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Abstract

In Denmark, many small-scale forest owners are affiliated to local district offices of The Danish Forestry Extension Service. Increasing economic pressure has caused a search for more efficiency in the Service, including potential reorganisation. In this paper, the efficiency of the different offices is evaluated using Data Envelopment Analysis (DEA) to approximate their production technology. Furthermore, recent theoretical developments in DEA-analysis are used to assess the gains from a number of potential mergers, and to decompose these gains into those from technological improvements, harmony effects and scale effects. It is found that technological inefficiency is the major source of inefficiency, mergers are only favoured through harmony gains, and for almost all potential mergers the scale effect seems absent or even negative.

Keywords: Data Envelopment Analysis (DEA), efficiency, reorganisation

1 Introduction

The fall of the Iron Curtain and the opening of the forests of Eastern Europe to the world market has put pressure on the prices of low-quality coniferous roundwood in Western Europe. This has increased the economic pressure on private forestry, including Danish small and medium scale private forest owners. In Denmark, many of these forest owners are affiliated to local district offices of The Danish Forest Extension Service (DFES), which they own on a corporate basis. DFES assists non-industrial forest owners in, e.g. preparing forest management plans, and in performing timber and Christmas tree sales, forest operations, purchases of seedlings, and different consultancy tasks. The increased economic pressure is also felt in DFES and has lead to discussions of exploiting potential gains from merging some of the offices.

The current study is not the first to apply Data Envelopment Analysis (DEA) to analyse the efficiency of different forestry related organisations. Rhodes (1986) used DEA to assess differences in the performance of national parks in the US. Kao and Yang (1991,1992) and Kao et al. (1993) applied DEA to analyse the efficiency of forest districts in Taiwan, and Viitala and Hänninen (1998) estimate the potential efficiency improvements of 19 regional forestry boards in Finland. Brännlund *et al.* (1998) evaluate the gains from emission trading in the Sewdish pulp and paper industry. Recently, Yin (2001) analysed the efficiency of pulpwood industries in several different countries, and Kao (2001) extends the analysis by Kao and Yang (1992). Other recent studies include Yin (1998) and Yin (1999) . All of these studies almost exclusively discuss the technological and allocative efficiency of independent production units, i.e. the potential gains from improved production techniques, procedures and routines in the individual units. The only exceptions are Kao and Yang (1992) and Kao (2001), who also consider the overall efficiency of a few hypothetical mergers of forest districts.

In this paper, we estimate the individual efficiency of the 14 offices constituting DFES. Furthermore, we evaluate the potential gains of merging a number of offices and use the decomposition principle recently developed by Bogetoft and Wang (1999) to identify the potential efficiency gains related to technology, harmony effects and economies of scale. This method is promising and likely to be applicable to a number of cases within forestry and forest industries.

In spite of rather limited data compared to, e.g. Bogetoft and Wang (1999), the method produces rather robust results. Furthermore, the results and their interpretation turn out to be in good accordance with current events within DFES. We find widespread overall inefficiency, as also discussed inside DFES. However, we find only limited gains from merging district offices. These gains almost exclusively arise from harmony gains, whereas the scale effect seems to be absent or even negative and hence reduces the incentive to merge. This may explain why many office boards are reluctant to take part in (large) mergers.

2 General production model

In this section, we introduce a general production model and we briefly describe the principle of DEA. We will not give a detailed introduction to the theory of efficiency measures or DEA. Instead, we focus on the method of decomposing merger gains into effects related to technology, harmony and scale, as described by Bogetoft and Wang (1999). For a textbook introduction to DEA, see Charnes *et al.* (1994). Kao and Yang (1991) provide a nice and accessible illustration of the principles of radial efficiency measures and returns to scale, see also Yin (2001).

Denote each of the existing or potential organisational offices a Decision Making Unit (DMU), and consider the case where each of n DMUs, $i \in I=\{1, 2, \ldots, n\}$, transforms p inputs into q outputs. Let $x^i = (x_1^i, \ldots, x_p^i) \in \Re_0^p$ be the inputs consumed and $y^i = (y_1^i, \ldots, y_q^i) \in \Re_0^q$ the outputs produced in DMU^i, $i \in I$. Also, let T be the production possibility set

$$T = \{(x,y) \in \Re_0^{p+q} \mid \text{ x can produce y}\}, \tag{1}$$

Let T be characterised by the classical assumptions of disposability, convexity and a returns to scale property, which can be constant (crs), varying (vrs), or decreasing (drs). DEA models partially relaxing the convexity assumptions are suggested in Bogetoft (1996) and Petersen (1990).

The model described in the following is input oriented. Hence, we focus on the reductions in input that are possible without decreasing the output. In the case of multiple inputs and outputs, the efficiency of a DMU, say DMU^i, (using input entities) is often measured by the so-called Farrell (1957) measures

$$E^i = \text{Min}\{E \in \Re_0 \mid (Ex^i, y^i) \in T\}, \tag{2}$$

where E^i is the maximal proportional contraction of all inputs that is feasible in T. In many applications, the underlying production possibility set T is unknown. However, given an appropriate data set, the DEA approach can be used to model and evaluate productive units in such cases. Assuming that $x^i = (x_1^i, \ldots, x_p^i) \in \Re_0^p$ are the observed inputs used and $y^i = (y_1^i, \ldots, y_q^i) \in \Re_0^q$ are the observed outputs produced in DMU^i, $i \in I$, the DEA approach approximates T from the observed data points and evaluates the observed productions relative to the estimated technology. The approximation of T, the empirical reference technology T*, is constructed according to the *minimal extrapolation* principle: **T*** is the smallest subset of $\Re_0^{p+q}$ that contains the actual production plans (x^i,y^i), $i \in I$, and satisfies the above presented technological assumptions specific to the given approach. Having T*, the efficiency of DMU^i may then be measured in input (or output) space using a Farrell-measure as described above with T* substituted for T.

Different DEA models invoke different assumptions about the technology. In addition to free disposability and convexity, the original model developed by Charnes *et al.* (1978, 1979) assumes constant returns to scale, where the models developed by Banker (1984) and Banker *et al.* (1984) use decreasing and varying returns to scale.

Because of the minimal extrapolation principle and more pragmatically, because new and potentially more efficient DMUs may be added to the empirical reference set, we note that DEA provides an inner approximation of the underlying production possibility set. The efficiency estimates are therefore inherently optimistic and the potential input savings and output expansions are underestimated. This also applies to the merger gains we shall estimate below. They, too, are in general downward biased. When we decompose the gains to identify alternative ways to capture the gains, the bias persists, but since it affects all estimates, the relative attractiveness of the different organisational remedies is not systematically affected. Recent advances in the literature show that statistical inference methods can be used to correct the bias of the efficiency measures, to estimate confidence intervals for the measures and to test the technology assumptions (Simar and Wilson 2000). Because of the limited data available and the non-trivial extensions of the standard measure we use, we have not undertaken any bias corrections or comprehensive testing.

3 Assessing and decomposing potential merger gains

Let us assume that it makes "organisational sense" to merge the J-DMUs, i.e. the DMUs with indices $j \in J \subseteq \{1, 2, ..., n\}$. In our application, we consider only mergers of DMUs that are geographical neighbours since proximity to customers are crucial. In other cases, it may be more important to have the same owners or similar organisational cultures for making a merger meaningful.

The merged unit is denoted DMU^J. Direct pooling of the inputs and outputs gives a unit, which has used $\sum_{j \in J} x^j$ to produce $\sum_{j \in J} y^j$. This corresponds to having a completely decentralised organisation with the decentralised units corresponding to the J-units. A radial input-based measure of the potential overall gains from merging the J-DMUs is therefore

$$E^J = \mathrm{Min}\{E \in \Re_0 \mid (E[\sum_{j \in J} x^j], \sum_{j \in J} y^j) \in T\} \tag{3}$$

E^J is the maximal proportional reduction of the aggregated inputs $\sum_{j \in J} x^j$ that allows the production of the aggregated output profile $\sum_{j \in J} y^j$. If $E^J < 1$, we can save by merging, and conversely, if $E^J > 1$, the merger is costly.

Inserting a DEA estimate of the production possibility set we get the following operational measures of the potential merger gains

$$\begin{aligned} &\text{Min} \quad E^J && (4)\\ &E^J, \lambda \\ &\text{s.t.} \quad E^J[\textstyle\sum_{j\in J} x^j] \ \geq \ \sum_{i\in I} \lambda^i x^i \\ &\qquad [\textstyle\sum_{j\in J} y^j] \leq \ \sum_{i\in I} \lambda^i y^i \\ &\qquad \lambda \in \Lambda(k), \end{aligned}$$

where k denotes the assumed return to scale (constant(crs), decreasing(drs) or varying(vrs)) and the λ restrictions are $\Lambda(crs) = \Re_0^n$, $\Lambda(drs) = \{\lambda \in \Re_0^n \mid \sum_i \lambda^i \leq 1\}$ and $\Lambda(vrs) = \{\lambda \in \Re_0^n \mid \sum_i \lambda^i = 1\}$. The input and output restrictions assure that the aggregated and possibly up-or down scaled inputs and the related outputs are feasible in the empirical technology, T*.

We observe that the program may have no feasible solutions. In such cases we define $E^J = +\infty$. The program may be infeasible because the merged unit may be large and the return to scale properties may not favour large units.

3.1 Technical improvements

Some or all of the units in J may be technically inefficient and this may be captured in E^J. Although a merger may bring in new management, which may facilitate the elimination of such inefficiencies, it is also possible to reduce technical inefficiencies through other means, e.g. by imitating the "best practices" of the better performers, sometimes referred to as the peer units. To avoid compounding the effects we project the original units to the production possibility frontier and use the projected plans as the basis for evaluating the remaining gains from the merger. Formally, we project (x^j,y^j) into $(E^j x^j,y^j)$ for all $j \in J$, where $E^j = E^{\{j\}}$ is the standard efficiency score for the single DMU^j, and we use the projected plans $(E^j x^j,y^j)$, $j \in J$, as the basis for calculating the *adjusted overall gains* from the merger

$$E^{*J} = \text{Min}\{E \in \Re_0 \mid (E[\sum_{j\in J} E^j x^j], \sum_{j\in J} y^j) \in T\} \tag{5}$$

When we insert a DEA estimate of the production possibility set, we get the following operational measure of the adjusted overall gains E^{*J}

$$\begin{aligned}
&\underset{E^{*J},\lambda}{\text{Min}} \quad E^{*J} \\
&\text{s.t.} \quad E^{*J}[\textstyle\sum_{j\in J} E^j x^j] \geq \sum_{i\in I} \lambda^i x^i \\
&\qquad [\textstyle\sum_{j\in J} y^j] \leq \sum_{i\in I} \lambda^i y^i \\
&\qquad \lambda \in \Lambda(k)
\end{aligned} \tag{6}$$

Letting $T^J = E^J/E^{*J}$ we get

$$E^J = T^J * E^{*J}, \tag{7}$$

where $T^J \in [0,1]$ indicates what can be saved by individual best practice adjustments in the different units in J.

The adjusted overall gains, E^{*J}, cover all the production economic effects of a merger that can not be captured by individual adjustments, i.e. by intra-unit adjustments. To realize the improvement potentials indicated by E^{*J}, adjustments across the units, i.e. inter-unit adjustments, are needed. Bogetoft and Wang (1999) suggest a procedure to decompose this potential gain into those arising from harmony/scope, and those arising as size/scale gains.

3.2 Harmony effect

The harmony effect of a merger is the potential gain arising from having different input and/or output mixes in the merged unit. These new mixes may place the merged unit in more "productive" parts of the product space. This is related to economies of scope, i.e. the idea that it may be cheaper to produce a group of products jointly rather than in separate units, cf. Bogetoft and Wang(1999).

To capture the harmony effect we take the average of the inputs and outputs of the J units. We look at the average input and average output, since we do not want the expansion of size to come into play yet. Using the average is most relevant if the J units are not too different in size to begin with. If the sizes differ considerably, we may be picking up scale effects, e.g. if some units are larger and some smaller than the "optimal scale size" as defined by Banker (1984).

The harmony gains, denoted H^J, capture how much of the average input could have been saved in the production of the average output

$$H^J = \mathrm{Min}\{H \in \Re_0 \mid (H[|J|^{-1}\Sigma_{j\in J}E^j x^j], |J|^{-1}\Sigma_{j\in J}y^j) \in T\} \qquad (8)$$

where $|J|$ is the number of elements in J. Again, the interpretation is that $H^J<1$ indicates a savings potential due to improved harmony, while $H^J>1$ indicates a cost of harmonising the inputs and outputs. As previously, we may insert a DEA estimate of the production possibility set and hereby obtain an operational linear programming measure of the potential harmony gains

$$\begin{aligned} &\text{Min} \quad H \\ &H, \lambda \\ &\text{s.t.} \quad H[|J|^{-1}\Sigma_{j\in J}E^j x^j] \geq \Sigma_{i\in I}\lambda^i x^i \\ &\qquad [|J|^{-1}\Sigma_{j\in J}y^j] \leq \Sigma_{i\in I}\lambda^i y^i \\ &\qquad \lambda \in \Lambda(k) \end{aligned} \tag{9}$$

3.3 Size effect

A merger leads to a unit that operates at a large scale. This may or may not be advantageous depending on the scale properties of the underlying technology. We capture the size gains, denoted S^J, by asking how much could have been saved by operating at full scale rather than average scale

$$S^J = \text{Min}\{S \in \Re_0 \mid (S[H^J \Sigma_{j\in J}E^j x^j], \Sigma_{j\in J}y^j) \in T\} \tag{10}$$

Note how the original inputs are scaled by the effects of technological efficiency gains and the harmony gains. The re-scaling of the merged units is advantageous, $S^J < 1$, if we have economies of scale, and costly, $S^J > 1$, if the return to scale properties do not favour larger units. Again, the corresponding DEA based operational measure of the size gains is

$$\begin{aligned} &\text{Min} \quad S \\ &S, \lambda \\ &\text{s.t.} \quad S[H^J \Sigma_{j\in J}E^j x^j] \geq \Sigma_{i\in I}\lambda^i x^i \\ &\qquad \Sigma_{j\in J}y^j \leq \Sigma_{i\in I}\lambda^i y^i \\ &\qquad \lambda \in \Lambda(k) \end{aligned} \tag{11}$$

3.4 The decomposition of merger gains

Having in this stepwise manner assessed the merger gains of the different types, we can now decompose the efficiency measures for the merged units. Based on the above we have that

$$E^{*J} = H^J * S^J, \tag{12}$$

and by $E^J = T^J * E^{*J}$ we get the basic decomposition

$$E^J = T^J * H^J * S^J \tag{13}$$

This corresponds to a decomposition of the basic merger index E^J into a technical efficiency index T^J, a harmony index H^J and a size index S^J. The technical efficiency measure, T^J, captures what can be gained by making the individual units efficient. The remaining potential gains, E^{*J}, arise from the harmony effect, H^J , and the size effect, S^J.

The decomposition of the overall efficiency measure E^J is important because full-scale mergers are typically not the only organisational option available, and alternative organisational changes may be easier to implement.

In case of low technical efficiency measure, T^J, one could let the inefficient DMUs learn from the practices and procedures of the more efficient ones. If the problem is not lack of skills but rather of motivation, one could improve the incentives, e.g. by using relative performance evaluation and yardstick competition based on the technical efficiency measures, cf. Bogetoft (1994,1995,1997, 2000) or other schemes. Of course, if the problem is scarcity of management talent, it may still be necessary to make a genuine merger to transfer control to the more efficient administrative teams and hereby improve the managerial efficiency (X-efficiency). In the present case of forest extension offices, there should be reasonable scope for sharing know-how across the different offices.

In case of low harmony measure, H^J, one could, in general, consider reallocating the inputs and outputs among the DMUs to create more "powerful" input mixes and more easily produced output mixes. This can be done inside a hierarchy, by long-term contracts or perhaps by creating a market for key inputs and outputs, cf. Brännlund et al. (1998). However, in the current empirical case this option mainly gives operational sense for neighbours and for some kinds of output.

Finally, in case of low size measure, S^J, full-scale mergers may be the only alternative. If we need a big amount of fixed capital, highly specialised staff, long run-lengths, or simply a critical mass to obtain sufficient return to scale, it may be relevant to merge. Also, and perhaps most important, this may be relevant if the reallocation through contracts or a market is associated with too many transaction costs to make it attractive, cf. the general discussion of the size of the firm in the industrial organisation literature, e.g. Tirole (1988). The forest district offices in the current empirical case have only limited amounts of capital, whereas highly specialised staff are likely to be crucial for performance. Furthermore, again because of the nature of the offices' business, mergers are only relevant for neighbouring offices.

We believe that the decomposition developed by Bogetoft and Wang (1999) is natural and provides valuable information. We note that a similar decomposition is possible in the output space, but stress that it will not, in general, lead to the same quantitative measures of the different effects.

4 Case Study

The Danish Forest Extension Service (DFES) consists of 14 district offices, each with staff of its own and serving a certain geographical region. Each office is a co-operative owned by the members, who for the entire organisation total app. 7,200 forest owners. The 14 offices run a small common head office, which supports with economic analyses and performs lobby-work towards governmental offices. The forest area administered by DFES comprises 16% of the total forest area in Denmark. The annual sale is about 240 million DKK and about 67 forest engineers and graduate foresters are employed.

In the following, we analyse the efficiency of the individual offices and a number of potential mergers. The data available for such analysis include a detailed description of number and types of employees; the annual economic surplus for the offices and its members; size of equity; costs related to employees and administration; sales related to timber, seedlings, Christmas trees, consultancy and entrepreneurs. The data concerns the period 1997-1999, implying that they reflect some of the fluctuations between years. As the data are confidential, we cannot reveal the names or locations of the offices.

In order to produce a reliable production model, the number of input and output variables must be adjusted according to the number of DMUs. Therefore, we aggregate the information into a description of the production process in terms of 1 input and 3 outputs for all three years. For each office, the input variable consists of all administrative costs, and the outputs are 1) annual economic surplus for each office, 2) annual economic surplus generated by the office to its members, and 3) annual sale of seedlings to owners. The latter output variable acknowledges that while the costs of seedlings show up as an expense when calculating the surplus of the members, regeneration activities imply a capital gain to them. Ideally, this could have been better expressed by a net present value estimate, but data did not provide sufficient details for such an approach. Hence, we approximate the capital gain with a measure of the expense endured to obtain it. This estimate is conservative and likely to underestimate the true value of the new forest established.

It was not possible to take into account other capital gains (or losses) accruing to the forest owner as a direct consequence of extension service activities. In particular we do not take into account changes in standing stock or increased estate value due to investments in amenity values. Hence we operate under the assumption that such gains or losses are not caused by the extension service activities.

5 Results

Efficiency of individual offices

We first estimate the overall efficiency of the individual units. Since all inputs and outputs in this analysis are in monetary terms, the overall efficiency measure reported in the following captures both technological and allocative efficiency in the sense of Farrel (1957). Each office is represented three times, one for each of the periods. With 14 offices, this gives a total of 42 units. If the technology is modelled using a crs-technology in the DEA approach, the average potential saving across units is estimated at 38.1 %, corresponding to an average efficiency measure of 61.9 % (Figure 1). Using vrs-technology, the average potential saving is only 26.3 % (Figure 2), corresponding to an average efficiency measure of 73.7%. One would expect to find high relative efficiency levels, because of the similarity of technologies and the widespread co-operation between offices. However, in both cases the distribution reflects that the performance varies considerably. This indicates that there may exist a large potential for improving efficiency through learning and co-operation. It may, however, also reflect that the set of variables used does not allow for a reasonable approximation of the technology. On the other hand, the small number of observations relative to the dimension of the production space should imply a bias towards larger efficiency measures. Compared to earlier analyses (Kao and Yang 1991, 1992, Bogetoft and Wang 1999), the number of efficient units is fairly low.

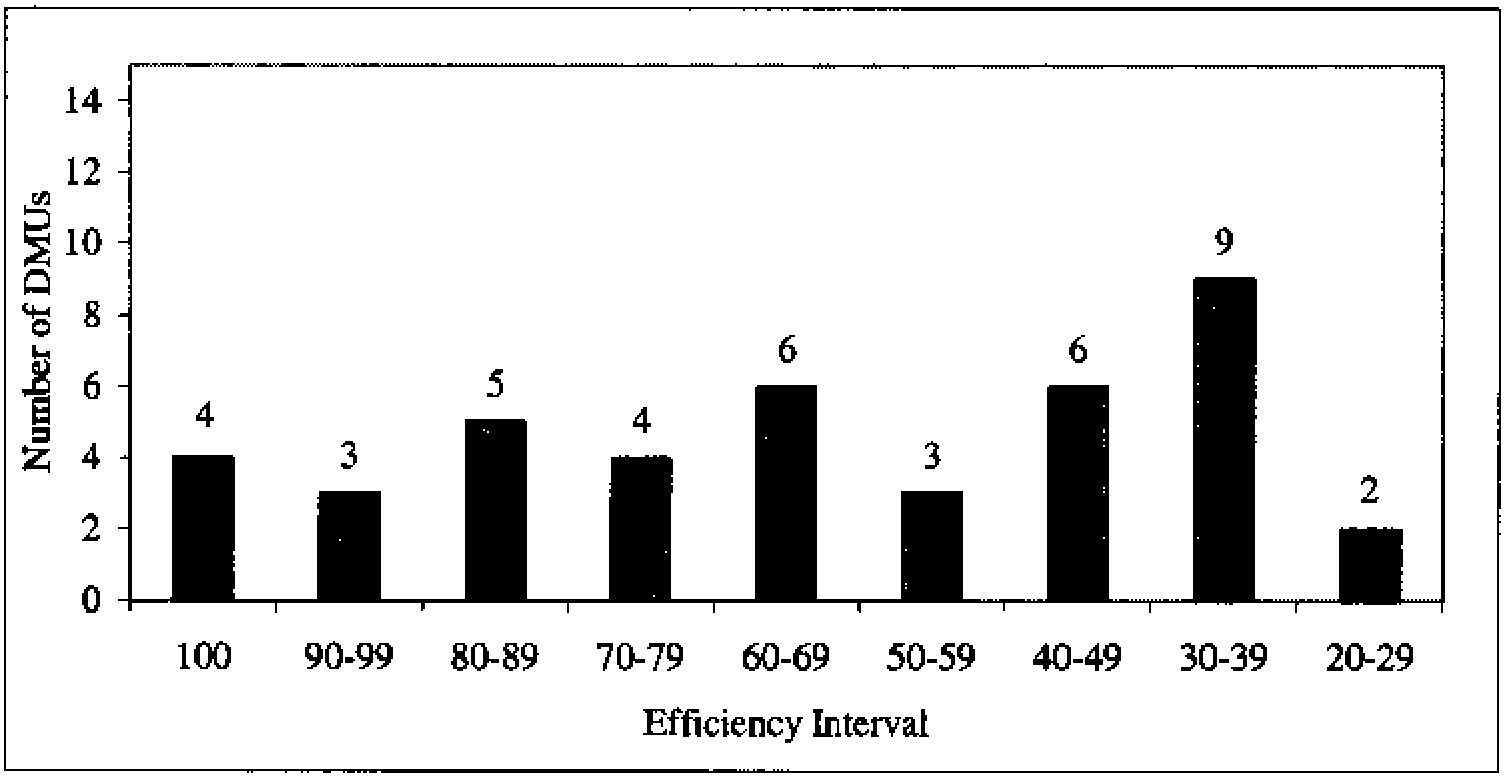

Figure 1. Efficiency distribution of the 42 DMUs using crs technology (Mean = 61.90%, STDEV=23.99%).

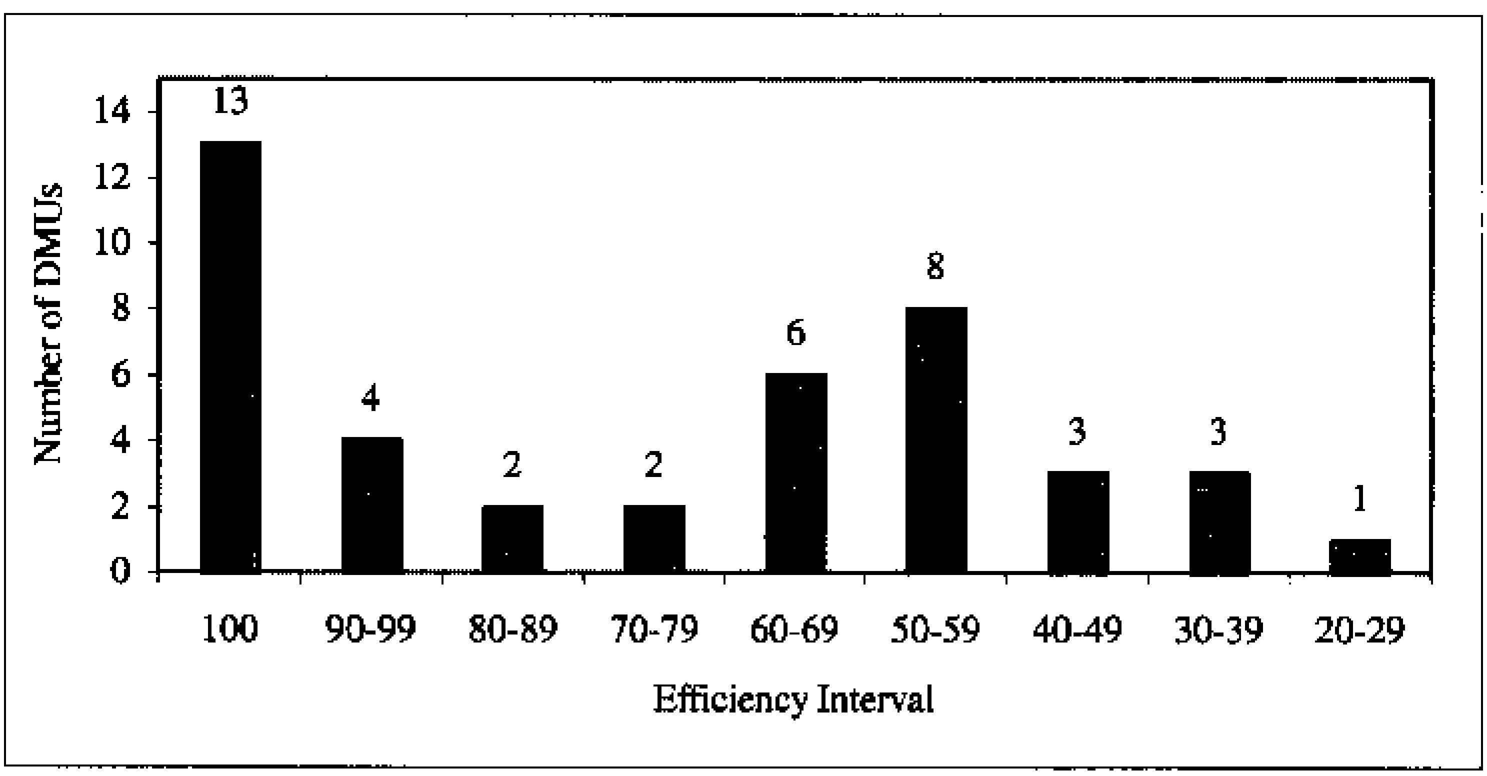

Figure 2. Efficiency distribution of the 42 DMUs using vrs technology (Mean = 73.69%, STDEV=26.82%).

The overall efficiency scores for each of the individual 14 extension offices in the three different years are reported in Tables 1 and 2. Using crs-technology, the ranking of the top 5 offices according to average efficiency scores is Offices 8,4,2,10 and 5. On the other hand, if we assume vrs-technology the ranking of the top 5 offices according to average efficiency scores is Offices 10,1,4,8 and 14. Hence, three out of five offices are still in the top 5 if we allow for varying returns to scale.

Table 1. Efficiency scores for the 14 extension offices using crs-technology

	E^J			
	1997	1998	1999	Average
Office 1	43.70%	43.91%	24.57%	37.39%
Office 2	100.00%	53.78%	79.11%	77.63%
Office 3	61.07%	72.02%	81.75%	71.61%
Office 4	83.43%	91.59%	71.98%	82.33%
Office 5	79.62%	92.38%	51.89%	74.63%
Office 6	42.64%	41.84%	47.76%	44.08%
Office 7	47.68%	100.00%	36.96%	61.55%
Office 8	100.00%	100.00%	65.64%	88.55%
Office 9	90.00%	63.82%	51.40%	68.41%
Office 10	81.91%	89.17%	61.36%	77.48%
Office 11	39.68%	36.31%	27.66%	34.55%
Office 12	63.15%	33.46%	30.13%	42.25%
Office 13	37.18%	37.81%	39.27%	38.09%
Office 14	67.89%	83.84%	32.45%	61.39%
Average	67.00%	67.14%	50.14%	

The return to scale properties of the individual offices can be evaluated from Figure 3. We see that the largest unit in terms of input with efficiency score 100 is approximately DKK 2,900,000. Hence, units above this level experience decreasing return to scale. This is also clear from the scale efficiency estimates $SE^J = E^J(crs)/E^J(vrs)$, cf. 3c.

Table 2. Efficiency scores for the 14 extension offices using vrs-technology

	E^J			
	1997	1998	1999	Average
Office 1	100.00%	97.85%	90.10%	95.98%
Office 2	100.00%	58.68%	79.29%	79.32%
Office 3	66.79%	72.61%	96.50%	78.63%
Office 4	100.00%	100.00%	83.65%	94.55%
Office 5	80.96%	100.00%	56.33%	79.10%
Office 6	45.36%	44.30%	57.61%	49.09%
Office 7	53.84%	100.00%	62.39%	72.08%
Office 8	100.00%	100.00%	65.88%	88.63%
Office 9	100.00%	63.92%	54.59%	72.84%
Office 10	100.00%	100.00%	100.00%	100.00%
Office 11	43.37%	39.79%	29.99%	37.72%
Office 12	66.87%	38.82%	36.52%	47.40%
Office 13	52.21%	52.12%	52.32%	52.22%
Office 14	95.46%	100.00%	65.25%	86.90%
Average	78.92%	76.29%	66.46%	

The largest unit with a scale efficiency of exactly 100% is the unit with an input of approximately 2,900,000 identified above. Note also that in the vrs-technology, the input level for the largest unit with efficiency score 100 is approximately DKK 3,900,000. For input (administrative costs) above this level, substantial inefficiencies exist in both technologies, i.e. the units cannot explain poor performance by decreasing return to scale, alone.

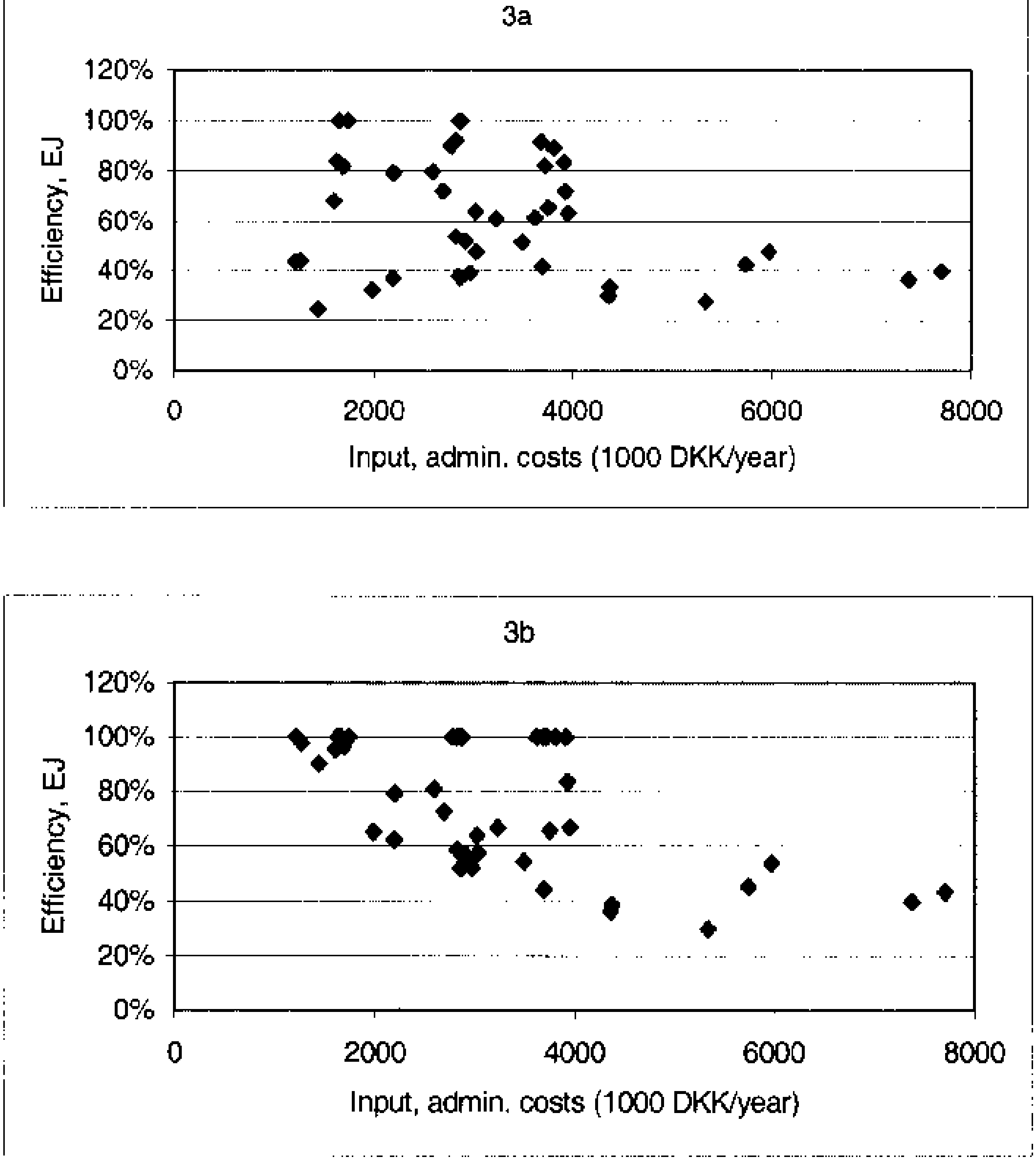

Figure 3. Return to scale effects based on crs(3a) and vrs(3b) technology.

Finally, to validate our findings, we asked the Head of DFES to identify the two units which by his subjective evaluation belonged to the most efficient and least efficient groups, respectively. He identified Offices 4 and 10 as belonging to the most efficient and Offices 1 and 7 to belong to the least efficient. Comparing with table 1 indicates a good match between the subjective opinion and our findings assuming crs-technology. The comparison with vrs-technology is less clear.

Merger gains

The extension offices are located in 14 different geographical regions and the nature of their business requires that the distance to customers, the forest owners, is not too large. Therefore, when evaluating potential mergers we examined only mergers of offices in neighbouring regions. The possible mergers involve two or three offices. The number of potential combinations is large, but we select 15 geographically feasible combinations. These combinations also include the potential mergers, which recently have been discussed by the individual offices. Some of the mergers have been constructed by splitting one office between two offices. They are noted as "½ " offices in Table 3.

Table 3 presents the efficiency scores of the 15 potential mergers under the crs assumption. The efficiency is decomposed into harmony (H) and technological (T) effects. By the crs assumption, the size effect will always be neutral (S=1). The most promising mergers are M2 and M11, each with a potential harmony gain of around 10%, followed by the mergers M8 and M4 with a potential gain of 7% and 5%, respectively. The decomposition is easily seen at work, consider e.g. DMU M11, which seems to have the potential for an average gain of 58.65%. This gain is the result of a potential harmony improvement of 10.38% arising from the merger and a potential improvement of 54.07% from technological inefficiency of the underlying units.

We also considered a vrs technology and hereby the possibility of positive and negative size effects. Under a vrs technology, the efficiency scores of three potential mergers are presented in Table 4. We left out the remaining twelve mergers because the merged units in these cases fell outside of the possibility set spanned by the individual units. The size effect works against merging offices. This is not surprising given the discussion of optimal scale size above. However, it seems as if some merger gains can be achieved by merging Offices 13 and 14. This gain is the result of, on average, a potential harmony improvement of 1.04%, a potential scale improvement of 31.13%, and a 35.12% improvement from technological inefficiency of the underlying units. Similarly, merging Offices 6 and 7 would imply a potential gain, mainly from scale effects and technological inefficiency. Merging Office 12 and half of Office 4 would imply a harmony gain, however the scale works against this improvement.

Table 3. Efficiency scores for potential mergers under crs technology.

	Merger	Year	E^j	$E^{*j}=H$	$T^j = E^j / E^{*j}$
DMU M1	Office 8 and 9	97	95.09%	99.99%	95.10%
		98	80.99%	99.48%	81.41%
		99	58.78%	99.99%	58.79%
		Avg	78.29%	99.82%	78.43%
DMU M2	Office 13 and 14	97	46.57%	96.69%	48.16%
		98	48.32%	88.67%	54.49%
		99	31.02%	84.88%	36.55%
		Avg	41.97%	90.08%	46.40%
DMU M3	Office 6 and 7	97	44.71%	98.90%	45.21%
		98	59.79%	100.00%	59.79%
		99	43.22%	100.00%	43.22%
		Avg	49.24%	99.63%	49.41%
DMU M4	Office 2 and 3	97	74.66%	99.99%	74.67%
		98	57.37%	91.52%	62.69%
		99	74.52%	92.85%	80.26%
		Avg	68.85%	94.79%	72.54%
DMU M5	Office 4 and 5	97	81.91%	99.99%	81.92%
		98	89.04%	96.85%	91.94%
		99	62.67%	98.82%	63.42%
		Avg	77.87%	98.55%	79.09%
DMU M6	Office 10 and 12	97	68.98%	95.48%	72.25%
		98	56.69%	95.45%	59.39%
		99	44.30%	99.99%	44.30%
		Avg	56.66%	96.97%	58.65%
DMU M7	Office 4,5 and 12	97	74.54%	99.63%	74.82%
		98	64.65%	94.49%	68.42%
		99	49.93%	98.95%	50.46%
		Avg	63.04%	97.69%	64.57%
DMU M8	Office 12,13 and 14	97	53.30%	96.55%	55.20%
		98	40.92%	92.81%	44.09%
		99	30.60%	91.23%	33.54%
		Avg	41.61%	93.53%	44.28%
DMU M9	Office 8,9 and 10	97	89.86%	99.99%	89.87%
		98	81.39%	96.36%	84.46%
		99	59.64%	99.99%	59.65%
		Avg	76.96%	98.78%	77.99%
DMU M10	Office 4,5,8,10,12, 13 and 14	97	70.40%	95.30%	73.87%
		98	69.68%	95.10%	73.27%
		99	50.22%	97.26%	51.63%
		Avg	63.43%	95.89%	66.26%

DMU M11	Office 6,7,9,11	97	44.66%	91.36%	48.88%
		98	46.43%	93.69%	49.56%
		99	32.97%	83.81%	39.34%
		Avg	41.35%	89.62%	45.93%
DMU M12	Office (½)4 and 12	97	69.38%	99.30%	69.87%
		98	48.10%	94.92%	50.67%
		99	43.12%	99.99%	43.12%
		Avg	53.53%	98.07%	54.56%
DMU M13	Office 4 and (½)5	97	81.26%	99.99%	81.27%
		98	88.84%	96.49%	92.07%
		99	58.93%	98.27%	59.97%
		Avg	76.34%	98.25%	77.77%
DMU M14	Office (½)9 and 10	97	84.11%	99.99%	84.12%
		98	79.18%	96.59%	81.98%
		99	58.12%	100.00%	58.12%
		Avg	73.80%	98.86%	74.74%
DMU M15	Office 8 and (½)9	97	96.74%	99.99%	96.75%
		98	87.21%	99.68%	87.49%
		99	61.12%	99.99%	61.13%
		Avg	81.69%	99.89%	81.79%

Table 4. Total decomposition of efficiency scores from potential mergers. Based on a vrs technology.

	Merger	Year	E^j	E^{*j}	T^j	H^j	S^j
DMU M2	Office 13 and 14	97	49.85%	73.65%	67.68%	99.67%	73.89%
		98	50.42%	72.58%	69.47%	97.70%	74.29%
		99	33.43%	58.14%	57.50%	99.51%	58.43%
			44.57%	68.12%	64.88%	98.96%	68.87%
DMU M3	Office 6 and 7	98	68.36%	111.16%	61.50%	100.00%	111.16%
		99	45.66%	76.59%	59.62%	98.69%	77.61%
			57.01%	93.88%	60.56%	99.35%	94.38%
DMU M12	Office (½)4 and 12	98	55.69%	97.82%	56.93%	90.40%	108.21%
		99	50.23%	98.20%	51.15%	89.56%	109.65%
			52.96%	98.01%	54.04%	89.98%	108.93%

Sensitivity analysis

As described above we have pooled the data across years. This pooling may affect the ranking of the individual units. To analyse for such effects, the efficiency of each DMU was evaluated in three different models, each model using only data from one year. The average performance of each

DMU in these models is compared with the performance of the DMUs in the pooled model, cf. Figures 4 and 5.

Pooling the data from the three years into one data set of 42 units implies a decrease in the average efficiency measure, as shown in Figures 4 and 5. This is not surprising as adding more observations to a DEA always implies a probability of adding new peer units and hence of decreasing the efficiency measures of a number of the existing observations. The Figures also show that even though the measures change, the overall pattern remains the same. For the crs-technology, Offices 2, 4, 5, 8, 9 and 10 are in both cases in the top end of the population, whereas Offices 1, 6, 7, 11, 12, 13 and 14 remain in the lower end. For the vrs-technology Offices 1, 2, 3, 4, 5, 7, 8, 9 and 10 are in both cases in the top end of the population, whereas Offices 6, 11, 12, and 13 form the low end. This indicates, that pooling the data does not seriously change the ranking of the different offices, while it probably provides the benefit of a better approximation of the production technology.

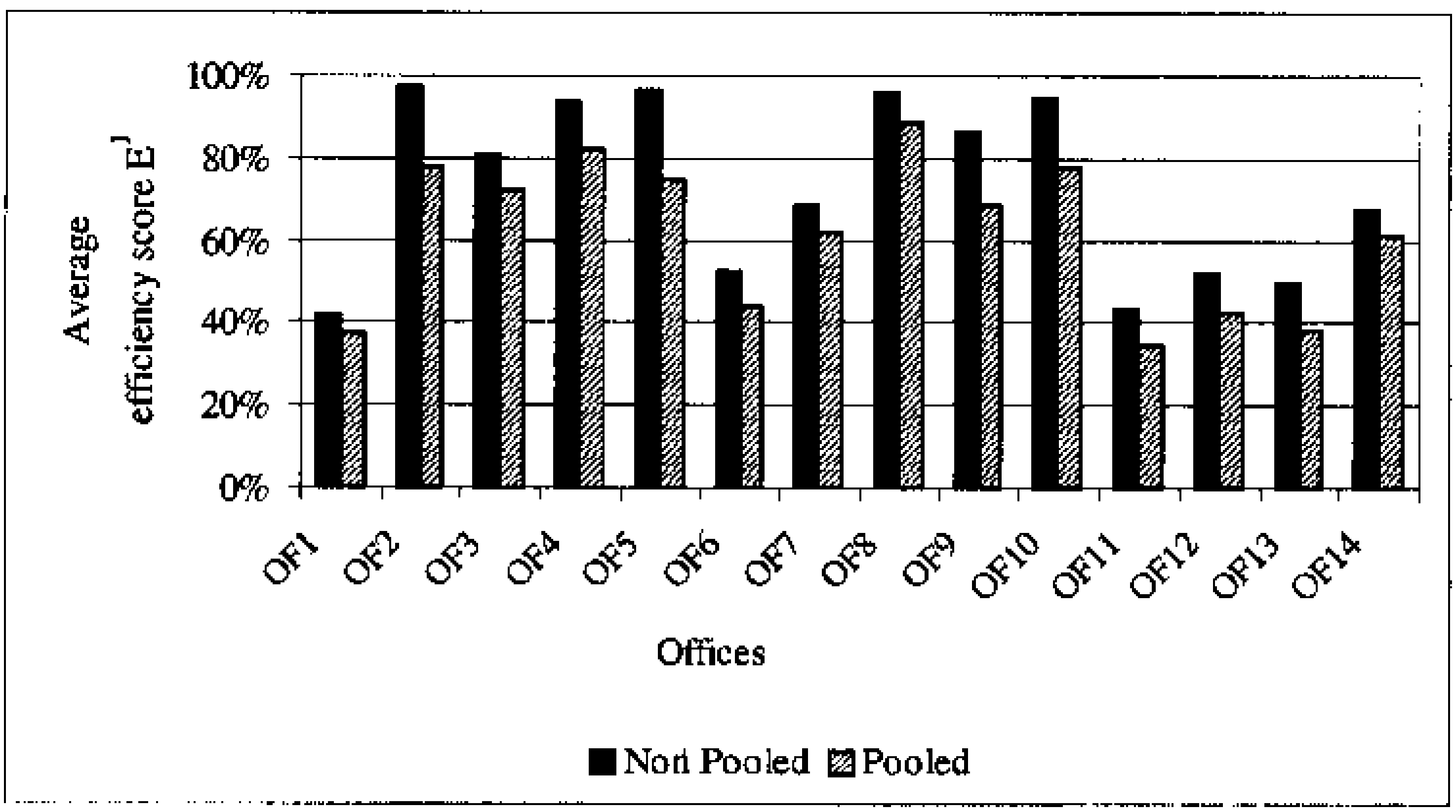

Figure 4: Average of efficiency scores for the 14 offices over the three years. The technology is estimated with and without pooling data from different years and assuming crs.

Often the time development of productivity change is assessed using the so-called Malmquist-index (Malmquist 1953). For two reasons this is not done here. First, in our case the number of periods in the time series is too short for making this index relevant. Secondly, and more important our data are in money terms, implying that we catch up some general price variation over time in our output data. Thus, the interpretation of the Malmquist index does not carry through.

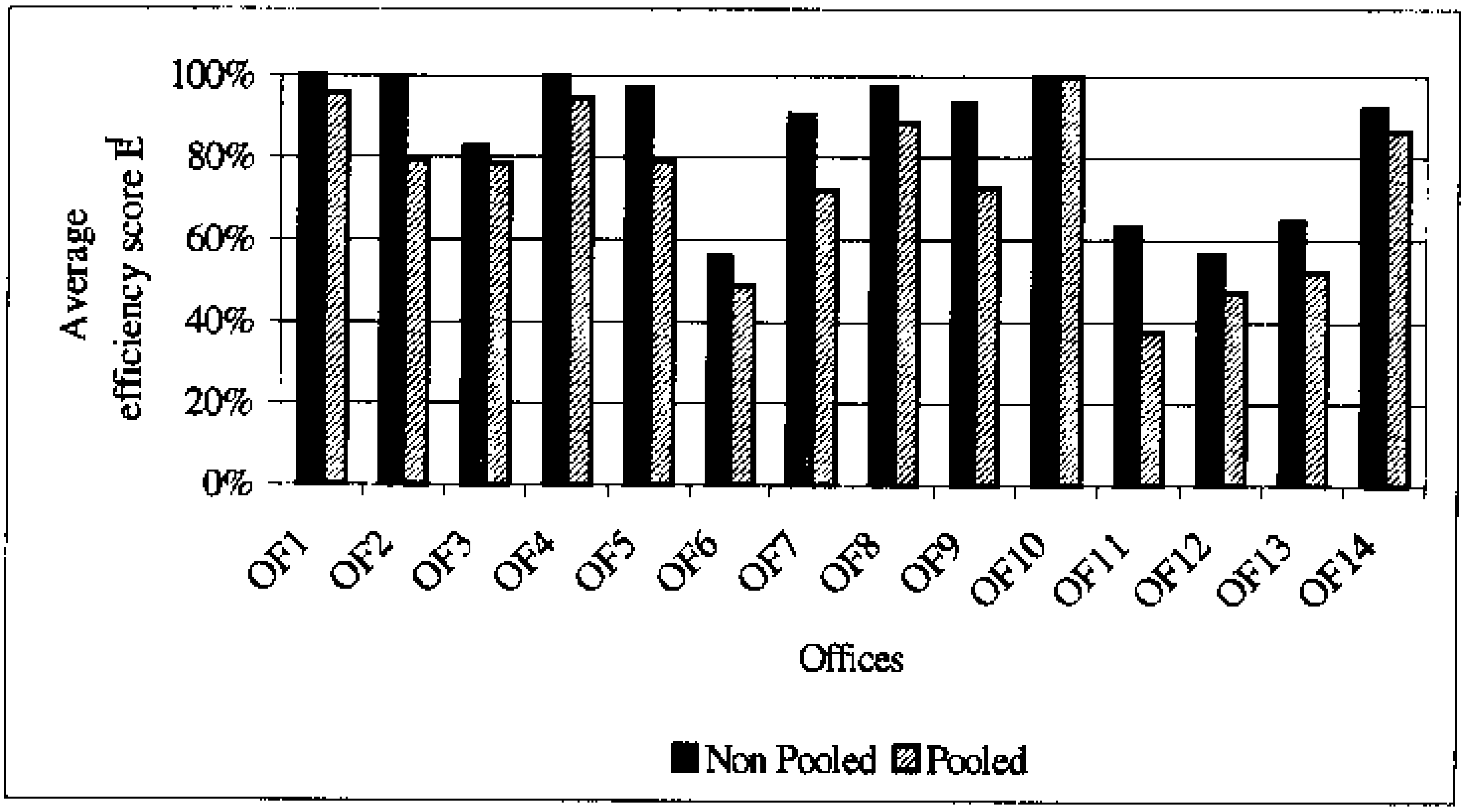

Figure 5: Average of efficiency scores for the 14 offices over the three years. The technology is estimated with and without pooling data from different years and assuming vrs.

In Table 5 we report at sensitivity analysis with respect to the most dominant peer units. By redoing the efficiency analysis of the individual units in a data set where a peer unit is eliminated, we can evaluate the impact of the peer and the possible idiosyncratic noise and events related to it. The unit with the strongest effect is the 1997 performance of Office 2. This had a rather strong impact on some units, resulting in an average increase of 3-6 percentage points, depending on the technology assumption. However, the overall result is that the average efficiency of the offices does not increase alarmingly when single peer units are excluded. Thus, in spite of the rather limited data compared to the data set of Bogetoft and Wang (1999) or even Yin (2001), the results seem rather robust to changes in the data set.

Table 5. Average increase in efficiency when excluding peer units (in percentage points).

	Technology	
Peer unit	crs	vrs
Office 1, 97	-	0.22%
Office 2, 97	5.25%	3.69%
Office 7, 98	0.98%	0.52%
Office 8, 97	0.07%	0.25%
Office 8. 98	1.72%	-

Finally, to check for missing variables, we plotted the efficiency score against a number of structural variables. Plots of efficiency scores against the average site indices of beech and Norway spruce in the respectively regions indicated a weak relationship between site index and efficiency. In particular, the offices located in poor regions tended to under-perform, while there where no evident difference between offices in average or good site regions. This may have a non-trivial impact on the evaluations, and in a subsequent analysis, one may therefore consider to introduce it as a non-discretionary input, cf. Charnes *et al.* (1994)). There seemed to be no significant relation between efficiency and the total serviced area by the DMUs, the forest area in the region nor the the sales of Christmas trees and greenery. Interestingly, plotting efficiency against the average number of associated forest owners over the period for each DMU revealed a non-linear pattern showing a significant decrease in efficiency for DMUs with more than app. 500 associated owners. Again, this is an indication of the potentially negative returns to scale in the present case. Of course, the use of regression techniques, although common in the literature, may not be entirely appropriate since the efficiency scores are not normally distributed. Still, the limited data set in the present study makes more elaborate techniques as suggested in Simar and Wilson(2000) or Asmild et al. (1999) somewhat unattractive.

5 Discussion and Conclusions

In this paper, we have described and applied a method to evaluate the efficiency of merged productive firms or other DMUs. The method, recently developed by Bogetoft and Wang (1999), allows us to separate the merger gains from the pure technological inefficiency of the underlying DMUs, and to decompose the potential gains of mergers into an effect of harmony gains and the effect of increased size. We applied this method to the Danish Forest Extension Service using data for the period 1997-1999 for the 14 regional offices.

The analyses revealed that there are great differences in efficiency across offices. Thus, there seem to be considerable scope for sharing information, and for imitation and co-operation. Currently, the scope for improving efficiency through merging different offices is discussed intensively in DFES. The economy of forest enterprises has been under increasing pressure for more than a decade. This has caused an increase in the out-sourcing of management activities to – among others the DFES. Now the forest owners are also demanding better performance from these management specialists. The Head of DFES categorised the offices into three categories: Those striving to generate as high as possible annual economic surplus for the office, denoted O, which he believed to be the more efficient. A second category denoted M, which is offices striving to generate as high as possible economic surplus to its member forest owners. This category, he believed *a priori* would be less efficient. Finally, a group of offices where categorised as pursuing a mixed strategy, denoted O/M. Figure 6 suggests that the O oriented offices seem to be more efficient than the offices with a members oriented (M) and a mixed O/M strategy. This is observed even though the DEA model used does not favour a priori either strategy

The important thing to note from this observation is, that in spite of the limited data available, the overall results seem to be in good accordance with the *a priori* beliefs of the head office. It turns out, that they are also in good accordance with current events in the DFES, cf. below.

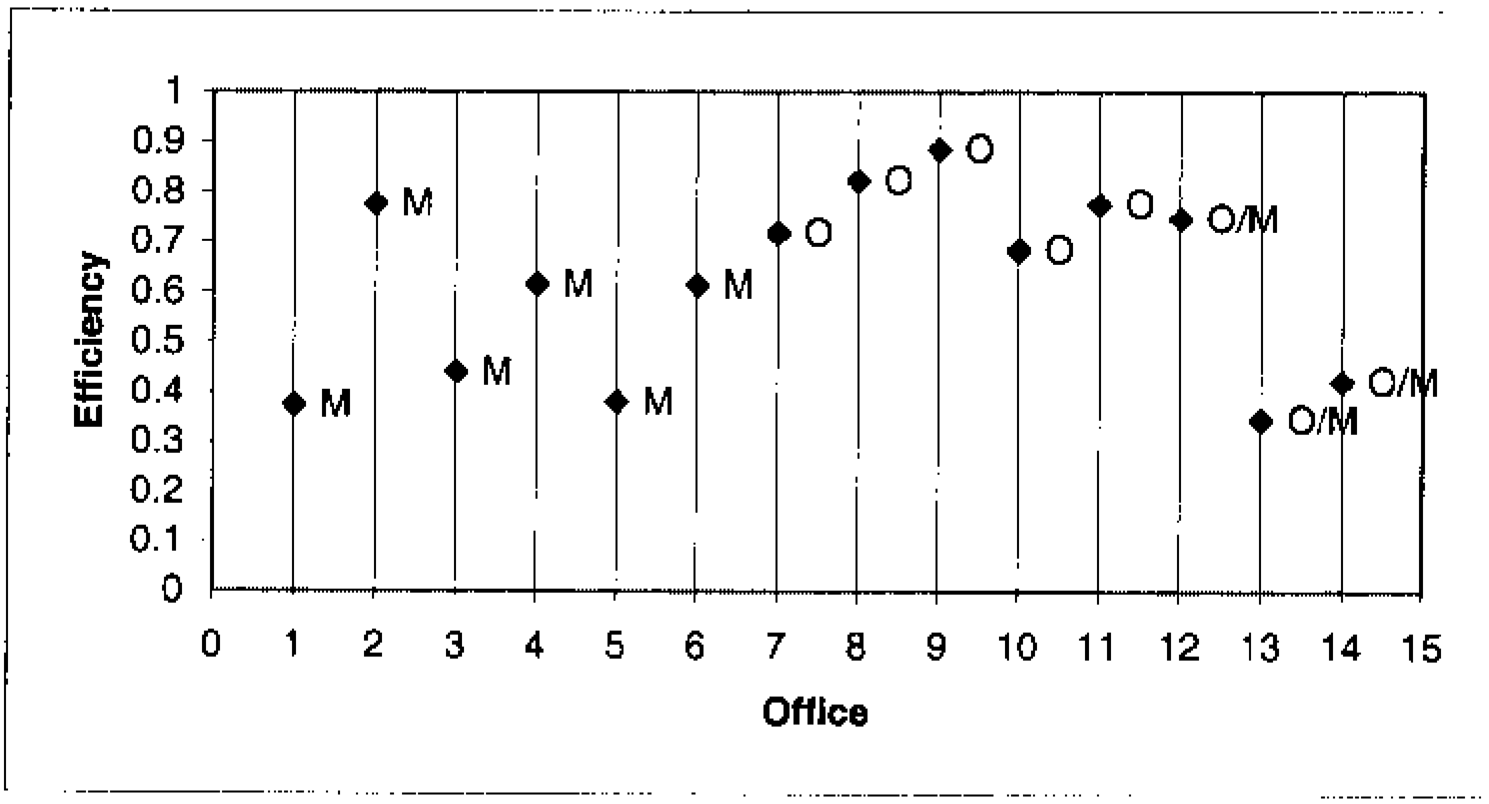

Figure 6: Efficiency scores for the 14 offices, which are categorised by the DFES as office surplus (O), member surplus (M) or both (O/M) oriented types assuming crs-technology.

The analyses reported here indicate that overall there seems to be some merger gains. They are, however, not widespread and rather limited in scale. Furthermore, the gains are mainly related to the harmony effect, i.e. to mergers creating a better mix of inputs and outputs. Only two potential mergers have some gains related to the economies of scale. Except for these two mergers, the effect of increased scale seem to be at best absent, but more likely it is negative. Interestingly, the only case for which the current analyses suggest that scale gains from merging exist, i.e. Offices 13 and 14, is likely to be implemented within this year. In many other offices and office boards, there is in general a reluctance to consider mergers as a way out of the current crisis. Thus the current effort to merge offices may be counterproductive. Instead, it seems that DFES should put an effort into dissemination of managerial know-how, co-operation among neighbouring offices and, of course, changes in the scale of the individual units.

These conclusions should, however, be read bearing in mind that the current model of the production technology may be flawed, e.g. the efficiency of the individual units may depend also on regional variations in the average quality of forests in terms of productivity, and tree species mix. These factors are unobservable in the current case, but may imply an underestimation of the efficiency of some offices. In addition, the number of observations is not overtly large, leaving few degrees of freedom. This works contrary to the previous argument, as it in general implies an over-estimation of efficiency.

Finally, we wish to point out some of the commonly known shortcomings of the DEA method. It is an approximation method, which – unlike statistical methods – does not explicitly take into account potential measurement errors in the data set. In some applications, e.g. Viitala and Hänninen (1998) and Yin (2001), the data set has also been made subject to statistical analysis, like stochastic frontier estimation. On the other hand, it is a major advantage of DEA that no specific assumptions are needed about the underlying form of the production function.

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