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80 Danish Hospitals

Torben Holvad
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Jens Leth Hougaard

European University Institute, Florence

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TORBEN HOLVAD
and
JENS LETH HOUGAARD

BADIA FIESOLANA, SAN DOMENICO (FI)

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European University Institute
Badia Fiesolana
I – 50016 San Domenico (FI)
Italy

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Torben Holvad & Jens Leth Hougaard*

Oct. 93

Abstract

In this paper the Danish hospital sector is analysed with respect to technical efficiency in the non-parametric tradition, i.e. the DEA-model and the FDH-model. The primary aim is to illustrate the mechanics of these methods. The chosen approach starts out with a standard model of hospital activity. This basic model is compared to other specifications in order to indicate the robustness of the efficiency results of the standard model. The robustness aspect is also analysed by use of regression analysis. The efficiency scores from the standard model are regressed on variables reflecting different specifications of hospital activities. This approach thus gives a link between the non-parametric efficiency measurement methods and parametric analysis.

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1 Introduction

This paper is the second of two papers on the measurement of technical input efficiency for similar production units. The present paper deals with an empirical analysis of the Danish hospital sector, hopefully illustrating some of the mechanisms behind the theoretical framework put forward in the first paper. Hence, the primary aim is not to make a thorough and complete analysis of the efficiency of the Danish health care sector but merely to illustrate some of the difficulties involved in efficiency evaluation with Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) methods. In doing this we also show the extent to which the efficiency information provided by DEA and FDH methods is usable and sufficient in relation to overall performance evaluation of production units.

Our approach is the following. First, we specify a standard model which, at first sight, seems to be appropriate with respect to hospital activities. Obviously this is only a crude model and hence we then present alternative specifications all of which are related to the standard model. Through looking at these various models we obtain an indication of robustness, that is of possible factors which may effect the efficiency variation in the standard model. Moreover, we analyse this aspect in a parametric way i.e. by a regression approach. The variables from the various models which proved to be of some importance with respect to the efficiency variation all enter as explanatory variables in one form or another. In this way we obtain a statistical basis for testing the significance of the included variables. Hence there is an interface between the non-parametric and the parametric approach to efficiency evaluation.

The Danish hospital sector has been chosen for two main reasons. Firstly, because this area is characterized by political attention partly due to the fact that it constitutes a large fraction of the total public expenditures at the regional or county level. Secondly, because the activity in the hospital sector is one of the few public areas well covered by highly disaggregated production statistics at a micro level. In Denmark, such statistics are made available through the annual publications "Virksomheden ved sygehuse" (Statistics on Hospital Activity) and "Personale- og Økonomistatistik for Sygehusvæsnet" (Statistics on Hospital Employment and Expenditures) from the Danish Ministry of Health.

In general the health care sector has been a rather popular area of applied studies of efficiency measurement. Table 1 offers a survey of earlier DEA-studies of health care activities.

This paper is organized as follows. Section 2 briefly describes the main characteristics of the Danish hospital sector. In section 3 the hospital data set is described; the source and the selection of data. The results of the application of FDH and DEA methods on the selected hospital data will be examined in section 4. This section will follow the outline of the theory in the first paper, (Holvad & Hougaard [1993]), and a range of results from models with different variables are interpreted with respect to a standard model. Section 5 attempts to put the information obtained from these different models together by regressing the efficiency scores from the standard model on variables reflecting the different models. Section 6 concludes with final remarks.

Table 1: *A survey of earlier studies of productive efficiency for hospitals.*

Author	Number of units	Type and period of data	Number of outputs/ inputs
1) Banker, Conrad & Strauss (1986)	114	Cross-section of North Carolina hospitals 1978	3 outputs 4 inputs
2) Bogetoft, Olesen & Petersen (1987)	96	Cross-section of Danish hospitals 1983	6 outputs 1 input
3) Bruning & Register (1989)	1254	US hospitals 1985	6 outputs 5 inputs
4) Fare, Grosskopf, Lindgren & Ross (1989)	17	Paneldata of Swedish hospitals 1970-85	3 outputs 4 inputs
5) Grosskopf & Valdmanis (1987)	22 public 60 private	Cross-section of Californian hospitals 1982	4 outputs 4 inputs
6) Sherman (1984)	7	Cross-section of Massachusetts university hospitals 1976	4 outputs 3 inputs

Remark: DEA-C, DEA-D and DEA-V denotes respectively a DEA-model with constant, decreasing and variable returns to scale. COLS (Corrected Ordinary Least Squares) is a parametric efficiency measurement method, where the production frontier is estimated in two steps: First the parameters are estimated by OLS, secondly the intercept is shifted up untill all residuals are non-positive. A * indicates that information on this category was not available.

Table 1 (continued):

Author	Types of outputs/ inputs	Methods	Inefficient units	Units pr. category
1) Banker, Conrad & Strauss (1986)	Patient days/ Working-hours, beds	DEA-C DEA-V COLS	77 (67.5%) 69 (60.5%)	16.30
2) Bogetoft, Olesen & Petersen (1987)	Patient days, emergency visits/ Net expenditures	DEA-C DEA-D DEA-V	78 (81.3%) 69 (71.9%) 65 (67.7%)	13.70
3) Bruning & Register (1989)	Patient days/ Physicians, nurses, other personnel and beds	DEA-C	1128 (90.0%)	114
4) Fare, Grosskopf, Lindgren & Ross (1989)	Discharges, patient days, emergency visits/ expenditures	DEA-C (Malmquist)	14 (82.4%)	2.42
5) Grosskopf & Valdmanis (1987)	Patient days, surgeries, outpatient visits/ Physicians, non-physicians, netplant assets and admissions	DEA-C DEA-V	* *	10.25
6) Sherman (1984)	Patient days, students/ Full-time employed doctors, available beds, expenditures	DEA	2 (28.6%)	1.00

2 A brief description of the Danish hospital sector

Almost all of the about 100 hospitals in Denmark are placed within the public sector. A few hospitals (6) are formally organized privately but are publicly financed and a single hospital is purely private. The public expenditures on hospitals accounted for 6.8 per cent of the total public spending in 1990.

The Danish health care system is not organized as a national health service. However there are 14 county councils (the regional public authorities) which by law are responsible for health care delivery within their geographical boundaries (the system in Copenhagen is different since the municipalities in that region in combination with the only existing state hospital (Rigshospitalet) are responsible for the provision of health care). In general, the structure of the hospitals at the county level consists of one large specialized region- or nationalhospital and a number of smaller local hospitals with a maximum of three departments. The almost total absence of direct consumer charges constitute a further characteristica of the provision of health care within the hospitals. The county system is based on the possibilities of each council to impose a proportional income tax on its residents, and budgets for the different hospitals are negotiated and allocated in advance on a one year basis by the county council administration. These budgets are thus the results of a political decision process. If a hospital spends more than the budget allows the concerned management is criticised by the higher level authority when there is no special reason for the overspending, but normally no further sanctions are imposed on the hospital. Surpluses at the end of the budget period are as a rule returned to the county council (however in recent years some possibilities for transfering money from one fiscal year to another have been allowed). This procedure for hospital resource allocation indicates that there is indeed a need for control of hospital activities.

3 The data

Data for the present study of productive efficiency for Danish hospitals are based on hospital statistics published yearly by the Danish Ministry of Health. The available statistics from this central source consist of records of the activity of individual hospitals as well as employment and budget information on a hospital level.

The activity statistics are provided from a central patient data base updated every year under the Ministry of Health to which each hospital is obliged to give information concerning every realized discharge. Thus for every discharge the hospital and department from which the discharge originates is registered as well as patient-identification, date of arrival and date of leaving the hospital, the course of treatment, diagnoses, operations etc. From the single discharge records it is possible to construct measures indicating the level of activity for each hospital such as the number of discharges, the number of patient days etc. These measures are only indications of the total production from each hospital, but they contain basic information about the demand for resources arising from the demand for hospital services that are satisfied (not considering rationing).

3.1 A description of data

The above mentioned statistics from the Danish Ministry of Health contain data on the number of yearly full-time employed personnel divided into 57 labeled job-categories. Furthermore, data indicating the activity level i.e. the number of discharges, the number of outpatient visits, the number of patient days and the number of beds (the latter indicates capacity rather than activity) exist. These activity data are divided into emergency versus non-emergency cases on a departmental level depending on the medical condition of the patient. Thus the total number of e.g. discharges for each hospital is found by aggregating over all hospital departments. These activity statistics are purely quantitative and therefore completely ignore the dimension of quality. Moreover, statistics on total expenditures consist of expenditures on wages, goods, services and materials and finally hospital earnings arising from transactions between county funds e.g. due to county refonds concerning patients treated at hospitals outside their own county. These groups are aggregates made by the ministry and thus more disaggregated information is supplied by the hospitals.

3.2 The choice of data set

In this study we use a reduced set of the data supplied by the Ministry of Health. The main reason for using a smaller data set is that the methods we intend to use for analyzing productive efficiency (DEA and FDH-methods) require a small number of inputs and outputs compared to the number of observations. Otherwise a large part of the observations will become noncomparable and thus will be classified as efficient making the whole exercise meaningless.

The reduction of the data set takes place at two levels. One level concerns the construction of the aggregates to obtain categories of inputs and outputs representing the activity of each hospital. The other level concerns the choice of hospital sample which must be comparable in each hospital given the aggregated information on activities.

The employment data on 57 job-categories offer a good base for aggregation of inputs since all categories are measured by the same units, i.e the number of individuals. Notice that in aggregating data one implicitly assumes internal homogeneity of the aggregated groups, e.g. that all the personnel within a particular group have the same productivity. For the standard model we have chosen to measure the personnel, or input, by aggregating the job-categories into the following 4 groups (capital letters represent the name of the variable in the applied models):

1. Doctors (DOCTOR)
2. Nurses (NURSE)
3. Other types of health care personnel (OCARE)
4. A residual group (OTHER).

The first group (DOCTOR) contains the number of doctors and other types of academic health care personnel e.g. dentists etc. NURSE is an aggregate of nurses and other types of nursing personnel. OCARE contains other types of non-academic health care personnel. Finally, OTHER includes administrative personnel, cleaning personnel etc. These four categories of employment do imply that some allowance for differences in quality between the employment categories are considered. However the four employment categories are mainly constructed in order to indicate differences in the way each group interacts in the production process rather than to indicate differences in quality. Realizing that these four categories may seem incomplete since data on capital as well as consumption of goods are excluded we will operate with alternative models. As a proxy for capital earlier studies of hospital efficiency (e.g. Banker, Conrad & Strauss [1986] and Sherman [1984]) have used the total number of beds. Indeed this is an incomplete measure for capital, however following this tradition we include the variable BED (see model C2 in section 4.1). Moreover, another alternative input measure may be the total current net expenditures[1] (in this study called EXP) as an aggregated variable which takes into account the consumption of all goods (including labour).

The outputs in this study are chosen as aggregates from the activity statistics. For the standard model we represent the outputs by the total number of discharges and the total number of outpatient visits[2]. Thus we aggregate over emergency cases and non-emergency cases for discharges and outpatient visits. Implicitly this kind of aggregation assumes that emergency cases and non-emergency cases are homogeneous with respect to the required amount of resources. That is:

a. Total number of discharges (DISCH)

[1]The total current net expenditures are defined as total current expenditures minus earnings obtained on patients from foreign counties. The reason for not using the total current expenditures is that the activity data concern patients from the county which the hospital is placed within. Thus the total current expenditures overestimate the costs of these patients since the total current expenditures also involve costs incurred on patients outside the county.

[2]Notice that in Denmark there is no official system like Diagnosis Related Groups (DRG) for aggregating outputs.

b. Total number of outpatient visits (AMBULA)

This basic model is incomplete in the sense that the above partitioning does not consider the fact that patients are different with respect to length of stay. Therefore we will operate with an alternative model using the total number of patient days (PDAY) instead of DISCH (see model B1 in section 4.1).

The total number of hospitals included in the statistics from the Ministry of Health is 111 in 1989. However, not all of these 111 hospitals are comparable in terms of the above stated variables. Psychiatric specialized hospitals and physiotherapeutic hospitals must be excluded due to their highly specialized activities and this concerns some of the somatic hospitals as well. This immediately reduces the number of hospitals to 80 which form our basic sample.

Table 2 shows some descriptive statistics of the above mentioned sample of 80 hospitals. Notice that the mean and the median of each category is almost identical indicating that the distributions are symmetric. In the sequel we will only consider data from 1989.

Table 2: *Descriptive statistics of the distribution of inputs and outputs in the standard model, pct.*

	DOCTOR	NURSE	OCARE	OTHER	DISCH	AMBULA
Max.	17.78	60.89	27.27	41.54	64.50	96.76
Min.	4.11	24.00	3.90	16.62	3.24	35.5
Mean	10.22	49.15	12.91	27.72	30.12	69.88
Std.	2.30	6.00	3.38	4.28	11.29	11.29
Med.	10.28	49.33	12.54	27.54	29.59	70.14

Remark: The numbers are based on data from 85-89, e.g. the mean is calculated over the whole range from 85-89.

4 The choice of modelling approach

The major disadvantage when turning from parametric approaches towards non-parametric approaches like DEA is the lacking foundation of statistical analysis. Hence recent developments in applied DEA point towards the introduction of statistical methods in the form of statistical tests, in order to reestablish robustness of the obtained results. In particular there has been a search for the "true model" describing the observed production relation. One such way to obtain a "true model" is considered through so-called stepwise DEA (Kittelsen [1992]). The idea of this procedure is to extend a basic model with a number of new variables included on the basis of a F-test for the relative difference in average efficiency. The inclusion of new variables stops when these variables become insignificant. However, in its present form this procedure seems to have some drawbacks. Firstly, one has to assume that the efficiency distribution is halfnormal or exponential which as such are rather strong assumptions. Secondly, and more important, the way the F-statistic is defined seems unfortunate in relation to the way in which it is used. According to the F-test a variable is significant when average efficiency increases due to the inclusion of the variable. In the worst case this implies that irrelevant variables may be included if they result in non-comparability of the units since non-comparability means high efficiency scores i.e. a higher F-value. Furthermore the inclusion of new variables depends crucially on the variables in the basic model. If these variables have been wrongly chosen the final model will be erroneous as well.

Also the non-parametric Mann-Whitney test[3] have been used, though not in order to determine the "true model". Shortly, the Mann-Whitney test is used to analyse whether two subgroups can be assumed to have been drawn from the same population. Consider the following example: Through a criteria of geographical location we can separate the hospital sample into two groups. If these groups fail to pass the Mann-Whitney test then they have not been drawn from the same population i.e. they differ in the distribution of efficiency scores due to geographical location. Recently Valdmanis [1992] and Magnussen [1992] have applied the Mann-Whitney test on hospital data from resp. USA and Norway. In both papers the overall idea is to analyze

[3]See e.g. Siegel & Castellan [1988]

the sensitivity of the obtained DEA efficiency scores with respect to different criteria.

As part of a larger framework we intend to apply yet another kind of test - the Spearman rankorder correlation coefficient[4] testing the degree to which two rankings are associated. In the proceeding sections we will follow the approach outlined below:

We define a standard model which at first hand seems representable.

Considering the results of the standard model we put forward a number of alternative models concerning e.g. the aggregation of some variables, the inclusion of new variables or the replacement of old ones etc.

The association of the obtained rankings are tested through Spearmans correlation coefficient.

In order to explain the efficiency variation we have chosen to follow a regression approach where the efficiency scores from the standard model are regressed on a vector of explanatory variables which include environmental factors. This kind of analysis can be seen as a parallel to the above mentioned Mann-Whitney test and as such it may have policy implications.

The focus is on input efficiency in the following, since the hospitals are assumed to take output as given i.e. to act as cost minimizers.

4.1 Measuring input efficiency by the radial Farrell index

Applying FDH and DEA-C[5] methods to the standard model of the four job-categories and the two output categories on the hospital sample of 80 Danish hospitals (as described in section 3.2) yields the efficiency results depicted in figure 1. Both models are based on Farrell's radial index of input efficiency. The immediate impression of these results corresponds to the intuitive expectation, since there is a relatively small number of efficient hospitals under the DEA-C technology and a very large number of efficient hospitals under

[4] See e.g. Siegel & Castellan [1988]

[5] The extentions on DEA, V, D, C means respectively DEA with variable returns to scale, decreasing returns to scale and constant returns to scale, see e.g. Holvad & Hougaard [1993].

the FDH technology. For 1989 the average efficiency score under DEA-C is 0.71 whereas 0.99 under FDH. In DEA-C, 6 out of 80 hospitals received score 1, whereas there are 75 out of 80 under FDH. Among these 75 efficient hospitals, 68 were undominated but non-dominating units. This large number corresponds to the findings in Tulkens [1990]. Even though this difference seems large, it was partly to be expected, since theoretically we know that the free disposal hull technology is a subset of the constant returns to scale technology. Moreover, the efficiency scores from DEA-C and FDH constitute the range of variation in technical efficiency where DEA-C provides the lower bound and FDH provides the upper bound. As an example the largest hospital Rigshospitalet can be mentioned. In 1989 it obtained the score 0.49 by DEA-C but 1.0 by FDH. This large variation is due to the fact that Rigshospitalet is "uncomparable" under FDH since it is the largest in the sample – and by definition it cannot be dominated by the other units in the sample.

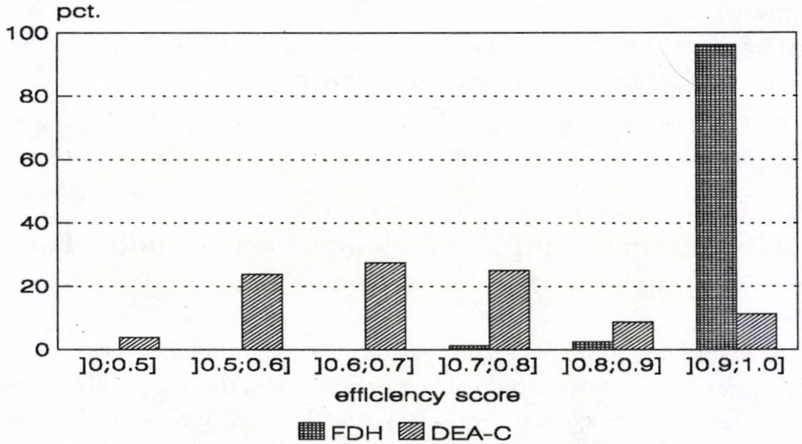

Figure 1. *DEA-C and FDH efficiency scores for 1989.*

Does this make FDH meaningless and DEA-C preferable when ranking the sample? The answer is classical in the sense that no direct conclusion can be drawn. At first sight the most interesting analysis seems to be DEA-C because it provides a usable ranking of the sample. However, the large variation in efficiency scores between FDH and DEA-C may indicate that constant returns to scale is too strong an assumption on the observed technology in favour of the FDH technology. At first hand it is not possible to conclude whether the variation in efficiency scores are caused by convexity or constant returns to scale (or both). However, by calculating the efficiency scores under the technological assumption of variable returns to scale we are able to examine this aspect. The results for 1989 are illustrated by figure 2. As could be expected the variable returns to scale technology is relatively close to the free disposal hull technology, but not identical – that is the scores obtained under variable returns to scale seem to indicate that convexity in fact is of importance.

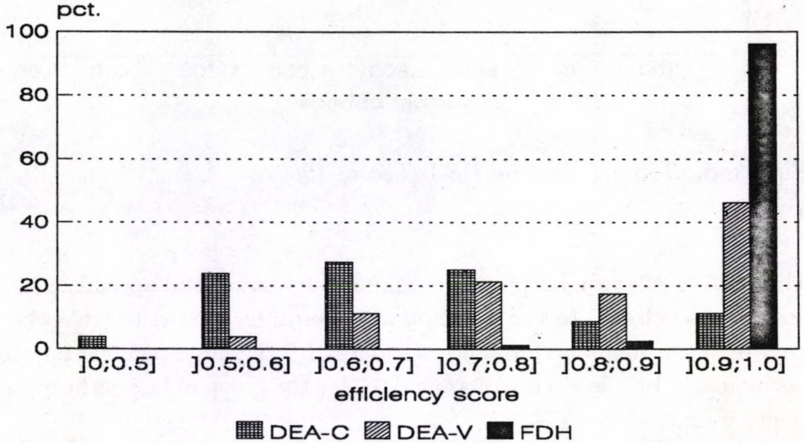

Figure 2. *DEA-C, DEA-V and FDH efficiency scores for 1989.*

Therefore at this early stage, there seems to be a real difference between choosing a DEA model or a FDH model – a difference which will be further examined in the following.

By introducing the DEA-V model, our results seems to indicate that unit size is negatively correlated with the DEA-C efficiency scores. This turns out to be a fact as illustrated by figure 3 where beds are used as a proxy for size, and it can be further confirmed through regression analysis[6].

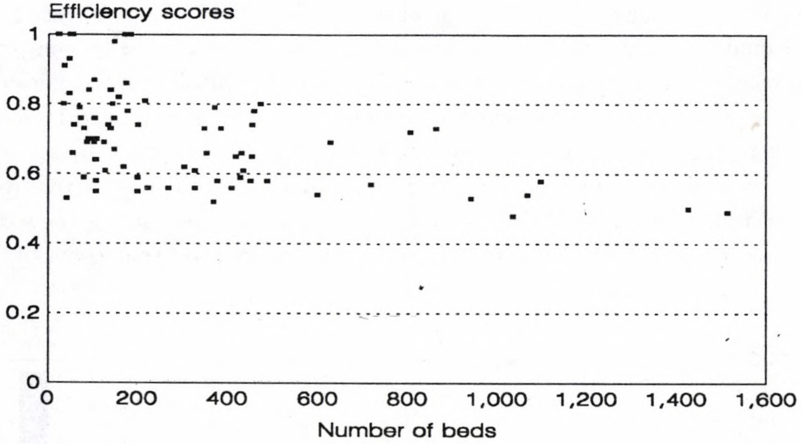

Figure 3. *Hospital size and DEA-C score 1989.*

The DEA-C efficient hospitals are mainly very small and specialized local hospitals which due to the assumption of constant returns to scale can be argued to set unfair performance standards for the large regional hospitals (as indicated by a low score of around 0.5 for the group of largest hospitals). Hence we introduce:

MODEL A: *Altering the hospital sample.* Since it can be argued that very small, specialized and hence efficient hospitals are setting unfair standards, it seems obvious to try to exclude such hospitals from the sample.

As a measure of size we have chosen to represent the hospitals by the total number of patient days and set a threshold at 2.5 pct. of the observed maximum. Thus hospitals with a total number of patient days smaller than that are excluded. Furthermore the excluded hospitals must be efficient in a DEA-V sense.

[6]It is worth noticing that the negative correlation is not found among the DEA-V scores.

This reduces the sample to 75 hospitals where we obtain the results illustrated by figure 4.

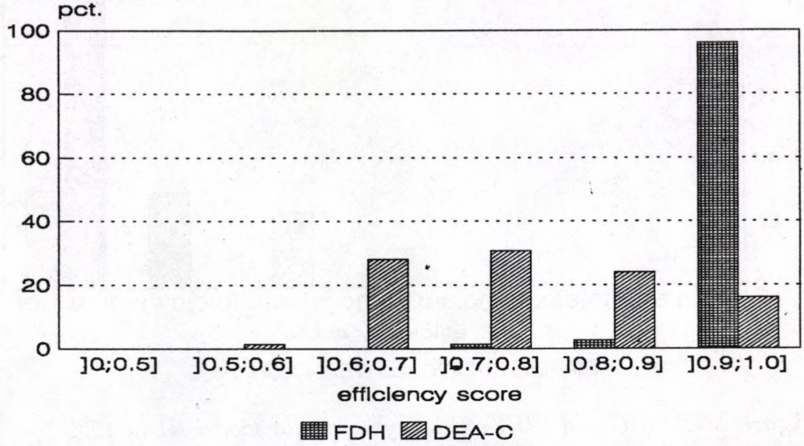

Figure 4a. *FDH and DEA-C efficiency scores with reduced sample in 1989.*

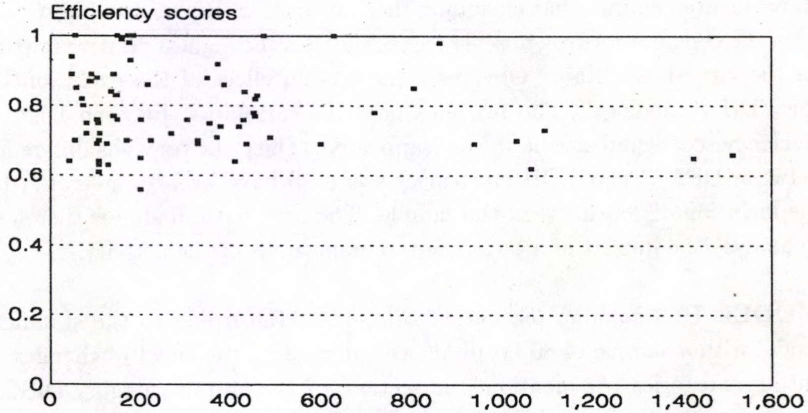

Figure 4b. *DEA-C efficiency scores and size with reduced sample in 1989.*

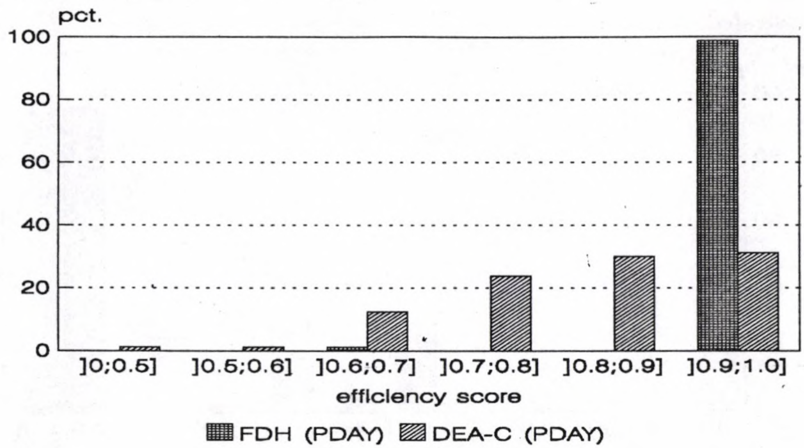

Figure 5. *DEA-C and FDH efficiency scores for model B1 in 1989.*

Notice that the variation betweeen FDH and DEA-C efficiency scores are reduced in particular for the largest hospitals. This follows from the above mentioned fact that excluding the five small and specialized hospitals from the constant returns to scale technology has the highest relative impact on the largest hospitals. Obviously there is no effect of the exclusion on the FDH technology. The previous negative correlation between DEA-C efficiency scores and size has also disappeared. Thus, the previous difference between DEA-C and FDH efficiencies seems to have been exaggerated by the inclusion of "outliers" in the sample. The next natural step is therefore to analyse the impact of alternative representations of the activity.

MODEL B: *Changing the output categories.* Returning to the standard model with a sample of 80 hospitals we will analyse the effect of changes in output categories. As mentioned in section 3.2 the output category DISCH consists of the total number of discharges, but this variable does not cover the fact that patients may differ with respect to length of stay. Hence, an obvious alternative will be to include the total number of patient days (PDAY) as a replacement of DISCH (model B1). These results are illustrated by figure 5. In general the efficiency scores tend to increase in both DEA-C and FDH by the introduction of PDAY. 14 hospitals were efficient under DEA-C and 78 under FDH. Among these 78 efficient hospitals 76 were undominated but non-dominating. A possible explanation can be that the small hospitals, which were efficient with the variable DISCH, may be characterized by a relatively large number of non-complicated patients. This would make the large hospitals with complicated patients dominated by the smaller hospitals. Such a feature may be revealed by the introduction of the variable PDAY to the extent that complicated cases are reflected in the length of stay. Furthermore, it is possible that aggregating emergency and non-emergency discharges implies biased efficiency results since emergency cases may interfere with hospital planning. Hence we try to include the emergency aspect explicitly by disaggregating both discharges and outpatient visits (model B2). As a result we obviously get a higher level of average efficiency (0.83) as well as more efficent hospitals. More interesting, though, is the fact that some hospitals with extreme emergency ratios have above average increases in efficiency. For example the hospital Sundby, which has a large number of emergency discharges, changes from 0.52 in the standard model to 0.88 if outputs are disaggregated.

MODEL C: *Changing the input categories.* As one possible change in input categories of the standard model we have chosen to aggregate inputs by prices into a single variable "total current net expenditures" (EXP), model C1. In this case, it is worth noticing that the interpretation of the efficiency scores as purely technical to a certain extent may be misleading. Introducing EXP causes the efficiency index to represent an indication of some sort of cost-efficiency. The results from this model are illustrated by figure 6. First, it is worth noticing that aggregating inputs reduces the number of efficient hospitals in both DEA-C (where the number is 2) and the FDH model (where the number is 64). Among the 64 efficient hospitals 46 are undominated but non-dominating. This is due to the fact that reducing the number of production categories obviously makes the units more comparable, since fewer dimensions causes less specialization. Secondly, being labour-efficient does not necessarily imply that the units are "cost-efficient". A possible difference may have several explanations. Obviously the hospitals could have an excessive use of other input factors than labour. Furthermore, measuring labour by the number of employees does not take into account neither the actual hours worked nor the "price" of these hours. This argument could

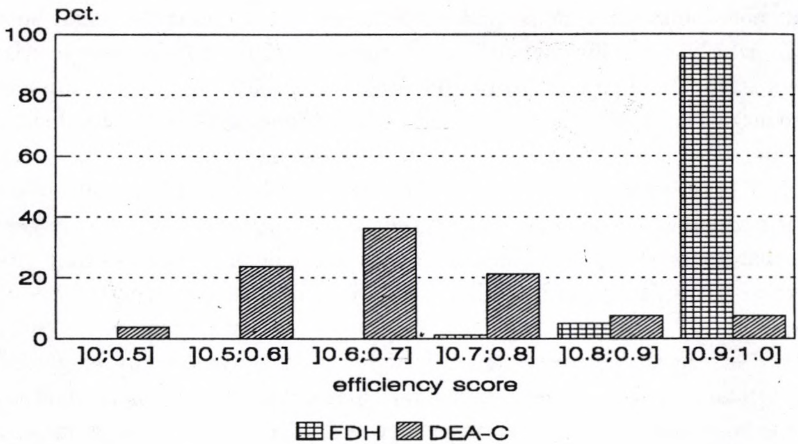

Figure 6. *DEA-C and FDH efficiency scores for model C1 in 1989.*

be further analysed by using the total salary bills as an aggregated input and compare the efficiency results with the results obtained in the standard model. As illustrated by figure 6, differences between labour and cost efficiency do in fact occur in our case.

If the expenditures of each hospital is multiplied by a factor defined as 1 minus the obtained efficiency score we obtain a proxy for excess spending – that is the amount which could have been saved if the hospital had been cost efficient. Table 3 shows the proportion of total expenditures which are due to excess spending for DEA-C and FDH models.

Table 3: *Excess spending in percentage of total current net expenditures.*

	FDH	DEA
Excess spending	1.7	40.7

Obviously the proportion of excess spending is largest under DEA-C since fewer hospitals are declared cost efficient. In fact this might be a practical argument in favor of the FDH-method since from an empirical point of view it seems unrealistic that the hospitals should be able to reduce their expenditures by 41 pct. as indicated by the DEA-C model. A point also emphasized by Vanden Eeckaut, Tulkens & Jamar [1991].

Furthermore, as mentioned in section 3, one can consider the capital factor through the proxy "total number of beds", model C2. If the number of beds is added to the standard model, the degree of capacity utilization becomes important when the efficiency variation is to be explained. Typically the small hospitals have a relative bad utilization of beds, but these hospitals are normally "labour"-efficient and hence they continue to be efficient when the standard model is extended. However, among the largest hospitals, which in general turn out as "labour"-inefficient, there are in general a relatively good utilization of beds and hence these hospitals all have above average increases in efficiency scores if BED is included. This is illustrated by figure 7. The figure shows a positive correlation between the change in

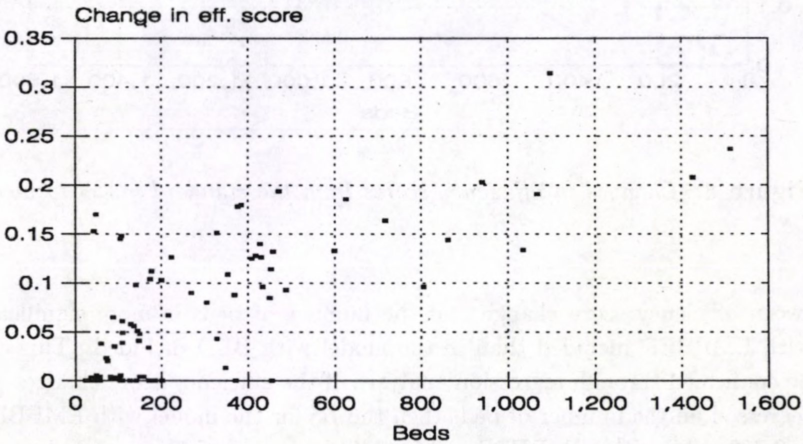

Figure 7. *Changes in efficiency scores from the standard model to model C2.*

efficiency score and BED, that is the larger the number of beds for a hospital the higher is the change in efficiency score. Thus the hospitals utilization of beds is of importance in the efficiency evaluation. This conclusion is further confirmed if instead the average time a bed is empty (EMPBED)[7] is added to the standard model, model C3. EMPBED measures more directly the capacity utilization. Therefore the model with EMPBED results in above average increases in the efficiency scores for the largest hospitals. This is illustrated in figure 8. Figure 8 indicates that the correlation be-

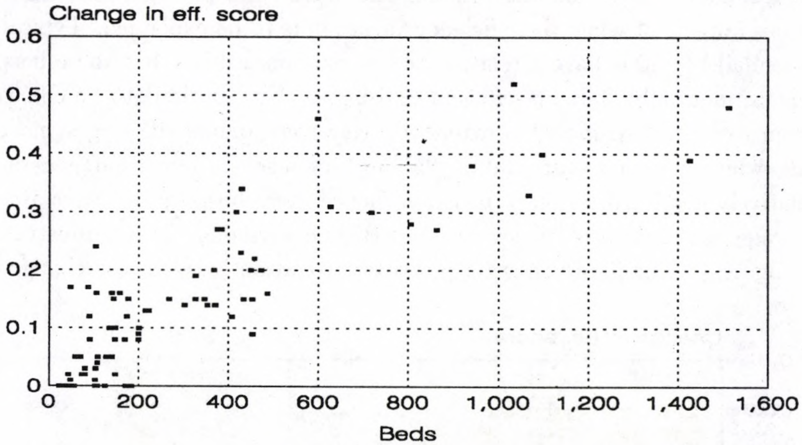

Figure 8. *Changes in efficiency scores from the standard model to model C3.*

tween efficiency score change and the number of beds is more significant with EMPBED included than in the model with BED included. This can be confirmed through regression analysis: If the efficiency score changes are regressed on the number of beds then the R^2 for the model with EMPBED is 0.723, while R^2 with BEDS is 0.514. This characteristic is related to the more direct modelling of the degree of capacity utilization with EMPBED than with BED. The largest hospitals do not only need a relatively smaller number of beds to generate discharges, but they utilize their capacity to a higher degree.

[7] The average time a bed is empty measures how much the average length of stay could be increased if the hospital utilized the bed capacity completely.

4.2 Rank-order correlation coefficients

To test whether the alternative rankings obtained from the models mentioned above are associated, we can compute the Spearman rank-order correlation coefficient (see e.g Siegel & Castellan [1988]). This non-parametric measure makes pairwise comparisons and results in a correlation coefficient as well as a test statistic in relation to the null hypothesis of no association.

Table 4: *Corrected Spearman rank-order correlation coefficients.*

	Coefficient	Test statistic
Standard DEA-C vs. standard FDH	0.298	2.645
Standard DEA-C vs. standard DEA-V	0.499	4.438
Standard FDH vs. standard DEA-V	0.389	3.459
Standard DEA-C vs. model A	0.830	7.143
Standard DEA-C vs. model B1	0.650	5.778
Standard DEA-C vs. model B2	0.878	7.804
Standard DEA-C vs. model C1	0.818	7.275
Standard DEA-C vs. model C2	0.830	7.379
Standard DEA-C vs. model C3	0.544	4.832

Remark: A value of the test statistic is significant at a 5 pct. resp. 1 pct. level if it exceeds 1.645 resp. 2.326.

In fact we use the corrected Spearman coefficient because of the presence of so called tied observations which are observations with identical ranking positions (in this particular case e.g. when observations have efficiency score 1). In table 4 the Spearman rankorder correlation coefficients are tabulated. The test statistic follows a standardized normal distribution.

For all pairwise comparisons in table 4 the Spearman correlation coefficient is significant at a 1 per cent level. Thus we can conclude that all the efficiency rankings are to some extent associated. This holds in particular for the comparisons: Standard DEA-C vs. model A, standard DEA-C vs. model

B2, standard DEA-C vs. model C1 and standard DEA-C vs. model C2. Obviously FDH has a low association to DEA-C due to the relatively large number of efficient units and likewise FDH vs. DEA-V has a low association. The high association between standard DEA-C and model A indicates that removing the five small hospitals does not alter the ranking of the remaining hospitals in a significant way. However, it is worth noticing that the average efficiency increases in model A. An aspect which the Spearman coefficient cannot take into account. If we consider model B1, i.e. change the output category DISCH for PDAY, we obtain a moderate degree of association – that is, it does seem to have an impact on the over all efficiency ranking result. On the other hand disaggregating DISCH and AMBULA to emergency and non-emergency does not seem to have significant effect on the ranking of the hospitals, although the average level of efficiency increases in this specification. If we compare the model where inputs are aggregated to total current net expenditures with the standard model there is a very high degree of association indicating that the aggregation is justified in the sense that information is preserved. Here it is worth noticing that around 70 pct. of the costs is composed of salary. Similar there is a high association between the standard model and the standard model extended with the number of beds (model C2). Thus although the average level of efficiency increases and especially the largest hospitals increase their efficiency score the ranking is preserved to a high extent. This is not the case for the standard model extended with the average empty bed time (model C3), which is rather weakly related to the standard model. Both model C2 and model C3 were constructed with respect to concerns about the bed capacity utilization, but they have indeed very different effects on the ranking from the standard model. Therefore it seems that including the variable EMPBED in the model does provide additional information about the hospitals' performance, whereas the variable BED does not include any significant new information about the performance.

4.3 The non-radial Färe-Lovell index

Replacing Farrell's radial efficiency index by the non-radial Färe-Lovell index provides additional and useful information about partial performance. Consider the following specific result concerning a single hospital (Rønne hospital) obtained with respect to the standard model under FDH. The scores are depicted in table 5.

Table 5: *Examples of partial Färe-Lovell input efficiency scores 1989.*

Hospital	θ_1	θ_2	θ_3	θ_4	E_{FL}
Rønne	0.88	0.87	0.87	0.54	0.79
Bispebjerg	0.47	0.73	0.39	0.34	0.48
Avg. eff.	0.68	0.78	0.62	0.57	0.66

Remark: $\theta_1, \theta_2, \theta_3, \theta_4$ refer to partial efficiency score for respectively DOCTOR, NURSE, OCARE and OTHER. $E_{FL} = (\theta_1 + \theta_2 + \theta_3 + \theta_4)/4$.

Notice that the obtained Färe-Lovell score on 0.79 is a mean of the four partial input efficiency scores, and hence difficult to interpret as such. The important information consists rather of the partial input scores themselves because they measure the ability to utilize each input category separately. From table 5 we notice that Rønne hospital seems to have a bad utilization of the input factor OTHER, whereas the utilization of DOCTOR, NURSE and OCARE are relatively good. In the case of Rønne the largest partial efficiency score is 0.88 for the input factor DOCTOR, which incidently is identical to the Farrell efficiency score. In general we will not have this proporty as demonstrated in Holvad & Hougaard [1993]. As a special feature of the FDH model the actual amounts of input weighted by their related partial efficiency scores yields the input vector characterizing the best-practice reference hospital. In the case of Rønne this is found to be Frederikssund hospital.

Consider table 5 again where the efficiency scores for Bispebjerg hospital are depicted. These results are obtained using the DEA-C model on the standard model and the sample of 75 hospitals. First, we notice that the largest partial score (NURSE = 0.73) is higher than the radial efficiency score 0.70. Secondly, weighting the input vector by the partial scores does not necessarily result in the input vector of an actually existing hospital. This follows from the assumption of convexity. The scores of Bispebjerg hospital are quite interesting because they illustrate the consequences of radial efficiency evaluation. Notice that except for NURSE all other factors are badly utilized by Bispebjerg, but if efficiency is evaluated radially the relatively good utilization of NURSE covers up this fact. Though, the radial efficiency score and the largest partial score are not completely identical, the latter determines the former.

The last line in table 5 shows the partial Färe-Lovell input efficiency scores for the 80 hospitals on average. The average score for DOCTOR is probably underestimated since output does not account for teaching activities. The relatively good utilization of DOCTOR and NURSE are mainly caused by fixed settings of the number of employees per bed. The bad utilization of OCARE and OTHER are partly a result of the fact that some hospitals have privatized cleaning which obviously interferes with OTHER.

5 The significance of non-included variables on the efficiency results of the standard model

As we observed in the various models there are several factors which have an impact on the efficiency ranking of the hospitals. Thus, there are variables which are not directly included in the standard model although they influence the obtained efficiency variation. In an attempt to estimate and systematize the relative significance of such non-included variables we have chosen to follow a regression approach where the efficiency scores of the standard model are regressed on a vector of different variables of which some of them are so-called environmental factors. Obviously we could have chosen to include all such variables directly in the DEA-model but this would often result in too many dimensions causing meaningless results as it was partly illustrated by the different models.

In the sequel we follow the standard procedure for regression analysis – that is:

1. Based on the efficiency variation from the standard model we specify a regression model and define the variables to be included.

2. Presentation of regression results.

3. Examination of some econometric issues related to whether the assumptions from the OLS estimator can be determined to be satisfied.

4. Residual analysis and model implications.

5.1 A regression model

As mentioned in Holvad & Hougaard [1993], we assume that the variation in efficiency scores can be approximated by the following log-linear model:

$$\ln(\theta) = Z\beta + e$$

where θ is the vector of efficiency scores, Z is a matrix of explanatory variables which includes both controllable organizational features and non-controllable characteristics for each hospital and e is a disturbance term with mean 0 and standard deviation σ. Variables in the matrix Z will be defined below. The above specification is chosen in order to obtain consistent estimates of β. The problem of consistency arises because the efficiency scores are restricted to take values between 0 and 1. This generates a dependency between the Z-variables and the disturbance term e. In the above specification we can only obtain consistent estimates of β if the efficiency scores are allowed to take values without an upper bound. Hence we will use the procedure for ranking the efficient observations described in Holvad & Hougaard [1993]. Inefficient observations obtain the same efficiency score, but the efficient observations ($\theta = 1$) can obtain scores above 1. These efficiency scores indicate how much an efficient observation could increase its inputs and remain efficient. This procedure is applicable only when constant returns to scale is assumed and thus we restrict our model to DEA-C. $\ln(\theta)$ is not defined for $\theta = 0$, but since all efficiency scores are greater than 0 this case does not represent a problem.

From the models in section 4.1 we know that at least the following non-included factors have importance on the obtained efficiency ranking in the standard model: specialization in outputs, hospital size, the number of patient days, capacity utilization approximated by the number of beds and the proportion of emergency cases. As it turns out in the regression analysis the following explanatory variables provide a satisfactory model estimation:

1. OUTPROP: The ratio of the number of outpatient visits to the number of discharges, i.e.

$$OUTPROP = \frac{\text{AMBULA}}{\text{DISCH}}$$

This variable describes an aspect of the output structure related to the case-mix and in this sense it also reflects the extent to which the hospitals are specialized with respect to the output specification in the standard model. From the standard model we knew that this type of output specialization influences the efficiency ranking. The expected sign in the regression analysis is positive since outpatient cases should be less resource demanding than inpatient cases. Obviously, this variable is not under the control of the hospital management.

2. RCMSHARE: The inverse of the ratio of the number of beds at the hospital to the total number of beds in the county of the hospital, i.e.

$$RCMSHARE = \frac{\text{Total beds in county } j}{\text{beds at hospital } i \text{ in county } j}$$

RCMSHARE is included as an indicator for the degree of centralization. A low value for this variable implies that a hospital is a major provider of health care in the county. As such this variable gives a better representation of the degree of centralization compared to e.g. the number of beds since the size of the other hospitals in the county is taken into account. Since the aspect covered by RCMSHARE is not explicitly included in the model specification it can be considered as an environmental factor and therefore outside the control of the management. The expected relationship between the efficiency scores and RCMSHARE is positive since larger hospitals (which have a low value of RCMSHARE) may have a more complicated case-mix, use more resources on teaching[8] and there is a possibility of scale effects as indicated by the DEA-C model.

3. MTIME: The average length of stay, defined as the number of patient

[8]Unfortunately it has not been possible to include a variable measuring the resources devoted to teaching directly in the regression model due to lack of centrally collected data.

days divided by the number of discharges, i.e.

$$MTIME = \frac{\text{PDAY}}{\text{DISCH}}$$

MTIME is also an environmental factor in relation to the actual model specification and can be taken as a proxy for the complication of the case-mix. Moreover inefficiencies might also appear through longer length of stay since it could be an indicator for slow treatment procedures or unnecessary tests, although other factors may influence the magnitude of the average length of stay. Thus the expected relationship between the efficiency scores and the average length of stay should be negative. In principle MTIME can be controlled by the management since it, to a certain extent, are able to control the number of patient days. It should be remarked that MTIME is one of the traditional indicators used in the hospital sector as performance measure and was considered, through the variable PDAY only, as an output in model B1.

4. EMPBED: The average time a bed is empty, defined as the average length of stay divided by the occupancy in per cent (CAPPCT) minus the average length of stay, i.e.

$$EMPBED = \frac{\text{MTIME-CAPPCT*MTIME}}{\text{CAPPCT}}$$

where

$$CAPPCT = \frac{\text{PDAY}}{\text{365*BEDS}}$$

EMPBED concerns the capacity utilization by measuring the average time a bed is empty, that is the average time between one patient leaves the hospital till the next arrives. A high value of EMPBED could indicate that the planning of the patient flow is bad such that the hospital could increase the number of patient days without capacity consequences. For two hospitals which only differ with respect to EMPBED the hospital with the highest value of EMPBED will other things being equal obtain the lowest production level. Thus we assume a negative relationship between the efficiency scores and EMPBED. Notice that EMPBED is one of the key variables used as traditional performance measure in the hospital sector. BED and EMPBED were considered as alternative inputs in model C2 and C3.

5. EPROPPD: The proportion of the patient days which is made up of emergency cases, i.e.

$$EPROPPD = \frac{\text{Emergency patient days}}{\text{PDAY}}$$

The variable EPROPPD is an environmental factor, and hence uncontrollable, which concerns the output structure with respect to patient days by measuring the proportion of emergency cases. A negative relationship between the efficiency scores and EPROPPD should be expected due to restricted possibilities of planning.

6. NEPROPAM: The proportion of the outpatient visits which is made up of non-emergency cases, i.e.

$$NEPROPAM = \frac{\text{Non-emergency outpatient visits}}{\text{AMBULA}}$$

The variable NEPROPAM is also a non-controllable environmental factor which describes a characteristic of the output structure concerning the outpatient visits AMBULA. If NEPROPAM is equal to 1 it implies that no outpatient visits are emergency cases since the hospital does not have an emergency clinic. As such this variable gives a better representation of the presence of emergency outpatient visits compared to a dummy variable indicating whether the hospital has an emergency clinic or not since the proportion of emergency cases is taken into account. In general, emergency cases tend to lower the efficiency of a hospital since they restrict the possibility of planning and the emergency clinic has to be with staff even when there are no patients. Thus the expected relationship between NEPROPAM and the efficiency scores is positive. The emergency aspect was considered in model B2.

7. LABPRBED: The ratio of the total number of employees to the number of beds, i.e.

$$LABPRBED = \frac{\text{Total number of employees}}{\text{BEDS}}$$

The variable LABPRBED is indeed controllable and represents a form of inefficiency namely too many employees pr. bed and as such it characterizes the organisation of the hospital production process. It indicates the intensity of the health care production which might cover certain quality aspects. However, the expected relationship between LABPRBED and the efficiency scores is negative since low values of LABPRBED will other things being equal give high efficiency scores through labour resource savings.

In table 6 the signs of the relationship between the above listed explanatory variables and the efficiency score θ are shown.

Table 6: *The expected relationship between the explanatory variables and the dependent variable* $\ln\theta$.

	$\ln\theta$
OUTPROP	+
RCMSHARE	+
EMPBED	-
MTIME	-
EPROPPD	-
NEPROPAM	+
LABPRBED	-

The dependent variable, $\ln\theta$, is based on the efficiency scores[9] from the standard model with DOCTOR, NURSE, OCARE and OTHER as inputs and the number of discharges (DISCH) and the number of outpatient visits (AMBULA) as aggregated output variables. The model is estimated by ordinary least squares OLS (although other estimation techniques could have been applied) for 1989. Table 7 shows some descriptive statistics for the variables in the regression model.

[9]The efficiency scores are as mentioned allowed to take values above 1.

Table 7: *Some descriptive statistics for the variables in the regression model.*

MEANS of VARIABLES

Ldeac	constant	outprop	rcmshare	empbed	mtime	eproppd	nepropam	labprbed
-.3461	1.0000	3.2629	16.1129	2.1406	6.8191	0.6780	.6823	2.6475

STANDARD DEVIATIONS OF VARIABLES

Ldeac	constant	outprop	rcmshare	empbed	mtime	eproppd	nepropam	labprbed
.2487	.0000	3.6318	22.1890	1.2767	1.3418	.1432	.1663	.5012

DURBIN-WATSON TESTS

Ldeac	constant	outprop	rcmshare	empbed	mtime	eproppd	nepropam	labprbed
1.2587	.0000	1.3282	1.1063	1.3220	1.7228	1.8678	1.8805	1.1977

CORRELATION MATRIX

	Ldeac	constant	outprop	rcmshare	empbed	mtime	eproppd	nepropam	labprbed
Ldeac	1.0000								
constant	.0000	1.0000							
outprop	.4061	.0000	1.0000						
rcmshare	.5845	.0000	.5102	1.0000					
empbed	.3018	.0000	.4830	.6812	1.0000				
mtime	-.3230	.0000	.2640	-.0161	.0123	1.0000			
eproppd	-.2996	.0000	-.4051	-.3394	-.4481	.0774	1.0000		
nepropam	.2011	.0000	.3585	.2218	.2334	.1474	-.3751	1.0000	
labprbed	-.5210	.0000	.1050	-.3427	-.4304	.0505	.0080	.1251	1.0000

5.2 Regression results

The regression results are displayed in table 8.

Table 8: *Regression results.*

EQ(1) Modelling Ldeac by OLS

VARIABLE	COEFFICIENT	STD ERROR	H.C.S.E.	t-VALUE	Par r^2
constant	1.21842	.12947	.30399	9.41079	.5516
outprop	.04255	.00414	.00739	10.27777	.5947
rcmshare	.00428	.00070	.00117	6.14493	.3440
empbed	-.12798	.01314	.02012	-9.74275	.5687
mtime	-.08366	.00848	.01324	-9.87052	.5750
eproppd	-.19151	.08969	.25501	-2.13535	.0596
nepropam	.24531	.07140	.07136	3.43576	.1409
labprbed	-.36465	.02645	.03553	-13.78742	.7253

R^2 = .8721101 σ = .0931671 F(7, 72) = 70.14 [.0000] DW = 2.048
RSS = .6249677471 for 8 Variables and 80 Observations
Information Criteria: SC = -4.413879; HQ = -4.556580; FPE = .009548
R^2 Relative to DIFFERENCE+SEASONALS = .89500

As we notice the regression model appears as (ignoring the disturbance term):

$$\ln(\theta) =$$

1.22 + 0.04OUTPROP + 0.004RCMSHARE - 0.13EMPBED - 0.08MTIME - 0.19EPROPPD + 0.25NEPROPAM - 0.36LABPRBED

This model can explain a high proportion of the variation in the dependent variable, $\ln(\theta)$, as reflected by $R^2 = 0.87$ (the adjusted $\bar{R}^2 = 0.86$). This is confirmed by the F-test where the null-hypothesis $\beta_{outprop} = \beta_{eproppd} = \beta_{rcmshare} = \beta_{labprbed} = \beta_{mtime} = \beta_{nepropam} = \beta_{empbed} = 0$ is rejected at the 1 percent level (the F-statistic is equal to 70.14 which is much greater than the critical value $F_{0.99}(7, 72) = 2.9$). As could be inferred from the different models in section 4.1 a large part of the differences in efficiency is related to the included explanatory variables. Thus it seems unlikely that other (non-included) variables should prove significant in relation to the overall sample. Other variables (e.g. whether the cleaning at the hospital is privatized or not) influences on the efficiency scores are covered by the included variables. The remaining variation in the efficiency scores is mainly due to statistical noise. Furthermore the significance of each variable examined by the t-test implies that for all variables the null hypothesis $\beta_i = 0$ is rejected at a 5 percent level. The included variables therefore seem to be relevant for the explanation of efficiency differences concerning the standard model.

Looking at the sign of the parameter estimates these have all obtained the expected signs. Thus the estimation confirm that hospitals with high proportions of non-emergency outpatient visits (NEPROPAM) and low proportions of emergency inpatient cases (EPROPPD) have higher levels of efficiency. In addition hospitals with high numbers of outpatient visits compared to the number of discharges tend to have higher efficiency scores. Similar hospitals with small proportions of the total county bed supply (RCMSHARE) tend to have higher efficiency scores. The sign for LABPRBED is positive meaning that hospitals with a high number of employees per bed tend to have lower efficiency scores. The coefficient to the average length of time (MTIME) is negative indicating that longer length of stay implies lower efficiency scores. Moreover hospitals with long average empty bed time (EMPBED) have lower efficiency scores.

5.3 Econometric issues

Before proceeding to a more detailed analysis of the estimated model concerning examination of the residuals and evaluation of the implications of the model we will turn to some econometric issues with respect to the estimation. First of all we will analyze the presence of heteroscedastic errors because if heteroscedasticity is present the desirable properties of the OLS estimator with respect to the minimum variance of the parameters fails to hold. We consider one possible source of heteroscedasticity namely the hospital size measured by the number of beds. Heteroscedasticity from this specific variable could arise from a larger variation in the patient flow as hospital size increases. This increased variation in the patient flow could be the result of higher proportions of patients from foreign counties, where this number could be more difficult to forecast than patients from the county where the hospital is situated. This hypothesis is tested with the Breusch-Pagan test for heteroscedasticity of a particular form. In this case the test consists of regressing the squared residuals on hospital bed size. The test statistic, l, is equal to the product of R^2 from this regression multiplied by the number of observations. l is asymptotically χ^2 distributed where the degrees of freedom is equal to the number of regressors. R^2 is equal to .018 and the number of observations is 80 giving a value of $l = 1.44$. The critical value for $\chi^2_{0.95}(1) = 3.841$. Thus we accept the null hypothesis of homoscedastic errors for this particular form, i.e. hospital bed size does not influence the errors in any systematic way.

The consequences of using OLS when errors are autocorrelated are the same as with heteroscedastic errors namely unbiased but inefficient estimates and problems with inference procedures. In the case of cross-section data the autocorrelation stems from other observations at the same time. One apriori explanation for autocorrelated errors in the present model is mainly due to the hospital data structure. Data are listed such that the county structure is preserved and one county's hospitals are followed by hospitals from a neighbourhood county. Moreover in general the largest hospitals in a county are listed before the smaller hospitals in the county. This data structure could clearly result in dependencies among the errors. We have applied the Durbin-Watson test for 1. order autocorrelation and obtained a $DW = 2.05$. DW-values higher than 2 means that the null hypothesis of non-autocorrelated residuals has to be contrasted to the alternative hypothesis of negative first-order autocorrelation. The values of the upper and lower bounds indicate that the null hypothesis of non-autocorrelated residuals can be accepted at the 1 percent level.

However this is only testing for 1. order autocorrelation. In order to test for higher order autocorrelation we have employed a Breusch-Godfrey test with the test statistic

$$l = n(r_1^2 + r_2^2 + ... + r_p^2)$$

where r_i is the i'th autocorrelation of the OLS residuals and n is the number of observations. Thus the test consider p. order correlation as the maximum. l is asymptotically χ^2 distributed with p degrees of freedom. We have chosen to use a model for autocorrelation where 10. order correlation is the maximum, i.e. $p = 10$ since the largest number of hospitals in a county is 10. The test statistic, l can thus be computed as:

$$l = 80(r_1^2 + ... + r_{10}^2) = 6.755$$

Since $\chi^2_{0.95} = 18.307$ we accept the null hypothesis of no autocorrelation. Possible dependencies among the errors due to the data structure can thus be rejected to influence the errors in a systematic way.

The assumption of normal distributed errors has only importance with respect to inference procedures, e.g. the possibility of using F- and t-tests. Thus non-normal errors as such do not change the attractable properties of the OLS estimator. In order to test for normality of the residuals we tested for whether Skewness and Excess Kurtosis are jointly zero, since both Skewness and Excess Kurtosis will be zero if the population of residuals has a normal distribution. The null-hypothesis is that the Skewness and Excess Kurtosis are jointly zero contrasted to the alternative hypothesis that Skewness and Excess Kurtosis are not jointly zero. The test statistic c is defined as: $c = \frac{(n-k)}{6}(SK^2 + \frac{1}{4}EK^2)$, where SK is Skewness, EK is the Excess Kurtosis and k is the number of regressors. c is asymptotically χ^2 distributed with 2 degrees of freedom if the null-hypothesis is true. For n=80 and k=8 c becomes equal to 8.296 and the critical value for $\chi^2_{0.99}(2) = 9.2103$. With $8.296 < 9.2103$ we conclude that the null hypothesis can be accepted, i.e. the population of residuals can approximately be taken to be normal distributed.

Finally we will consider the presence of significant multicollinearity. It is apriori possible that some of the independent variables are highly correlated and thus can result in more uncertain parameter estimates. The possibility arises because some of the independent variables can be structurally related, e.g. hospitals with small proportions of emergency outpatient visits could be expected to have small proportions of emergency patient days as well. A crude indicator for multicollinearity is high R^2 combined with many insignificant coefficients, but in our case we have a fairly high R^2 combined with significant coefficients for all variables. Another indicator for multicollinearity is if the parameter estimates obtain the theoretical wrong signs, but this is not the case. Moreover looking at the correlation matrix reveals only few somewhat highly pairwise correlated variables. Thus only two correlation coefficients are higher than +0.5 or -0.5. The problem with this procedure for detecting multicollinearity is that it only considers pairwise dependencies but not more complicated collinearity patterns. However it should be noted that the problem of multicollinearity is dependent of the intended application of the regression results. If the purpose is to examine the sign of single coefficients then multicollinearity represents a problem. On the other hand if the purpose is to explain as much of the variation in the dependent variable as possible then multicollinearity is of less importance. In our case both applications are interesting but based upon the correlation matrix and the other crude indicators multicollinearity does not seem to be significant.

5.4 Residual analysis and model implications

The size of the residuals provide information concerning how well the model explains the dependent variable for each hospital – a positive (resp. negative) value of the residual implies that the actual efficiency is larger (resp. smaller) than predicted by the model. Obviously there may be local explanatory variables considering the residual of a single hospital, but such variables are not included in the model since they are not of general significance with respect to the chosen regression model. The (non-scaled) residuals take values in the range from -0.153 to 0.275. All residuals are quite small although the largest residual of 0.275 covers a difference between observed and estimated efficiency score of 0.22. Thus overall we have a good fit of the estimated efficiency scores compared to the actual efficiency scores which is indicated by the low standard deviation of the residuals equal to 0.09 around the mean of 0.

As an example of how the model is functioning we consider the largest positive residual of 0.275 obtained by Ærøskøbing hospital. This residual is the difference between an efficiency score on 0.91 and the estimated score of 0.69. The estimated efficiency score is obtained from the following Z-values: OUTPROP = 1.40, RCMSHARE = 68.58, EMPBED = 3.72, MTIME = 8.44, EPROPPD = 0.80, NEPROPAM = 0.84 and LABPRBED = 2.22. The most important contribution to the variation stems from LABPRBED followed by MTIME and EMPBED. The model underestimates the actual efficiency score due to an unusual output structure at Ærøskøbing hospital. Normally small hospitals have high proportions of non-emergency cases for both inpatient treatment and outpatient treatment. In the case of Ærøskøbing hospital the high proportion of non-emergency outpatient visits is accompanied by a high proportion of emergency patient days.

If we consider the average percentage contribution of each explanatory variable to the overall model explanation, we obtain the results as listed in table 9[10].

As noticed previously the included explanatory variables differ with respect

Table 9: *Average percentage contribution of the explanatory variables to the overall model explanation.*

OUTPROP	5.8
RCMSHARE	2.8
EMPBED	12.2
MTIME	24.0
EPROPPD	5.7
NEPROPAM	7.5
LABPRBED	42.0
Total	100.0

to the possibilities of control from the view of the hospital management. In general, variables related to the output structure are non-controllable by the hospital management – that is OUTPROP, EPROPPD and NEPROPAM which covers a total of 19 pct. of the variation. These variables are determined mainly by the patient flow although also influenced by the hospital facilities. Moreover the proportion of beds for a given hospital to the total

[10]The average percentage contribution is calculated by multiplying the average values of the explanatory variables by the estimated parameters and then calculate the ratio of the absolute value of each such pair to the sum of the absolute values of all pairs.

county bed supply is not controlled by the hospital but by the regionally authorities. In addition, assuming the patient flow to be exogenously for the hospital management, reducing MTIME in order to improve efficiency can only be obtained by an increase in EMPBED and thus leaving the efficiency unchanged. Thus only LABPRBED seems to be adjustable by the hospital management but this variable is very influential with respect to the variation in efficiency. It has the highest numerical parameter and can account for around 40 per cent of the variation. Although some part of the 40 per cent could be caused by non-excessive labour usage (e.g. hospitals with teaching commitments or hospitals providing high-quality care) it still indicates that decreasing the labour per bed ratio could be a possible way to obtain efficiency improvements.

The variables included in the estimated model were chosen according to the information obtained from the models described in section 4.1. This information compressed by the Spearman correlation coefficients indicated that especially including the number of patient days or a measure for the capacity utilization had strong effects on the efficiency ranking. This is indeed confirmed by the estimation of the regression model as illustrated in table 9, since MTIME and EMPBED are those variables which next to LABPRBED on average contribute most to the explanation of the efficiency variation. Excluding these variables in the standard model implies that part of the measured inefficiency is caused by these variables exclusion from the model. The low percentage contribution of RCMSHARE indicating the relatively size of the hospital is surprising due to the clear correlation between beds and the efficiency scores from the standard model. However a part of the potential explanation of RCMSHARE is taken over by EMPBED since this variable has a higher influence the larger the hospital. The relatively low average contribution to the model explanation by the two emergency-related variables corresponds to the relatively high spearman correlation coefficient between the standard model and model B2. Thus disaggregating the output categories into emergency and non-emergency cases did not induce a significantly changed ranking. The same holds for the variable OUTPROP (indicating the extent of output specialization) which has a low contribution to the model explanation and a high spearman correlation coefficient for the association between the standard model with 80 hospitals and the standard model with 75 hospitals. Thus in general the information from the non-parametric analysis and the parametric analysis correspond in large to each other.

The validity of the results described above is examined by using the reduced data set with the 5 non-comparable hospitals excluded. This analysis can be viewed as testing for possible influence of outliers or extremal observations on the estimation results. The dependent variable $\ln \theta$ is based on the DEA-C efficiency scores from model A with 75 hospitals except for the efficient observations where we again use the scores obtained from the procedure for ranking the efficient units. In table 10 we have compared the parameter signs from these two data sets:

Table 10: *Parameter estimates for the regression model from the complete data set and the reduced data set.*

	80 hosp.	75 hosp.
OUTPROP	0.04	0.11
RCMSHARE	0.004	0.004
EMPBED	-0.13	-0.10
MTIME	-0.08	-0.09
EPROPPD	-0.19	-0.02
NEPROPAM	0.25	0.16
LABPRBED	-0.36	-0.28
R^2	0.87	0.81

In general, we obtain identical signs for the estimates and moreover, the size of the estimates are approximately the same. However, the variable EPROPPD is an exception since the estimate is much lower and insignificant with the reduced data set. This insignificance is caused by a very strong relation between the 5 hospitals and EPROPPD. Reducing the data set lowers the standard deviation which drops from .14 to 0.10. But from an overall point of view the chosen model seems to be robust with respect to changes in the hospital sample.

6 Concluding remarks

We can summarize the above efficiency results by the following table:

	Standard	DEA-V	A	B1	B2	C1	C2	C3
DEA								
Min	0.48	0.57	0.56	0.45	0.54	0.41	0.55	0.55
Mean	0.71	0.86	0.79	0.84	0.83	0.68	0.78	0.84
Std	0.14	0.13	0.11	0.12	0.14	0.12	0.12	0.13
FDH								
Min	0.79	-	0.79	0.64	0.87	0.78	0.79	0.88
Mean	0.99	-	0.99	0.99	0.997	0.982	0.995	0.997
Std	0.03	-	0.03	0.04	0.02	0.05	0.03	0.02

As noticed, the FDH-method is fairly uninteresting since almost nothing can be concluded while DEA offers a usable ranking but imposes strong restrictions concerning the production technology. The standard model was changed in a number of different ways, which revealed that other non-included variables did have an effect on the efficiency results. The non-parametric analysis was in a second step supplemented with a parametric regression analysis where the efficiency scores of the standard model was regressed on explanatory variables chosen according to the different models. This approach implies an interesting link between parametric and non-parametric analyses and provides a procedure for introducing statistical evaluation of the obtained findings.

The practical relevance of this kind of analysis concerning hospital planning and management can be contested due to the fact that the analysis includes wide range of hospitals, which may not appear as similar as demanded by theory. However the basic procedures seem applicable. If one finds it unrealistic to compare hospitals as such we could restrict the analysis to cover departments etc. Furthermore DEA has in general been fairly successfully applied on Scandinavian hospital data[11]. Thus DEA seems to be a promising tool for analysing the extent of inefficiency within health care producers.

[11] Roos [1993] examines productivity changes for Swedish hospital data and Magnussen [1992] considers efficiency differences among Norwegian hospitals.

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