academicJournals

Vol. 7(38), pp. 3953-3962, 14 October, 2013
DOI: 10.5897/AJBM11.670
ISSN 1993-8233 © 2013 Academic Journals
http://www.academicjournals.org/AJBM

African Journal of Business Management

Full Length Research Paper

The measurement of productivity growth and benchmarking in the academic departments

Mohammad Mahallati Rayeni[1*] and Faranak Hosseinzadeh Saljooghi[2]

[1]Department of Management, Institute of Technology of Bahonar, Zahedan, Iran.
[2]Department of Mathematics, University of Sistan and Baluchestan, Zahedan, Iran.

Accepted 5 October, 2013

The purpose of this paper is to analyze efficiency, measuring productivity growth of the academic departments and benchmarking for them. Efficiency measures are calculated by a non-parametric approach known as data envelopment analysis (DEA). Productivity is measured by the Malmquist index. The paper shows how DEA-based Malmquist productivity index can be employed to evaluate the technology and productivity changes resulted in the university. Total productivity growth, in two periods of time 2005-2006 and 2009-2010 academic years, has been calculated and indicated decline productivity, but there is a variation among individual units; also the frontier productivity and technical efficiency change (TEC) indices which are parts of the decomposed total productivity have been shown. To ensure long-term effectiveness in productivity, window analysis is adopted to seek the most recommended set of performance by measuring the performance changes over time. The study uses window analysis for benchmarking. Benchmarking is a process of defining valid measures of performance comparison among peer decision making units (DMUs), using them to determine the relative positions of the peer DMUs and, ultimately, establishing a standard of excellence. DEA can be regarded as a benchmarking tool, because the frontier identified can be regarded as an empirical standard of excellence. With window analysis, the performance of a DMU in one period is compared not only with the performance of other DMUs but also with its own performance in other periods. The proposed mechanism can provide guidance to the departments for aggregate planning so as to improve their efficiency. The results did not indicate improving performance.

Key words: Performance assessment, efficiency, data envelopment analysis, malmquist productivity index, technical efficiency change, frontier shift benchmarking.

INTRODUCTION

Universities are in the present arena, one of the major sponsors of education and provision of efficient manpower needed for the country. So, assessment of their performances and determination of their weak and strong points can continuously be effective in reaching their aims. Performance measurement and evaluation are fundamental to management planning and control activities, and accordingly, have received considerable attention by both management practitioners and theorists. Data envelopment analysis (DEA) is a non-parametric method to evaluate the relative efficiency of decision-making units (DMUs) which are based on multiple inputs and outputs (Charnes et al., 1978; Banker et al., 1984). The major advantage of the DEA approach is that DEA does not require any assumptions about the function form. The performance measure of a multiple inputs and multiple outputs production system can hardly be described by a concrete function form. Therefore, DEA is particularly suitable for analyzing multiple inputs and multiple outputs production systems. Thus, there is a high

*Corresponding author. E-mail: m_mohallati@yahoo.com.

potential for DEA applications; DEA has been widely used in different industrial sectors in the area of industrial management for performance evaluation and benchmarking studies. The theory, development and applications of DEA, as well as its strengths and weaknesses, have been discussed in many papers, and therefore, only a brief review is presented here (Cooper et al., 2007; Chen et al., 2010; Rayeni and Saljooghi, 2010;Lu et al., 2010).

The second object of this study measures productivity growth in university, in addition, focuses on the investigation of the causes of productivity change and on its decomposition. Such decompositions promote the understanding of the determinants of better performance and provide valuable information for managers and planners in both the private and the public sector.

Productivity growth is one of the major sources of economic development and a thorough understanding of the factors affecting productivity is very important. In recent years the measurement and analysis of productivity change has enjoyed a great deal of interest among researchers studying firm performance and behavior.

The Malmquist index is known as the standard approach to productivity measurement within the non-parametric literature. The concept of this index was first introduced by Malmquist (1953), and has further been studied and developed in the non-parametric framework by several authors. See for example, among others, Caves et al. (1982), Fare et al. (1994a, b). The Malmquist index approach to productivity measurement has many advantages. It is an index representing Total Factor Productivity (TFP) growth of a Decision Making Unit (DMU), in that it reflects (1) progress or regress in efficiency along with (2) progress or regress of the frontier technology between two periods of time. It is based on multi input–output frontier representations of the production technology (Charnes et al., 1987). In the empirical context, the results are obtained using mathematical programming techniques (DEA) that rely on minimum assumptions regarding the shape of the production frontier. Finally, the index decomposes into multiple components to give insights into the root sources of productivity change. DEA-based Malmquist productivity index measures the technical and productivity changes over time.

The third part of this paper is dedicated to benchmarking. Benchmarking has not received much attention in Academic department of universities, because of the lack of appropriate methodological tools to aid the benchmarking process. The main benchmarking methods can be classified as either average or frontier-oriented (Jamasb and Pollitt, 2001). The main average-based methods are ordinary least squares and total factor productivity. The most widely used frontier-based techniques are DEA and stochastic frontier analysis. DEA is suggested to aid traditional benchmarking activities and to provide guidance to managers (Cooper et al., 2007). DEA is useful in identifying the best performing units to be benchmarked against as well as in providing actionable measures for improvement of a company's performance. DEA constructs the best performance "frontier" and reveals the relative shortcomings of inefficient decision-making units. Cook et al. (2004) developed a set of DEA-based benchmark models. In this paper, we present a DEA-based benchmarking method where each DMU is evaluated against a set of given benchmarks and apply it for benchmarking the universities.

The study applies window analysis for introducing the suitable benchmark of each department. The underlying assumption of window analysis is that of a moving-average analysis and that each DMU's efficiency is represented in the window several times, instead of being represented by a single summary score. Each DMU in a different period is treated as a different DMU, and the performance of a DMU in a period can be contrasted with its own performance in other periods as well as to the performance of other DMUs.

The remainder of this paper is as follows. The second section presents a summary the methodology; i.e. DEA and the Malmquist productivity index and benchmarking. The next section shows the data, also DEA and the decomposed Malmquist index are applied and the results presented. Discussion performs the fourth section. Conclusion is given in the final section.

MATERIALS AND METHODS

Data envelopment analysis

Data envelopment analysis (DEA) has been recognized as an excellent method for analyzing performance and modeling organizations and operational processes, particularly when market prices are unavailable. Unlike the statistical regression method that tries to fit a regression plane through the center of the data, DEA floats a piecewise linear surface to rest on top of the data by linear programming techniques (Odeck, 2000). In other words, the statistical regression method estimates the parameters in the assumed functional form by a single optimization over all decision making units (DMUs) whereas DEA uses optimizations for different DMUs without a priori assumptions on the underlying functional forms. Because of this unique feature, DEA has been applied to various areas of efficiency evaluation, for example, individual physician practice, program evaluation, macroeconomics performance of countries or cities, pollution prevention, reorganization of forest districts and pupil transportation, and others.

The main advantages of DEA that make it suitable for measuring the efficiency of DMUs are: (i) it allows the simultaneous analysis of multiple outputs and multiple inputs, (ii) it does not require an explicit a priori determination of a production function, (iii) efficiency is measured relative to the highest observed performance rather than against some average and (iv) it does not require information on prices.

Suppose we have n DMUs, each DMUj (j=1,…,n) produces a vector of outputs $y_j = (y_{1j}, \dots, y_{kj})$ by using a vector of inputs $x_j = (x_{1j}, \dots, x_{mj})$. In DEA, the ratio of weighted outputs and inputs produces a single measure of productivity called relative efficiency.

Let us take one of the DMUs, say the oth DMU, and maximize its efficiency according to the formula given following.

$$\theta_o^* = \text{Maximize} \quad \theta_o = \frac{\sum_{r=1}^{k} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

$$\text{subject to} \quad \frac{\sum_{r=1}^{k} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \qquad j = 1,2,....,n$$

$$u_r \ge 0 \qquad r = 1,...,k$$

$$v_i \ge 0 \qquad i = 1,...,m \qquad (1)$$

Where

θ_o^* is the efficiency of the oth DMU,
y_{rj} is rth output of the jth DMU, u_r is the weight of that output,
x_{ij} is ith input of the jth DMU, v_i is the weight of that input, j = 1, 2, …, n, and
y_{ro} and x_{io} are rth output and ith input, respectively, of the oth DMU.

Note that here n includes o.

DMUs that have a ratio of 1 are referred to as efficient and lie on the frontier. The DMUs on the efficiency frontier are the best performing peers. The units that have a ratio less than 1 are less-efficient relative to the most efficient unit. A DMU that is not efficient and is inside the frontier can choose efficient DMUs on the frontier, and selected efficient DMUs is named its reference set. Hence, depending on the size and scope of a DMU, each DMU will have a different set of reference set. Note that model (1) is fractional program. It is generally difficult to solve fractional program. It can be converted to simpler formulation, such as the linear programming (LP) format, and then they can be solved easily. The simplest way to convert this fractional program to linear program is to normalize the denominator of the fractional programming objective function; with this variation, model (1) convert to linear model (2).

$$\text{Maximize} \qquad \theta_o = \sum_{r=1}^{k} u_r y_{ro}$$

Subject to

$$\sum_{r=1}^{k} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1,2,....,n$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$u_r \ge 0 \qquad r = 1,...,k$$

$$v_i \ge 0 \qquad i = 1,...,m \qquad (2)$$

Model (2) is called CCR DEA model (Charnes et al., 1978). If we present optimal solution of model (2) as (θ_o^* , v*, u*) then DMU_o is efficient if θ_o^* = 1 and there exists at least one optimal (v*, u*), with v* > 0 and u* > 0. Otherwise, DMU_o is inefficient.
When DMU_o has θ_o^* < 1(inefficient), then there must be at least one constraint (or DMU) in the first constraints model (2) for which the weight (v*,u*) produces equality between the left and right hand sides since, otherwise, θ_o^* could be enlarged. Let the set of such $j \in \{1,\ldots,n\}$ then $E_o = \{j | \sum_{r=1}^{s} u_r^* y_{rj} = \sum_{i=1}^{m} v_i^* x_{ij}\}$. The set E_o, composed of efficient DMUs, is called the reference set or the peer group to the DMU_o.

DEA and productivity

DEA can be applied to panel data to measure the productivity changes between two periods of activities fulfilled by a specific set of DMUs. For example, Fare et al. (1994a, b) studied the productivity change in Swedish individual hospitals operating in a non-market environment. The specific approach used is called Malmquist productivity index in which DEA efficiency scores are used. Chen and Ali (2004) applied the DEA Malmquist productivity measure to the computer industries by the CCR model to assess the four distance functions of Malmquist productivity. They further analyzed the properties of two ratios of frontier shift, the backward and forward frontier shifts. The DEA models used in the Malmquist productivity index can either be input or output oriented. Consequently, the Malmquist productivity index can be input-oriented when the outputs are fixed at their current levels or output-oriented when the inputs are fixed at their current levels.
To measure Malmquist productivity index, consider n DMUs which each DMUj (j=1,…, n) produces a vector of outputs $y_j^t = (y_{1j}^t, \ldots, y_{kj}^t)$ by using a vector of inputs $x_j^t = (x_{1j}^t, \ldots, x_{mj}^t)$at each time period t. According to duality of model (2), the efficiency DMU_o as follows:

$$\begin{aligned} \theta_o^t = Min \quad & \theta_o \\ \text{S.t.} \quad & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij}^t \le \theta x_{io}^t && i = 1,2,\ldots,m \\ & \textstyle\sum_{j=1}^{n} \lambda_j y_{rj}^t \ge y_{ro}^t && r = 1,2,\ldots,k \\ & \lambda_j \ge 0 && j = 1,2,\ldots,n \ . \ (3) \end{aligned}$$

Model (3) is input-oriented, because it considers the possible radial reductions of all inputs when the outputs are fixed at their current levels.
It can be seen that (i) if $\theta_o^t = 1$; then DMU_o is unable to proportionally reduce its inputs and therefore DMU_o is on the empirical production frontier (EPF); (ii) if $\theta_o^t < 1$; then DMU_o can reduce its inputs and therefore DMU_o is operating below the EPF. By replacing x_j^t and y_j^t with $x_j^s$and y_j^s; respectively, we have the technical efficiency of θ_o^s for DMU_o at the time period s, From t to s; DMU_0's technical efficiency may change or (and) the EPF may shift. Based upon model (3), the Malmquist productivity index can be calculated via (Fare et al., 1994a, b).

(i) Comparing x_o^t to EPF at time t; namely, calculating $\theta_o^t = \theta_o^t(x_o^t, y_o^t)$;
(ii) Comparing x_o^s to EPF at time s; namely, calculating $\theta_o^s = \theta_o^s(x_o^s, y_o^s)$
(iii) Comparing x_o^t to EPF at time s; that is, calculating $\theta_o^{'} = \theta_o^s(x_o^t, y_o^t)$ through the following linear program:

$$\begin{aligned} \theta_o^{'} = Min \quad & \theta \\ \text{S.t.} \quad & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij}^s \le \theta x_{io}^t \quad i = 1,2,\ldots,m \\ & \textstyle\sum_{j=1}^{n} \lambda_j y_{rj}^s \ge y_{ro}^t \quad r = 1,2,\ldots,k \\ & \lambda_j \ge 0 \quad j = 1,2,\ldots,n \end{aligned} \qquad (4)$$

(iv) Comparing x_o^s to EPF at time t; namely, calculating $\theta_o^{''} = \theta_o^t(x_o^s, y_o^s)$ through the following linear program:

$$\begin{aligned} \theta_o^{''} = Min \quad & \theta \\ \text{S.t.} \quad & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij}^t \le \theta x_{io}^s && i = 1,2,\ldots,m \\ & \textstyle\sum_{j=1}^{n} \lambda_j y_{rj}^t \ge y_{ro}^s && r = 1,2,\ldots,k \\ & \lambda_j \ge 0 && j = 1,2,\ldots,n \end{aligned} \qquad (5)$$

The technical efficiency change (catch-up) term relates to the degree to which a DMU improves or worsens its efficiency, while the frontier-shift (or innovation) term reflects the change in the efficient frontiers between the two time periods.

$$\text{Technical Efficiency Change} = \text{TEC} = \frac{\theta_o^s}{\theta_o^t}$$

TEC > 1 indicates progress in relative efficiency from period t to s, while TEC = 1 and TEC< 1 respectively indicate no change and regress in efficiency.

In addition to the technical efficiency change term, we must take account of the frontier-shift (innovation) effect in order to fully evaluate the productivity change since the technical efficiency change effect is determined by the efficiencies being measured by the distances from the respective frontiers.

$$\text{Frontier shift} = FS_o = \sqrt{\frac{\theta_o^{''}\ \theta_o^t}{\theta_o^s\ \theta_o^{'}}}$$

This indicator, also decomposes+ to parts $\frac{\theta^t(x^s,y^s)}{\theta^s(x^s,y^s)}$ and $\frac{\theta^t(x^t,y^t)}{\theta^s(x^t,y^t)}$, which is called the backward and forward frontier shifts, respectively.

$FS_o > 1$ indicates progress in the frontier technology around DMU_o from period t to s (t < s), while $FS_o = 1$ and $FS_o < 1$ respectively indicate the status quo and regress in the frontier technology.

The Malmquist index (MI) is computed as the product of (Technical efficiency change) and (Frontier shift), i.e,

MI_o = (Technical efficiency change) × (Frontier shift) = $\left[\frac{\theta_o^s\ \theta_o^{''}}{\theta_o^t\ \theta_o^{'}}\right]^{\frac{1}{2}}$.

MI_o measures the productivity change between periods t and s. Productivity declines if $MI_o < 1$; remains unchanged if $MI_o=1$ and improves if $MI_o>1$.

DEA and benchmarking

A benchmarking analysis normally includes the selection of methods aiming at answering the following three questions: How is best practice or other norms properly determined in a specific analysis? What characterises best practice? How much and in which way does each organisation deviate from the norm?

Benchmarks for performance evaluation need not reflect best practice, but could be chosen arbitrarily as performance goals in a regulation process.

Benchmarking experts suggest multistep approaches to the process of benchmarking (Camp, 1998; Spendolini, 1992). There are three basic steps of benchmarking that analysts agree on:

(i) identifying the best performers; (ii) setting benchmarking goals; and (iii) implementation.

The first step entails identifying a DMU (or set of DMUs) that is acknowledged as the best performer. At second step, DMUs measure their own efficiency and the efficiency of the best performers. The third step, implementation of best practices, has been the point of focus for most DMUs that engage in benchmarking. Implementation involves effecting business practices in order to emulate competitors that have the best performance.

Methodology of benchmarking should be able to identify a specific best-performing peer group to be used as a comparison group, and it should be able to assist managers in setting goals in specific areas. A benchmarking tool should have the ability to analyze multiple inputs and multiple outputs that may comprise efficiency, and provide feedback concerning areas for needed improvement. However, in order to be managerially relevant, a benchmarking technique should provide a single measure of overall efficiency that can be computed for every DMU and compared with competitors. The next section demonstrates how DEA can be used in the benchmarking processes.

DEA produces an efficient frontier consisting of the set of most efficient performers, allowing a direct comparison to the best performers. The distance between a DMU and the frontier provide the goals for benchmarking. A unit can become efficient by moving towards the frontier by reduce inputs or increase outputs produced or a combination of both. Since efficiency is the ratio of output to input, a DMU can become efficient by increasing output or decreasing input. Such measurable and actionable goals satisfy the requirements of step 2 of the benchmarking process. In other words, a DMU becomes efficient by moving towards the frontier.

Having identified the reference set and the areas for needed improvement, step 3 of the benchmarking process, implementing benchmarking, can be done. Management can evaluate the operations of the peer group units or reference set to determine what changes in inefficient unit can be made.

In the original DEA analysis, each DMU is observed only once. In many actual studies, observations for DMUs are frequently available over multiple time periods, and it is often important to perform a panel data analysis to focus on changes in efficiency over time.

To evaluate the long-term performance of DMUs, we adopt the DEA window analysis in this paper for two reasons. One, window analysis can effectively analyze the relative performance of DMUs in multiple periods and the variation of performances among the periods. Two, more input and output factors can be included in window analysis so that discriminating power can be increased.

DATA DESCRIPTION AND FINDING

To evaluate educational system cannot be used of market evaluation mechanisms such as benefit assessment to determine DMU performance or inputs and outputs economic value, because inputs and outputs generally stand in the education, research and service departments which the measurement or presentation of an assessment unit is very difficult. DEA method also emphasizes university targets for inputs and outputs choice, and makes possible the choice of qualities input and output indicators to the system.

In this article, the Zabol University's educational departments are viewed as DMUs. Input and output variables were chosen after consultation with the management. Input variables included the number of registered student (x_1), the number of teaching staff (x_2) and Guest lecturers' number of units (x_3). Three output variables were selected to represent both teaching and research outcomes: the number of graduates (y_1), the number of passed students to higher levels (y_2) and the performed research work (y_3). Our original data consist of the annual statistics for the years 2005/06 and 2009/10 collected in each of the 21 departments of the university. From these data the outputs and inputs are as shown in Table 1.

The relative efficiencies of each DMU in the period t and s are calculated under models (3), (4) and (5). The

Table 1. The gathered information to assess educational departments of Zabol University, Academic years 2005-2006 and 2009-2010.

Education department	Number of registered students in academic		Scientific board's concession		Guest lecturers number of units		Number of graduates		Number of students passing to higher level		Research work	
	2005	2009	2005	2009	2005	2009	2005	2009	2005	2009	2005	2009
Civil	205	350	7	10	40	42	62	82	7	10	60	85
Mechanics	190	330	4	5	65	71	56	79	4	5	35	65
Chemistry	310	550	20	22	5	6	92	109	15	17	120	195
Electronics	222	495	6	8	40	49	73	97	4	4	25	30
Computer	159	375	3	5	70	78	65	85	3	5	35	55
fishery	320	692	10	14	7	8	128	138	15	14	85	135
Economics	297	472	12	12	4	5	104	121	12	12	55	125
Persian literature	312	593	16	16	3	4	89	119	16	14	105	130
Geography	301	497	16	15	0	6	91	103	13	12	110	165
English	292	521	9	10	11	15	81	109	6	8	45	100
architecture	242	435	12	13	8	10	72	99	15	16	95	140
laboratory sciences	301	451	12	12	4	5	92	103	11	11	65	130
Physics	212	423	8	11	7	10	76	97	4	5	75	120
Biologics	352	597	14	15	4	6	101	119	15	14	175	190
Law	322	521	12	12	8	10	98	122	16	15	45	70
statistics	225	492	5	5	25	32	90	118	10	12	40	55
librarianship	219	397	12	12	9	12	81	101	11	9	80	105
Arabic language	240	452	12	13	8	10	80	103	13	14	75	110
Mathematics	329	533	10	11	16	22	71	99	6	10	100	145
Agriculture	615	894	28	29	2	6	171	194	34	42	235	300
Veterinary	440	695	10	12	6	8	133	163	16	15	185	205

models are implemented in an MS-Excel worksheet and are solved by using the DEA Solver software and LINDO software. The productivity indices for DMUs are presented in the Table 2.

The study now computed efficiency improvement and how to identify appropriate benchmarks for inefficient departments to imitate. To ensure long-term effectiveness in productivity, window analysis is adopted to seek the most recommended set of performance by measuring the performance changes over time. With this method, the performance of a DMU in one period is compared not only with the performance of other DMUs but also with its own performance in other periods. The proposed mechanism can provide guidance to the departments for aggregate planning so as to improve their efficiency. The results of DEA-based benchmarking in Zabol University are indicated in Table 3.

DISSCUSION

The study first looks at the technical efficiency changes. The columns 3 and 4 in Table 2 report the DEA technical efficiency and the associated the technical efficiency changes from 2005/06 to 2009/10. In both academic years, nine departments are efficient, while the average efficiency in 2005/06 is 0.921 and in 2009/10 is 0.973; also the average technical efficiency changes of the departments is 1.062, which is improved by 6%.

According to Figure 1, which shows technical efficiency changes of DMUs, Six departments are efficient in each time period, that is, no technical efficiency change is indicated by TEC. However, the authors would like to point out that caution should be paid when a DMU is a frontier DMU in time period t and time period s, that is, although, TEC = 1 indicates no improvement in technical efficiency, these departments stand for the best practice in each year. On the other hand, we note that TEC >1 only indicates an improvement in technical efficiency (e.g. Civil, Management, Chemistry …). This does not necessary mean that these departments have a better performance in improving its technical efficiency than others that are efficient in each two period.

We next look at the frontier shift. The column 8 in Table 2 reports the Malmquist frontier shift component, FS. It can be seen that on average, the frontier shift decreased

Table 2. The productivity indices for the DMUs.

No.	Education department	θ_o^t	θ_o^s	$\theta_o^{'}$	$\theta_o^{''}$	TEC	FS	MI_o
1	Civil	0.841	0.946	1.2048	0.679	1.125	0.708	0.796
2	Mechanics	0.752	0.993	1.171	1.367	1.321	0.940	1.242
3	Chemistry	0.960	1	1.272	0.723	1.042	0.739	0.770
4	Electronics	0.815	0.795	1.282	0.665	0.976	0.729	0.711
5	Computer	1	0.938	1.640	0.880	0.938	0.756	0.709
6	Fishery	1	0.835	1.604	0.762	0.835	0.754	0.630
7	Economics	0.966	1	1.400	0.919	1.035	0.796	0.824
8	Persian literature	0.943	1	1.251	0.840	1.061	0.795	0.843
9	Geography	1	1	1.259	0.749	1	0.771	0.771
10	English	0.693	0.848	1.082	1.180	1.223	0.944	1.154
11	Architecture	1	1	1.356	0.839	1	0.786	0.786
12	laboratory sciences	0.845	0.964	1.230	0.782	1.141	0.747	0.852
13	Physics	0.997	0.958	1.398	0.715	0.961	0.730	0.701
14	Biologics	1	1	1.419	0.863	1	0.780	0.780
15	Law	0.960	0.9731	1.305	0.774	1.0133	0.765	0.775
16	Statistics	1	1	1.615	1.99	1	1.110	1.110
17	Librarianship	1	0.995	1.524	0.734	0.995	0.696	0.692
18	Arabic language	0.976	0.939	1.428	0.713	0.962	0.720	0.693
19	Mathematics	0.702	0.892	0.947	1.100	1.271	0.956	1.217
20	Agriculture	1	1	2.644	1.103	1	0.646	0.646
21	Veterinary	1	1	1.355	1.580	1	1.080	1.080

Table 3. Efficiency score, Ranking and Reference set of departments.

DMUs-2005	Score	Reference
Civil-05	0.841	Computer-05 , Fishery-05, Biologics-05
Mechanics-05	0.752	Computer-05, Fishery-05, Statistics-05, Veterinary-05
Chemistry-05	0.960	Fishery-05, Biologics-05, Architecture-05, Agriculture-05
Electronics-05	0.815	Computer-05, Fishery-05
Computer-05	1	Computer-05
Fishery-05	1	Fishery-05
Economics-05	0.966	Fishery-05, Geography-05
Persian literature-05	0.943	Fishery-05, Architecture-05, Agriculture-05
Geography-05	1	Geography-05
English-05	0.693	Computer-05, Fishery-05
Architecture-05	1	Architecture-05
Laboratory sciences-05	0.845	Fishery-05, Geography-05
Physics-05	0.997	Fishery-05, Biologics-05, Librarianship-05
Biologics-05	1	Biologics-05
Law-05	0.959	Fishery-05, Architecture-05, Agriculture-09
Statistics-05	1	Statistics-05
Librarianship-05	1	Librarianship-05
Arabic language-05	0.976	Fishery-05, Architecture-05
Mathematics-05	0.706	Computer-05, Fishery-05, Biologics-05, Veterinary-05
Agriculture-05	1	Agriculture-05
Veterinary-05	1	Veterinary-05
DMUs-2009		
Civil-09	0.679	Fishery-05, Fishery-05, Biologics-05, Veterinary-05, Architecture-05

Table 3. cont'd

Mechanics-09	0.872	Computer-05, Statistics-09
Chemistry-09	0.723	Biologics-05, Agriculture-05
Electronics-09	0.610	Computer-05, Statistics-05, Statistics-09
Computer-09	0.834	Computer-05, Veterinary-05, Statistics-09
Fishery-09	0.762	Geography-05, Veterinary-05
Economics-09	0.919	Geography-05, Veterinary-05
Persian literature-09	0.840	Geography-05, Veterinary-05
Geography-09	0.749	Biologics-05, Biologics-05, Veterinary-05
English-09	0.733	Fishery-05, Veterinary-05, Statistics-09
Architecture-09	0.836	Architecture-05, Statistics-05, Veterinary-05, Agriculture-09
Laboratory sciences-09	0.782	Geography-05, Veterinary-05
Physics-09	0.715	Computer-05, Fishery-05, Biologics-05, Veterinary-05
Biologics-09	0.863	Biologics-05, Veterinary-05
Law-09	0.774	Statistics-05, Veterinary-05, Agriculture-09
Statistics-09	1	Statistics-09
Librarianship-09	0.734	Computer-05, Fishery-05, Biologics-05, Veterinary-05
Arabic language-09	0.710	Fishery-09, Statistics-05, Veterinary-05, Architecture-05, Agriculture-09
Mathematics-09	0.713	Veterinary-05
Agriculture-09	1	Agriculture-09
Veterinary-09	1	Veterinary-09

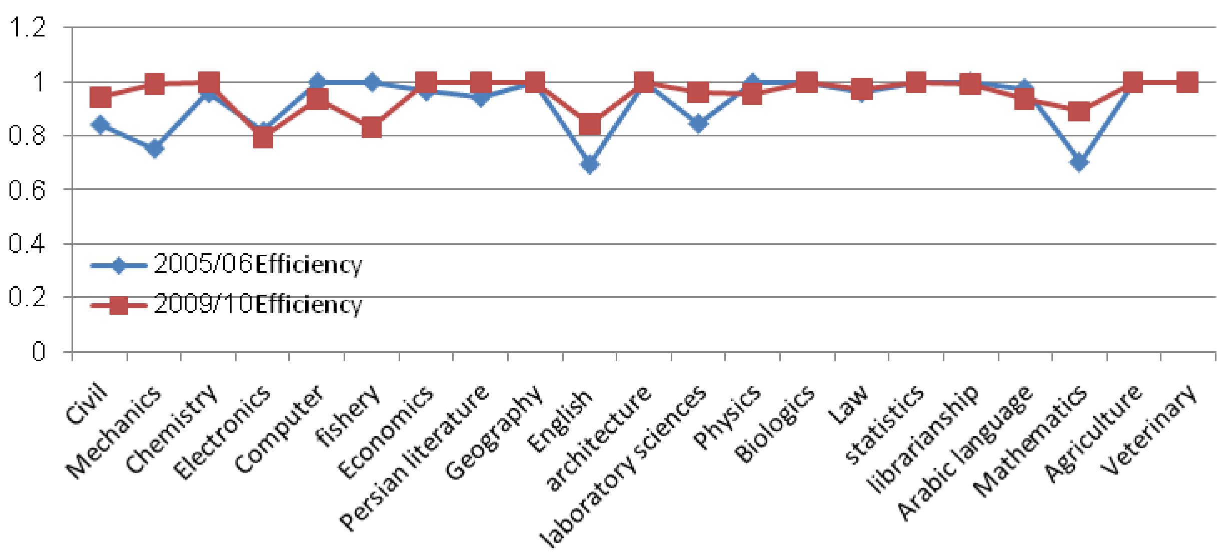

Figure 1. The efficiency of DMUs in two periods of time.

21.31% from 2006 to 2010. As indicated by FS, all of the departments show a negative shift. Table 4 reports the component shifts in technology frontier (According to Chen and Ali, 2004).

It can be seen on average the departments' technology frontier has a pure negative shift. Technology change at the DMU level shows the two ratios associated with the frontier change index are larger than 1 for none of departments, indicating that all departments do not stay with a consistent operations strategy and all departments show a move between two facets, indicating that these departments have a change in operations strategy. The technology of two departments (Chemistry and Geography) moves from a negative shift facet towards a

Table 4. The backward and forward frontier shifts.

No. of dept	$\frac{\theta^t}{\theta^s}$	$\frac{\theta^t}{\theta^s}$	No. of dept	$\frac{\theta^t}{\theta^s}$	$\frac{\theta^t}{\theta^s}$
1	0.718	0.698	12	0.811	0.687
2	1.377	0.642	13	0.746	0.713
3	0.723	0.755	14	0.863	0.705
4	0.836	0.636	15	0.795	0.736
5	0.938	0.610	16	1.99	0.619
6	0.913	0.623	17	0.738	0.656
7	0.919	0.69	18	0.759	0.683
8	0.84	0.754	19	1.233	0.741
9	0.749	0.794	20	1.103	0.378
10	1.392	0.640	21	1.58	0.738
11	0.839	0.737			

positive shift facet, indicating an unfavorable strategy change.

Third, the study looks at the Malmquist productivity index. The column 9 of Table 2 reports Malmquist productivity index, MI. It can be seen that from academic year 2005/06 to 2009/10, the total productivity indices for the average unit show a decrease with scores of 0.847, with standard deviation of 0.191. Mechanics department has maximum productivity, that is 1.242, and fishery department has maximum regress in productivity, that is 0.630. The values of inputs in two periods 2005/06 and 2009/10 represent increasing 76.3, 10.1 and 21.4%, respectively; also the values of outputs represent increasing 23.8, 7.3 and 43.9%, respectively. The distribution of total productivity, technical efficiency change and frontier shift across units is presented in Figure 2. The results show that five departments have productivity gain since its MI is greater than 1 (MI > 1).

DEA-based benchmarking

In order to compare every DMU against itself and against other DMUs overtime, the study applies window analysis as useful tool to detect efficiency trends over time. This approach considers each DMU for each of the periods as different DMUs. The results of window analysis in two periods were shown in Table 3. The purpose of department-05 is department in academic year 2005/06 and department-09 that is department in academic year 2009/10.

In results Table 3, the departments that have an efficiency score of 1.0 are considered to be efficient and hence, lie on the efficiency frontier. In this case, there are 12 departments that are efficient, and 30 that are inefficient. DEA allows us to take one step further and identify a smaller group of best performers specific to the characteristics of an individual department (based on the weights given to the inputs and outputs).

Electronics-09 department is the least efficient unit (efficiency=0.610). In order to identify its reference set of benchmarking targets, we use DEA. The efficient units identified by DEA analysis (Table 3) are units' computer-05, Statistics-05 and Statistics-09. Therefore, for Electronic-09 department to become efficient, it would have to emulate those three units. This addresses step one in the benchmarking, identifying the peer group. Step 2, setting benchmarking goals, is also handled well through DEA analysis. DEA calculates slacks which specify the amount by which an input or output must be improved in order for the unit to become efficient. The nonzero slacks and/or the value of (efficiency score < 1) identify the sources and amounts of inefficiency in each input and output of the DMU being evaluated. The efficiency of DMU can be improved if the input values are reduced by the ratio "efficiency score" and the input excesses recorded in "input slack" are eliminated. Similarly efficiency can be attained if the output values are augmented by the output shortfalls in "output slack".

In the case of inefficient Electronics-09 department, it is seen that there is one output slack, research work. In order for this department to become efficient, it must add work research by 6.183 (Table 5).

Step 3 of the benchmarking process, implementing benchmarking, can now be done through the traditional means. Electronics-09 department can be efficient if it increase third output, that is, it should encourage its scientific board to more research works.

For more illustration, consider Mathematics-09 department. Efficiency of this department is 0.713 and its reference set is department of Veterinary-05. We see that there are two input slacks and three output slacks. In order for Mathematics-09 department to become efficient, it must cut the number of registered student by 345 and the guest lecturers' number of units by 5, while add outputs to 104, 12.5 and 145, respectively. Therefore, this department must decrease the number of registered student -35.30% and the guest lecturers' number of units -78.62%, while it increase the number of graduates and the number of passed students 5.3% and 25.4%, respectively (Tables 5, 6).

Given that it may not be realistic to achieve this goal of cutting input while maintaining or increasing outputs, one may sometimes not be able to fully implement benchmarking. In other words, a DMU may never become completely efficient.

In this analysis, benchmarking is performed only for departments in academic year 2009/10, because benchmarking must be introduced for DMUs present.

Conclusion

This paper explored the evolution of efficiency and productivity of the university departments operating in the University of Zabol's education departments for the period 2005/06 to 2009/10. Since the Zabol's education

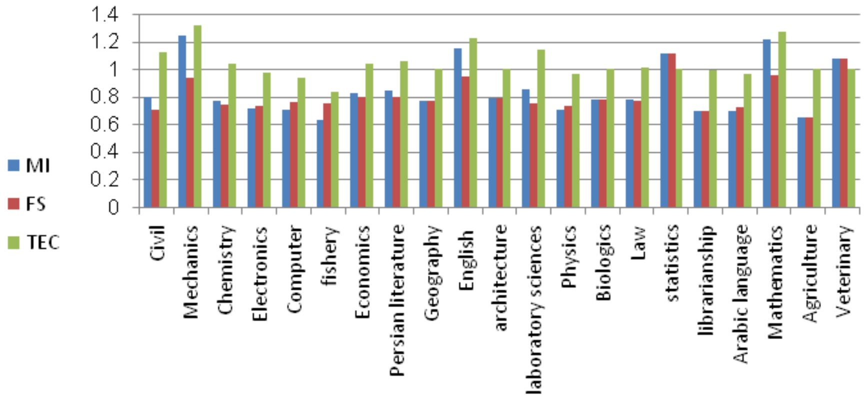

Figure 2. The distribution of total productivity, technical efficiency change (catch-up) and frontier shift across units.

Table 5. The values of slack of inputs and outputs.

DMUs-2009	Score	Excess Input x_1	Excess Input x_2	Excess Input x_3	Shortage Output y_1	Shortage Output y_2	Shortage Output y_3
Civil-09	0.679	0	0	24.39	0	0	0
Mechanics-09	0.872	0	0	39.66	0	3.07	0
Chemistry-09	0.723	0.79	0	0	4.76	0.19	0
Electronics-09	0.610	0	0	0	0	6.18	14.26
Computer-09	0.834	0	0	32.04	0	3.006	0
Fishery-09	0.762	70.7	0	0	0	2.67	56.43
Economics-09	0.919	33.40	0	0	0	2.99	39.82
Persian literature-09	0.840	104.17	0	0	0	1.32	27.41
Geography-09	0.749	12.74	0	0	2.95	2.20	0
English-09	0.733	0	0	0	0	4.61	25.08
Architecture-09	0.836	0	0	0	7.90	0	0
Laboratory sciences-09	0.782	12.01	0	0	0	1.76	10.30
Physics-09	0.715	0	0	0	0	6.67	0
Biologics-09	0.863	100.94	0	0	3	2.35	0
Law-09	0.774	0	0	0	1.004	0	92.49
Statistics-09	1	0	0	0	0	0	0
Librarianship-09	0.734	0	0	0	0	3.23	0
Arabic language-09	0.710	0	0	0	0	0	0
Mathematics-09	0.713	34.91	0	10.97	5.24	2.54	0
Agriculture-09	1	0	0	0	0	0	0
Veterinary-09	1	0	0	0	0	0	0

Table 6. The changed values of inputs and outputs for attaining to efficiency.

	Electronics -09 (0.610)			Mathematics (0.713)		
	Current value	New value	Percent of change	Current value	New value	Percent of change
Input (x_1)	495	301.96	-39.00%	533	344.86	-35.30%
Input (x_2)	8	4.88	-39.00%	11	7.84	-28.75%
Input (x_3)	49	29.89	-39.00%	22	4.70	-78.62%
Output(y_1)	97	97	0.00%	99	104.24	5.30%
Output(y_2)	4	10.18	154.56%	10	12.54	25.41%
Output(y_3)	30	44.26	47.53%	145	145	0.00%

departments are part of the public sector where economic behavior is uncertain and there is no price information on the services produced, the Malmquist index based on DEA approach is well suited for productivity measurement in this sector.

With regard to productivity indices, the picture that emerges decrement productivity, due to increasing the outputs which are asymmetric with the inputs, in real, increasing the inputs are very more of increasing the outputs. The decomposed index shows that departments have progress in technology efficiency change, but the frontier shift is not suitable.

Also, in this article is discussed efficiency improvement and how to identify appropriate benchmarks for inefficient departments to imitate by using window analysis. The study argues that the most relevant benchmark is the most similar efficient departments. The DEA-based benchmarking approach considers inefficiency as the result of a lack of knowledge or managerial ability and it is not the result of a lack of motivation or effort. In these cases, efficiency improvements may be achieved if the inefficient department is able to learn better education production routines. Benchmarking is a common tool used by decision makings that want to improve their understanding of the most successful practices in their field. We investigated efficiency and benchmarking in Zabol University in the two academic years 2005/06 and 2009/10, which has 21×2 departments. The comparison results two periods indicate the average efficiency of departments in academic year 2009/2010 is 0.802, while the average efficiency in 2005/06 is 0.926; that show decline in efficiencies. These results confirm productivity outcomes. The benchmarks of almost all the departments in academic year 2009/10 are departments in 2005/06.

REFERENCES

Camp RC (1998). Global cases in benchmarking. Milwaukee (WI)7 ASQ Quality Press.

Caves DW, Christensen LR, Diewert WE (1982). The economic theory of index numbers and the measurement of input, output and productivity, Econometrica 50: 1393–1414.

Charnes A, Cooper WW, Rhodes E (1978). Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2: 429–444.

Chen Y, Ali AI (2004). DEA Malmquist productivity measure: New insights with an application to computer industry. Eur. J. Oper. Res. 159: 239–249.

Chen L, Hsiao C, Tsai C (2010). Three-stage-DEA model selections and managerial decision. Afr. J. Bus. Manage.4(14): 3046-3055.

Cook WD, Seiford LM, Zhu J (2004). Models for performance benchmarking:Measuring the effect of e-commerce activities on banking performance, Omega, 32(4): 313-322.

Cooper WW, Seiford LM, Tone K (2007). Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software. Boston: Kluwer Academic Publishers.

Fare R, Grosskopf S, Lovell CAK (1994a). Production Frontiers. Cambridge University Press, Cambridge.

Fare R, Grosskopf S, Lindgren B, Roos P (1994b). Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach Data Envelopment Analysis: Theory, Methodology and Applications. Kluwer Academic Publishers. pp: 253–272.

Jamasb T, Pollit M (2001). Benchmarking and regulation: international electricity experience. Utilities Policy 9: 107–130.

Lu Y, Shen C, Ting C, Wang C (2010). Research and development in productivity measurement: An empirical investigation of the high technology industry. Afr. J. Bus. Manage.4(13): 2871-2884

Malmquist S (1953). Index numbers and indifference surfaces, Trabajos de Estatistica 4: 209–242.

Odeck J (2000). Theory and Methodology Assessing the relative efficiency and productivity growth of vehicle inspection services: An application of DEA and Malmquist indices. Eur. J. Oper. Res. 126: 501-514

Rayeni MM, Saljooghi FH (2010). Benchmarking in the Academic Departments using Data Envelopment Analysis. American J. Appl. Sci.7 (11): 1464-1469.

Spendolini MJ (1992). The benchmarking book. New York American Management Association.