Analysing industrial accidents in European countries using Data Envelopment Analysis

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Abstract: There is been increasing interest in improving working conditions and in reducing occupational accidents and diseases in the European Union. This paper examines the performance of fifteen European countries with respect to the number of industrial accident by means of the non-parametric approach to efficiency measurement, represented by Data Envelopment Analysis (DEA).
A linear programming framework is therefore used to construct a production frontier which allows measurement of relative efficiency among national institutions in the sample considered.

Keywords: Occupational safety and health (OSH), Accidents at work, Technical efficiency, Data Envelopment Analysis (DEA), Undesirable outputs.

1. Introduction

National institutions have various macroeconomic objectives, for instance a high level of real GDP per capita or a low rate of inflation. Recently, another objective that needs to receive considerable attention is safety and health at work. Safety and health at work is now one of the most important and most highly developed aspects of EU's policy on employment and social affairs. Nowadays, the development and implementation of holistic approaches and strategies towards occupational safety and health (OSH) becomes more and more important to further improve the working conditions in the EU Member States.
Creating more and better jobs: that was the objective the European Union set itself at the Lisbon European Council in March 2000 (Commission of the European Communities, 2002). The current Community strategy aims to achieve 25% cut in accidents at work across the EU by 2012. An accident at work is defined as an external, sudden, unexpected, unintended and violent event during the execution of work or arising out of it, which causes damage to the health of or loss of the life of the employee. There are many methods of preventing or reducing industrial accidents, including anticipation of problems by risk assessment, safety training, control banding, personal protective equipment, respiratory equipment, safety guards, mechanisms on machinery, safety barriers, etcetera.

A key concept and fundamental pillar for reaching the objectives of this Community strategy is the development and implementation of coherent national strategies in the EU member states. Hence, the performance of national institutions needs to be evaluated in terms of their ability to maximise macroeconomic objectives while minimising accidents at work. So there is an increasing need for tools that allow proper measurement of the performance of organizations with respect to this issue.

The aim of the present paper is to measure the technical efficiency of fifteen European countries for 2005 and our objective is to adapt the techniques of the efficiency measurement literature, such as Data Envelopment Analysis (DEA), to the problem at hand, where outputs do not refer only to goods, but we have also undesirable outputs.

While in traditional DEA models we have two categories of factors (inputs and outputs), now we consider a third kind of factor, undesirable outputs, that could be generated from the production process, such as industrial injuries. To effect the rankings, we propose therefore a new model type of DEA, that includes an assessment of performance of European countries with respect to the number of industrial accident.

The paper is organized as follows. Section 2 reviews some of the theoretical background, Section 3 presents the data used and lists the results obtained and Section 4 gives the conclusions.

2. Method

The term efficiency is widely used in economics and refers to the best use of resources in production. In particular, modern efficiency measurement began with Farrell (1957), who drew upon the work of Debreu (1951) and Koopmans (1951) and introduced a measure for technical efficiency. He suggested measuring the efficiency of a firm in terms of distance to the best unit on the production frontier, represented by the production function of the efficient units. The efficiency frontier is unknown, and it must be estimated from sample data. Drawing inspiration from his argument, two classes of methods, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), were developed for estimating the efficiency of organisational units, also called Decision Making Units (DMUs). DMUs are homogeneous organisational units: they perform the same function, by using the same types of resources to produce the same kinds of goods or services. Each DMUs represents an observed correspondence of multiple input-output levels.

Data Envelopment Analysis is a non-parametric method for assessing the relative efficiency of Decision Making Units. Rather than explicitly stating the functional form of the best practice frontier, DEA measures efficiency relative to a deterministic frontier using linear programming techniques to envelop observed input/output vectors as tightly as possible. The basic DEA models measure the technical efficiency of a DMU in terms of the maximal radial contraction to its input levels (input orientation) or expansion to its output levels feasible under efficient operation (output orientation).

The first DEA model, proposed by Charnes et al. (1978) and known as CCR, assumes the DMUs to be assessed operate within a technology where efficient production is characterised by constant returns to scale (CRS). Under input orientation (whose objective is to minimise inputs while producing at least the given output levels) the relative efficiency of a DMU j_0 is obtained from the following linear model:

$$e_0 = \min \theta_0$$

subject to

$$\theta_0 x_{ij_0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1,\ldots,m \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0}, \quad r = 1,\ldots,s \tag{2}$$

$$\lambda_j \geq 0, \quad \forall j \tag{3}$$

where y_{rj} is the amount of the r-th output to DMU j, x_{ij} is the amount of the i-th input to DMU j, λ_j are the weights of DMU j and θ_0 is the shrinkage factor for DMU j_0. The linear programming problem must be solved n times, once for each unit in the sample, for obtaining a value of θ for each DMU. The value of θ_0 obtained is termed the technical input efficiency of DMU j_0 and it is bounded between 0 and 1: a technical efficient unit, according to Farrell (1957) definition, will have a score of unity, while inefficient ones will have a score less than unity.

The technical efficiency of DMU j_0 can be also determined under output expansion orientation, whose objective is to maximise outputs while using no more than the observed amount of any input. Due to the CRS assumption, the relative efficiency score h_0 of the output-orientated model relates to that of the input-orientated model via $e_0 = 1/h_0$.

Subsequent papers have considered alternative sets of assumptions, such as Banker et al. (1984), who modified the basic CCR model to permit the assessment of the productive efficiency of DMUs where efficient production is characterised by variable returns to scale (VRS). The VRS model, known as BCC, differs from the basic CCR model only in that it includes in the previous formulation the convexity constraint:

$$\sum_{i=1}^{n} \lambda_j = 1 \tag{4}$$

The presence of the convexity constraint in the BCC model reduces the feasible region for DMUs, which, in general, results in an increase of efficient units; otherwise CRS and VRS models work in the same way. In general, under the VRS assumption the model orientation (input or output) affects the projection point on the frontier and the resulting efficiencies may not be the same. Thus, for inefficient DMUs we may have $e_0 \neq 1/h_0$, although the subset of efficient DMUs is the same irrespective of model orientation.

However, although this method has been extensively applied to many areas of economics as an instrument of efficiency measurement, few authors have used it to take into account undesirable outputs.

It was mentioned already in the seminal work of Koopmans (1951) that the production process may also generate undesirable outputs. Undesirable outputs are prominent in the ecological context ("environmental harmful effects" or "harms", Thore & Freire, 2002), such as pollution emissions generated in air or in water, waste, poisonous metals dumped into the soil, but they may as well appear in non-ecological applications (Smith,

1990) including health care (complications of medical operations) and business (tax payments).
Classical DEA models measure the relative efficiency of a DMU described by its input and output quantities in terms of maximal radial contraction to its input levels or expansion to its output levels feasible under efficient operation, but this is not valid any longer in contexts where also “bads” have to be considered (Chung et al., 1997; Dyckhoff & Allen, 2001). In the literature several approaches for incorporating undesirable outputs in DEA models have been proposed, but a general protocol is not clear (Scheel, 2001). We must underline that efficiency scores, and rankings, may change for different approaches (Dyson, 2001).
We propose a modified DEA model that incorporates undesirable outputs as inputs, while also seeking to minimise them (Nissi and Rapposelli, 2005; Coli et al., 2008). This factors will be included directly into the linear programming problem, just like inputs that have to be radially reduced. Hence, the general DEA formulation introduced above must include the following constraint:

$$\theta_0 h_{tj_0} - \sum_{j=1}^{n} \lambda_j h_{tj} \geq 0, \quad t = 1,\ldots,z \tag{5}$$

where h_{tj} is the amount of the t-th input to DMU j. The multiplier θ shrinks both inputs and environmental variables in an equi-proportional manner.

3. Data and results

We apply the efficiency concept seen before to 15 European countries for the year 2005. For our analysis, we consider three non-financial business economy sectors, according to NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) definition: manufacturing, construction and distribution trades.
In an assessment of comparative performance the first and the most important stage is the identification of the input and output variables. In order to model relative efficiency of a set of DMUs it is necessary to define a production function which captures the key points of the production process. We define a model characterised by a single input, the number of persons employed, and a single desirable output, the value added (in Euros) for each sector. Moreover, as mentioned in the introduction, the application of efficiency techniques to this context has motivated the inclusion of a special kind of output, an undesirable output, represented by the number of industrial accidents resulting in three days or more off work. All data were obtained from Eurostat.
The non-parametric efficiency measures are computed by using the modified input-oriented DEA model under a variable returns to scale assumption, because of the large variation in size of the units (VRS assumes that changing inputs will not result in a proportional change in outputs). The linear program associated with the model is solved using DEA-Solver, a software developed by Kaoru Tone (Cooper et al., 2000).
DEA technique provides very detailed information about the analysed DMUs, providing individual efficiency scores for each of them, peer groups and production and consumption objectives for those that are inefficient. Table 1 shows, for each sector assessed, the efficiency ratings obtained from the input-orientated BCC model.

DMU	Manufacturing	Construction	Distribution trades
Belgium	0.7436	0.6155	1
Denmark	0.4120	0.7322	0.9899
Germany	1	0.5461	1
Greece	0.2652	0.4764	0.4826
Spain	0.6836	0.4755	0.6737
France	0.8844	0.6137	1
Ireland	1	1	1
Italy	0.6974	0.4781	0.7586
Luxembourg	1	1	1
Netherlands	0.8077	0.7501	0.9480
Austria	0.5569	0.5972	0.8651
Portugal	0.1469	0.1887	0.3657
Finland	0.4763	0.6080	0.9690
Sweden	0.8186	1	1
United Kingdom	1	1	1

Table 1: Efficiency scores by European countries for the year 2005

Evaluation of DMUs in manufacturing sector by means of our model shows that there are 4 top performers, but many countries do not have very high ratings. In construction sector, four DMUs are BCC-efficient, while several of the others receive very low ratings. Finally, we examined the distribution trades sector. Seven of the units form the efficient frontier and one country (Denmark) is very close to the frontier having the efficiency rating of 0.9899. The remaining countries are sub-efficient but they do not show very low ratings.

Table 2 presents a summary of the efficiency ratings for all sectors analysed. We can see that the distribution trades sector shows a higher average efficiency score and displays less variability than other sectors.

	Manufacturing	Construction	Distribution trades
Mean	0.6995	0.6721	0.8702
Minimum	0.1469	0.1887	0.3657
Maximum	1	1	1
Standard deviation	0.2671	0.2338	0.2007

Table 2: Summary statistics for DEA efficiency scores

On the basis of these results we proceed to a correlation analysis among the efficiency measures obtained for the three different sectors. We observe quite high Spearman rank correlation coefficients between the technical efficiency rankings (Table 3).

	Manufacturing	Construction	Distribution trades
Manufacturing	1		
Construction	0.666	1	
Distribution trades	0.828	0.783	1

Table 3: Spearman rank correlation coefficients

DEA also gives information on the extent to which an efficient unit is used as an efficient peer for other DMUs. Table 4 displays the frequency with which efficient countries appear in the peer group of the inefficient ones. In manufacturing sector, Ireland and United Kingdom appear very frequently in the reference sets (9 and 6 times, respectively). In other sets, the most frequent units are Ireland (9 times), United Kingdom (8) and Sweden (6) in construction sector and Belgium (5) and Ireland (4) in distribution trades sector. On the other hand, Luxembourg and Germany are not likely to be a better role models for less efficient units to emulate.

Peer set – Manufacturing	**Frequency to other DMUs**	**Peer set – Construction**	**Frequency to other DMUs**	**Peer set – Distrib. trades**	**Frequency to other DMUs**
Germany	0	Ireland	9	Belgium	5
Ireland	9	Luxembourg	1	Germany	1
Luxembourg	3	Sweden	6	France	0
United Kingdom	6	United Kingdom	8	Ireland	4
				Luxembourg	0
				Sweden	1
				United Kingdom	1

Table 4: Reference sets

4. Conclusion

The aim of this work was to evaluate the technical efficiency of 15 European countries in three economy sectors, manufacturing, construction and distribution trades, by means of DEA method. We can conclude that the results are not substantially different between the sectors considered: DMUs are not operating at a very high level of efficiency and there is room for improvement in several countries.
However, we must underline that the efficiency degree obtained by each unit is relevant only in the context analysed, so only relative to the chosen model and to the sample examined: if we include a new DMU in the sample or if we assume different model specifications, we could obtain different efficient units or different efficiency degrees.
It must be remembered that the model employed in this work can be improved. First of all, we could include additional key variables or we could apply the model proposed to further application studies, for comparing the performance in other territorial systems, such as Italian regions, European countries, etc. Moreover, we could carry out a performance analysis over time (Sengupta, 2000).

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