

A Case Study Of Non-Technical Institutions-DEA Approach

Dr.R.P.Sreedevi

Abstract— In this paper we apply DEA techniques to evaluate the comparative efficiency of 25 Non –Minority Technical Institutions Under JNTUH, Andhra Pradesh. By using three inputs and two outputs at the institutional-level, we are able to identify the most technically efficient institutions that may work as benchmark in the sector. The results suggest that a great portion of institutions may be working inefficiently, contributing to a significant waste of resources. Technical Institutions are playing an important role in making India a knowledge hub of this century. There is still great diversity in their relative performance, which is matter of concern to the education planner. This article employs the method of data envelopment analysis (DEA) to compare the relative efficiency. The identification of the strongest and the weakest parameters of various Technical institutions could be very useful in improving their efficiency and performance. DEA is essentially an optimization algorithm, which develops efficiency scores for all DMUs on a scale of zero to 100%, with units receiving 100% efficiency score being called efficient.

Index Terms— DEA, DMUS,CCR Model, Technical Education,Technical Efficiency Score, Ranks, Peer count

1 INTRODUCTION

The concept of efficiency is an essential part of the process of evaluating the performance of technical institutions which consist of three main components: efficiency, effectiveness and productivity. The efficiency is an expression of the success of the production unit in tightening the relationship between resources used and outputs in an efficient manner designed to maximize output and reduce input. The efficiency is an expression of the success of the production unit in achieving its objectives through the comparison between planned objectives and what has already been achieved. Hence, the concept of economic efficiency of higher education includes two types of efficiency: Technical Efficiency which means the ability of the institution to produce the maximum amount of production using available inputs and the functional efficiency or allocative efficiency which refers to the ability of the institution to use the optimal mix of inputs, taking into account the prices of these inputs and production techniques available. Thus, the overall economic efficiency means the ability of educational institutions to achieve technical efficiency. There are other studies that add another type of efficiency, especially when analyzing the efficiency of institutions of higher education which is the dynamic efficiency and that relate to the ability of the institution to innovate in production methods.

2. Back ground

Throughout the literature, it is well recognized that DEA is attributed to the seminal work of Charnes, et al. (1978) while SFA is jointly due to Aigner, et al. (1977) and Meeusen and van der Broeck (1977). Contributions in further developing the approaches since those beginnings are numerous and well documented elsewhere. That need not be repeated here. Rather, methodological advancements along with empirical applications and implementation issues are provided by Cooper, et al. (2007) and Cook and Zhu (2008) for DEA and by Coelli, et al, (2005) and Kumbhakar and Lovell (2003) for SFA. These works are further supported by some 4000 published DEA research papers (Em-

rouznejad, et al., 2008). That volume of literature cannot be reviewed here. Instead, the following presents an overview of the empirical literature pertaining to DEA and SFA comparative efficiency estimates. That subset of the literature appears to consist of eight studies only one of which is an application of both DEA and SFA to higher education. The studies are wide in variety and investigate the operating efficiencies of Hawaiian swine farms (Sharma et al., 1997), Dutch dairy farms (Reinhard, et al., 1999), Bangladesh farms (Wadud and White, 2000), United Kingdom hospitals (Jacobs, 2001), English Channel fisheries (Tingley, et al., 2005), Canadian universities (McMillan and Chan, 2006), Greek dairy farms (Theodoridis and Psychoudakis, 2008), and Indian leather companies (Bhandari and Maiti, 2011). These studies rely on the basic idea that efficiency is based on firms producing the maximum output for a given set of inputs. A corresponding production frontier exists. Efficiency scores range from zero to one with the latter referring to efficient firms resting on the frontier while inefficient firms lie below the frontier with scores below the value of one. In the Hawaiian swine farm study by Sharma, et al. (1997), mean efficiency estimates range from 0.64 under DEA estimation to 0.75 under SFA estimation. In the evaluation of Dutch dairy farms, Reinhard, et al., (1999) develop models of both technical and environmental efficiencies and find a mean efficiency range of 0.44 to 0.89. For Bangladesh farms, Wadud and White (2000) find that mean efficiencies vary between 0.79 using DEA and 0.86 using SFA. For UK hospitals, a host of different model specifications employed by Jacobs (2001) generated mean efficiencies ranging from 0.65 under DEA to 0.88 under SFA. The Tingley, et al. (2005) investigation of three different fishing fleets results in DEA vs. SFA efficiency estimates ranging from 0.56 to 0.65, 0.63 to 0.76, and 0.61 to 0.79. McMillan and Chan (2006) evaluated the operating efficiencies of 45 Canadian universities. In using different variables to define four DEA and four SFA models, the efficiency estimates range from an average of 0.91 to 0.98 under the DEA versions and from 0.89 to 0.95 under the SFA versions. The study by Theodoridis and Psychoudakis (2008) reports Greek dairy farm efficiencies on the order of 0.63 and 0.68 using DEA

and 0.81 using SFA. A single comparative evaluation was not possible for the Bhandari and Maiti (2011) study of Indian leather companies. They present multiple specifications by year over seven years. Using an average of their 2002-03 results, there appears to be a 0.55 efficiency arising from DEA estimation and a 0.83 average efficiency derived from SFA estimation. In summary, the average estimated efficiencies range from a low of 0.44 under DEA estimation to a high of 0.98 using a SFA model. The minimum efficiency difference was found to be 0.07 while the maximum difference was more than six times greater at 0.45. The studies by Reinhard, et al., (1999), Wadud and White (2000), and McMillan and Chan (2006) indicate that DEA relative to SFA technical efficiencies are somewhat greater. The remaining five studies find greater efficiency scores in using SFA as opposed to DEA. However, the results come from eight different industries housed in seven different countries. In addition, each study uses a different set of variables, employs different times, and performs the analysis under different model specifications.

3. Data Envelopment Analysis

The Data Envelopment Analysis (DEA) means by which efficiency of like institutions can be effectively ranked and ordered in terms of their relationship to a best practice standard. In the case of non-parametric technique, DEA, the best practice standard is the most efficient institution(s) in the group while with the parametric estimation technique, a best practice (maximum output attainable) frontier is estimated. With DEA, there will always be some institutions that are deemed to be on the frontier while with SFA, none of the institutions need to be on the frontier (Johnes, 2003). DEA does not allow hypothesis testing and assumes that every observation unit operates under the same technology. It treats individual differences as fixed, ignoring the possibility to be random (Horne and Hu, 2005). With DEA, frontiers are constructed so that they can envelop the observed data points using a linear programming methodology. In this approach, the efficiency of a firm is measured relative to the efficiency of all firms, subject the restriction that all firms are on or below the frontier (Cruz, 2003). Efficient points are defined to be the best-practice frontier. Nonetheless, points below the best-practice frontier are the inefficient points. The distance of a point below the frontier reveals the inefficiency of that observation. With DEA, assumptions are made such that random influences are less of an issue, multiple-output production is important, prices are difficult to define and behavioral assumptions such as cost minimization or maximization are difficult to justify (see Coelli, Rao, Battese, 1998).

4. CCR Model

The CCR model which was initially proposed by Charnes, Cooper and Rhodes in 1978. Tools and ideas commonly used in DEA are also introduced and the concepts developed and extended. There, for each DMU, we formed the virtual input and output by (yet unknown) weights $\{v_i\}$ and $\{u_r\}$

$$\text{Virtual input} = \sum v_i x_{ij} - \sum \lambda_j - \sum v_m X_{m0}$$

$$\text{Virtual output} = \sum u_r y_{rj} + \sum \lambda_j + \sum u_g Y_{g0}$$

Then we tried to determine the weight, using linear programming so as to maximize the ratio

$$\frac{\text{virtual input}}{\text{virtual output}}$$

The optimal weights may (and generally will) vary from one DMU to another DMU. Thus, the "weights" in DEA are derived from the data instead of being fixed in advance. Each DMU is assigned a best set of weights with values that may vary from one DMU to another.

Suppose there are n DMUs: DMU₁, DMU₂, ..., and DMU _{n} . Some common input and output items for each of these $j = 1, \dots, n$ DMUs are selected as follows:

1. Numerical data are available for each input and output, with the data assumed to be positive for all DMUs.
2. The items (inputs, outputs and choice of DMUs) should reflect an analyst's or a manager's interest in the components that will enter into the relative efficiency evaluations of the DMUs.
3. In principle, smaller input amounts are preferable and larger output amounts are preferable so the efficiency scores should reflect these principles.
4. The measurement units of the different inputs and outputs need not be congruent. Some may involve number of persons, or areas of floor space, money expended, etc.

5. Empirical Investigation

The efficiency score of DMUS 2,9,10,11,12, 17, 18, 19 is 1.000. To measure over all input technical efficiency implicitly we have assumed that environment is scale efficient and these are no non-performing assess, when these conditions are imposed, consequently the institutions arise with 100 percent of technical efficiency. The Efficiency score of DMU 1 is 0.978, It is nearer to attain 100 percent efficiency score. If returns to scale are constant it could have produced its current outputs 0.98 percent of inputs. It means 0.02 percent of inputs are freely disposed. DMU 13 had the least efficiency score is $0.705 \approx 0.71$, it attained only 71 percent of inputs to produce its current outputs and 19 percent of inputs are cost lessly disposed. DMUS 7(0.934), 8(0.901), 14(0.946), 21(0.940), 22(0.947), 25(0.962) attained above 90% over all technical efficiency. Ranks will be allotted based on peer count. The Efficient DMUs will be awarded ranks based on their peer count. The Efficient DMU with highest peer count will be awarded first, the next highest will be second as it follows.

Table: Technical Efficiency Score & Ranks of DMUS

DMUS	Technical Efficiency	Ranks
1	0.978	
2	1.000	1
3	0.892	
4	0.769	
5	0.865	
6	0.830	
7	0.934	
8	0.901	
9	1.000	3
10	1.000	
11	1.000	
12	1.000	4
13	0.705	
14	0.946	
15	0.889	
16	0.885	
17	1.000	
18	1.000	
19	1.000	2
20	0.865	
21	0.940	
22	0.947	
23	0.962	
24	0.874	
25	0.905	

6. Conclusion

The core aim of the technical education policy in any country is establishing a competitive, qualitative higher education with efficiently operating institutions. The question of efficiency needs increased attention not only because of the decline of the state support but also the rapid rise of the student mass. In the education system, especially higher education, it's not easy to measure its efficiency. The situation is more complicated since those institutions have multiple inputs and outputs. In this case, a possible method of determining efficiency is Data Envelopment Analysis. In this paper I adopted the two stage efficiency analysis and used it to compare the efficiency of 25 Non-Minority Technical Institutions in JNTUH, Andhra Pradesh. And then I used the to bit regression to determine the most environmental factors that affect the efficiency of this institutes. The analysis shows that the most influential factors affecting efficiency are the growth rate, private share, and public expenditure on education. The main results of the model are the negative impact of technical education and economic growth on technical education efficiency, while there is positive relationship between government expenditure on education and technical education efficiency.

7. References

- [1] Aigner, D. J., Lowell, C. A. K. & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21-37.
- [2] Banker, R. D., Charnes, A. & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30, 1078-1092.
- [3] Battese, G. E. & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3(1/2), 153-169.
- [4] Bhandari, A. K. & Maiti, P. (2011). Efficiency of the Indian leather firms, some results obtained using the two conventional methods. *Journal of Productivity Analysis*, 37(1), 73-93.
- [5] Charnes, A., Cooper, W. W. & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6), 425-444.
- [6] Coelli, T., Prasada, J. D., Rao, S., O'Donnell, C. J. & Battese, G. E. (2005). *An Introduction to Efficiency and Productivity Analysis*. Springer, New York.
- [7] Cook, W. D. & Zhu, J. (2008). *Data Envelopment Analysis*. Wade D. Cook and Joe Zhu.
- [8] Cooper, W., Seiford, L. & Tone, K. (2007). *Data Envelopment Analysis*, Springer, New York. 452
- [9] Emrouznejad, A., Parker, B. R. & Tavares, G. (2008). Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. *Socio-Economic Planning Sciences*, 42(3), 151-157.
- [10] Jacobs, R. (2001). Alternative methods to examine hospital efficiency, Data envelopment analysis and stochastic frontier analysis. *Health Care Management Science*, 4(2), 103-115.
- [11] Kumbhakar, S. C. & Lovell, C. A. K. (2003). *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge.
- [12] Martin, J. C. & Roman, C. (2006). A benchmarking analysis of Spanish commercial airports. A comparison between SMOP and DEA ranking methods. *Networks and Spatial Economics*, 6(2), 111-134.
- [13] Meeusen, W. & van-den-Broeck, J. (1977). Efficiency from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2), 435-444.
- [14] McMillan, M. L. & Chan, W. H. (2006). University efficiency, a comparison and consolidation of results from stochastic and non-stochastic methods. *Education Economics*, 14, 1-30.
- [15] Reinhard, S., Knox Lovell, C. A. & Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency, an application to Dutch dairy farms. *American Journal of Agricultural Economics*, 81(1), 44-60.
- [16] Sav, G. T. (2004). Higher education costs and scale and scope economies. *Applied Economics*, 36(6), 607-614.
- [17] Sav, G. T. (2012). Managing operating efficiencies of publicly owned universities: American university stochastic frontier estimates using panel data. *Advances in Applied Economics and Management*, 2(1), 1-23.
- [18] Sharma, K. R., Leung, P. & Zaleski, H. M. (1997). Productive

efficiency of the swine industry in Hawaii, Stochastic frontier vs. data envelopment analysis. *Journal of Productivity Analysis*, 8, 447-459.

[18] Theodoridis, A. M. & Psychoudakis, A. (2008). Efficiency measurement in Greek dairy farms, Stochastic Frontier vs. data envelopment analysis. *International Journal of Economic Sciences and Applied Research*, 1(2), 53-67.

[19] Tingley, D., Pascoe, S. & Cogan, L. (2005). Factors affecting technical efficiency in fisheries, stochastic production frontier versus data envelopment analysis approaches. *Fisheries Research* 73, 363-376.

[20] Wadud, A. & White, B. (2000). Farm household efficiency in Bangladesh, a comparison of stochastic frontier and DEA methods. *Applied Economics*, 32(13), 1665-1673.

IJSER