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The Efficiency of Public Forestry Organizations: A Comparison of Different Weight Restriction Approaches

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Abstract

Data Envelopment Analysis (DEA) has become an increasingly popular approach to analyze the efficiency of public sector organizations. However, the underlying assumption of the method is that it is equally acceptable to specialize in producing any output or consuming any input. In many cases this kind of free specialization is not acceptable or desirable. In this paper, we use three extensions developed to the DEA method to incorporate additional judgment into the DEA models and study the sensitiveness of the efficiency scores. The results indicate that even moderate restrictions on output weights in the optimization problem may lead to substantial changes in efficiency. It also seems that by analyzing only the technical efficiency, e.g., using only standard DEA without placing some kind of constraints on input and output weights, may lead to highly unreliable conclusions.

Keywords: Data Envelopment Analysis, Overall Efficiency, Economic Efficiency, Assurance Regions.

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The Efficiency of Public Forestry Organizations: A Comparison of Different Weight Restriction Approaches

Tarja Joro
Esa-Jussi Viitala

1. Introduction

The productivity and efficiency of public organizations have received increasing attention during recent years. However, for some reasons this kind of research has mostly been lacking in forestry and there appears to be only four studies dealing with the efficiency of public forestry organizations: Kao and Yang (1991, 1992) and Kao *et al.* (1993) measured the efficiency of forest districts in Taiwan whereas Viitala and Hänninen (1998) evaluated the efficiency of public Forestry Boards in Finland. One of the main conclusions of the latter study was that there was a substantial variation in efficiency across Forestry Boards with a potential for input saving of 20% on average.

All the above studies used a nonparametric linear programming method, Data Envelopment Analysis (DEA) originally proposed by Charnes *et al.* (1978), to form a deterministic production frontier and to calculate the technical efficiencies. In DEA, a unit is efficient if there is no other unit – existing or virtual – that can either produce more outputs by consuming the same amount or less inputs, or produce the same amount or more outputs by consuming less or the same amount of inputs as the unit under consideration.

However, one of the disadvantages of the DEA method is that it treats all outputs (and/or inputs) as equally valuable by allowing total flexibility of input and output weights in the optimization problem. In practice, the method attempts to show each unit in the best possible light by assigning the greatest weight to those outputs where the ratio between inputs and outputs is relatively high. Thus, it is implicitly assumed that it is equally acceptable to specialize in producing any output or consuming any input. As a result, it is possible that a unit is rated efficient due to a single input or output while practically ignoring all the other inputs and outputs.

In many cases this kind of free specialization is not acceptable or desirable. For example, in the public forestry organizations and in the service sector organizations in general, one input (salary expenditures, number of employees) usually overwhelms all other inputs, and ignoring this aspect may lead to biased efficiency results. Organizations might also produce some outputs that require considerably more resources than others and this marginal rate of substitution between outputs should somehow be taken into account when calculating efficiency.

If we want to avoid the problem of free (and often undesirable) specialization, input and output weights should be constrained in DEA. In other words, we need to have a mechanism to incorporate the judgment of preferences over different inputs and outputs into the model. The classical way to do this is to restrict the weights assigned to different outputs and inputs in the optimization problem.[1] This is often possible since we typically know something about the input prices (e.g., salaries, capital costs, overheads) although they are not necessarily market goods or services. In many cases, some preference, cost, or value information concerning the outputs is also available.

In the literature, several weight restriction schemes exist that can be used in DEA, see e.g., Thompson *et al.* (1986, 1990), Dyson and Thanassoulis (1988) and Roll *et al.* (1992). In their review, Allen *et al*. (1997) concluded that the different weight restricting approaches have been developed to respond to the needs of a specific application. However, until now there has been no attempt to empirically compare the impacts of different weight restriction approaches on the efficiency results.

In this study, we use three different extensions developed to the DEA method to incorporate additional judgment into the efficiency models and compare their effects on the efficiency scores of a public forestry organization. Whereas the earlier DEA applications in forestry have concentrated purely on technical efficiency and thereby have been interested in whether the units do the things in the right way, our extensions — incorporating preference information — are an attempt to evaluate whether the units also do the right things; that is, whether their input and output combination is optimal according to some profitability criteria.

This paper proceeds as follows. First, we describe the various approaches that have been suggested to incorporate value and judgment information in DEA. After this, we empirically test the impacts of different weight restriction approaches on the efficiency scores; first, by adding ordinal information about the value of various outputs, second, by setting so-called assurance regions to output weights, and finally, by using explicit per unit cost information concerning outputs to calculate the overall (economic) efficiencies. The last section concludes the paper.

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[1] In addition to restricting weight flexibility in the optimization problem, other approaches also exist to incorporate preferences into DEA, see e.g., Halme *et al*. (1999) and Thanassoulis and Allen (1998).

2. Approaches to Incorporate Additional Information into DEA

Generally, the weight restriction approaches can be divided into two main categories: absolute and relative weight restrictions. In the first category, some *absolute* upper and/or lower bounds are placed on the weights in the optimization problem. For example, one may require the weight (price) of an output to be at most, say 0.0003. However, the obvious disadvantage of this approach is that the magnitude of the input and output weights depend on the magnitude of the inputs and outputs. Because absolute weights are also scaling factors, it is not necessarily easy to determine meaningful absolute bounds and to interpret them.

The second category attempts to overcome these problems by assigning *relative* weight restrictions. The simplest form of relative weight restrictions is the (weak partial) ordering of input and output weights in order to avoid nonrealistic pricing. This approach was first suggested by Golany (1988), and later Ali *et al.* (1991) proposed the use of strict (partial) ordering. The idea is to maintain the ordering of the prices in the weighting; thus if we know, for instance, that one unit of output A is more valuable than one unit of output B, the weights should reflect this. However, the model does not use any information on how much more expensive the unit price is of output A.

Probably the most widely used weight restriction approaches are the so-called assurance region (AR) models by Thompson *et al.* (1986, 1990). In these models upper and lower bounds are introduced to the relations between two output (or input) weights (AR I), or to the relation of an output and an input weight (AR II). In the optimization problem one may, for example, require that the weight (price) of output A is at least three and at most five times that of output B. The obvious advantage of AR I restrictions is that they reflect the marginal rates of substitution, which makes them relatively easy to interpret. In the case of one input, the AR II restrictions, in turn, reflect the relative prices of outputs in terms of the input.

One way to see this kind of additional information in DEA is that it defines a range for prices (see Charnes *et al*., 1990). Hence, the above models that attempt to incorporate preference information into DEA can be seen as some kind of intermediate approaches between the traditional DEA analysis, concentrating only on technical (and scale) efficiency, and the analysis of overall efficiency that requires price information on inputs and outputs.

Indeed, when moving from weight restriction models to the analysis of overall efficiency, precise price information instead of price ranges is incorporated into the analysis. If cost minimization is assumed, the units are compared to a cost isoquant of the cost minimizing input vector at their own output level, which is defined by the output quantities. Respectively, when revenue maximization is assumed the units are compared to a revenue isoquant of the revenue maximizing output vector at their own input level.[2]

[2] A similar approach has been used in the distance function literature (see Färe *et al*., 1994).

Later in this work, we propose a modification of the overall efficiency model where price information both on inputs and outputs are used. The approach is technically an AR I model with equality constraints applied to both inputs and outputs but the relation of the weights is restricted to a single given ratio instead of a range. The difference to technical efficiency is, of course, that with cost minimization the output level is now defined by the aggregated monetary value of the outputs — the revenue — instead of output quantities.

3. Data and Methods

3.1. Data

We use the same data as Viitala and Hänninen (1998) who specified one input (total costs) and 15 outputs in their model.[3] The input data (for 1993–94) were based on official and detailed records of activities that are kept in each Forestry Board (hereafter FBs), whereas data concerning outputs were obtained from annual reports of FBs and National Extension Services.

As there were only 19 FBs, the large number of outputs caused a problem in the original study: if all of the outputs had been included into the model, all FBs except one would have been denoted as efficient. Hence, an alternative approach was used where a different model was constructed for each of the six main activities namely, forest road construction, ditching, forest management planning, training, inspection, and handling administrative matters of forest improvement. Each of the main activities had two or three outputs. After calculating the efficiency scores of these six activities, Viitala and Hänninen (1998) constructed a composite efficiency score by forming a weighted average of the resulting efficiency scores, weights being the cost shares of the activities in each FB. This bears some similarity to the approach proposed by Wong and Beasley (1990) where the proportions *virtual output* devoted to some output is restricted. The interpretation is to restrict the *contribution* that each output can provide to the efficiency score. In Viitala and Hänninen (1998), no such additional restrictions are explicitly used, but due to the way the composite score is formed, no activity can contribute more to the composite efficiency score than its cost share.

3.2. Methods

In this study, we continue with the composite efficiency score approach and calculate the results using two different output weight restriction approaches; that is, ordering of weights and assurance regions (AR I). Although the market prices for outputs were not available, the National Forestry Centre has collected data from the study period about the cost shares of different activities in each FB. Using this cost data, output quantities, and expert opinions about the output marginal rates of substitution in each activity enabled us

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[3] Since the model used input quantities and prices to calculate total costs, the results do not solely reflect technical efficiency.

to calculate the average per unit costs for each of the 15 outputs.[4] This information was then used to determine the weak ordering of output weights and to construct assurance regions. Hence, the output weights used in the various DEA models define the trade-off between different outputs, in terms of the amount of resources used to generate a unit of output.

In order to construct the assurance regions, we also needed information about how much the output per unit costs may vary between FBs due to environmental factors beyond managerial control, such as climate and vegetational conditions and average size of forest holdings, as well as due to possible inaccuracies in the data. The experts in the National Forestry Centre suggested that in most outputs the variation is less than 25%. However, in the two administrative outputs (forest improvement projects approved, regeneration plans approved), the upper limit for the variation was set at 20%, and in training and extension it was 50%. The high variation in the last activity results from the fact that the quality regarding the two outputs, namely forest owners having been offered face-to-face assistance and forest owners attending group extension meetings, may vary in an uneven fashion between FBs.[5]

In order to attain a more comprehensive picture of the sensitivity of the efficiency scores to different weight restriction approaches, we also calculated the overall (economic) efficiencies using the precise output per unit cost information. Since the composite efficiency score approach itself is a weight restriction model and does not fully reveal the impacts of different weight restriction schemes described above, for comparison we also used the traditional DEA approach by including all of the 15 outputs and one input *simultaneously* into each model. Thus, in total, we ended up computing six different efficiency models (*Table 1*).

Table 1: The Efficiency Models.

	Ordering of Weights	Assurance Regions	Overall Efficiency
Composite model	OW-C	AR-C	OE-C
Traditional model	OW	AR	OE

In the OW-C and OW models, the output weights (prices) are restricted to have the same weak ordering as the average per unit costs across FBs. In models AR-C and AR, in turn, the relations between output weights are restricted to a certain interval which was defined by using the average per unit costs and their allowed variation. Finally, models OE-C and OE restrict the relations between output weights to be exactly the same as those between average per unit costs. In the two last models, the deviation from the average per units costs in each output is interpreted to be due to inefficiency although it is possible that environmental and stochastic factors are also relevant in this sense. The models are presented in more detail in Appendix 1.

[4] By expert opinions we refer to our discussions with the foresters of the National Forestry Centre who are responsible for following and guiding FBs' actions. Their opinions are based on long experience in this field and official data of records regarding output per unit costs that has been kept in the National Forestry Centre.

[5] The outputs are described in more detail in Viitala and Hänninen (1998).

4. The Results

4.1 Composite Efficiency Scores

The results show that the composite efficiency scores decreased as more restrictive weight restrictions were placed on the outputs (*Table 2*). For example, after including weak ordinal relationships to reflect the relative worth of various outputs, the average composite efficiency score decreased from 0.77 to 0.74. Although the decrease was moderate in most FBs, the efficiencies of two units (FBs 15 and 16) decreased substantially, by 10% and 13%, respectively. As will be seen later, this characterized the impacts of assigning weight constraints also in general; in some cases the results were consistent with the original model, while in others the efficiencies changed substantially.

When more restrictive weight restrictions were placed on the outputs, the composite efficiency scores declined more and the largest changes occurred again in the same two FBs. Using assurance regions, their composite efficiency scores decreased by 17% and 19%, and when the precise per unit cost information was applied (under the conditions of variable returns to scale, VRS) the tendency toward diminished scores continued. This time, the decreases were in some cases over 20% and most FBs had already an efficiency rating below 0.70. Although the efficiency of other FBs seemed to be fairly consistent across the models — FB 11, for example, was considered to be a high performer in all models — the Wilcoxon signed-rank test indicated significant differences between the models at the 1% level.

Table 2: Comparison of Results from Different DEA Models.

Forestry Board	Composite score in Viitala and Hänninen (1998)	Composite score with ordinal restrictions	Composite score with ARI restrictions	Composite score with cost information (VRS)
1	0.74	0.73	0.72	0.72
2	0.71	0.67	0.66	0.65
3	0.72	0.65	0.62	0.61
4	0.66	0.65	0.64	0.63
5	0.65	0.62	0.60	0.59
6	0.76	0.75	0.73	0.73
7	0.65	0.64	0.64	0.63
8	0.75	0.71	0.70	0.69
9	0.73	0.72	0.70	0.69
10	0.72	0.69	0.67	0.65
11	0.91	0.91	0.91	0.90
12	0.70	0.66	0.59	0.58
13	0.94	0.88	0.84	0.82
14	0.87	0.87	0.85	0.85
15	0.87	0.78	0.72	0.70
16	0.79	0.69	0.64	0.61
17	0.83	0.81	0.76	0.72
18	0.85	0.82	0.79	0.72
19	0.86	0.83	0.77	0.76
Mean	0.77	0.74	0.71	0.70
SD	0.09	0.09	0.09	0.09
Min	0.65	0.62	0.59	0.58
Max	0.94	0.91	0.91	0.90

Changes in Rankings

Rankings are often used to evaluate different units and therefore it is interesting to study how they changed when weight restrictions were incorporated into the models. Applying the ordering of weights caused only minor changes in the rankings of the FBs compared to the original model except, again, for the same two units, FBs 15 and 16 (*Table 3*). The situation did not change essentially when assurance regions were used or overall efficiency was calculated; the Spearman rank correlations, compared to the original model, were quite high (r=0.87 and 0.83, respectively) and statistically significant at the 1% level.

Table 3: Comparison of Rankings in Composite Model

Forestry Board	Composite score in Viitala and Hänninen (1998)	Composite score with ordinal restrictions	Composite score with ARI restrictions	Composite score with cost information (VRS)
13	1	2	3	3
11	2	1	1	1
15	3	7	9	9
14	4	3	2	2
19	5	4	5	4
18	6	5	4	8
17	7	6	6	7
16	8	13	15	17
6	9	8	7	5
8	10	11	11	11
1	11	9	8	6
9	12	10	10	10
10	13	12	12	13
3	14	16	17	16
2	15	14	13	12
12	16	15	19	19
4	17	17	16	14
7	18	18	14	15
5	19	19	18	18

Consistency of the High and Low Performers

Further insights can be gained by analyzing the consistency of the two most interesting groups, high and low performers. It appears that FBs 11 and 14 were identified as high performers in all of the models and thus can be regarded as valid benchmarks. On the other hand, in the earlier analysis FB 15, for instance, was ranked as the third best performer but now this conclusion seems to be highly questionable. When the ordering of weights was used it was rated seventh, and when overall efficiency was calculated it was only ninth, i.e., it was performing worse than the average FB.

In addition, the low performers were quite consistent across the models but considerable changes occurred in the rankings of the other FBs. The use of assurance regions, for example, caused the ranking of six FBs to change at least three positions, while the calculation of overall efficiency scores resulted in this number increasing to eight. It is likely that the discrepancy between rankings occurred because the output mixes of these particular FBs in the optimization solutions were unilateral.

4.2 Efficiency Scores by Activities

Next, we compared the robustness of efficiency scores in different activities. It appears that the largest efficiency changes occurred in road construction and ditching. Using the ordering of output weights resulted in the average efficiency scores of these activities to decrease by 7 % and 13%, respectively, compared to the original results. As before, in some cases the changes were substantial; in the original DEA analysis FB 16, for example, was considered to be efficient in ditching but after the ordering of weights was assigned, its efficiency score dropped drastically to 0.67. Similarly, two units (FBs 6 and 13) that were originally denoted as fully efficient in ditching suffered from significant efficiency decrease when the ordering of output weights was used; their efficiency ratings decreased to 0.88 and 0.84, respectively. As a result, the number of FBs that had formed the efficient frontier in ditching was reduced from six to three. In forest road construction the weight restrictions caused similar effects.

Using assurance regions, the efficiency scores in road construction and ditching dropped even more, on average by 12% and 15%. However, the impacts were once again varying among FBs. In some units, the efficiency scores did not change at all while in others they decreased over 30%. Overall efficiency scores in road construction and ditching were on average 14% and 16% lower than the original scores, but in some cases the decreases were over 40%. Thus, the results suggest that some FBs had obtained their high technical efficiency in road construction and in ditching by concentrating on producing the less resource consuming (cheaper) outputs.

In forest management planning — the most important activity measured by allocated resources — the original efficiency scores of the FBs did not change at all when the ordering of weights was assigned. As output weights were restricted more, the efficiency scores decreased but the individual changes were still relatively moderate; all were less than 3% under assurance regions and less than 8% when overall efficiency was calculated. The only exception was FB 18, which suffered from an efficiency decrease from 1.00 to 0.87 in the latter case. Otherwise the production frontier was robust, which indicates that in this particular activity the FBs had quite a balanced output mix.

In addition, in training, inspection, and handling the administrative matters the efficiency changes of FBs, if occurred, were small (less than 3%) and there were no changes among the efficient units when the ordering of weights was applied. However, there were clear indications of the sensitiveness of the results. In the original model FB 2, for example, had an efficiency score of 0.94 in training but after applying the ordering of weights its score dropped drastically to 0.62. When assurance regions and precise cost information were used, the changes were, as expected, more substantial. Again, the impact of weight restrictions were very heterogeneous; in most FBs the efficiency change was rather moderate (less than 5%), while in others the scores decreased as much as 20–50%.

Overall Efficiency Graphically

Additional insights can be obtained by examining the overall efficiency of the units graphically (see also Belton and Vickers, 1993). For each FB, the outputs were combined using the precise cost information into a single virtual output representing the aggregated value of the outputs. This virtual output was then graphed against the only input, total costs. *Figure 4.1* illustrates productivity and overall efficiency in forest management planning, and *Figure 4.2* in training.

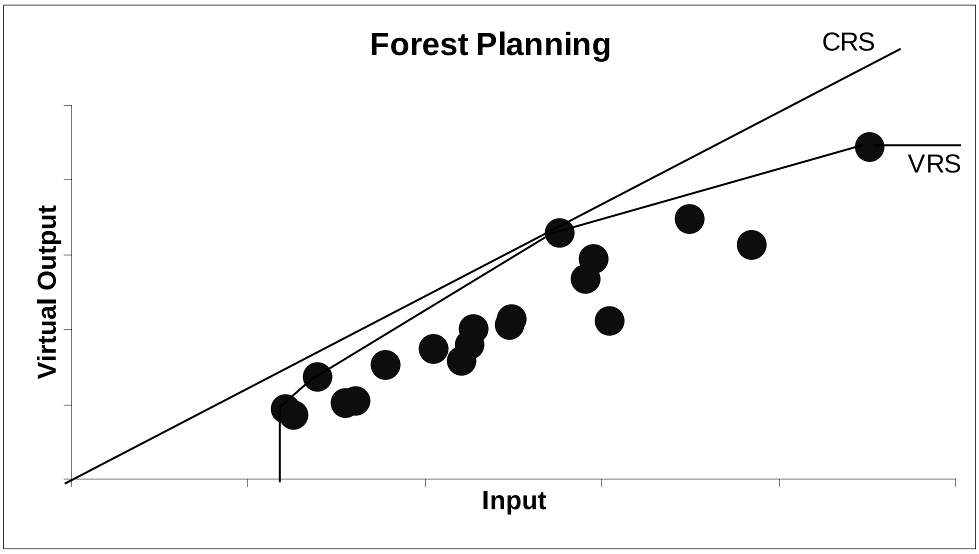

Figure 4.1: Analysis of Overall Efficiency in Forest Management Planning.

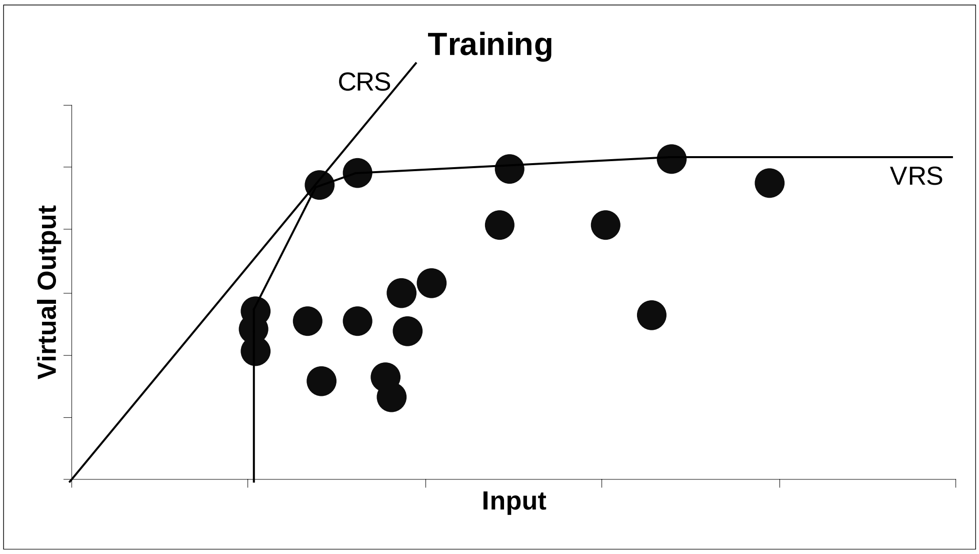

Figure 4.2: Analysis of Overall Efficiency in Training.

In forest management planning all FBs are relatively close to the efficient frontier regardless of whether constant or variable returns to scale is assumed. This indicates that all FBs are performing quite well in this core activity. In training, on the other hand, the observations are very much scattered and the degree of inefficiency (distance from the efficient frontier) appears to depend considerably on the assumption on the scale properties and the choice of orientation (input-saving vs. output maximization). This gives rise to different inferences concerning the overall efficiency in training. Nevertheless, since the cost share of training is relatively low, this activity has only a marginal effect on the composite efficiency scores.

4.3 The Traditional DEA Model

It is interesting to examine what kind of effects the weight restrictions would have had if all of the fifteen outputs and one input had been included simultaneously in the same model. The results suggest that without placing output weight restrictions, all except one FB would have been denoted efficient (*Table 4*). After constraining the ordering of weights, the number of efficient FBs decreased to thirteen and when assurance regions were used it decreased further to six. Note that in some FBs even minor weight restrictions (ordering of weights) caused substantial moves away from the efficient frontier. As with the composite model, the largest relative decrease in the average efficiency occurred when the ordering of weights were replaced by assurance regions. Calculating overall efficiencies and assuming variable returns to scale resulted in only three FBs remained on the efficient frontier.

Table 4: Comparison of Different DEA Model: Efficiency Scores from the Traditional Model.

Forestry Board	Scores of the unrestricted model	Score with ordinal restrictions	Score with ARI restrictions	Score with cost information (VRS)	Score with cost information (CRS)
1	1.00	1.00	1.00	1.00	0.55
2	1.00	1.00	0.85	0.84	0.65
3	0.98	0.86	0.79	0.77	0.75
4	1.00	0.88	0.81	0.80	0.56
5	1.00	1.00	0.78	0.72	0.71
6	1.00	1.00	0.81	0.78	0.72
7	1.00	0.86	0.78	0.74	0.72
8	1.00	1.00	0.87	0.81	0.79
9	1.00	1.00	0.84	0.82	0.73
10	1.00	1.00	0.86	0.80	0.78
11	1.00	1.00	1.00	0.90	0.90
12	1.00	0.98	0.84	0.76	0.76
13	1.00	1.00	1.00	1.00	1.00
14	1.00	1.00	1.00	1.00	0.97
15	1.00	1.00	0.85	0.81	0.81
16	1.00	0.96	0.81	0.76	0.75
17	1.00	1.00	1.00	0.87	0.87
18	1.00	1.00	0.99	0.83	0.82
19	1.00	1.00	1.00	0.88	0.88
Mean	1.00	0.98	0.89	0.84	0.78
SD	0.01	0.05	0.09	0.09	0.12
Min	0.98	0.86	0.78	0.72	0.55
Max	1.00	1.00	1.00	1.00	1.00

Most of the Spearman rank correlations between different weight restriction models were significant at the 1% level (except for the unrestricted model) suggesting that the rankings were quite consistent. However, now the correlations were much lower than with the composite efficiency model. Note also that the three units (FBs 11, 13, and 14) which appeared to be high performers in the composite models, were also high performers according to the traditional DEA models. Again, the Wilcoxon signed-rank test indicated significant differences between the models at the 1% level (5% between the unrestricted model and the ordinal restrictions model).

Graphical analysis of overall efficiency shows that all of the FBs are performing rather close to the efficient frontier (*Figure 4.3*). In assuming constant returns to scale, only FB 13 forms the efficient frontier, while under variable returns to scale the number of efficient units increases to three (FB 1, 13, and 14). The figure, as well as comparing the results of the two overall efficiency models, VRS and CRS, reveals that in general the scale properties had only a minor effect on the attained efficiency scores. However, scale had an important role in determining the efficiency of the three smallest units (FBs 1, 2, and 4). Since there are no FBs operating on the area of decreasing economics to scale —

scale being determined by the turnover — and the smallest FBs operate on the area of increasing returns to scale, it can be concluded that economies of scale could be utilized. In this respect, the reorganization of FBs by combining the small units seems to be justified from a financial point of view, as was concluded also in the previous study by Viitala and Hänninen (1998).

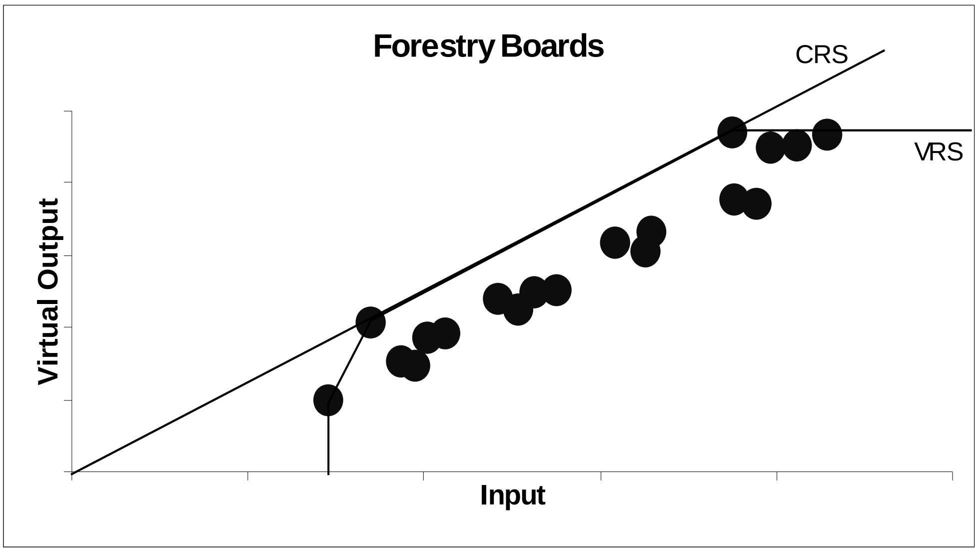

Figure 4.3: Analysis of Overall Efficiency of Forestry Boards

4.4 Explaining the Differences in Efficiency

Finally, we turn our attention to analyzing whether the prime factors determining the efficiency scores remain the same as in the original analysis. Previously, it was found that of the internal factors, management support and style, were most closely associated with organizational efficiency (*Table 5*).[6] This conclusion seems to hold also when the new composite efficiency scores were used as dependent variables in Tobit models. The contribution of these two variables to efficiency in fact increased and became statistically more significant as more restrictive weight constraints were placed on the outputs.

However, in contrast to the previous analysis, forest stocking, which described the environmental factors beyond managerial control, gradually lost its significance as output weights were more constrained. At the same time, a principal component describing employees' perceptions about job design and job satisfaction gained importance and appeared to be statistically significant at the 5% level. In the earlier study, a comparative case study was also performed to explore, in more detail, the relationship between factors under management control and efficiency. The attained conclusions of this study seem to

[6] Two principal components labelled "management support" and "management style" were highly interrelated (r=0.70) and therefore only the first factor was included in the original model. Nevertheless, management style was also found to be statistically significant at the 1% level if management support was excluded, see Viitala and Hänninen (1998).

hold because the two specific units that were originally chosen to represent the high performers (FB 13) and low performers (FB 3) belong to these groups also according to the new analyses.[7]

Table 5: Estimated Results for the Tobit Composite Efficiency Models.

Independent variable	The original model of Viitala and Hänninen (1998)	Composite score model with ordinal restrictions	Composite score model with ARI restrictions	Composite score model with cost information (VRS)
	Coefficient (t-value)			
Constant	0.930 (15.50)	0.834 (13.40)	0.739 (11.76)	0.669 (10.59)
Job clarity	-0.040 (-0.48)	-0.079 (-0.90)	-0.128 (-1.45)	-0.114 (-1.28)
Management support	0.177 (2.38)	0.234 (3.04)	0.286 (3.68)	0.303 (3.88)
Job design and satisfaction	0.082 (0.91)	0.168 (1.79)	0.215 (2.25)	0.225 (2.36)
Organizational climate	-0.025 (-0.57)	-0.034 (-0.72)	-0.035 (-0.74)	-0.036 (-0.75)
Forest stocking in the area	-0.001 (-2.77)	-0.011 (-2.01)	-0.001 (-1.07)	0.000 (-0.31)
Importance of forestry in the area	-0.001 (0.16)	0.004 (0.61)	0.005 (0.77)	0.006 (0.94)
Sigma	0.055 (6.16)	0.057 (6.16)	0.058 (6.16)	0.058 (6.16)
N	19	19	19	19
Log-likelihood	28.1	27.4	27.2	27.1
Pseudo $R^{2\,a}$	0.45	0.42	0.44	0.42

[a] Pseudo $R^2 = \beta'\Sigma_x\beta/(\sigma^2+\beta'\Sigma_x\beta)$ where Σ_x is the sample covariance matrix of the regressors (see e.g., Laitila, 1993).

[7] The results of the qualitative case study suggested that there were significant differences in management support and style between the high and low performing unit. In the high performing FB, the employees felt that an open and informal internal communicational climate had been established, innovative teamworks and flexibility had been encouraged while in the low performing FB, on the other hand, management support and feedback was not common practice, management style was reactive instead of proactive and employees tended to remain in their traditional assignments.

5. Discussion and Conclusions

In this paper we described and incorporated different weight restriction approaches into DEA. The novelty of the paper is that we also compared their effects empirically using data concerning public forestry organizations. The comparison of different DEA models illustrates the importance of controlling for input and outputs weights in the optimization problem. The results indicate that concentrating only on technical efficiency and allowing total flexibility of input and output weights may lead to highly biased conclusions because the relative value of different outputs (and inputs) is ignored.

Note, however, that in our models the full effects of the various weight restriction approaches were somewhat limited for two reasons. First, contrary to traditional DEA models we aggregated all inputs to one cost measure (total costs) because information on salary expenditure, capital costs, and overheads were readily available. Second, regarding the composite score model, the effects of the weight restriction schemes were limited also because efficiency was first calculated separately for each of the six main activities and then composite efficiency score was formed in such a way that each activity could not contribute more to the composite score than its cost share. One would expect that results of the traditional DEA model, in which all the inputs and outputs are simultaneously included without using any preference information, are even more unreliable.

The main conclusion of the study is that when DEA is used the efficiency results can be very sensitive to input and outputs weights. A traditional DEA analysis may show a unit as technically efficient but even a slight restriction of output weights may change the results considerably. Although most empirical studies using DEA to date have considered only input and output quantities, it appears that in many cases it would be very useful to incorporate some kind of additional judgment into the efficiency models in terms of, for instance, ordinal preferences which are often readily available. The more we can incorporate this kind of additional information into DEA, the more reliable efficiency results will be attained and the more practical relevance they will have. The role of weight restrictions is especially important when the various outputs (and inputs) are not of equal value, which is often the case in the service sector and in public forestry organizations.

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Appendix 1: DEA Models

Assume we have n DMUs each consuming m inputs and producing p outputs. Let $\mathbf{X} \in \Re_{+}^{m\times n}$ and $\mathbf{Y} \in \Re_{+}^{s\times n}$ be the matrices, consisting of non-negative elements, containing the observed input and output measures for the DMUs. We further assume that there are no duplicated units in the data set. We denote by $\boldsymbol{x}_j$ (the jth column of $\mathbf{X}$) the vector of inputs consumed by DMUj, and by x_{ij} the quantity of input i consumed by DMUj. A similar notation is used for outputs. Furthermore, we denote $\boldsymbol{1} = [1, ..., 1]^{T}$. We reproduce here the basic input oriented DEA formulations: CCR model with constant returns to scale (Charnes *et al.*, 1978) and BCC model with variable returns to scale (Banker *et al.*, 1984).

Input-Oriented CCR and BCC Primal (CCR_P – I, BCC_P - I)	Input-Oriented CCR and BCC Dual (CCR_P – I, BCC_P - I)
$max\ Z_I = \theta + \varepsilon(\boldsymbol{1}^T\boldsymbol{s}^+ + \boldsymbol{1}^T\boldsymbol{s}^-)$ s.t. (1a) $\mathbf{Y}\lambda - \boldsymbol{s}^+ = \boldsymbol{y}_0$ $\mathbf{X}\lambda + \theta\boldsymbol{x}_0 + \boldsymbol{s}^- = \boldsymbol{0}$ $\lambda \in \Lambda$ $\lambda, \boldsymbol{s}^-, \boldsymbol{s}^+ \geq \boldsymbol{0}$ $\varepsilon > 0$ ε *is a Non-Archimedeal infinitesimal*	$min\ W_I = \mu^T\boldsymbol{y}_0 + \xi$ *s.t.* (1b) $\nu^T\boldsymbol{x}_0 = 1$ $\mu^T\boldsymbol{Y} - \nu^T\boldsymbol{X} + \xi\boldsymbol{1}^T \leq \boldsymbol{0}$ $\xi = \begin{cases} 0, & \text{in a CCR model} \\ \text{free}, & \text{in a BCC model} \end{cases}$ $\mu, \nu \geq \varepsilon\boldsymbol{1}$ $\varepsilon > 0$

Define the set

$$\Lambda = \begin{cases} \{\lambda \mid \lambda \in \Re_{+}^{n}\}, & \text{for a CCR model} \\ \{\lambda \mid \lambda \in \Re_{+}^{n} \text{ and } \boldsymbol{1}^T\lambda = 1\}, & \text{for a BCC model.} \end{cases} \quad (2)$$

A DMU is efficient if $Z_I^* = W_I^* = 1$ and all slack variables $\boldsymbol{s}^-$, $\boldsymbol{s}^+$ equal zero; otherwise it is inefficient (Charnes *et al*., 1994).

Weight restrictions are additional constraints placed on weights of the dual model (1b). In models OW-C and OW, additional weight restrictions of type (3) were used

$$\mu_{r1} \geq \mu_{r2} \geq ... \geq \mu_{rs} \geq \varepsilon. \quad (3)$$

The models AR-C and AR incorporated AR I restrictions of type (4). Here α and β contain the information on the marginal rates of substitution. Equation (4) defines a range for the relation of output weights.

$$\alpha_r \leq \frac{\mu_r}{\mu_{r+1}} \leq \beta_{r.} \tag{4}$$

In OE-C and OE models the relations between the outputs are restricted to a given ratio:

$$\frac{\mu_r}{\mu_{r+1}} = \gamma_{r.} \tag{5}$$

The computations are easier to carry out by calculating the virtual input and virtual output using the weights derived from the ratios and use these as an input and output in one-input – one-output DEA model with CRS or VRS assumptions. It is straightforward to show that this leads to similar results than placing restrictions of type (5).