# DEA based yardstick competition in natural resource management

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## Abstract

In this paper, we discuss the pros and cons of using Data Envelopment Analysis (DEA) to evaluate and enhance the efficiency of natural resource management. The need for a multi-dimensional production frontier approach is sketched, along with examples from other regulated multi-output industries. Also, reviews of the basic properties of DEA and DEA based yardstick competition are provided. Finally, we discuss the use of DEA based yardstick to evaluate bids in multi-dimensional procurement auctions.



## Keywords

Regulation, incentives, performance evaluation, yardstick competition, data envelopment analysis (DEA)


## Introduction

Data Envelopment Analyses (DEA) has become a tremendously popular relative performance evaluation tool. It was first proposed by Charnes *et al.* (1978, 1979). A recent bibliographic survey (`www.deazone.com`) identified more than 1000 papers from all sectors of society, including several studies within agriculture, forestry, and fishery. Many of these have been published in high quality economics, management science and operations research journals.

Regulators soon realized the usefulness of DEA. DEA studies have for many years been informing their decision making. More recently, DEA has also been used more directly (or mechanically) to define regulatory incentives. In particular, it has been used in incentive regulation of energy utilities. For example, in the regulation of electricity distribution, countries like Norway (`www.nve.no`), Holland (`www.dte.nl`), and Finland (`www.energiamarkkinavirasto.fi`) have introduced DEA based revenue and price cap systems. Furthermore, DEA has - together with more traditional statistical methods - been used to determine reasonable cost norms in countries like Australia, England, New Zealand and Sweden.

Given this trend, it is natural to discuss the potential use of DEA in the regulation of natural resource management. This is the aim of the present paper. To the best of our knowledge, there has been no formalized regulation of natural resource management using DEA.

Farmers and forest owners produce - and use - environmental goods like recreation, clean ground water, and habitats for indigenous plants and animals. However, as no conventional market exists for these goods, the unregulated production levels are presumably below their social optima. A private farmer or forest owner is likely to prioritize the production of marketable goods, e.g. corn or timber. Environmental regulation plays an important role in trying to correct this market failure, one of the means being subsidies. Subsidies are usually granted on a flat-rate basis, say per acre, or they are determined from assessments of opportunity costs. Due to asymmetric information, the better-informed farmers and forest owners will usually extract information rents. Part of the problem in environmental regulation is therefore to limit these rents. Relative performance evaluation using, e.g. DEA may be an important tool for just such a purpose.

In this paper, we discuss when and how DEA based relative performance evaluations can support the regulator.

DEA can be used to model costs and can hereby assist in the design of an *ex-ante* regulation, i.e. a system where subsidies are based on past data. *ex-ante* systems like "CPI-$x$-$x^{i}$", where the compensation over the years is increased by a (consumer) price index (CPI) and decreased by the general productivity development ($x$), as well as possibly the individual improvement ($x^i$), are commonly used in many sectors. DEA can assist in the determination of the general and individual productivity developments, $x$ and $x^i$.

DEA can also be used in an *ex-post* regulation, where the additional information acquired during the regulation period is used to set reasonable costs. The principle here is that the *ex-ante* commitment to *ex-post* regulation effectively creates a pseudo-market among the agents, each of which is trying to do at least as well as the others.

DEA can finally support *procurement design*. While both *ex-ante* and *ex-post* regulation seek to reduce the costs of producing given outputs, the focus in procurement is on the choice of agents (to operate in a market), as well as their multiple dimensional output vectors.

The outline of the paper is as follows. We first provide a brief literature review in the second section, and we identify some key issues in natural resource incentive provision and regulation in third section . Next, we give a non-technical introduction to DEA in fourth section. In fifth section, we discuss why DEA has become so popular among regulators, as well as some of the main criticism that has been raised against the use of DEA for regulatory purposes. We then discuss earlier research on DEA based incentive plans, using this to suggest a reimbursement plan for natural resource management regulation in sixth section. In seventh section, we suggest that DEA can be used to evaluate and screen bids, rather than actual performances. We discuss how this could form the core of an auction design, e.g. when a government wants to procure forest and landscape qualities, reduce nitrogen leaching, etc. Final remarks are provided in eighth section.

## Environmental Regulation

The theory of market-based instruments to enhance environmental benefits is growing. The theory originates from the traditional theory of economic incentives for environmental protection, cf. e.g. Baumol & Oates (1988); Hanley *et al.* (1997).

A significant body of research is concerned with problems in European and US agriculture. Intensive cultivation of the land conflicts with a growing demand for public environmental goods. This increases the need for incentives. The literature focuses on the evaluation of existing schemes, cf. e.g. Shoemaker (1989); Whitby *et al.* (1998); Roberts *et al.* (1996); Vukina *et al.* (2000). It also contains more theoretical contributions, e.g. Chambers (1997).

With hidden information and a high social value of environmental benefits, private landowners are in general overcompensated, i.e. the compensation they receive exceeds the opportunity costs of producing the environmental benefits. The hidden information allows landowners with low opportunity costs to imitate landowners with high opportunity costs. The extraction of such information rents can be reduced by using auctions or yardstick competition, or a combination thereof, as incentive mechanisms.

There is a large amount of literature on the theory and practice of auctions. Important theoretical contributions include Maskin & Riley (1984, 2000); McAffee & McMillan (1987); Laffont & Tirole (1987), while Klemperer (1999) offers an overview. Within agriculture, studies on the use of auctions include Baneth (1995); Latacz-Lohmann & van der Hamsvoort (1997, 1998); Vukina *et al.* (2000). Auctions as incentive instruments are used in few cases, the most significant being an American set-aside scheme (CRP), Shoemaker (1989); Vukina *et al.* (2000).

There is also a great amount of literature on relative performance evaluations. This

In terms of the *technology*, it clearly varies between agents facing different environmental conditions. Also, the natural resource production is characterized by a high degree of jointness. This means that the input or output we may want to regulate or incentivize, may affect the marginal products or costs of other inputs and outputs as well. To capture such dependencies, it is necessary to work with rather complex multiple input/multiple output production structures with easy and flexible allowance for non-controllable factors.

Last but not least, at the *sector* level we typically have many "similar" units. This facilitates practical modeling. Also, it facilitates incentive provision by allowing for relative performance evaluations to reduce rents. In general, we also have large amounts of high quality data collected, using standardized natural science procedures. This makes the pure (idiosyncratic) noise elements less important than the uncertainty of the underlying structural relationship between inputs and outputs.

In the rest of this paper, we examine the design and usefulness of DEA based evaluations and incentives in such contexts with a complex technology, rather good data but considerable amounts of asymmetric information, unclear social priorities, non-trivial impact of local conditions, and conflicts of interest among the agents in the sector.

## Data Envelopment Analysis

In this Section, we provide a short, not too technical introduction to the main ideas and constructs in Data Envelopment Analysis (DEA). For a textbook introductions, see Charnes *et al.* (1994); Coelli *et al.* (1998); Cooper *et al.* (2000).

### Rational Ideal Evaluations

Consider the problem of evaluating a given production unit or production plan. In the DEA literature, the evaluated units, say the farmers or forestry estates, are usually called Decision Making Units (DMUs). One can think of the DMUs as actual organizational units, as production plans or more generally, as multiple dimensional performance descriptions at a given time. Note that there is no technical difference between times series and panel data in the DEA model. Past performances of a unit may therefore be used to evaluate current behavior.

A DMU transforms resources into products and services. The transformation is affected by non-controllable variables as well as non-observable skills and efforts in the organization. The *inputs* in a farm could e.g. be the employees, the machinery, the buildings, the fields, the animals or the pesticides. The *outputs* might include the crops produced, the animals feeded, the sales revenue or indeed, the landscape preserved. The *non-controllable* variables will depend on the time horizon, etc. but could include large parts of the fixed costs, the weather conditions, the genetic health conditions of the herd, and the market conditions.

Taking the standard micro-economic approach, we would ideally like to evaluate the performance of a given DMU by its ability to choose the best means to pursue its aims. The rational ideal performance evaluation can, e.g. be summarized by comparing the actually attained goal level to the maximum goal level that can be achieved. Figure 9.1 illustrates this idea in the case of a fixed bundle of inputs and non-controllable variables. Here, the goal is $U(.)$ and the possibilities are given by the set $T$. The effectiveness of DMU $D$ is evaluated by its obtained utility level $U(D)$, compared to the maximally obtainable utility level $U(ideal)$ given the set of possibilities.

In real evaluations, it is not easy to apply the micro-economic cookbook recipe. In the typical evaluation, we lack clear priorities $U$ as well as clear information about the production possibilities $T$. DEA provides a way of overcoming the informational limitations. The idea is illustrated in Figure 9.2 and commented on below.

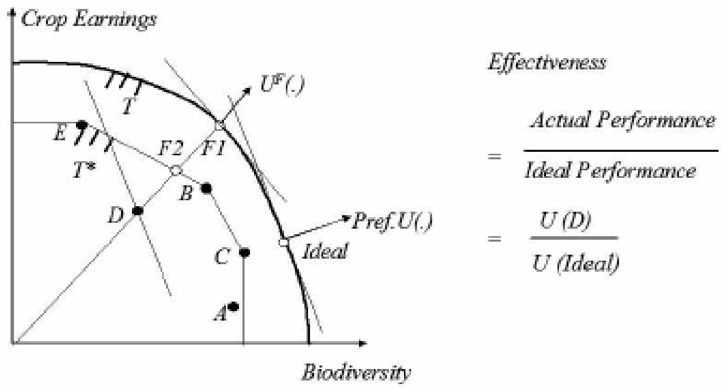


Figure 9.1: *The Rational Ideal Evaluation*

### From Effectiveness to Efficiency

Consider first the *lack of clear priorities* as to how the resource spent and the products created, should be evaluated and traded-off against each other. In Figures 9.1 and 9.2 this corresponds to a lack of information about the $U$ function. The lack of priority information includes the problem of trading-off the different benefits created by a landowner. DEA overcomes this problem by moving from an evaluation of effectiveness, i.e. goal attainment, to an evaluation of efficiency. Efficiency here is broadly defined as the production of the most outputs using the least inputs. The efficient plans in Figure 9.1 are all the plans on the northeast frontier.

To quantify the extent of inefficiency, the DEA literature uses different measures of the distance between a given DMU, say DMU $D$, and the frontier of efficient plans. Most studies use the so-called Farrell (1957) measures that take into account the multiple dimensional character of the inputs and outputs by looking for proportional expansions and contractions. Thus the Farrell output and input based measures are:

- $F$ = largest proportional expansion of all outputs that are possible without using additional inputs
- $E$ = largest proportional contraction of all inputs that are possible without reducing any output

Thus, e.g. $F = 1.2$ means that all output could be increased by 20%, while $E = 0.6$ means that all inputs could have been reduced by 40%. In Figure 9.1, the Farrell base output efficiency is approximately 200%, therefore all outputs could have been increased by 100% without introducing additional inputs, namely by moving from $D$ to the Farrell projection plan $F1$.

The resulting evaluations can also be interpreted in the following manner. The lack of a priori information about priorities like $U$ in Figure 9.1 is overcome by choosing the priorities that put the evaluated DMU in the best possible light. For DMU $D$ in Figure 9.1, this would be the priorities corresponding to the stipulated preference structure $U^F$. Hence, in DEA, each and every DMU is evaluated according to prices or priorities that make its effectiveness look as high as possible. The lack of knowledge about priorities is handled by allowing for all possible priorities, corresponding to all possible slopes of the indifference curves in Figure 9.1. Of course, if some perhaps partial preference information is available, this can be used to refine the evaluations.

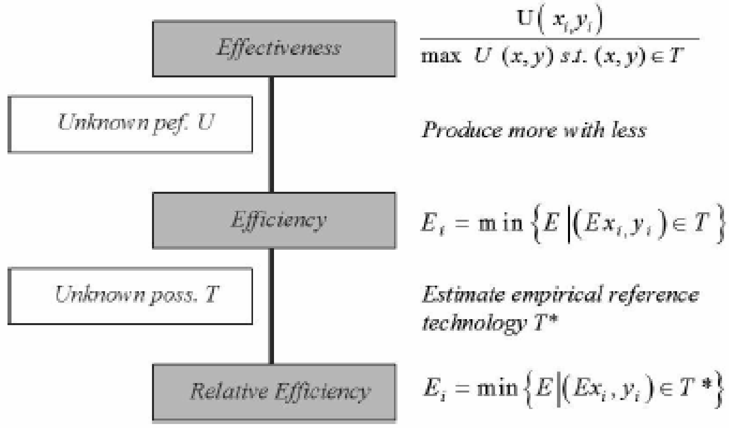


Figure 9.2: *The Basic DEA Idea*

### From Absolute Efficiency to Relative Efficiency

Consider next the other fundamental problem in practice, namely the lack of sufficient a priori information about the underlying, potentially complex technology. In Figure 9.2 this corresponds to the set $T$ and it reflects the technology in a broad sense, i.e. the socio-technical possibilities of transforming combinations of inputs into combinations of outputs. DEA overcomes this problem by estimating the technology $T*$ from observed historical or cross-sectional actual plans. Performance is then evaluated relative to the performance of other DMUs, rather than relative to an absolute norm.

The idea of substituting an underlying but unknown production possibility set with an estimated one is of course not unique to the DEA approach. It is also done in performance evaluations using traditional statistical methods, accounting approaches, etc. What is particular about the DEA approach is the way the approximation of the technology is constructed and the resulting properties of the evaluations.

The technology is estimated using a so-called *minimal extrapolation principle*. By this we mean that DEA constructs the smallest possible set of production plans that constrain the observed ones and satisfy a set of (weak) regularity conditions. By constructing the smallest set containing the actual observations, the method extrapolates the least.

The minimal extrapolation idea is illustrated in Figure 9.2 by the set below the piecewise linear line. Effectiveness, if we know the priorities $U$, or efficiency $F$ if we do not know $U$, can now be evaluated relative to $T*$ rather than $T$. Since we evaluate compared to an empirical norm set by the other DMUs and since we do not compare to an absolute norm, we say that we evaluate relative effectiveness or efficiency. In the case of DMU $D$, the relative efficiency is now approximately 1.3, suggesting only a 30% improvement potential since we now compare to the point $F2$.

Different DEA models are distinguished by the set of production economic regularities imposed on the set $T*$. They typically include some of the following:

- $A1$: Free disposability, i.e. the ability to produce less outputs using less inputs
- $A2$: Convexity, i.e. the ability to make weighted averages of production plans
- $A3$: s-Return to scale, i.e. the ability to scale freely (crs), down (drs) or not (vrs)

The four most commonly used DEA models are then the original constant returns to scale (crs) DEA model proposed by Charnes *et al.* (1978, 1979) invoking $A1$, $A2$ and $A3$(crs), the decreasing returns to scale (drs) and (local) variable returns to scale (vrs) models developed by Banker (1984); Banker *et al.* (1984) with appeal to $A1$, $A2$ and $A3$(drs) and $A1$, $A2$ and $A3$(vrs), respectively, and the free disposability hull (fdh) model proposed by Deprins *et al.* (1984) by invoking only $A1$. The resulting models in a single input single output case are illustrated in Figure 9.3.

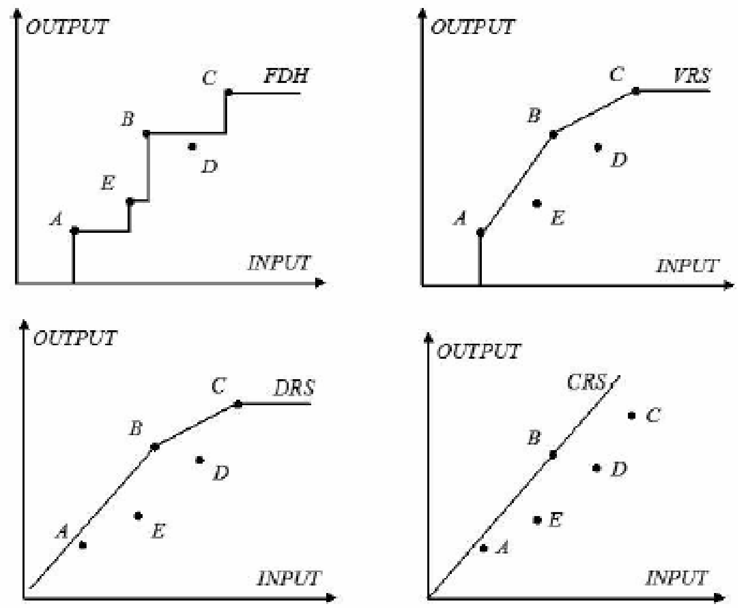


Figure 9.3: *The free disposable hull (fdh), variable returns-to-scale (vrs), decreasing returns-to-scale (drs), and constant returns-to-scale (crs) technologies for DMU $A$, $B$, $C$, $D$, $E$*

In the multiple output case the vrs, drs and crs models could look like the $T*$ technology in Figure 9.2, while the fdh technology would correspond to a step-function between points $A$, $B$, $C$ and $E$.

To understand the flexibility of the DEA approach, it is worthwhile noting that the fdh model simply assumes that production and cost functions are increasing. The vrs model simply assumes that production functions are increasing and concave, and that cost functions are increasing and convex. The remaining models add the scaling possibilities, but even the crs model is much more flexible than a linear model (as soon as there are multiple inputs or outputs).

To summarize, DEA copes with two fundamental problems in real evaluations. The lack of clear preference or priority information is handled by moving from effectiveness to efficiency, while the lack of technological information a priori is handled by making weak a priori assumptions, by doing the estimation via the minimal extrapolation principle, and by evaluating efficiency relative to be best practice. Figure 9.2 summarized the basic ideas.

### Using Mathematical Programming to Assess Relative Efficiency

To calculate the Farrell efficiencies in a realistic, many dimensional context, it suffices to solve simple linear programming (LP) problems. Let us assume that we have for each of n production units, DMU$^i$, $i = 1, \ldots, n$, the following data available: The inputs used, perhaps just as costs, $x^i \in \mathbb{R}^p$, and an r-dimensional environmental improvement vector, $y \in \mathbb{R}^r$. In addition, the regulator and the firms know a series of non-controllable, environmental variables $z \in \mathbb{R}^q$ like the type of land, weather conditions, and distance to reservoirs, etc. In the formulations below, we model the non-controllable variables as inputs.

Now, to formalize the basic ideas of DEA, we may think of an underlying, but unknown production possibility set:

$$T = \{(x, z, y) \in \mathbb{R}_+^{p+q+r} | (x, z) \text{can produce} \;\; y\} \tag{9.1}$$

The three classes of production economic regularities may then be formalized as:

- $A1$: Free disposability:

$$(x, z, y) \in T, \; x' \geq x, z' \geq z \;\text{ and }\; y' \leq y \Rightarrow (x', z', y') \in T, \tag{9.2}$$

- $A2$: Convexity:

$$(x, z, y) \in T \text{ and } (x', z', y') \in T \Rightarrow \alpha(x, z, y) + (1 - \alpha)(x', z', y') \in T \forall \alpha \in [0, 1] \tag{9.3}$$

- $A3$: s-Return to scale:

$$(x, z, y) \in T \Rightarrow k(x, z, y) \forall k \in K(s) \tag{9.4}$$

where $s =$ "crs", "drs", "vrs" or "fdh", and where $K(\text{crs}) = [0, \infty)$, $K(\text{drs}) = [0, 1]$ and $K(\text{vrs}) = K(\text{fdh}) = \{1\}$.

Now, given the available data, the minimal extrapolation estimate of $T$, TDEA, can easily be determined as:

$$T^{\text{DEA}}(s) = \left\{ (x, z, y) | \exists \lambda \in \mathbb{R}_0^n : x \geq \sum_{j=1}^{n} \lambda^j x^j, z \geq \sum_{j=1}^{n} \lambda^j z^j, y \leq \sum_{j=1}^{n} \lambda^j y^j, \lambda \in \Lambda(s) \right\} \tag{9.5}$$

Here, $\Lambda(s)$ is an index set that is determined from the reference technology and in particular from the axioms imposed hereon. In the vrs technology, invoking free disposability and convexity, we have:

$$\Lambda(\text{vrs}) = \left\{ \lambda \in \mathbb{R}_0^n | \sum_{j}^{n} \lambda^j = 1 \right\} \tag{9.6}$$

while the drs and crs technologies, invoking in addition decreasing and constant return to scale assumptions respectively, we have:

$$\Lambda(\text{drs}) = \left\{ \lambda \in \mathbb{R}_0^n | \sum_{j}^{n} \lambda^j \leq 1 \right\} \tag{9.7}$$

and

$$\Lambda(\text{crs}) = \mathbb{R}_0^n \tag{9.8}$$

In the less demanding so-called fdh technology, invoking only free disposability of inputs and outputs, we have:

$$\Lambda(\text{fdh}) = \left\{ \lambda \in \mathbb{R}_0^n | \sum_{j}^{n} \lambda^j = 1, \;\; \lambda^i \;\text{ or }\; 1 \;\; \forall j \right\} \tag{9.9}$$

It follows that the Farrell input efficiency for DMU$^i$ , i.e. the largest possible contraction of controllable inputs that is possible in given the estimated technology $T*$, can be determined by solving a simple LP problem with $n+1$ variables and $p+q+r(+1)$ constraints, see e.g. Charnes *et al.* (1994); Coelli *et al.* (1998); Cooper *et al.* (2000):

$$
\begin{aligned}
\min E^i & & \\
s.t.\ \ E^i x^i & \geq \sum_{j=1}^{n} \lambda^j x^j \\
z_i & \geq \sum_{j=1}^{n} \lambda^j z^j \\
y_i & \leq \sum_{j=1}^{n} \lambda^j y^j \\
\lambda & \in \Lambda(s)
\end{aligned}
\tag{9.10}
$$

Observe that in the fdh case, the mathematical program is not actually an LP problem, but rather a mixed integer programming problem. In fact, the fdh problem can be solved much more easily by a series of straightforward pair wise comparisons, cf. e.g. Deprins *et al.* (1984).

In some cases, the non-controllable variables $z$, e.g. the climate conditions, are best thought of as an ordinal or even categorical variable, for which the idea of convexity and rescaling makes little sense. In this case, the DEA approach essentially operates by splitting the comprehensive evaluation program into a series of sub-problems corresponding to different values of the categorical variable, cf. e.g. Charnes *et al.* (1994), Chapter 3.

## Pros and Cons of DEA

We have argued that relative performance evaluations and regulation are necessary in several sectors, including the natural resource sector. We have also described how DEA solves some of the fundamental problems in real evaluations, namely the lack of preference and possibility information. We shall now look a little closer at some of the implied pros and cons of DEA.

### Pros

The way we estimate the production possibilities in DEA has several implications. The use of the minimal set containing the actual points suggests that DEA provides an inner approximation of the underlying production possibility set. The (in)efficiency estimates are therefore *cautious* or conservative in the sense that the potential output expansions or input savings are underestimated. We have already seen this for DMU D in Figure 9.1 where the expansion possibilities were estimated as 30% with $T*$ and 100% with $T$.

The use of the minimal extrapolation principle and hereby, the construction of the largest inner approximation, also implies that the technology identifies so-called *best practice*. This is attractive in many cases, since the methods and procedures of the best units are more likely targets for other units. Thus, e.g. if $D$ in Figure 9.1 is to learn, it would probably find little to learn from looking at $F$. It would be more interesting to look at what units like $B$ and perhaps $E$ have done differently. A further consequence of using the DEA approach is that real peers are identified. In Figure 9.1, $D$ has two peers, $B$ and $E$, since $F2$ is located on the line between these two units. $B$ is the primary peer, since $F2$ is located close to $B$. Of course the construction of best practice norms, as opposed to average norms, must also influence the way we design incentive schemes. We shall return to this below.

The third and in many cases most important implication of the DEA estimation approach is its ability to work with weak a priori assumptions and associated extremely flexible models of the technology. DEA models generally allow for the underlying best practice production structure to take many different forms. If we estimate a cost function using DEA, e.g. we may assume that it is simply any increasing function - or any increasing convex function. We do not need to assume that the substitution possibilities between the outputs are, e.g. fixed. No parametric statistical model or any cost function constructed by different accounting practices allow for a similar flexibility in the technology model. There are many versions of the DEA approach, corresponding to the introduction of different combinations of a priori assumptions. In all cases, however, the imposed a priori regulatory is mild compared to competing approaches.

Cons

The single most problematic feature of DEA is the risk of mistaking *noise* for efficiency or inefficiency, and the *luckiest practice* for the best practice.

If a DMU by chance faces particularly favorable circumstances that are not accounted for in the model, or if the registration of the outputs by luck (or intent) is biased upwards and the inputs downwards, the units will appear to have performed particularly well and have little if any inefficiency. Similarly, there is a risk of non-favorable circumstances or registrations leading to groundless claims of inefficiency in a DEA analysis. The case of overly optimistic registrations is particularly problematic, since it might influence the evaluation of others that may now face tougher standards by being compared to a unit with a windfall gain.

These observations have led theorists as well as practitions to question DEA and advocate instead the use of statistical methods, including so-called stochastically frontier analyses SFA. SFA is like a traditional statistical model except that the noise is composed of two terms, a one-sided (in)efficiency term and a two-sided traditional noise term.

The appropriateness of DEA depends to a large extent on how well it is executed and in which contexts it is used. DEA is - similar to any other operations research technique - just a tool that can be used with success, if put in the right hands and used optimally.

To be *well executed*, a DEA analysis must involve careful data collection, serious sensitivity analysis (using Monte Carlo techniques, peeling techniques, alternative technologies, etc), perhaps stochastic programming and if possible specification and significance testing. There are by now numerous contributions involving re-sampling, bootstrapping, and asymptotic test theory, cf. Simar & Wilson (2000) for a recent survey. Still, the state-of-the-art in this respect is still lacking compared to what can be done in parametric models.

In terms of *context*, we note that in a regulatory context, it will often be at the regulator's discretion how much inefficiency to eliminate in the coming periods. In such cases, by acting generously, the regulator may effectively create a safeguard against noise. Also, we note that given the flexibility in the production structure, individual noise or outlier problems may only have a local impact. Lastly but most importantly, we suggest that the impact of noisy registrations and mis-specified models should also be viewed with the uncertainty about the underlying (average) production structure in mind. If we have very little a priori information about the technology and if it is potentially complex, the DEA approach may have clear advantages over parametric statistical methods and simple accounting models.

Intuitively, it would seem natural to conclude therefore that if one faces a simple technology and very noisy data, the use of parametrical, statistical models are preferable from an inference perspective. If on the other hand, we have relatively high quality data, but a complex technology with considerable uncertainty about the structure of the input-output correspondences (the rates of substitution, etc.), DEA is preferred. More formal models of the pros of DEA in regulation with considerable structural uncertainty will be surveyed below.

A couple of more pragmatic observations are relevant here as well. DEA is easy to use given the existing computer implementations, the limited a priori assumptions needed and - somewhat counter intuitively - the lack of good standard indicators of mis-specified models!

Also, DEA may be considered easy to *defend*. Again, this rests on the mild regularity assumptions, the ability to handle multiple inputs and outputs and the apparent ease of explaining DEA. Counter to these properties is the fact that the generation of explicit peers may not always be attractive. If, e.g. a regulated firm questions the regulator's decision in court, the existence of explicit peers make the regulator vulnerable, since it seems straightforward for the firm to find circumstances by which the regulated firm deviates non-favorably from the peer units. Using instead an econometric model, the exact basis of comparison becomes blurred, actually creating strategic advantages. Casual empiricism from the use of DEA in energy regulation suggests that this is more than an academic possibility. Hence, although we do like the explicitness in the DEA analyses, we realize that in the less than ideal world of reality, even a black box approach may have its advantages. Also, the risk possibly entangling slack and noise, inefficiency and noise, may make the DEA approach harder to defend.

Another drawback of the DEA approach, as of efficiency studies in general, is the lack of focus on the goals of the organization. The impressing progress that can be made in the evaluation without much preference information should not lead one to forget the importance of doing the right things and not just doing things right. It may be better to move slowly in the right direction than to run fast in the wrong direction. The importance and potential gains from giving more attention to preference modeling and less to the evaluation with possibly naïve priorities, has been emphasized in the multiple criteria literature, cf. e.g. Bogetoft & Pruzan (1991). Also, it has gradually been included into the DEA literature as well, c.f. e.g. Ali *et al.* (1991); Golany (1988b,a); Halme *et al.* (1999); Joro *et al.* (1998).

### Summing Up

To summarize our discussion, we have identified a series of pros and cons of DEA. The pros include:

- Requires no or little preference, price or priority information
- Requires no or little technological information
- Handles multiple inputs and multiple outputs
- Provides real peers
- Identifies best practice
- Cautious or conservative evaluations (minimal extrapolation)
- Supports learning and - as we shall argue in the next Section - planning and motivation and the cons include
- Relatively weak theory of significance testing (sensitivity, resampling, bootstrapping, asymptotic theory)
- Lack of focus on goals

## DEA and Incentives

We now give a brief introduction to some key results about incentive provision using DEA analysis.

### The Literature

The first conjectures as to the likely responses to DEA control go back to Banker (1980); Banker *et al.* (1989). They provided game theoretical interpretations of the scoring problem in the standard DEA models given realized inputs and outputs.

The study of the *ex ante* motivation game of choosing inputs, outputs, efforts, skills etc using formal agency models was initiated by Bogetoft (1990). It has subsequently been the subject of several papers and books including Bogetoft (1994a,?, 1995, 1997, 2000); Agrell & Bogetoft (2001); Agrell *et al.* (2002a,b). The main results concern the use of so-called super-efficiency, cf. Bogetoft (1990, 1994a,?, 1995), the design of static incentives with noise and risk adverse agents Bogetoft (1994) and - as we shall focus on below - the design of incentives for risk neutral agents in a context with considerable technological uncertainty and asymmetric information about a regulated agent's actions (moral hazard) and working conditions (adverse selection), cf. Agrell & Bogetoft (2001); Bogetoft (1997, 2000), and in a dynamic setting Agrell & Bogetoft (2001); Agrell *et al.* (2002a,b).

Similar ideas have been used in other studies, including Bowlin (1997) proposal for designing employment contracts for government managers, Dalen (1996) analysis of the interaction between performance measurement and bureaucratic slack, and Dalen & Gomez-Lobo (1997, 2000) cost estimation and yardstick analyses of buses, Resende (2001) study of yardstick competition in electricity distribution, Sheriff (2001) use of DEA in the design of (agrarian) contracts, Thanassoulis (2000) analysis of DEA and its use in the regulation of water companies, and the Ph.D. dissertation by Wunsch (1995) on peer comparison and regulation of mass transit firms in Europe.

### The Setting

The basic problem addressed in this literature is the following: Given a cross section, a time series or panel information on the multiple inputs and outputs of several DMUs, what should a manager, a regulator or an owner ask the DMUs to do in the future, and how should he motivate and compensate the DMUs for their effort and other private costs?

The answer to these questions depends intimately on the organizational context and in particular on the technological, informational and preferential assumptions of the parties, i.e. the regulator (principal) and DMUs (agents).

In general, we consider the case where the principal (regulator) faces considerable uncertainty about the technology. In a single input multiple output cost setting, he may, e.g. know that the cost function is increasing and convex, but otherwise have no a priori information about the cost structure.

The general case also empowers agents to take private actions, which the principal cannot observe. The action could, e.g. be to reduce costs or increase the quality of the work. This leads to the usual moral hazard problem since the principal and the agents may conflict as to which actions the agents should take. The traditional setting depicts the agents as work averse, tempted to rely on their good luck, and to explain possibly bad performances with unfavorable circumstances. In general, however, it is simply one way to model the underlying conflicts giving rise to a motivation problem.

Usually, we also consider the possibility that the agents have superior information about the working conditions, before contracting with the principal. A farmer may, e.g. have good information about the production conditions on his land and therefore the likely loss in crop revenue from reduced N application. The regulator trying to reduce N-usage, on the other hand, may have little information about the cost at a specific farm. This leads to the classical adverse selection problem, where an agent will try to extract information rents by claiming to be operating under less favorable conditions.

As regards the preference of the parties, we generally assume that the principal is risk neutral and that the agents are either risk averse or risk neutral. The principal's aim is to minimize the costs of inducing the agents to take the desired (hidden) actions in the relevant (hidden) circumstances. An agent's aim is usually to maximize the utility from payment minus the disutility from private effort. The general set-up and timeline is illustrated in Figure 9.4.

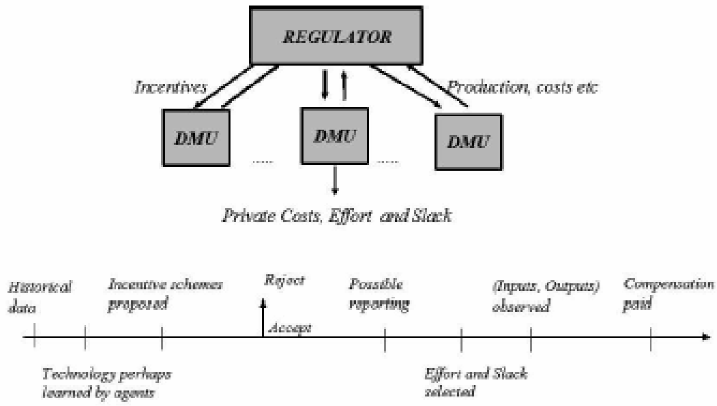


Figure 9.4: *Agency Structure with Timeline of Events*

### DEA based Yardstick Theory

In Bogetoft (1997, 2000), we consider the combined adverse selection and moral hazard context. We assume - in the simplest possible version - that the only observable input is the realized costs, i.e. the input is one-dimensional $x^i = c^i \in \mathbb{R},\ i = 1, \ldots, n$. The question is how much, $B$, to reimburse a DMU using costs $c$ to produce $y \in \mathbb{R}^r$ with environmental (non-controllable) variables $z \in \mathbb{R}^q$.

In terms of technology and information, we assume that there is considerable uncertainty and asymmetric information about the underlying cost structure. The DMU is supposed to have superior technological information. In an extreme case, it knows with certainty the underlying true cost $C(y;z)$, i.e. the costs of producing $y$ under environmental conditions $z$. Of course, we do not have to assume that the DMU knows these costs for all possible output profiles $y$ and environmental conditions $z$. In fact, it will ease the design of good schemes if it has only local information, say the costs for a limited set of possible output vectors and given its specific local conditions.

The regulator, on the other hand, only knows the general nature of the cost function a priori, say that

$$C(.;.) : \mathbb{R}^{r+p} \rightarrow \mathbb{R} \tag{9.11}$$

belongs to a set to a class $\mathbb{C}$ of possible cost functions. The classes we consider here are

$$\begin{aligned}
\mathbb{C}(\mathrm{crs}) &= \{c(.;.) : \mathbb{R}^{r+q} \rightarrow \mathbb{R} | c(.;.) \text{ is in-(de)-creasing in } y \text{ (and } z\text{), convex, crs}\} \\
\mathbb{C}(\mathrm{drs}) &= \{c(.;.) : \mathbb{R}^{r+q} \rightarrow \mathbb{R} | c(.;.) \text{ is in-(de)-creasing in } y \text{ (and } z\text{), convex, drs}\} \\
\mathbb{C}(\mathrm{vrs}) &= \{c(.;.) : \mathbb{R}^{r+q} \rightarrow \mathbb{R} | c(.;.) \text{ is in-(de)-creasing in } y \text{ (and } z\text{), convex}\} \\
\mathbb{C}(\mathrm{fdh}) &= \{c(.;.) : \mathbb{R}^{r+q} \rightarrow \mathbb{R} | c(.;.) \text{ is in-(de)-creasing in } y \text{ (and } z\text{)}\}
\end{aligned} \tag{9.12}$$

where $C(.;.)$ being crs means that $C(ky;kz) = kC(y;z)$ for all $k \geq 0$ and $C(.;.)$ being drs means that $C(ky;kz) = kC(y;z)$ for all $1 \geq k \geq 0$. In addition, the regulator knows that the realized productions plans are possible, i.e. that

$$x^i \geq C(y^i;z^i),\ i = 1, \ldots, n \tag{9.13}$$

We note that the analysis below can be undertaken using different assumptions about the information available to the regulator. Thus, e.g. the regulator may know that there are fixed unit costs of the different outputs, but be uninformed about the exact unit costs, cf. Bogetoft(2000). Also, the classes of possible cost functions could be extended, cf. Bogetoft (1994a, 1997).

In terms of *preferences*, we assume that the DMU is risk neutral and has limited liability, and that it seeks to maximize a weighted sum of profit and slack. The risk neutrality is a simplification compared to, e.g. Bogetoft (1994a,?). Assuming that the incentive payments only introduce marginal variations, however, it is not an invalidating assumption. Moreover, the DMU's liability is assumed to be limited in the sense that it will only participate in the schemes if the resulting utility exceeds a minimum value, $Q$, with certainty. This may reflect risk aversion as well.

The DMU's resulting utility is assumed to be the utility from payment and disutility from effort

$$U(B,c,y,z) = (B-c) + \rho(c - C(y;z)) \tag{9.14}$$

when it uses costs $c$ to produce $y$ with environmental variables $y$ and is reimbursed $B$. The first term, $B-c$, is the profit. The second term is the excess costs or slack, $c - C(y;z)$, multiplied by the value of slack compared to profit, $\rho$.

The aim of the regulator is simply to minimize the costs of inducing the DMU to produce output $y$ in the context of $z$.

Assuming that the realized costs $c$, outputs $y$ and environmental variables $z$ are all verifiable, the regulator's problem for any given output vector $y$ and any given environment $z$ is one of minimizing the expected costs of making the agent accept implement $y$ given $z$. This can be formulated as one of designing a $(x,y,z)$ contingent reimbursement plan $B(x,y,z)$ that solves the following contract design problem

$$\begin{array}{ll}
\min E_C[B(x(C,y,z),y,z)] & \\
x(.,.,.) & \\
\text{s.t.} & \\
B(x(C,y,z),y,z) - x(C,y,z) + \rho[x(C,y,z) - C(y;z)] \geq Q \forall C(.,.) & (IR) \\
B(x(C,y,z),y,z) - x(C,y,z) + \rho[x(C,y,z) - C(y;z)] \geq & \\
\quad B(x',y',z) - x' + \rho[x' - C(y';z)] \forall C, x', y' : x' \geq C(y';z) & (IC)
\end{array} \tag{9.15}$$

In this problem, $x(C,y,z)$ is the cost level chosen by the DMU when the cost function is C, the output is y and the environmental variables are $z$. This is a usual contract design problem, where the individual rationality constraint $(IR)$ ensures that the DMU will participate for all possible cost functions, while the incentive compatibility constraint $(IC)$ ensures that it is a best response for the DMU to pick cost strategy $x(.,.,.)$ and produce $y$ with environmental variables $z$.

If some of the variables $(c,y,z)$ can not be contracted upon, additional constraints may be introduced. Thus, e.g. if the actual costs $c$ is non-verifiable, we impose $B(x,y,z) = B(y,z) \forall x$.

The solution to this problem can be derived following the lines in Bogetoft (2000), extended by the introduction of the non-controllable environmental inputs $z$. Let $C^{\text{DEA}}(y;z)$

be the DEA estimated cost function of producing $y$ given $z$, i.e.

$$
\begin{aligned}
C^{\mathrm{DEA}}(y;z) = \min c & \\
\text{s.t.} \quad c &\geq \sum_{j=1}^{n} \lambda^j c^j \\
z &\geq \sum_{j=1}^{n} \lambda^j z^j \\
y &\leq \sum_{j=1}^{n} \lambda^j y^j \\
\lambda &\in \Lambda(s)
\end{aligned}
\tag{9.16}
$$

where $s$=crs, drs, vrs or fdh depending on the regulator's assumed a priori knowledge about the class of underlying costs functions. (This problem may not have feasible solutions. Ways to deal with this are discussed in Bogetoft (1997, 2000)).

Now, when the actual costs cannot be contracted upon, $B(x,y,z) = B(y,z)\forall x$, the optimal solution is to use the following revenue cap with non-verifiable cost information:

$$B(y,z) = Q + C^{\mathrm{DEA}}(y;z) \tag{9.17}$$

i.e. the optimal reimbursement equals a lump sum payment to cover the reservation utility, $Q$, plus the DEA-estimated cost norm for the given output y and environmental variables $z$.

If instead, we assume that the actual costs of the DMU can be contracted upon, the optimal reimbursement scheme becomes

$$B(c,y,z) = Q + c + \rho(C^{\mathrm{DEA}}(y;z) - c) \tag{9.18}$$

i.e. the optimal reimbursement equals a lump sum payment, $Q$, plus the actual costs, $c$, plus a fraction $\rho$ of the DEA-estimated cost savings, $\rho(C^{\mathrm{DEA}}(y;z) - c)$.

The structure of this payment scheme can be interpreted as a DEA based yardstick model: Using the performance of the other DMUs, the regulator creates a cost yardstick and the regulated DMU is allowed to keep a fraction $\rho$ of his saving compared to the yardstick costs as his effective compensation. Figure 9.5 illustrates this reimbursement scheme.

Several extensions and generalizations of these results are possible. Most significantly, we show in Bogetoft (1997) how the above setting can be extended to a simultaneous game among multiple DMUs in the spirit of traditional yardstick competition, cf. Shleifer (1985). The contract design problem in this case becomes a multiple agents model, where the (IC) constraints define a Bayesian equilibrium among the agents. Assuming verifiable costs information, the resulting yardstick scheme is like the one above. For a given DMU, one just needs to interpret the DEA based cost function as the cost model that can be derived *ex post* from the observation of the other units. This corresponds to the use of so-called super-efficiency in a usual DEA model, cf. also Bogetoft (1997). Hence, in the simultaneous yardstick model, the regulator commits himself a priori to making a DEA super-efficiency evaluation *ex post*, and to let this evaluation determine the revenue to the DMUs.

In Bogetoft (1997), we also show how to extend the yardstick setting to cases, where the regulator can observe more detailed input consumptions and possibly different factor prices. In this case, the DEA cost function used above shall simply be derived from the underlying detailed DEA model, i.e. the DEA based cost norm for DMU$^i$ becomes

$$C^{\mathrm{DEA}-i}(y^i;z^i,\omega^i) = \min_x \{\omega^i x | (x,z^i,y^i) \in T^{\mathrm{DEA}-i}\} \tag{9.19}$$

where $\omega$ is the factor prices for DMU$^i$, and $T^{\mathrm{DEA}-i}$ is the DEA approximation of the technology based on detailed data from all units except unit $i$.

In Bogetoft (2000), we also show how the structure of the optimal scheme is essentially unaffected by introducing decentralized decision making (where the DMU, e.g. the forest owners, decide on the output mix), as well as participatory budgeting arrangements (where non-verifiable costs estimates are communicated a priori).

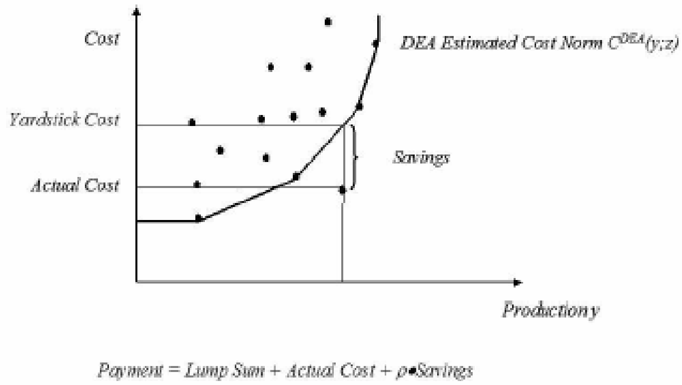


Figure 9.5: *The DEA Yardstick Model in the Production-Cost Space*

In Agrell *et al.* (2002a,b), we introduce a time dimension in the yardstick model. The dynamic perspective gives rise to several new issues. One is the possibility of accumulating and using new information. Another is the need to avoid the ratchet effect, i.e. deliberate sub-performance in early periods to avoid facing standards that are too tough in the future.

Nevertheless, the structure of the optimal dynamic scheme is similar to the ones developed above. Thus, the optimal revenue cap for a DMU is found as a DEA based yardstick norm. Assuming verifiable actual costs, the optimal scheme taking into account the generation of new information, the ratchet effect and the possibility of technical progress becomes:

$$Bt(c_t, y_t, z_t) = Q + c_t + \rho(C^{\text{DEA}}_{1-t}(y_t, z_t) - c_t) \tag{9.20}$$

i.e. the optimal reimbursement to the DMU in period $t$, $B_t(c_t, y_t, z_t)$, equals a lump sum payment, $Q$, plus actual costs in period $t$, $c_t$, plus a fraction $\rho$ of the DEA estimated cost savings in period $t$, $\rho(C^{\text{DEA}}_{1-t}(y_t, z_t) - c_t)$, using all the information from the other DMUs generated in periods 1 through $t$.

In Agrell *et al.* (2002a,b), we also consider how to modify the schemes to take into account the possibly of limited catch-up capacity, i.e. the fact that it may take time for a DMU to learn the best practice and the possible cost of innovation (frontier movements).

We close this Section by noting that the use of yardstick schemes is not new to farmers. Elements of yardstick competition have long been part of existing production contracts. Yardstick competition in these contracts, however, is typically introduced to cope with a single aspect, say the impact of sowing time or feed quality, cf. Bogetoft & Olsen (2002); Olsen (2002) for recent and rather advanced examples. To the best of our knowledge, however, the use of multiple dimensional yardstick schemes like the ones suggested have not previously been part of the natural resource management literature. To the extent that multiple dimensional aspects have been dealt with, it has been done by introducing a common aggregation of the different dimensions a priori, rather than by using agent specific, endogenous aggregations as it is implicitly done in the DEA approach.

## DEA and Procurement Auctions

In the traditional DEA literature, the focus is on the evaluation of past performances using past production data. In the DEA incentive literature, the focus is on the use of historical or future production data to monitor the agents and to motivate them to take proper actions by committing *ex ante* to a payment principle *ex post*.

We now introduce a third potential use of DEA, namely to evaluate non-realized multi-dimensional bids (as opposed to realized production plans) in a procurement setting (as opposed to a control setting). In particular, we suggest that an allocation and price setting mechanism along the lines of the DEA based yardstick schemes can be a useful generalization of a second price sealed bid auction mechanism.

### Multi-Dimensional Auctions

Although there are many practical instances of multidimensional auctions, e.g. the conservation reserve program in the USA, cf. e.g. Vukina *et al.* (2000), and the Department of Defence procurement auctions for weapon systems in the USA, cf. e.g. Che (1993), the theoretical literature on multi-dimensional auctions is sparse.

In a standard auction or procurement context, where a single quality product is supplied, the revenue equivalence between first price and second price auctions is the most central result. It was suggested by Vickrey (1961), but remained a puzzle until 1981 where Riley & Samuelson (1981); Myerson (1981) simultaneously solved the problem. They show that in an independent private value model, the different mechanisms give the same expected revenue (or costs) to the principal.

Che (1993) shows how the existing theory can be generalized to multidimensional auctions. He considers allocating contracts containing a price $p$ and a one-dimensional quality parameter $q$. The principal's utility function is $U(p,q) = V(q) - P$, where $V(q)$ is a concave function that values quality. An agent DMU$^i$ that wins a contract earns profit $\pi^i(p,q) = p - c(q,\theta_i)$, where $p$ is the price he is paid, $q$ is the quality he must deliver, $\theta_i$ is his type and $c(q,\theta_i)$ is his costs of producing quality $q$. The principal selects a quasi-linear score function: $S(p,q) = s(q) - p$. The agents with highest scores are offered a contract. The exact terms of the contracts depend on which mechanism is chosen. Che (1993) considers two different mechanism:

- First score auction - the bidder with the highest score wins and the winner has to meet the highest score. A first score auction can be compared with the first price auction.

- Second score auction - the bidder with the highest score wins and the winner has to meet the second highest score. A score auction can be compared with the second price auction.

He shows an equivalence theorem for the two types of score auctions. Both auctions are optimal second best mechanisms.

### DEA Based Procurement

We now propose a DEA based procurement scheme that generalizes the second price scheme to a multiple dimensional context. It leads to truthful revelation of costs and works with a broad class of underlying cost functions like the DEA based yardstick scheme.

We consider a principal who wants one or more of $n$ agents or DMUs to improve the environment. To determine which agents to call upon and the compensation to award them, the regulator organizes a multiple dimensional, multiple unit procurement auction. Initially, the agents submit bids, and based hereon the regulator determines which offers to use and how to compensate the corresponding agents. Next, the agents pick the actual production plans, including slack, and payment is realized when the promised outputs are delivered.

A bid from $\mathrm{DMU}^i$ is now an $r$-dimensional environmental improvement vector $y^i \in \mathbb{R}^r$ and a cost $c^i \in \mathbb{R}$. In addition, a series of non-controllable variables $z^i \in \mathbb{R}^q$ like type of land, distance to reservoir, etc. is common knowledge to the agents and the regulator. The underlying costs of producing $y^i$ in the context of $z^i$, $C(y^i, z^i)$, is private information to the agents. The regulator simply knows that the costs originate from a common cost function $C(.;.)$ from a class $\mathbb{C}(s)$, where $s =$ crs, drs, vrs or fdh.

To keep things simple at this stage, we assume that $\mathrm{DMU}^i$ can only choose one production plan $y^i$. Also, we assume that the production plans $y = (y^1, \ldots, y^n)$ and non-controllable context or state variables $z = (z^1, \ldots, z^n)$ can be perfectly verified and hence costlessly contracted upon. (In a generalized setting, each $\mathrm{DMU}^i$ will have a whole set $Y^i$ of technically feasible production plans given its other activities and each $\mathrm{DMU}^i$ will submit multiple bids corresponding to the different productions in $Y^i$).

We assume that the agents are risk neutral and that they maximize profit and slack with a relative value of slack compared to profit. That is, when $\mathrm{DMU}^i$ gets compensated $B^i$ for producing $y^i$ and when he actually uses $(x^i, z^i)$, he is left with a utility of $B^i - x^i + \rho(x^i - C(y^i; z^i))$.

Also, we assume that the regulator maximizes the value of environmental gains $U(., \ldots, .)$ minus the costs of inducing the agents to undertake the production. The costs needed to pay the agents are inflated with $(1+k) > 1$, to reflect the economy wide misallocations resulting from the generation of the necessary funding via tax payments.

Before formalizing the regulator's problem, we note that the cost (types) of the different DMUs are correlated. We know that the actual costs of the DMUs all originate from the same underlying cost function. The set of possible cost functions, however, is very large. This means that types are not perfectly correlated. On the other hand, they are also not independent. We argue that the assumed correlation is very natural by its relationship to production theory. The underlying cost function may be interpreted as the long run cost function while the costs of the individual DMUs may be thought of as originating from local, short run cost curves.

We will now formalize the regulator's problem, suggest a procurement procedure and discuss the basic properties of the procedure.

To do so, we introduce decision variable $d^i, i = 1, \ldots, n$ to reflect which agents are actually selected to produce the desired outputs, $\{i \in \{1, \ldots, n\} | d^i = 1\}$, and which are not, $\{i \in \{1, \ldots, n\} | d^i = 0\}$. Note that in general, the decision variables will depend on all the bids of all the agents, $d^i = d^i(c, y, z)$. Using the revelation principle, we can without loss of generality impose truth-telling constraints, i.e. assume that the costs reported by $\mathrm{DMU}^i$ together with a $(y^i, z^i)$ is $c^i = C(y^i; z^i)$. The regulator's problem (with a variable budget) can therefore be formulated as

$$
\begin{array}{lr}
\max_{d(.),B(.),x(.)} & \\
E_c\left[U(d^1(c,y,z)(z^1,y^1),\ldots,d^n(c,y,z)(z^n,y^n)) - (1+k)\sum_i d^i(c,y,z)B^i(c,y,z)\right] & \\
\text{s.t.} & \\
E_{c^{-i}|c^i}\left[d^i(c,y,z)((B^i(c,y,z) + \rho(x^i - C(y^i;z^i)) - Q^i\right] \geq 0, \forall C \in \mathbb{C}(s), i = 1,\ldots,n & (IR) \\
E_{c^{-i}|c^i}\left[d^i(c,y,z)((B^i(c,y,z) - x^i) + \rho(x^i - C(y^i;z^i)) - Q^i\right] \geq & \\
\quad E_{c^{-i}|c^i}\left[d^i(c^{i*},c^{-i},y,z)((B^i(c^{i*},c^{-i},y,z) - x^{i*}) + \rho(x^{i*} - C(y^{i*};z^i)) - Q^i\right] & \\
\quad \forall C \in \mathbb{C}(s), c^{i*}, x^{i*}, i = 1,\ldots,n & (IC) \\
d^i(c,y,z) \in 0,1 \forall c,y,z, i = 1,\ldots,n & \\
c^i = C(y^i;z^i) \leq C(y^i,z^i) \forall C \in \mathbb{C}(s), i = 1,\ldots,n & \\
 & (9.21)
\end{array}
$$

The objective function is the expected environmental value minus social costs. Expectation is taken with respect to the underlying, unknown costs, $c$, to the DMUs of producing the outputs. The regulator's choice variables concern which DMUs to accept in the program, $d$, and what to pay, $B$. In addition, the regulator must predict the actual costs that the accepted agents will use, $x$. The first set of constraints is the individual rationality constraints. They ensure that all DMUs, given their private information about their costs, expect to get at least their reservation utility of $Q^i$ if they are selected. Note that in the chosen formulation, we assume that the DMUs only know their own costs, not the costs of the other DMUs. The second set of constraints is the usual incentive compatibility constraints. They say that no agent would ever like to deviate from truth-telling about costs, $c^i$, and from choosing actual costs according to $x^i$.

Consider now the following DEA based procurement auction to deal with this problem:

**Stage 1: Bidding.** The DMUs submit (cost, context, output) bids $(ci, zi, yi), i = 1, \ldots, n$

**Stage 2: Cost Norms.** The regulator uses the submitted bids to determine DEA based cost norms. The cost norm for DMU$^i$ , $C^{textDEA} - i(y^i; z^i)$ is determined, based on the bids of the other units

$$\begin{aligned}
&C^{\mathrm{DEA}} - i(y^i; z^i) = \min c \\
&\text{s.t.} \\
&c \geq \sum_{j \neq i} \lambda^j c^j \\
&z^i \geq \sum_{j \neq i} \lambda^j z^j \\
&y^i \leq \sum_{j \neq i} \lambda^j y^j \\
&\lambda \in \Lambda(s)
\end{aligned} \tag{9.22}$$

**Stage 3: Selection.** The regulator selects DMUs by solving

$$\begin{aligned}
&\max U(d^1(z^1, y^1), d^2(z^2, x^2), \ldots, d^n(z^n, y^n) - (1+k) \textstyle\sum_i d^i(Q^i + C^{\mathrm{DEA}-i}(y^i; z^i) \\
&\text{s.t.} \quad d^i \in \{0,1\}, \text{for } i = 1, \ldots, n
\end{aligned} \tag{9.23}$$

**Stage 4: Payment.** If DMU$^i$ is selected, $d^i = 1$, it is instructed to produce $y^i$ and it is paid $B^i(c, z, y) = Q^i + C^{\mathrm{DEA}} - i(y^i; z^i)$.

The idea of this procedure is simple. The regulator uses the bids from the bidding round to estimate DEA based cost norms for the individual DMUs. Using these cost norms, the regulator then makes the necessary trade-offs between the environmental benefits and the costs of acquiring them. Finally, the payments to the selected DMUs are settled as the DEA estimated cost norms plus reservation utilities, just like in the yardstick competition model with non-verifiable actual costs.

The DEA based procurement auction gives a feasible and cost efficient solution to the regulator's procurement problem. To see this, assume truthful cost revelation to all DMUs but DMU$^i$. It follows from the minimal extrapolation principle that $C(y^i; z^i) \leq C^{\mathrm{DEA}-i}(y^i, z^i)$. Now, since the value of slack is less than 1, the best response of DMU$^i$ is to choose $c^i = C(y^i; z^i)$ and $x^i = C(y^i; z^i)$, i.e. to reveal the true costs and to produce outputs at least possible costs. We therefore have that the suggested scheme is 1) individually rational and 2) incentive compatible. Moreover, we note that the resulting solution is 3) cost efficient in the sense that no DMU would like to introduce slack in the final production plan.

Also, the DEA based procurement auction will sometimes be an optimal solution to the regulator's procurement problem. To see this, consider a case with considerable environmental benefits $B$ such that we would ideally like all DMUs to produce the environmental goods. In such cases, it cannot be part of an optimal solution to ration production, i.e. to forgo production in some cases, i.e. for some cost types to make production for other cost types cheaper. Now, to make sure that it is individually rational for all to produce under all possible cost functions, we cannot pay less that $B^i(c, z, y) = Q^i + C^{\mathrm{DEA}} - i(y^i; z^i)$ since for some cost types, we will have $Q^i + C^{\mathrm{DEA}} - i(y^i; z^i) = Q^i + C(y^i; z^i)$. Therefore, if he was paid anything less, it would not be a best response to accept the offer. Since other cost types can imitate this one, no one can be paid anything less than $Q^i + C^{\mathrm{DEA}} - i(y^i; z^i)$, i.e. the solution is optimal when rationing cannot be accepted.

Finally, we suggest that the DEA based procurement auction will often be near-optimal. To see this, note that the DEA approximation of the cost structure will provide a close fit in many cases. Having observed $n-1$ observations on the $C(.;.)$ curve, the piecewise linear approximation will typically not deviate too much for points close to the observed ones. (If every DMU could submit multiple bids, the approximation would even improve).

The DEA based schemes above can of course be extended in several directions. In particular, one could combine the initial bidding with an *ex-post* evaluation and verification of actual costs using a yardstick scheme like in the previous section. Also, to save on the information rents, it may be attractive for a regulator with not overly large benefits to ration away some production. As suggested in Bogetoft (1997), the optimal rationing procedure would correspond to including artificial plans in the estimation of the DEA cost norms. We leave such extensions to future research.

## Final Remarks

In this paper, we have discussed the pros and cons of using Data Envelopment Analysis (DEA) to evaluate and enhance the efficiency of natural resource management.

Natural resource management problems often involve complex production structures, with joint production of multiple products simultaneously. Moreover, there are non-trivial inputs to the production process that cannot be controlled. There are also non-trivial elements of asymmetric information about the conditions and preferences of the different landowners. Last but not least, there are often several entities performing similar operations, and this allows the recording of relatively good and detailed data on practices in a large number of units. The DEA modeling is particular useful in these circumstances because of its ability to handle multiple inputs and outputs, to work with flexible production structure, to incorporate local variables, and to work with limited or no preference information. Moreover, the need in DEA for good data from several, similar units is often possible to fulfill.

To cope with delegated production and incentive problems, the DEA approach can also be useful. We reviewed some basic results on DEA based incentive schemes. These schemes can be used in motivating landowners to take desired decisions, e.g. to reduce N-leaching. Finally, we indicated how a DEA based procurement procedure could be used to select farmers and forestowners for a program, e.g. to enhance environmental qualities.

There are several, relevant extensions of the research reported here. We suggest that future research should focus in particular on the development of multi-dimensional procurement auctions. The discrepancy between practical ad hoc procedures in coping with multiple dimensions and the simplified, usually single dimensional theoretical models, is particularly striking. We believe that developments along the lines of the DEA based auctions may lead to new approaches that can solve real problems using sound theory.

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