports comparative measures using financial factors and production efficiency factors driving performance of Indonesian public and private sector firms over 1992-2001. Both finance and production theories are used: financial ratios and Malmquist data envelopment analysis. The results suggest that the Malmquist-type DEA measure is not only comparable to the traditional accounting ratios, but also can help to identify policy relevant conclusions on how to evaluate performance of state-owned enterprises and private sector enterprises by identifying the inefficiencies in the use of inputs.

***JEL classification**: C23; L33*
***Keywords:** DEA-Malmquist; Technical Efficiency; financial performance; state-owned enterprises; private sector firms*

INTRODUCTION

The existence of Indonesia's state-owned enterprises (SOEs) can be traced to the Dutch colonial government, which started the SOEs in the late Nineteenth and at the beginning of Twentieth centuries. These companies were established to produce essential products and services. The new national government that took over in 1945 nationalised these firms. On the other hand, the establishment of the private sector firms (PSEs) in Indonesia based upon ownership by private individuals. It is formalised by the Chapter 10 of the Rule and Regulation of The Indonesian Chambers of Commerce and Industry (Gitosardjono, 2000) as well as the laws passed by the State.

Since public and private sector firms cover different purposes, therefore they are different in various management styles and regulations, which often lead to different goals and thus performance differences. In many other developing countries, public sector firms are typically found to be less efficient than their counterparts in the private sector firms, although this conclusion is not yet firmly established in the literature. For example, in China, SOEs are generally found to be operating inefficiently compared to the PSEs (see, Huang, Cai and Duncan, 1997; Lin, Cai and Li, 1998, and Wu, 1998).

The most widely applied measure to evaluate public and private sector firms are financial ratio measures, which is not the same as production efficiency, which motivates this study. Ratios provide tools for managing information in order to analyse a firm's financial condition and performance (Shapiro *et al.* (2000; 36). These can provide a profile of a firm's economic characteristics, competitive strategies, operating, financial, and investment decisions relating to other firm or industry (White *et al.* (1998; 41)). However, there are some limitations of the financial ratios as performance measures. The fundamental limitation of the traditional univariate ratio analysis is that the choice of a single ratio does not provide enough information about the various dimensions of the *performance* of a firm. In fact, the firm's performance represents the complexity of multidimensional outputs and inputs. Since a firm' performance is a complex phenomenon, it requires more than a single ratio or even selected ratios to characterise it (Smith, 1990). Another limitation of the financial ratio analysis is the choice of a benchmark against which to compare a univariate or multivariate scores from ratio analysis. Since the choice of benchmark is purportedly by users, different users may require different benchmark for different purposes.

To overcome these problems in ratio analysis, a newer method of addressing the issue of efficiency measures is appropriate. One such technique which has been widely used is the data envelopment analysis (DEA). This method is able to assess multiple variables simultaneously; therefore, we can consolidate multiple measures of financial performance, such as sales, margin, total assets, etc, into a single summary of performance measure. Necessarily, there must be a relationship between the production efficiency and the financial performance of the firm. This aspect of connection between the two approaches to performance has still not been sufficiently studied. Hence this study is a modest effort to start looking at this connection.

This study aims to measure and then compares the financial and production efficiency performance of SOEs and PSEs (2) examines whether there is an association between the traditional accounting ratios and the production efficiency measures, and (3) examine whether the technical efficiency is dependent on a firm's specific variables such as size, age, and the use of leverage. Findings reported in this paper would be very useful for describing the aspects investigated while economic/financial policymakers could benefit fromour findings reported in this study.

The results employing the DEA -Malmquist methodology show that both public and private sector firms experienced productivity *declines* during the study period. The declines were primarily due to technological regression. The public sector firms were suffering more on this ground than their counterparts. However, there was a catching-up effect in both sectors over time during the ten-year study period. Using the stochastic frontier approach, we also examine the existence of technical inefficiency effects in the model. In contrast with Battese and Coelli (1993), Lundvall and Battese 2000), Pitt and Lee (1972), Meagistae (1996), and Brada, King and Ying Ma (1997), we find that firm's size have a negative correlation with the technical inefficiency. As in Hill and Kalirajan (1993), the age of firms has a negative and significant influence on inefficiency scores in the public sector firms but positive in the private firms. Another factor, financial leverage is strongly associated with inefficiency scores in SOEs: this is interpretable as unique to Indonesian firms loaded with too much debt. The effect is positive for both sectors, which means that firms with more debt appear to have more inefficiency. Our test shows that there is a linkage between the traditional accounting ratios and the efficiency scores. In addition, we also find a similar pattern with those of production efficiency performance measures from the DEA Malmquist and the Stochastic Frontier methods. Overall, the result indicates that private sector firms outperformed public firms, although the performance is nowhere near to indicate efficiency gains.

DATA AND METHODOLOGY

This study based on unbalanced panel of 141 firms with the total of 1410 observations in two sectors, public and private sector firms, expressed in nominal monetary value of the country with a high inflation.[1] Thus these data need to be adjusted for inflation[2] (Ma *et al.* (2002; 298-312)), using the *Consumer Price Index* (CPI) with base year as 1993 prices, to obtain real values. It employed the output-orientated constant returns to scale, CRS, formulation is used to compute the Malmquist index for 141 firms to measure the change in productivity over the period 1992 to 2001. To evaluate the productivity performance, we use three output and three input variables taken from the firms' financial statements. The output measures are: total assets (output 1), sales (output 2), EBIT (output (3), while the input measures are material cost (input 1), labour cost (2) and depreciation expenses (3): the last item is a proxy for capital, which is computed from data on depreciation. The stochastic frontier production function is used to examine firms' technical efficiency to identify also the factors influencing the technical inefficiency of

[1] The average inflation rate during 19992-2001 is 8 per cent.

[2] I acknowledge with thanks Alan Farley for his suggestion to adjust the variables for inflation.

matched public and private sector firms. These variables are chosen based on the assumption that firms' performance is multidimensional in nature and that there exist a various indicators of firms' performance. The input indicators represent three production input In addition, the output variables represent possible various outputs produce by a firm.

We also apply accounting-cum-financial performance models on SOEs and PSEs. The accounting and financial measures used in this study are: ROE, ROA, pre-tax profit (EBT/TA), and operating profit on total assets. These measures indicate overall performance, and are commonly found in the literature. The analysis is also extended to an examination of components of ROE. (1) A ratio is devised to indicate operating performance after debt, which indicates performance of firm to shareholders before tax is deducted. (2) Operating performance before debt indicates firm's performance to all capital providers before paying interest cost of debt. (3) Margin, indicates gross profit upon sales, which is an important indicator of operating performance before charges for debt and taxation are applied. Firms must show positive performance at this level to be in business, which establishes that the costs of productions are recovered if the margin is zero (with no debt). (4) Sales turnover performance is a fourth component, which indicates how much sales are generated from using each unit of assets, which is an indicator of capital usage effectiveness. Thus, examining these components – something that the literature appears to have ignored to-date - may lead to an assessment of overall performance. ROE will also provide clues as to overall sources of performance differences between SOEs and PSEs: however, this ratio (unlike the others designed for this study) assumes that public sector firms have profit motives, which is not exactly correct. The last ratio is leverage (5), which indicates firm's ability to leverage equity with more debt, which again is not expected of public sector firms receiving State budget support.

FINDINGS

Findings I: Production Efficiency

The productivity performance of SOEs and PSEs demonstrate that, over the 10-year period observed, there are fluctuations in all indices in public sector firms. On average, productivity growth of SOEs (0.924) is less than the PSEs (0.956). However, both sectors experienced TFP decline, which is primarily due to technological regression. A potential reason behind the productivity decline was the financial and political crisis that destabilised the economy severely in the later half of the test period. For example, over at the worst period of the crisis in 1997/1998, the decline was 30.5 percent.

Mann-Whitney rank-sum tests are performed to test the null hypotheses that efficiencies are equal between SOEs and PSEs. Z-statistics for the null hypotheses of equal efficiencies shows that the productivity performance of SOEs is lower than that of PSEs. However, public sector firms have a higher efficiency growth than their counterparts, although the difference is not significant. It indicates that there is no strong evidence of difference in overall efficiency between SOEs and PSEs during the study period.

The results from the technical inefficiency effect model show that the firms' size and age of the SOEs has negative association with their technical inefficiencies except for leverage. This result indicates that the firms with more employees tend to be more technically efficient than firms with fewer employees. In addition, the older firms are more technically efficient than those younger firms. This is consistent with theory that learning takes time, and learning is associated with improved efficiency and establishes growth (Jovanovic, 1982, 1995). A positive coefficient of leverage would appear to suggest that technical inefficiency is decreased by more debt. However, only age variable has significant effect on the technical efficiency in this sector.

In private sector firms, the estimation of coefficients of the firms' specific variables in the model for technical inefficiency effects indicates no strong influence of the firm's specific variables on the technical efficiency. We observed that the size of the firms (proxied by the number of employees) has negative effect in the PSEs. The negative sign indicates that the firms with more employees tend to be more technically efficient, than those with fewer employees. The estimated coefficient associated with age is positive in this sector. The positive sign indicates that the older firms are more technically inefficient than those younger ones. This is consistent with the theory that learning exhibits diminishing returns. Firms' leverage has positive sign in PSEs. The positive association in PSEs implies that firm with greater use of leverage tended to be more technically inefficient: public sector firms have greater access to finance. A positive coefficient for PSEs would appear to suggest that technical inefficiency is increased by more debt. A potential reason for this is the incentives of banking system that lend to related parties – the powerful connected state firms - in underdeveloped banking system that has plagued the country for five decades.

Findings II: The linkage between financial performance and production efficiency.

Examining the link between the two performance measures in both sectors, the results show that there is a link between the two measures. This is indicates by the rejection of the null hypothesis except for the PSEs, where we found no association between the two measures when using TFP change as the independent variable. The association between the firms' efficiency changes with operating performance after debt of SOEs and PSEs is strong and statistically significant at five percent probability level. However, the association is negative in the SOEs but positive in the PSEs. The positive result is consistent with theory that the firm's managerial efficiency increases as more profit is gained. In contrast, the negative association in the public sector firms indicates that they operated inefficiently. This result supports both of their production efficiency and financial performances.

Results from stepwise regression indicate there are five (out of 14) financial ratios which have strong association in the cases of SOEs. Among the five ratios, three ratios prevail: margin performance, asset turnover and leverage performance have positive coefficients. This means that the technological efficiency performance increases with increases of those financial performances. These results are consistent with the theory that the firms' efficiency increase as they earned more profit on sales. In addition, technological efficiency performance also increases as the firms have high leverage. This result is not consistent with theory, however, there is anecdotal evidence suggesting that Indonesian SOEs are heavily financed by debt in order to adopt a new technology, a result which is consistent with findings reported in the previous results, especially in a country where capital is scarce, and is often rationed by the lenders/providers. In the case of the PSEs, only return on equity (ROE) ratio has an association with the technological changes of the private sector firms. However, the association is negative, which means that increases in firms ROE will decrease the technological efficiency

The firms' total factor productivity (TFP) gain is associated with two ratios: sales turnover and the leverage performance in the SOEs. Both ratios have strong and positive association with the TFP gain. This indicates that the TFP gain increases with increases in sales and firms' assets. This result is consistent with the theory that firms' sales and assets are two significant factors which can boost efficiency. In contrast, none ratios has an association with the TFP gains in the PSEs.

CONCLUSIONS

This study provides new findings on the comparative study of the production efficiency and financial performance of the public and private sector firms. It makes three significant contributions to the study of the performance of public and private sector firms in Indonesia, especially using multiple approaches to address the research issue of performance. First, this is the first comparative study of Indonesia's public and private sector firms, using matched unbalanced samples of firms from both sectors. Second, this study employs two production efficiency measures: DEA-Malmquist and Stochastic Frontier for the first time by augmenting the value of findings from this study by using the traditional accounting-cum-financial performance measures. The Malmquist DEA method is applied for the first time in the calculation of productivity change and its decomposition of a matched sample of public and private sector firms over a long term study period of 10 years. Such decomposition makes it possible to examine if one sector has improved its productivity simply through a more efficient use of existing technology or through technological progress. In addition, the application of the stochastic frontier method, to a matched sample of public and private sector firms, allows us to investigate factors contributing to the efficiency performance. Finally, this study observes for the first time the linkage between the firms' performance using the traditional accounting-financial ratios with their production efficiency performance employing the Malmquist-type DEA methodology.

The results indicate that in general, private sector firms' are more efficient than that of public sector firms, which result is consistent with the most studies on SOEs and PSEs. The null hypothesis that there is no linkage between the production efficiency performance and the accounting-financial performance is rejected. It implies that in general, there is a connection between the two approaches. Accounting and financial ratios which have association with the efficiency performance are limited to only few: operating profit, operating profit after debt, pre-tax profit, margin performance, turnover, leverage performance and return on equity. ROE, the most common ratio, is not found to be relevant. The limitation of this study is that there are no comparable literatures for the linkage investigated: this could be explored in replications of the method with other data sets.

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DATA ENVELOPMENT ANALYSIS IMPROVES EXPENSE REDUCTION IN HOSPITALS

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ABSTRACT

The purpose of this paper is to present an instrument to promote the reduction of health costs through the combination of a method of nonparametric frontier estimation and the information of the manage accounting.

In other to illustrate the potential of this instrument a comparing 58 Portuguese hospitals, which provide in-patient treatment for general surgery, is carried out.

The goal is to make a useful instrument which could allow the hospital administration to identify the deficiencies that affect their resources and the causes of these deficiencies, so that they can initiate corrective actions to eliminate or at least reduce them. As regards the National Health Service, this instrument should allow the comparison between different adopted contexts, by stimulating new policies which reduce the health costs, or by maintaining the costs, while providing better services for all citizens.

INTRODUCTION

In economic sectors like health, where the socio-demographic changes, the new additive technologies and the growing expectations of the public cause an increase in demand and a rise in costs, it is inevitable worry about making good use of the resources[1].

The higher expenses in the national health systems of the OECD countries have been the public expenses with hospitals, which represent more than half of the total public health expense[2].

The present study shows one of the possible instruments to promote the reduction of health costs by increasing the efficiency of Portuguese public hospitals.

METHODOLOGY

In the words of the Economy Nobel Prize Kenneth Arrow[3], among others like Culyer et al[4] and Lucena et al[5], the health sector is completely different from the other sectors.

The hospital is a complex organisation because of the technical, professional and technological means involved. This is due to the expectations it rises and to the economic impact it makes. Because of its multiple inputs and outputs, it is difficult to estimate a theoretical function which could explain a functional relation[6].

The proposed method to assess the efficiency of the services in Portuguese hospitals is the Data Envelopment Analysis[7] (DEA) which generalises the measures of productive efficiency of Farrel[8] by using the mathematical programming to assess the efficiency of multi-inputs and multi-outputs production units through the reduction to one single "virtual" output and to one single "virtual" input. The ration between the "virtual" output and the "virtual" input gives us one efficiency measure (yardstick), which is the function of the multiplicators[9].

Thanassoulis [10], Athanassopoulos et al[11] and Coelli et al[12], among others[13,14], confirm in their own studies the advantages of the DEA when compared to other techniques to assess the levels of efficiency, such as neutral nets and regression analysis.

This method was conceived to assess the efficiency of homogeneous units (generally called *Decision Making Units* – DMUs) in which the market prices of the inputs and outputs are not available. It also estimates one maximum performance measure for each DMU relating to all the others, provided that all the units are on the frontier or below it. The efficiency of every observation below the frontier is measured in relation to a DMU or to a combination of DMUs and the best practices observed and which constitute the nearest convex frontier, thus facilitating the decision-making process [15].

In this sector there are signs of lack of elasticity in demand and the demand is insufficient, which is made clear by the long waiting lists. The supply induces the demand in the sense that the demand is not constricted by prices, but the supply is constricted by costs [16,17]. The optimisation will preferably be achieved through the maximization of production in an output oriented model.

The question is: how much can the production increase while using the same available resources?

The adopted model in this study was the *non-increasing returns to scale* (NIRS). Since the public hospital sector doesn't operate to its maximum efficiency, the demand is unpredictable and there are financial restrictions and units which operate in uneconomies of scale (DMUs in which the variations of the outputs are inferior to the proportional variations of inputs).

Definition and selection of the DMUs up for analysis

Because the DEA is a technique to assess the relative efficiency of comparable units and to improve these units' performance, it demands that the unit be part of a homogeneous group where comparisons between DMUs make sense[8].

In this paper we will only study the in-patient services in Portuguese public hospitals for general surgery. The analysed units perform the same activities and have the same goals. The variables "input" and "output" that characterise the performance of all units of the group are the same, except for differences in intensity and magnitude.

The analysed DMUs represent an intentional sample made up of 58 hospitals among a total of 69 hospitals with in-patient services for general surgery, which represent 81 % of the in-patients. subheading. This is third subheading. This is third subheading.

Selection of the input and output variables

Usually the performance of a system is measured by a ratio of system output per unit input or system input per unit output. In a hospital, these ratio-indices, such as "number of discharged patients per number of doctors", "number of beds per number of doctors" or "patients per bed" are very common. Because these are relatively simple statistical indicators, it is difficult for the partial indicators to contain all the aspects of every situation that takes place in a hospital. Studies show that one should be wary of its use[18] and prove that different indicators produce different evaluations of the same institution[19,20].

The purpose of a performance indicator is to objectively assess a real-life situation by taking a previously established and consensual pattern into account.

It is therefore necessary to use a wider and more realistic set of information[21]. The analysis of this information should contribute the decision-making process. Not only do the indicators give us the knowledge of past and present, but they are also essential as instruments for the development of planning.

With a view to giving a true and adequate image of the inputs used by hospitals, the 2002 manage accounting[22] was used for the selection of the input factors. All possible costs which could affect the DMUs up for analysis were also included in six categories, since the underestimation of an input can bring about differences between the DMUs. Each category is the result of a homogenisation of the inputs contained by it.

Advantages of the rendering of accounts and of the manage accounting: Since these are obligatory and uniform documents, they are subject to accounting principles, norms of accounts and single budgetary principles, thus allowing a greater level of standardization, consciousness, materiality and comparison[23,24].

In order to choose the best representation of the outputs it is necessary to recognise that the quality of the output of a service often depends on the behaviour of the patient or on certain external factors, which the hospital service cannot control. For example, a brilliant doctor who uses all the available resources in the treatment of a patient with a serious disease may not to able to save his or her life simply because the patient's body didn't react as expected. The results of the hospital services are the consequence of the patient's characteristics, the adequate treatment and of external factors[25,26].

Because it is so difficult to measure how the patients' health has improved because of what the hospital services have done, the investigators now use intermediate measures, which can be more easily measured, such as the number of patients, the number of discharges, days of in-patient treatment, among others[27].

As regards this study, the calculation of the in-patient treatment is based on the joined information of two indicators: the number of discharged patients and the days of in-patient treatment. The inefficient hospitals should then maximise the number of patients without lowering the quality standards (reduction of the average duration of stay-long treatment).

The isolated use of the indicators would cause undesirable incentives for the in-patient service, as described by Carreira[28].

Number of discharged patients multiplied by the case-mix index[29] - Diagnostic Related Groups in each hospital, contemplating individual differences in the disease profile and severity which affect the result, independently of the care provided.

$$CM_j = \left[\sum_{i=1}^{k} W_i P_{ij}\right] / \left[1/n \sum_{i=1}^{k}\sum_{j=1}^{n} W_i P_{ij}\right]$$

CMj represents the case-mix index for the hospital j; Wi represents a factor of reflection for the category I; j represents the number of hospitas and Pij represents a proportion of cases of the category I in hospital j.

Y2: number of days of in-patient treatment

The hospital service was considered a DMU that transforms inputs, such as staff expenses, pharmaceutical products, material for clinical use, depreciation charges, other expenses and indirect costs (diagnosis), into outputs that consist of the number of discharged patients x case mix and days of in-patient treatment.

Application of the dea model and analysis of the results

By combining different combinations of inputs, two models were created, also taking the degree of freedom of the hospital administrators into account.

In model 1 two inputs were considered: the direct costs include staff expenses, pharmaceutical products, material for clinical use, depreciation charges and other expenses; indirect costs are the second input.

In model 2 the objective is to analyse the hospital's efficiency taking six inputs into account. The administration may freely distribute the resources only to its own category.

The cost of depreciation charges input was considered a variable which cannot be totally controlled by the administration, but it can indicate the used capital, the age of the equipments and the adopted accounting and fiscal criteria.

It is not enough that the hospital services are aware of their efficiency rates. They will also have to be able to identify the deficiencies that affect their resources and the causes of these deficiencies, so that they can initiate corrective actions to eliminate or at least reduce them. Chilingerian[30] concluded that the DEA can be an instrument to increase the knowledge about the location and nature of the hospital deficiencies.

INPUTS		
Direct Elements		**X6: Indirect Elements**
X1: Staff expenses	**X2: Pharmaceutical Products**	Clinical anatomy
		Clinical pathology
		Imageology
Payment for directive organs	Material for clinical use	Physical Medicine and Rehabilitation
Payment for technical staff		Imunohemotherapy
Managing staff	**X3:Material for clinical use**	Anesthesiology
Medical staff		Operating block
Health technicians		Nuclear Medicine
Social services technicians	Material for clinical use	Radiotherapy
Other superior technicians		Cardiologic techniques
Nursing staff	**X4: Depreciation charges**	Gastroenterology techniques
Diagnosis and therapy technicians		Neurological techniques
Other technicians		Ophthalmologic techniques
Professional technicians	Depreciation charges for the financial year	Otorrinolaringology
Administrative staff		Pneumological techniques
Working and auxiliary staff	**X5: Other Expenses**	Urological techniques
Teaching staff		Sterilization
Other staff		Pharmaceutical services
Overtime	Merchandise	Social services
Nights and supplements	Food	Gynaecology and Obstetrics
Shift allowance	Material for hotelery	Dermatology techniques
Allowance for losses	Material for administrative use	Nephrology
Meal allowance	Material for maintenance and conservation	Other clinical support services
Subsistence costs	Other consumables	Workshops
Other additional payments	Subcontracts	Water treatment plant
Holiday pay and Christmas bonus	Supplies and external services	Vapour plant
Pensions	Indirect taxes	Emergency electrical plant
Taxes on salaries	Other operational costs	Medical gases plant
Insurance schemes for accidents at work and occupational diseases	Provisions for the financial year	Incineration plant
Voluntary social contributions	Financial costs and losses	Car service
Other staff expenses	Extraordinary cost and losses	Parks and gardens
		Feeding and dietetic service
		Laundry service
		Hygiene and cleaning service
		Security and support services
		Other hotel services
		Administrative sections

Y1: number of patients x case-mix

Inputs		Outputs
X1: Staff expenses	Hospital	Y1: Patients x case-mix
X2: Pharmaceutical products		
X3: Material for clinical use		
X4: Depreciation charges for current year		Y2: Days of inpatient treatment
X5: Other expenses		
X6: Indirect elements		

We take any inefficient DMUj which corresponds to the point of co-ordinates (x_j, y_j). That point can be projected to the frontier, that is to a hypothetical composite unit of co-ordinates (x'_j, y'_j) which can be expressed as a convex combination of points or DMUs and efficient co-ordinates (x_k, y_k), k=1,...,l, that is, x'_j = ? ?$_k x_k$ e y'_j = ? ?$_k y_k$ with ? ?$_k$=1, ?$_k$=0. The adoption of this procedure made possible to present of the effective and potential values as follows:

	Output oriented	
	Model 1	Model 2
DMU 02.12	100,00%	100,00%
DMU 04.12	100,00%	100,00%
DMU 07.12	100,00%	100,00%
DMU 08.12	100,00%	100,00%
DMU 12.11	100,00%	100,00%
DMU 13.11	100,00%	100,00%
DMU 18.11	100,00%	100,00%
DMU 22.22	100,00%	100,00%
DMU 23.22	100,00%	100,00%
DMU 28.21	100,00%	100,00%
DMU 29.21	100,00%	100,00%
DMU 33.21	100,00%	100,00%
DMU 47.31	100,00%	100,00%
DMU 61.51	100,00%	100,00%
DMU 42.32	99,92%	100,00%
DMU 32.21	98,96%	100,00%
DMU 49.31	96,41%	100,00%
DMU 31.21	95,28%	100,00%
DMU 21.22	95,21%	100,00%
DMU 53.31	94,48%	100,00%
DMU 25.21	93,76%	100,00%
DMU 20.22	90,68%	100,00%
DMU 40.32	88,68%	100,00%
DMU 58.41	88,44%	100,00%
DMU 27.21	85,20%	100,00%
DMU 06.12	84,42%	100,00%
DMU 14.11	76,75%	100,00%
DMU 16.11	73,76%	100,00%
DMU 30.21	66,95%	100,00%
DMU 10.12	84,85%	99,64%
DMU 03.12	54,49%	98,04%
DMU 38.21	93,98%	96,18%
DMU 54.42	93,25%	94,78%
DMU 44.32	88,90%	94,51%
DMU 15.11	87,47%	91,37%
DMU 36.21	90,68%	90,85%
DMU 05.12	79,86%	90,59%
DMU 09.12	72,61%	88,80%
DMU 60.51	83,09%	88,63%
DMU 26.21	62,48%	88,55%
DMU 56.41	76,56%	87,94%
DMU 17.11	86,23%	87,83%
DMU 41.32	80,23%	86,85%
DMU 52.31	76,91%	84,75%
DMU 39.32	75,16%	83,52%
DMU 37.21	76,45%	82,24%
DMU 50.31	70,24%	80,70%
DMU 57.41	76,65%	80,50%
DMU 59.52	75,24%	79,46%
DMU 34.21	57,24%	78,27%
DMU 11.11	63,64%	77,08%
DMU 19.22	70,57%	76,80%
DMU 45.32	68,94%	73,38%
DMU 46.31	62,62%	71,61%
DMU 46.31	62,62%	71,61%
DMU 43.32	60,77%	67,48%
DMU 55.41	59,13%	66,54%
DMU 51.31	48,24%	57,55%

Model 1

Micro Level – Hospital:

Considering the presuppositions of model 1, an inefficient aleatory DMU (DMU 25.21) with an efficiency rate of 93,76 % should have attended more 6,63% patients and should have had more 23,11% days of in-patient treatment, in order to achieve the expected efficiency level. The benchmarking units are units 22.22, 33.21 and 28.21.

The cause of this inefficiency is the excessive use of resources in direct and indirect costs in a proportion of 6,50% and 6,48% respectively, which corresponds to 2,74% of the hospital's global budget.

Macro Level – National Health Service:

Generally speaking, model 1 presents an efficiency rate of 83,57%. By reducing the waiting lists (increase the number of patients and days of in-patient treatment), the national health system would be capable of attending more 18,81% (21045 patients) and of offering more 18,81% days of in-patient treatment (145185), and would also reduce the costs of the general surgery service by 2,57% (€ - 6.271.428,47).

By reducing the inputs (cost containment), the national health service, only by having the unit of general surgery operating in an optimal level of efficiency, would be able to reduce the costs of general surgery by 18,92% (€ -46.096.747,76), saving the budgets of 58 hospitals 3,56% and also promoting an increase in attended patients by 1,58% and in days of in-patient treatment by 1,69%.

Model 2

Micro Level – Hospital:

Considering the presuppositions of model 2, an inefficient aleatory DMU (DMU 17.11) with an efficiency rate of 87,83 % should have attended more 13,84% patients and should have had more 18,17% days of in-patient treatment, in order to achieve the expected efficiency level. The benchmarking units are units 07.12, 08.12, 12.11, 22.22 and 23.22.

The cause for this inefficiency is the excessive use of resources in staff expenses (24,79%), pharmaceutical products (14,8%), other expenses (34,57%), material for clinical use (14,6%) and indirect costs (14,9%), which corresponds to a saving of 19,79% in the global budget for the general surgery service and of 6,81% in the hospital's global budget.

Macro level – National health service:

Generally speaking, model 2 presents an efficiency rate of 91,21%. By reducing the waiting lists (increase the number of patients and days of in-patient treatment), the national health system would be capable of attending more 9,35% (10460 patients) and of offering more 10,74% days of in-patient treatment (77300). The national health system would also reduce the costs of the general surgery service by 3,55% (€-8.636.280,99).

By reducing the inputs (cost containment), the national health service, only by having the unit of general surgery operating in an optimal level of efficiency, would be able to reduce the costs of general surgery by 12,49% (€ -30.421.431,26), saving the budgets of 58 hospitals 3,56% and also promoting an increase in attended patients by 0,61% and in days of in-patient treatment by 0,82%.

CONCLUSION

The great advantage of this instrument to promote the efficiency is the fact that, when used systematically, it can contribute to cost containment in hospitals through the reduction of wastes, which can be achieve by reorganising the services and processes. Based on this information, the hospital administration should be able to best distribute its resources to each hospital service by identifying deficiencies that affect their resources and the causes of these deficiencies, so that they can initiate corrective actions to eliminate or at least reduce them.

The pertinence of its actions can also be extended into the political level, by stimulating new ways of thinking about the adopted policies and thus making the comparison between different hospital contexts possible.

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