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Using data envelopment analysis for the assessment of technical efficiency of units with different specialisations: An application to agriculture☆

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ABSTRACT

In this paper we consider the use of data envelopment analysis (DEA) for the assessment of efficiency of units whose output profiles exhibit specialisation. An example of this is found in agriculture where a large number of different crops may be produced in a particular region, but only a few farms actually produce each particular crop. Because of the large number of outputs, the use of conventional DEA models in such applications results in a poor efficiency discrimination. We overcome this problem by specifying production trade-offs between different outputs, relying on the methodology of Podinovski (J Oper Res Soc 2004;55:1311–22). The main idea of our approach is to relate various outputs to the production of the main output. We illustrate this methodology by an application of DEA involving agricultural farms in different regions of Turkey. An integral part of this application is the elicitation of expert judgements in order to formulate the required production trade-offs. Their use in DEA models results in a significant improvement of the efficiency discrimination. The proposed methodology should also be of interest to other applications of DEA where units may exhibit specialization, such as applications involving hospitals or bank branches.

1. Introduction

One of common challenges in applications of data envelopment analysis (DEA) is the low discriminating power of the models used—this is the ability of the DEA models to differentiate between good and bad performing decision making units (DMUs) by reflecting their performance in a sufficiently wide range of efficiency scores [11,42]. It is well-known that the discrimination of a DEA model depends on a number of factors, including the number of inputs and outputs in relation to the number of units, the type (variable or constant) of returns-to-scale assumed (VRS and CRS, respectively) and, more generally, the particular data set that is under the investigation [7,33].

In this paper we consider another contributing factor that negatively affects the discriminating power of DEA models—the specialisation of DMUs in the production of different subsets of the full set of outputs. According to a recent study by Liu et al. [22], the three largest areas of reported applications of DEA are banking, health care and agriculture. Examples of specialism can easily be found in all of these fields.

Indeed, in healthcare applications of DEA, hospitals often have different specialisations (in terms of treatments available), and may also have other non-clinical outputs reflecting their engagement in research, education and community services [24, 26]. In banking applications, bank branches may offer a full or reduced range of services—e.g. bank branches on university campuses or at airports may not offer mortgages or home-improvement loans [19,40].

In agriculture the problem of specialisation of units (agricultural farms) is ubiquitous, and is further exacerbated by a large number of possible farm outputs. Indeed, it is common for farms from the same geographical region to produce a variety of different crops and livestock products. While the majority of farms (but not necessarily all of them) may produce several common outputs, e.g. wheat or potatoes, there are usually many other crops each produced only by a small number of farms.

Theoretically, it is clear why DMUs with specialised profiles are often shown as efficient, or almost efficient, by standard DEA models: such DMUs have very few, if any, comparators among the other DMUs. In particular, if a DMU produces an output that no other unit does, then such a DMU cannot be outperformed by any

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combination of the other units, and by definition is considered efficient regardless of the levels of its other outputs and inputs.

1.1. Existing approaches

The DEA literature suggests several ways of dealing with applications in which DMUs have different specialisations, or production profiles.

1.1.1. Removal of outliers and clustering

If the number of specialised DMUs is small, these can be removed from the data set as outliers, together with their specialised outputs. For example, Golany and Storbeck [19] remove the banks that perform unique activities from their data set. It may also be possible to cluster units by their specialism (as well as other characteristics such as scale and location), as discussed in Thanassoulis [40]. Both techniques may be acceptable on the grounds of homogeneity, i.e. making an assumption that the units in different clusters employ a different technology or operate in different environments. This does not, however, increase (and in fact reduces) the number of comparators for the remaining units, and therefore does not improve the discrimination of the model. The two described approaches are of little use in agricultural applications of DEA where the number of clusters of farms that produce the same sets of outputs may be too high, with few farms in each cluster.

1.1.2. Using only the most common outputs

In some agricultural applications of productivity analysis, including DEA, only the most common and important farm outputs are included in the model, such as rice in Ray and Bhadra [35], pork products [18], and cereals and oilseed in Luik et al. [23]. A potential problem with this approach is that, if farms produce other outputs in any significant quantities, they will not be able to justify their resources within the technology in which such outputs are omitted, and this approach would favour the farms that produce only the outputs specified in the model. In principle, this problem may be overcome by using as the inputs only the proportion of all resources that have been used in the production of the selected farm outputs. In reality, this may be complicated by the fact that the resources are often reported in an aggregate form, and any disaggregation requires additional assumptions [20].

1.1.3. Aggregation using output prices

Agricultural applications of DEA and other efficiency and productivity assessment methods often aggregate different farm outputs using their unit prices, into a value (revenue) output [16,25,27,12,39,38]. While addressing the criticisms with the above two approaches (clustering and the use of only the main common outputs), the aggregation using prices is not without problems itself.

- The aggregation of individual outputs (or inputs) into a single value dimension using price information changes the nature of assessment from the measurement of technical efficiency of units to the measurement of their allocative efficiency [43,18]. The latter is theoretically generally lower than the former [11]. If the technical efficiency is the main objective of the comparative study, the assessment of allocative efficiency instead of it will generally create an underestimation bias [43].
- The aggregation of outputs into a single dimension forgoes much of the information that might otherwise be observed from the original full-dimensional efficient frontier. For example, it becomes impossible to assess the range of shadow prices of individual outputs and based on them rates and elasticities of substitution and transformation between different outputs and/or inputs [32,8].
- It is not necessarily clear what prices should be used for the aggregation of different outputs. In agriculture, these are often the prices that the farmers in the region are paid for their products. As noted by Acquaye et al. [1], such prices may be policy-distorted and the whole aggregation approach is "somewhat questionable, but standard". An alternative is to use the market prices where available. However, in the global economy the prices may fluctuate and be influenced by the droughts, increased demand and other events affecting the major world producers and markets. This may considerably affect the monetary value of agricultural production of individual farms and misrepresent their actual technical performance.
- This aggregation method cannot be used in most public sector applications such as health care, where unit prices of outputs generally do not exist.

1.1.4. Using weight restrictions

Weight restrictions are additional constraints on the input and output weights incorporated in multiplier DEA models. These are often used as a means to improve the discrimination of DEA models [4,41]. In particular, weight restrictions may be used in the analysis of DMUs with specialised production profiles—an example is an application to Danish hospitals reported by Olesen and Petersen [24]. Because weight restrictions are usually constructed (or assessed) based on value judgements, their use generally results in an unsubstantiated enlargement of the production technology and leads to a well-known drawback: namely, this generally invalidates the meaning of efficiency as a technologically feasible improvement factor [4].

1.2. Proposed methodology

In this paper we suggest that the problem arising from the specialisation of DMUs with a large overall number of outputs can successfully be overcome by the use of the trade-off approach to DEA [28]. We illustrate our development by an application involving wheat-producing farms in Turkey.

The main idea is to relate the production of different outputs to the main output by specifying the production (technological) trade-offs between them, in the form of lower and upper bounds. In our application we relate all specialist crops to the production of the main crop—wheat. The trade-offs are estimates of the use of resources required for the production of specialist crops in relation to the production of wheat. An example of a trade-off taken from our application is as follows: the resources required for the production of 1 t of wheat are definitely sufficient for the production of at least 0.75 t of barley, at any farm in the region.

The application to Turkish agriculture showed that the use of the suggested methodology resulted in good efficiency discrimination among the farms. In some regions of Turkey the models with trade-offs discriminated well even if the number of inputs and outputs was larger than the number of farms. In contrast, in these regions all or almost all farms were efficient in the conventional VRS and CRS models.

In comparison to the existing methods discussed above, the proposed methodology has several advantages.

- There is no need for the clustering of units, removal of outliers or specialist outputs for the sole purpose of reducing the dimensionality and improving the efficiency discrimination. (There may nevertheless be other reasons for doing so, for