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ΘΑΛΗΣ: Ενίσχυση της Διεπιστημονικής ή και Διιδρυματικής έρευνας και καινοτομίας με δυνατότητα προσέλκυσης ερευνητών υψηλού επιπέδου από το εξωτερικό μέσω της διενέργειας βασικής και εφαρμοσμένης έρευνας αριστείας

Μεθοδολογικές Επεκτάσεις στην Περιβάλλουσα Ανάλυση Δεδομένων (DEA) και Εφαρμογές στην αξιολόγηση των Ελληνικών ΑΕΙ

ΠΕ3: Ανάπτυξη Συστήματος Υποστήριξης Ομάδας Αξιολόγησης Πανεπιστημίων

ΠΕ3: ΚΕΦΑΛΑΙΟ

APPLICATIONS OF DEA IN HIGHER EDUCATION: INSTITUTION LEVEL

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in

"APPLICATIONS OF DATA ENVELOPMENT ANALYSIS IN EDUCATION"[1],[2]

By

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1. Introduction

Education at any level involves the augmentation of human capital. But there are some key differences between the various levels of education. Primary education is typically delivered by generalist teachers, while secondary education involves specialist teachers. Nevertheless, at least at lower secondary level, the curriculum is broad and this imposes a degree of similarity of experience of students at different schools. At higher education level, the experience is considerably more specialised, and the distribution of subject specialisms varies more across institutions.

There are some additional features of higher education that serve to distinguish it from primary and secondary schooling, and these might make the sector intensely competitive and hence have implications for efficiency. For example, in most countries education is compulsory for students up to some level of secondary, but participation in higher education is optional. In addition, primary and secondary education is typically financed through the tax system, but students in higher education in many countries have to pay (often substantial) tuition fees. Finally, higher education is often undertaken during the early years of adulthood, and so students are not longer geographically constrained: many students choose to study at a location that is distant from their parental home.

Unlike staff in secondary or primary education, most if not all academics employed in higher education institutions (HEIs), contractually are expected to undertake research. Hence specialist teaching represents only some of the output of HEIs. Within each subject area, they also produce research and engage in knowledge transfer activities – that is, they first create new knowledge, and then they work with various organisations to exploit it.

All of the above considerations throw into sharp focus the need to consider, in any evaluation of higher education efficiency, the nature of providers in this sector as multi-output organisations. This, alongside the availability of good quality data, has made the higher education sector an important test bed for empirical applications of frontier methods generally and DEA in particular. DEA has been employed to assess cost efficiency and technical efficiency. Network DEA can offer insights into the production process and provide more detail to managers and policy-makers on how to improve efficiency.

2. Assessments of cost efficiency in higher education institutions using DEA

Assessments of cost efficiency provide potentially useful information on economies of scale and scope and therefore can inform decisions on, for example, how the higher education sector might best be expanded, as well as on how HEIs might become more cost efficient.

An analysis of costs and efficiency in English higher education institutions is provided by Thanassoulis *et al.* (2011)[3]. This analysis includes an input-oriented variable returns to scale DEA model using three years of data (2000-01 through 2002-3). The input-output variables are shown in Table 1.

Table 1: Set of inputs and outputs used in Thanassoulis *et al.* (2011)

Input	Outputs
Total operating cost (measured at constant prices and including depreciation, but excluding catering and student accommodation),	FTE[4] undergraduate numbers in medicine; FTE undergraduate numbers in other sciences; FTE undergraduate numbers in non-sciences; FTE postgraduate numbers; Research funding (quality-related funding council grants and other research grants, measured at constant prices); 'third mission' or 'knowledge transfer' activity, measured by income from other services rendered (again, at constant prices).

Data is sourced from the Higher Education Statistics Agency and cover some 121 English HEIs. These institutions vary considerably in nature – from the ancient universities of Oxford and Cambridge through to civic universities and the new universities of the 1960s to institutions that received university status after 1992. In some institutions costs are distorted by the presence of substantial medical facilities, while in others they are not. The

[3] This follows earlier work by, for example, Athanassopulos and Shale (1997) and Johnes (1998; 1999).
[4] FTE represents full-time equivalent

analysis is therefore undertaken both by considering the sample as a whole and separately within four distinct groups:

- pre-1992 institutions with medicine;
- pre-1992 institutions without medicine;
- institutions that were granted university status around 1992 (typically former polytechnics); and
- institutions that have gained university status more recently (typically former colleges of higher education, affiliated with GuildHE).

In conducting the DEA, a small number of outliers was identified and excluded from subsequent analysis.[5] The mean DEA technical efficiency of the sample (pooled over time and type of institutions but excluding outliers) was estimated to be about 86%. This figure appears to be quite high, reflecting the competitive pressures that exist in this sector. The observation at the first quartile had an efficiency score of 79.3%, again suggesting that inefficiencies are largely competed away. There was, nonetheless, a tail – the minimum efficiency observed was 27.5%. This likely reflects heterogeneity in the sample of institutions. In particular, small, specialist institutions are likely to have costs that are high in relation to their outputs. This underlines the importance of conducting a more disaggregated analysis.

DEA is applied separately to institutions in each of the four subgroups identified above. Given that this essentially involves estimating a separate frontier for each group, comparisons across groups are valid only in terms of measures of relative homogeneity of efficiency. Mean efficiencies varied considerably across groups and was lowest for institutions that have gained university status more recently. Even within this last group there was a tail of institutions where efficiency was below 0.3. This likely reflects heterogeneity, since this group comprises a particularly wide diversity of institutions – from specialist agricultural and arts colleges to generalist universities. Results for this category of institutions should therefore be treated with an appropriate degree of caution.

[5] Following Thanassoulis (1999), the outliers have super-efficiencies (Andersen and Petersen 1993) in excess of 100% and there is at least a 10 percentage point gap between the super-efficiencies of the outliers and the other observations.

The DEA model assumed variable returns to scale. Institutions that have increasing, constant, or decreasing returns to scale were identified using the DEA models applied to separate sub-groups of institutions. Most HEIs have constant or decreasing returns to scale. This gave HEIs further information as to how they might be able to change scale size in order to exploit economies of scale. We return to this point below.

In order to estimate an 'efficient' unit cost for each type of output one of the approaches proposed in Thanassoulis (1996) termed 'DEA-RA' (DEA followed by Regression Analysis) was deployed. The purpose of this approach is to obtain estimated parameters for the efficiency frontier. This is done as follows: DEA is performed to identify the efficient and inefficient HEIs. Inefficient HEIs are then projected on to the Pareto efficient frontier by estimating efficient output levels for them using an output oriented radial DEA model, adding any slacks to radial projections. Finally, total operating cost (in pounds sterling) was regressed against the vector of 'efficient' output levels to derive an estimated linear cost function. For the full sample of institutions, the cost equation estimated was given by

$$\begin{array}{l} C = \underset{(12.0)}{13121X_m} + \underset{(19.6)}{5657X_s} + \underset{(18.9)}{4638X_a} + \underset{(7.1)}{3829X_p} + \underset{(84.9)}{1376R} + \underset{(14.4)}{1537K} \end{array}$$

where t-statistics appear in parentheses.[6] Here C denotes costs, X_m, X_s, and X_a denote respectively the output of undergraduates in medicine, other sciences, and non-science disciplines, X_p is the output of postgraduates, and R and K denote respectively research income and knowledge transfer as defined in the outputs above. This specification of the cost function assumes no fixed costs. Thus in effect the estimated expression is a linear approximation to the CRS part of the piecewise linear VRS frontier.

The unit output costs derived are reasonable and in considerable accord with the unit costs of the same outputs estimated by a quadratic cost function using the same data in Johnes *et al.* (2005); they indicate that, at undergraduate level, medical education is the most costly

[6] The t statistics should be treated with caution. They are high because the regression fits a line through a scatterplot that comprises observations that lie perfectly on piecewise linear segments.

to provide at just over £13,000 or about US$20,000) per student. This is followed by tuition in the other sciences. Postgraduate education at £3829 per student is estimated to be, on average, less costly to provide than undergraduate education. DEA is not likely to have a very accurate picture here as, more than at UG level, institutions offer very diverse postgraduate courses ranging from expensive MBA degrees to much cheaper PhD degrees. The latter are likely to lower the estimated cost per postgraduate student further because many research postgraduates engage in both undergraduate teaching and joint research activity with staff; while the one-to-one supervision that such postgraduates receive is resource-intensive, their activities also serve to reduce the costs associated with undergraduate provision and with research.

Similar equations showing the relationship at the efficiency frontier between costs and outputs are derived by Thanassoulis *et al.* (2011) for each of the groups of institutions defined above. The broad picture, with medical education being the most costly, followed by other sciences, is replicated across all groups. The costs associated with postgraduate education vary markedly across different types of institution, however, this being most costly in pre-1992 institutions without medical schools.

Broadly comparable results are reported using a suite of alternative, parametric, estimation strategies, using as data the full sample of institutions. These include stochastic frontier, random effects, and generalised estimating equations to evaluate the parameters of a quadratic cost function, from which average incremental costs associated with each output type are calculated (Baumol *et al.* 1982). Whatever method is used, the cost associated with undergraduate tuition is highest for medicine, followed by the other sciences. In each of these statistical methods, however, the average incremental costs associated with postgraduate provision is estimated as being higher than that associated with undergraduate provision (other than in medicine). DEA is likely to give a better estimate of postgraduate cost per student once the sample is subdivided into four more homogenous types of HEI as postgraduate provision is now more homogeneous within each sub-group.

By pooling the data over the three years, Thanassoulis *et al.* (2011) also investigate change over time in both the frontier and the position of each institution relative to that frontier.

This is done using the Malmquist index approach.[7] It is established that, over the period from 2000-1 through 2002-3, the Malmquist index (measuring total factor productivity) shifted very little for pre-1992 universities without medical schools and for post 1992 universities. This index declined quite markedly in the other two groups, however, the median institution suffering a 6% drop in productivity. Decomposing this change into the components due to shift of the frontier and changes in efficiency of individual units indicates that the decline is *all* due to a shifting frontier. The authors note that this may be an artefact of the data. To be specific, over this period prices associated with the purchases of higher education institutions tended to be rising more quickly than is indicated by general price inflation; consequently the data used for real operating costs may overestimate the real value of inputs in the later years of the study. It is not clear, however, why this would affect some types of university but not others.

Another aspect investigated by Thanassoulis *et al.* (2011) was the possible augmentation of output levels, notably student numbers, that would be feasible at current levels of expenditure if inefficiencies were to be eliminated. They did this using the output oriented DEA model in two ways. Firstly the model was used in its classical format which scales all outputs equiproportionately maintaining the mix of all outputs (students, research and third mission) in order to gain Pareto efficiency. The potential output augmentations based on this model showed that across the sector there was scope for about 10% rise in undergraduate science, 15% in non-science undergraduates and 17% in postgraduate student numbers. About two thirds of these gains were possible through the elimination of technical inefficiency and the remainder through the additional elimination of scale inefficiencies (i.e. exploiting economies of scale). Looking at the different types of institution the largest rise in student numbers possible in relative terms was at higher education colleges ranging from 20% for undergraduate science to 36% for postgraduate students through a combination of scale and technical efficiency gains.

A second variant of the DEA model Thanassoulis *et al.* (2011) used was to vary the priorities for output expansion so that only student number augmentations are used to gain efficiency. There were significant differences between these and the preceding results

[7] The index developed by Malmquist (1953) was adapted for use in a DEA context by several researchers in the 1990s. See, for example, Førsund (1993) and Färe and Grosskopf (1996).

when priorities were uniform across all outputs. They report that when both technical and scale inefficiencies had been eliminated the percentage rise in science undergraduates doubled from 11% to 22% and there was a 10 percentage point rise in the number of postgraduate students from 17.52% to 27.16%. The least change was in undergraduate non-science students where the percentage gain rose from 15.26% to 19.81%. These were large potential gains because the model is such that it seeks for each HEI to raise those student numbers where the maximum gain in absolute terms can be made, unconstrained by the need to maintain the mix of outputs. In some cases the model suggested only one type of student be augmented (e.g. at one university only science students rise), because that is where the maximum potential for gain in student numbers lies within given resource levels. In this sense the results represent the potential for gains not only by eliminating scale and technical inefficiency, but also eliminating '**allocative**' inefficiency in the sense of maximising aggregate student numbers by altering the mix of students where appropriate. The authors do sound, however, a note of caution as the model may be overestimating potential gains as the 4 categories of students used are not sufficiently uniform within each category and so DEA by its nature would base results on those institutions which have the 'cheapest' type of student within each category (e.g. there may be a substantial cost differential between educating say mathematics and biology students yet the model treats both types as simply science students.)

The data set used by Thanassoulis *et al.* (2011) has been used to derive further results by Johnes *et al.* (2008). This work focuses on statistical approaches and includes consideration of stochastic frontier methods that allow evaluation of efficiency scores while estimating parametric cost functions. This work is usefully considered alongside non-parametric approaches such as DEA. The statistical approach, pioneered by Aigner *et al.* (1977), has, like DEA, its origins in the work of Farrell (1957), but rather than using linear programming to find the frontier it employs a variant of regression analysis in which the unexplained residual term is defined to include a non-normally distributed component due to inefficiency. By taking this approach, the full toolkit of statistical inference becomes available. The results obtained by Johnes *et al.* (2008) are broadly in line with those produced by DEA and discussed earlier – efficiency scores obtained using the different methods are positively correlated (though the correlation is not particularly strong). The study is notable for its attempts to include location and the quality of student intake as determinants of costs, though neither appears to be statistically significant.

Johnes and Johnes (2013) provide an update of these statistical frontier analyses, and, using panel data, allow for heterogeneity across institutions by using the latent class variant of the stochastic frontier model (Lazarsfeld and Henry 1968; Orea and Kumbhakar 2004; Greene 2005). The results are broadly supportive of earlier studies.[8] A more refined method that can be used to accommodate heterogeneity is the random parameter stochastic frontier model (Tsionas 2002; Greene 2005), and this is used in another study by Johnes and Johnes (2009). Once again, the qualitative nature of the results confirms the findings of other studies. Broadly speaking, as more allowance is made for inter-institutional heterogeneity, the efficiency score attached to the typical institution increases, though outliers at the bottom end remain.

This raises an important conceptual issue surrounding the evaluation of efficiency. Some institutions produce a given vector of outputs at a higher cost than other institutions for quite legitimate reasons. For example, the ancient universities have real estate that is expensive to maintain and that may be less than ideally suited for purpose; their costs are therefore high relative to those of other institutions. This should not be considered a reflection of inefficiency, as these universities are providing a wider service to society through the maintenance of architectural heritage. Now there may be any number of factors of this kind that explain higher costs in one institution than another. Whether any one of these factors is legitimate or not – and hence whether the higher costs are due to inefficiency or not – is essentially a judgement call. While DEA and other frontier methods produce output that may be interpreted as measures of efficiency, there is always scope for debate about what exactly this output means.

[8] We should note, however, that, when the panel is broken into several sub-periods and models estimated on each sub-period separately, the magnitude of some parameters varies widely across sub-periods suggesting that the results should be treated with caution. Moreover, the latent classes determined by the data are puzzling: one might expect *a priori* that each class would comprise HEIs with common characteristics (perhaps with research intensive institutions, and other institutions in another). But this is not the case, and the common factor relating the HEIs in a group is not obvious.

3. Assessment of technical efficiency in higher education institutions using DEA

The cost function approach of the previous section assumes that firms wish to minimise costs (a potentially dubious assumption in the context of a not-for-profit sector such as higher education). Technical efficiency provides an indication of how well (efficiently) HEIs are using their physical inputs to produce outputs. DEA can be used to estimate output distance functions and hence technical efficiency in this context. While most of the studies which examine technical efficiency are at the level of the HEI, DEA can also be applied to data at student level. This compares with the assessment of secondary schools using pupil-level data as described in section 2.3. Such student-level studies can be useful in disentangling the effects of HEI efficiency from that of a student's effectiveness (Johnes 2006a; 2006b). This type of information is useful for choosing a strategy for improving both institutional and student value added.

Johnes (2008) provides an example of an output distance function for higher education estimated using DEA[9]. Staff (both academic and administrative), students (both undergraduate and postgraduate) and expenditure on academic services are the inputs into the process which produces teaching (graduates from undergraduate and postgraduate programmes) and research (income for research purposes). A Malmquist productivity analysis finds that productivity has grown (on average) by 1% per annum over the period 1996/96 to 2004/05 and that this is a consequence of improvements in technology that have outweighed decreases in technical efficiency. Rapid changes in the higher education sector over the study period (such as growth in student numbers and the use of online support materials (for example, routine use of online multiple choice questions and virtual learning environments) appear to have had a positive effect on the technology of production (pushing the frontier outwards) but this has been achieved at the expense of lower technical efficiency (as inefficient HEIs have struggled to keep up with best-practice performance).

[9] Earlier studies using DEA to estimate output distance functions for higher education include Athanassopulos and Shale (1997), Flegg *et al.* (2004) and Johnes (2006a). The last is noteworthy for its pioneering application of statistical tests for comparing nested DEA models (Pastor *et al.* 2002) and for testing for differences in production frontiers of distinct groups of DMUs (Charnes *et al.* 1981).

One problem with these results is that they are based on a set of inputs and outputs which do not incorporate quality of student intake and of exit qualifications. A more recent study which attempts to address this problem (at least in terms of undergraduate teaching inputs and outputs) focuses on the effects on efficiency of mergers (Johnes 2014a). Undergraduate student numbers are adjusted by entry qualification while graduates from undergraduate programmes are adjusted by category of degree result. The remaining inputs and outputs are as in the earlier study. An output-oriented DEA is applied to an unbalanced panel data set from 1996/97 to 2008/09. The sample is unbalanced for a number of reasons. First, some HEIs merged during the study period. Following merger the new institution was treated as a different entity from the HEIs which merged to form it. In addition, some HEIs entered the data base[10] during the period.

The results of applying DEA to the pooled data set indicate that technical efficiency across the sector is around 80% (similar to estimates of cost efficiency). The study also makes a preliminary examination of the effect on efficiency of merger activity. HEIs are identified as pre-merging (those institutions which will merge at some stage in the study period), post-merger (those institutions formed from unions of others) and non-merging. The DEA results suggest that post-merger HEIs are typically more efficient than either pre- or non-merging HEIs. These broad conclusions are confirmed using parametric techniques. It is worthy of note, however, that the underlying characteristics of pre-, post- and non-merging HEIs are very different and so the observed efficiency differences could be a consequence of something other than merger. Moreover, a closer examination of the individual mergers indicates that while *mean* efficiency is higher following merger, the efficiency effects can vary by case and there are both winners and losers in the merging process.

Some recent work on efficiency in higher education has focused upon international comparisons. Agasisti and Johnes (2009), for example, use (both constant and output-oriented variable returns to scale) DEA models to compare the performance of institutions in Italy and England over the period between 2002-3 and 2004-5. This analysis employs a rich set of input variables, with data on the student intake, staff, and financial resources; as outputs, numbers of graduates at various levels and a measure of research activity are used.

[10] Data were obtained from the Higher Education Statistics Agency HESA).

The analysis is conducted both by running separate DEA exercises for the two countries and – as a distinct exercise – running a DEA on the data combined across countries. From the latter analysis, it is established that technical efficiency measures are typically lower in Italian institutions than in their English counterparts; the mean technical efficiency for Italian institutions is just 64%, compared with a mean score of 81% in England. In the country-specific analyses, the mean efficiency of institutions is virtually identical in England and Italy, suggesting that the efficiency differences observed across the two countries are primarily attributable to country level effects. Meanwhile analysis of the Malmquist indices, suggests that the Italian institutions are closing the gap. While little change in total factor productivity is observed in English institutions over this period, average efficiency of Italian institutions increased.[11] This finding is in line with the characteristic catching up process whereby less efficient institutions learn good practice from their peers.

4. Conclusion

This chapter has provided insights into the richness of DEA in education literature. By applying technical and allocative efficiency and productivity change techniques to educational data, policy relevant insights are obtained at both student level, institution and system level. While this Chapter provided an overview of recent work, it is definitely not complete. De Witte and López-Torres (2015) and Johnes (2014b) provide two complementary literature reviews on the efficiency in education literature. Their reviews show that many authors in various countries working with heterogeneous data sources are contributing to the literature. Despite these common efforts, there are still many aspects of efficiency in education to be explored.

De Witte and López-Torres (2015) argue that it is remarkable that the DEA (or Operations Research) literature studying education is still a distinct literature from the standard parametric 'economics of education literature'. The latter literature pays significant attention to the issue of causality, while this is not an issue in the DEA literature yet. Only few DEA studies acknowledge that the presence of endogeneity (e.g., due to omitted variable bias, measurement errors or selection bias) results in internal validity problems (notable exceptions are Ruggiero 2004; Haelermans and De Witte 2012; Cordero-Ferrera *et al.* 2013; Santín and Sicilia 2014). If the DEA literature on education aims to have more impact on the policy

[11] The productivity of institutions on the frontier in Italy slipped back over this time period, but the gain in efficiency of other institutions more than compensated for this, yielding an average efficiency increase across the country of a little under 10%.

debate and on policy making, it should focus more on endogeneity and causal interpretations. The results from the DEA literature can now be easily criticised because of the lack of causal evidence. In relation to this, De Witte and López-Torres (2015) argue that the DEA literature should be more outward looking. Important developments in the economics of education literature, like experiments and quasi-experiments, have been largely ignored. There are few DEA studies that exploit experimental or quasi-experimental evidence (an interesting exception is Santín and Sicilia 2014). Yet, applying DEA to data from experiments or natural experiments in education might yield promising results. One may think of examining the efficiency of educational innovations, or changes at system level. Applying DEA to this type of data would help to bridge the gap between the DEA efficiency in education literature and the parametric efficiency in education literature.

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