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Using Value Efficiency Analysis (VEA) to Measure Productivity Efficiency in Primary Health Care

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PERMANENT SEMINAR ON EFFICIENCY AND PRODUCTIVITY

USING VALUE EFFICIENCY ANALYSIS (VEA) TO MEASURE PRODUCTIVE EFFICIENCY IN PRIMARY HEALTH CARE

Eduardo González♣ and Vicente García*

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Abstract: Measuring productive efficiency in health organizations requires using flexible methods like Data Envelopment Analysis (DEA) capable to account for the enormous complexity of health care activities. However, the empirical application of DEA is subject to serious limitations. A recurrent problem of DEA is its scant discriminating power when the number of dimensions is large and the sample is not. This paper explores the ability of Value Efficiency Analysis (VEA) to increase the discriminating power of DEA. The VEA model uses qualitative information to constraint the range of shadow prices allowed in the programs. Applying VEA to a sample of 61 health care centres in Asturias (Spain) we certified a notable improvement in the discriminating power of DEA. The number of efficient centres decreases from 19 to 13. The results also reveal an important scale problem in some centres. We also find some relationships between managerial efficiency and some contextual variables.

Key words: Data envelopment analysis, health economics, primary health services, Shadow prices, value efficiency analysis

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1. Introduction

The measurement of productive efficiency in health care is a very complex task. The main problem is to correctly approach the output of the production process (Kooreman, 1994). One approach is to consider the general health level of the population as an indicator of output. But the health level is also affected by many factors that cannot be attributed to health production organizations, such as the environment, genetic and biological endowment, life styles, etc. Not to mention the difficulties to precisely define what we mean by the word “health”. Therefore, it is common to approach the production of health services by intermediate outputs (García et al., 1999).

But even defining intermediate outputs for health organizations is not simple. This is especially true in the case of primary health care. It is difficult to identify a specific and own product of primary care, apart from traditional indicators such as the number of patients, visits, assistance pressure or frequentation. The use of these indicators as measures of output is problematic. For instance, it is not clear that more visits will translate into a better health. In all production contexts, but especially in health, it would be misleading to measure efficiency only in terms of quantity (Salinas and Smith, 1996; Puig, 2000; Pinillos, 2003).

A way around this problem is using indicators that approach assistance quality, as, for instance, the average duration of the visit, the satisfaction of the population, the coverage of the population or the accomplishment of some technical quality standards (Pujol et al., 2006). The Coverage of the Services Portfolio (Alonso et al, 1995) may be interpreted as a measure of quality in primary health production. It approaches the coverage of the target population assigned to a centre with respect to its services portfolio. This indicator may be complemented with the degree of accomplishment of technical quality standards for the different services. Although, these quality indicators are not perfect they are the best we have, so far. Some other quality indicators are now in phase of development but are experiencing measurement problems. Proposals as the Ambulatory Care Groups have already been validated, but are difficult to implement in the practice (Juncosa et al., 1999; Orueta et al., 1999).

On the inputs side, traditional inputs like pharmaceutical expenditure and labour should be complemented with the volume of diagnostic tests or derivations to specialists. This information is fully documented in the management contracts that each primary health centre sign with the regional health service.

Once input and output data are gathered for the health centres under evaluation an analytical technique must be employed to obtain efficiency scores. Some approaches evaluate efficiency by means of simple ratios of one output to one input. The problem with this approach is that no single ratio can measure efficiency in a multiproduct-multiinput context, which is definitely the case of health care production (Giuffrida and Gravelle, 2001). Another problem of the simple ratio approach is that individual indicators do not always vary in the same direction. Thus the optimal level of a single ratio becomes controversial (Goñi, 1999).

Data Envelopment Analysis (DEA) overcomes some of the flaws of partial ratios analysis. The extreme flexibility of this technique and its ability to handle multiple outputs and inputs in the specification of the production process explains why it has been so extensively adopted in measurement of health efficiency (Hollingsworth et al., 1999; Puig, 2000; Worthington, 2004). However, DEA also has some drawbacks. One of the most important limitations of DEA is its low discriminating power when many dimensions are taken into account and the sample size is limited (Ali, 1994). In those cases, DEA results show a considerable number of efficient DMUs, even though some of them will be clearly considered inefficient with a more delicate inspection of the data. These DMUs obtain a score of 100% simply because they are not comparable to the rest of the sample in one on other dimension[1]. Some recent advances in the DEA methodology can limit the severity of this problem, at the cost of an increased level of analytical complexity.

The objective of this paper is to obtain technical efficiency scores for the whole population of public primary health care centres in the Spanish region of Asturias. For that purpose we compare activity data that includes both quantity and quality indicators of production. To avoid the limitations of DEA discussed above, we use a method called Value Efficiency

[1] Using the lowest quantity of an input, for instance.

Analysis (VEA) that is based on DEA but adds a constraint on input and output weights. VEA significantly improves the discriminating power of DEA by supplying additional information about a reference DMU which shows an appropriate combination of inputs-outputs. The empirical application also examines which factors are related to the VEA efficiency scores. The paper is structured as follows. Section 2 briefly reviews the VEA model as an extension of conventional DEA. Section 3 presents the data and Section 4 discusses the empirical results. Concluding remarks are provided in the final section.

2. Methods

To compute the VEA scores of efficiency we must first construct the DEA frontier for the health care centres. The DEA frontier identifies the centres that may be considered technically efficient under certain (conservative) assumptions. Even though there are many variants of DEA programs, in this paper we apply the traditional specifications of Charnes et al. (1978) for the constant returns to scale frontier (CRS) and Banker et al. (1984) for the variable returns to scale frontier (VRS). About the orientation of the efficiency model we choose an output orientation because some inputs are quasi-fixed and, more important, the problem of the health care centres in Asturias is to eliminate waiting times and to be able to dedicate some more time to each patient. Thus, in this particular setting, the capacity to increase output is a managerial goal that is preferred to the ability to contain input consumption. The CRS DEA model with an output orientation requires solving the next mathematical program for each DMU *i* in the sample:

$$
\begin{aligned}
& \min \frac{\sum_{m=1}^{M} v_m x_{im}}{\sum_{s=1}^{S} u_s y_{is}} \\
& s.a: \\
& \frac{\sum_{m=1}^{M} v_m x_{jm}}{\sum_{s=1}^{S} u_s y_{js}} \geq 1 \quad , \quad \forall j \\
& u_s, v_m \geq 0 \quad , \quad \forall s, m
\end{aligned}
\tag{1}
$$

where x_{im} represents the consumption of input m by DMU i, y_{is} represents the production of output s by DMU i, v_m is the shadow price of input m, and u_s is the shadow price of output s. The program finds the set of shadow prices that minimizes the production cost of unit i with respect to the value of its product, conditioned to obtain ratios larger or equal to 1 for all the other DMUs in the sample. If DMU i is efficient optimal shadow prices will give the minimum possible value of the ratio, i.e. 1. Inefficiency would be reflected by a value greater that 1 for the objective function. Fractional program (1) involves some computational complexities. Thus, it may be preferable to solve the next equivalent linear program:

$$\begin{aligned}
&\min \sum_{m=1}^{M} v_m x_{im} \\
&s.a: \\
&\sum_{s=1}^{S} u_s y_{is} = 1 \\
&\sum_{s=1}^{S} u_s y_{js} - \sum_{m=1}^{M} v_m x_{jm} \leq 0 \quad , \quad \forall j \\
&u_s, v_m \geq 0 \quad , \quad \forall s, m
\end{aligned} \tag{2}$$

This program finds the shadow prices that minimize the cost of DMU i, but normalizing the output value to 1. If DMU i is efficient it will obtain a cost equal to 1, while if it is inefficient it will obtain a value greater than 1. If DMU i is inefficient then the solution to the linear program must identify another DMU in the sample that obtains the minimum cost of 1 with the shadow prices that are most favourable to DMU i. Program (2) is solved for every DMU in the sample, and each of them will obtain its most favourable shadow prices for inputs and outputs and the corresponding relative efficiency scores. For an easier interpretation, it is common to use the inverse of the objective function in (2) as the efficiency score. Therefore, the score is bounded within the (0,1) interval and values lower than 1 reflect the degree of productive inefficiency.

Banker et al. (1984) relax the CRS assumption modifying linear program (2) to allow for VRS:

$$
\begin{aligned}
& \min \sum_{m=1}^{M} v_m x_{im} + e_i \\
& s.a: \\
& \sum_{s=1}^{S} u_s y_{is} = 1 \\
& \sum_{s=1}^{S} u_s y_{js} - \sum_{m=1}^{M} v_m x_{jm} - e_i \leq 0 \quad , \quad \forall j \\
& u_s, v_m \geq 0 \quad , \quad \forall s, m
\end{aligned} \tag{3}
$$

where the intercept e_i is added to relax the CRS condition that forced the objective function to pass through the origin in (2). In program (3) that condition will only be satisfied if e^*_i=0. For values greater or smaller than 0 the reference in the frontier for the DMU will be located in a local zone with decreasing or increasing returns to scale, respectively.

Comparing the scores obtained under the alternative assumptions of CRS and VRS we obtain a measure of scale inefficiency (SE), which is attributed to an inappropriate scale of the DMU:

$$SE = \frac{EF_{CRS}}{EF_{VRS}} \tag{4}$$

A distinctive feature of DEA is the absolute flexibility in the way the linear program can assign weights (shadow prices) for each particular DMU in the sample. Recall that the program is solved independently for each DMU and, then, shadow prices for inputs and outputs may be completely different from one DMU to another. The main argument to defend extreme weight flexibility in DEA is the convenience to obtain an evaluation of the inefficiency of each DMU under its most favourable scenario. However, extreme flexibility may also be object of criticism because it often produces an extreme inconsistency in the values of the shadow prices across DMUs. To avoid this inconsistency the DEA literature has suggested some solutions to restrict the range of acceptable values for those weights (Thompson et al. 1986; Dyson and Thanassoulis, 1988; Allen et al. 1997; Roll et al. 1991; Wong and Besley, 1990; Pedraja et al. 1997; Sarrico and Dyson, 2004).

In turn, the problem of weights restriction methods is that they require making value judgements about the range of shadow prices that is considered appropriated. In order to facilitate the implementation of weight restrictions in practice Halme et al. (1999) proposed an alternative methodology under the name Value Efficiency Analysis (VEA). The objective of VEA is to restrict weights using a simple piece of additional information that must be supplied by an outside expert. The most notable difference between VEA and conventional methods of weights restriction is that instead of establishing appropriate ranges for shadow prices, the expert is simply asked to select one of the DEA-efficient DMUs as his Most Preferred Solution (MPS). Once the MPS is selected, the standard DEA program is supplemented with an additional constraint that forces the weights of the DMU under evaluation (*i*) to make the MPS (*o*) efficient. In other words, the new linear program requires that the optimal shadow prices selected by DMU *i* must also be good for the MPS. As this requirement is made for all the DMUs in the sample, the optimal shadow prices of all the linear programs must be good for the MPS. Thus, the MPS forces some degree of consistency of shadow prices across DMUs. An immediate effect of the VEA constraint is that DMUs that obtained a DEA score of 1 just because they had a extreme value in one input or output will only obtain a VEA score of less than 1 if they can’t resist the additional comparison with the MPS.

The VRS VEA program with an output orientation can be expressed as follows:

$$
\begin{aligned}
&\min \sum_{m=1}^{M} v_m x_{im} + e_i \\
&s.a: \\
&\sum_{s=1}^{S} u_s y_{is} = 1 \\
&\sum_{s=1}^{S} u_s y_{js} - \sum_{m=1}^{M} v_m x_{jm} - e_i \le 0 \quad , \quad \forall j \\
&\sum_{m=1}^{M} v_m x_{om} + e_i - \sum_{s=1}^{S} u_s y_{os} = 0 \\
&u_s, v_m \ge 0 \quad , \quad \forall s, m
\end{aligned}
\tag{5}
$$

Program (5) is identical to program (3) but the MPS constraint has been added. Thus, the MPS (*o*) must obtain a value of 1 with the shadow prices of DMU (*i*). Indirectly, this requirement restricts the range of shadow prices allowed to the range that makes the MPS (*o*) efficient.

3. Data

We are interested in measuring value efficiency scores for the public primary health care centres that cover the Spanish region of Asturias. The sample includes a total of 61 DMUs, after the exclusion of non-comparable centres. To apply measurement techniques such as DEA or VEA, which are based in making comparisons, it is fundamental to assure that the terms of comparison are homogeneous across DMUs. For this reason, we excluded from the sample the health centres that cover special mountainous zones. The data on inputs and outputs were obtained from the activity reports of the Primary Health Management Offices in the year 2002.

In the context of health activity it is not simple to select a set of inputs and outputs that captures the whole complexity of the production process (Pinillos, 2003). We have considered a set of 4 output indicators and 4 input variables. Table 1 summarizes the variables used to approach the input-output dimensions in the provision of primary health care in Asturias. We also took 3 additional variables that cannot be considered as inputs or outputs but capture important contextual dimensions. We will check if there is any relationship between efficiency scores and these contextual variables.

Table 1. Variables selected to approach primary health production in Asturias

Inputs	Outputs	Contextual variables
Labour	Visits	Teaching (MIR)
General expenses (Ch II)	In-house visits	Geographic dispersion (G)
Pharmacy expenses (Ch IV)	Services portfolio	% Aged population (AGED)
Derivations	Accomplishment of technical standards	

To approach the output of the health care centre we take the number of visits attended at the health centre and also at the house of the patient. We added up all the visits attended at the health centre (general, paediatric, and nurse visits). As a measure of medical performance we must admit that the visits variable is subject to some criticism. An increase in the number of visits is not necessarily an indicator of better performance. In other words, *ceteris paribus*, more visits with the same population and resources is not always a desirable goal, because it would imply less time per visit and perhaps a lower level of quality[2]. This, in turn, may even translate into more visits that will be needed to treat the same health problem that could have been solved in the first visit. However, an indication of volume is needed to justify the volume of inputs used in the production model. Most of the literature about the production and organization of the Spanish public primary health care system use visits as one of the most important outputs[3] (Martí and Grenzner, 1999; García et al., 1999; Pinillos, 2003). Therefore we will use the number of visits as a volume indicator of output in our model although we will complement it with quality variables.

Several papers have suggested the use of the value of the services portfolio of the health centre as an output indicator (Puig, 2000; García et al., 1999). This variable approaches the set of services that the health centre offers to its target population. It is defined as the percentage of the target population that receives each of the services in the portfolio (coverage) weighted by the workload that is required to provide that service (INSALUD 1997, García and Minué 1998). Thus, the coverage of a service expresses the relationship between the number of people included in the program of that service and the target population for that service. The weights (technical value) that express the workloads of the different services were established by a group of experts that used as the basic reference (value 1) the influenza vaccination service (INSALUD 1997).

The product of the technical value times the coverage of the service determines the value of the first component of the services portfolio. The final value of the whole services portfolio would be determined by the ratio of the sum of all the products to the maximum

[2] This problem would also hold for in-house visits although to a much lesser extent.

[3] Frequently the only output that is considered.

value that could be obtained if the coverage was 100% in all the services. The result is expressed as a percentage. In this paper we multiplied the value of the services portfolio by the target population of the health care centre to introduce a quantitative weight on it. Analytically:

$$\frac{\sum_{i=1}^{I} \frac{n_i}{N_i} TV_i}{100 \cdot \sum_{i=1}^{I} TV_i} \cdot P \tag{6}$$

where,

n_i : Patients included in service *i*

N_i : Patients expected (target) in service *i*

TV_i : Technical value assigned to service *i*

P: Target population of the health care centre

As a final output we included a quality variable that reflects how well the centre accomplishes a series of technical standards associated to the services portfolio. This variable is taken as a proxy of the quality in the provision of the service. A large accomplishment of technical standards indicates a service of good quality.

With respect to the inputs used in the production of the services provided, most papers include labour as the first resource to be considered. We have approached this variable with the total number of people that works at the centre. We also use two variables of expenditure that measure current expenses (Ch II) and pharmacy expenses (Ch IV). Both variables are taken from the budgets of the centres. The fourth input dimension accounts for the consumption of resources that is generated in other levels of the health system by the activity of the health centre. Although no monetary cost is expressed in the budget of the centre for these activities it is clear that they represent opportunity costs. We approach these costs by the number of derivations for radiology, laboratory and specialty visits. We added up the three variables in a fourth input that we call derivations.

Finally, we are also interested in discussing the impact of the social context of the centre on its level of production efficiency. As we lack indicators of severity, we have used as a proxy the percentage of aged people in the target population (older than 65). This can be considered a proxy of the severity and a determinant of resource consumption. As an indirect indicator of geographical dispersion and also of the urban-rural character of the target population we use the value G assigned to the zone. A large value G implies great dispersion and a rural environment. Finally, we use a dummy variable that indicates if the centre is a teaching or a non-teaching centre to account for the level of intellectual capital (MIR).

4. Results

Table 2 summarizes the results of the DEA analysis, including a description of the efficiency scores calculated with respect to the CRS frontier, to the VRS frontier and the residual index of scale efficiency (SE). The results evidence a high level of productive efficiency, since overall efficiency (EF_{CRS}) reaches an average of around 90%. If we check the sources of overall inefficiency we observe that the main contribution comes from the presence of inefficient scales of production. Scale efficiency scores indicate that an average increase of 6,4% in the outputs would be attainable if the centres could adjust their scales of production to the optimal scale. In contrast, pure (managerial) technical inefficiency (EF_{VRS}) is only responsible for a loss of output around 4%. With respect to the scale problem we must indicate that most scale inefficiency is caused by decreasing returns to scale in the largest health care centres. Of all the centres that have a problem of scale inefficiency only one operates with increasing returns to scale. The rest all produce within the zone of decreasing returns to scale.

The table also shows the number of health care centres that are located on the frontier and, therefore, are completely DEA-efficient. This number is considerably large, especially when using the VRS frontier, which locates 57% of the DMUs on the frontier. This finding evidences the poor discriminating power of DEA when the number of dimensions (inputs+outputs) is large in comparison with the sample size.

Table 2. Descriptive statistics of DEA efficiency scores

	Average	Std. Dev.	Min.	N eff.	% eff
EF_{CRS} (overall)	89,8	9,9	67,5	19	31,1
EF_{VRS} (managerial)	95,8	7,0	72,2	35	57,4
SE (scale)	93,6	6,8	73,9	19	31,1

If we base our conclusions on the DEA scores we would make a very positive evaluation of the efficiency in the provision of primary health care services in Asturias. Except for 2 centres that score under 80%, most centres obtain notably high scores, 31% do not show any kind of inefficiency and 57% are managerially efficiency. However, as we have already mentioned in this paper, DEA is extremely flexible with the shadow prices each DMU selects to justify its activity data. Thus, the linear program of each centre selects the set of shadow prices of inputs and outputs that is most favourable to show a high efficiency score. More often than not this extreme flexibility results in a considerable degree of inconsistency in the shadow prices of the different DMUs.

To avoid this problem and force a higher rationality in the shadow prices selected by each DMU, we can choose one of the efficient health centres as representing an appropriate behaviour regardless of the shadow prices we use to defend its production vector. We call this DMU the Most Preferred Solution (MPS). The selection of the MPS can be done by an expert or can be based on the DEA results. Here we have used a mixture of both criteria. Outside experts point to centre 3 (in our sample) as a model health care centre in Asturias. Centre 3 is also the DMU that appears more times as reference for other DMUs in our DEA analysis. It actually serves as a DEA reference for 26 of the 42 inefficient centres of the sample.

VEA adds the constraint that the shadow prices for all the DMUs in the sample make DMU 3 completely efficient. In other words, the shadow prices allowed in all the linear programs must be reasonable for the MPS. Table 3 summarizes the VEA results. The decrease in the number of efficient DMUs (from 19 to 13) is remarkable. Thus, 7 health care centres were obtaining a DEA score of 1 but this score was based on input and/or output weights that are unreasonable for our MPS (DMU 3). The results evidence the notable improvement that can be achieved in the discriminating power of DEA by simply adding the VEA consistency constraint. The number of pure efficient DMUs, with respect to the VRS frontier, also changed from 35 to 26, which represents a reduction of 26%.

Table 3. Descriptive statistics of VEA scores

	Average	Std. Dev.	Min.	N eff.	% eff
EF_{CRS} (overall)	87,9	10,4	66,7	13	21,3
EF_{VRS} (managerial)	93,7	8,1	72,2	26	42,6
SE (scale)	93,7	6,4	73,6	13	21,3

VEA results (Table 3) also show some other interesting differences with respect to DEA results (Table 2). It can be noticed that now the main contribution to overall inefficiency does not arise from problem with the scales of production. On average, both scale and managerial inefficiencies are equally important determinants of overall VEA-efficiency. In any case, we reassert that the average level of efficiency is quite high.

Table 4 shows how the dispersion in optimal shadow prices for the DMUs in the sample reduced dramatically after the VEA constraint was added to the DEA formulation. The numbers represent the variation in the standard deviation of each shadow price. Only the input labour increased shadow price dispersion in the VEA analysis. The rest of the dimensions achieved considerable reductions in shadow price dispersion. The inputs derivations (-59.1%) and general expenses (-40,9%) attain the greatest reductions in weights dispersion. With respect to the outputs, in-house visits (-40.6%) and visits (-30.3%) experienced the greatest reductions. On average, the use of the VEA methodology forced an average 27.8% reduction in the standard deviation of the shadow prices of inputs and outputs. This result certifies the notable improvement in the degree of congruence of the shadow prices implicit within the DEA results.

Table 4. Changes in the standard deviations of shadow prices with VEA

Inputs	%	Outputs	%
Labor	10.3	Visits	-30.3
General expenses (Ch II)	-40.9	In-house visits	-40.6
Pharmacy expenses (Ch IV)	-32.4	Services portfolio	-9.4
Derivations	-59.1	Accomplishment of technical standards	-19.8

We are also interested in studying the possible relationship between the VEA scores and several contextual variables that approach the conditions under which the health services are produced. For that purpose, in a first approach, we estimated a regression model with the VEA score of managerial efficiency (EF_{VRS})[4] as de dependent variable. The contextual independent variables are the percentage of aged population (AGED), the coefficient of geographic dispersion (G Value), and a dummy variable that takes the value 1 if the DMU is a teaching centre (MIR) and the value 0 otherwise.

Table 5. Contextual factors related to VEA managerial inefficiency (EF_{VRS})

	Beta	Std. Beta	t
Intercept	1,00		25,8***
AGED	-0,006	-0,46	-3,08***
G Value	0,022	0,26	1,78*
MIR	0,013	0,08	0,63
R^2	*0,156*		

*** Significance level 0,01 ** Significance level 0,05 * Significance level 0,1

[4] We also regress the score of scale efficiency against these three variables but we did not find any significant relationship.

There is a clear negative and significant relationship between managerial efficiency and the percentage of aged population. The regression also shows a positive coefficient for the variable that measures the degree of geographic dispersion (G). In contrast, we do not find any significant relationship between teaching and VEA efficiency.

These results can be questioned for some statistical reasons. First, there is a large correlation (0.57) between the variable G and the percentage of old population. Rural areas have a large percentage of old population and a big value G. This causes a multicolineality problem that prevents the correct interpretation of the effect of each variable on the dependent variable. Second, VEA scores (as well as DEA scores) are not iid and are not normally distributed. Thus, some assumptions of regression analysis are violated. For these reasons, we proceed with a second battery of non parametric tests that do not impose such strong assumptions on VEA scores.

We used a rank test (Mann and Whitney) to test the hipothesis that there were no differences in managerial efficiency between teaching and non-teaching health care centers. The results are shown in Table 6. Although teaching centers show a higher average rank, the difference is not statistically significant and, therefore, we can't reject the null hipothesis. Therefore, we do not appreciate an effect of teaching on managerial efficiency.

Table 6. Relationship between managerial efficiency and teaching

	N	Average rank
MIR=0 (non-teaching)	34	29,87
MIR=1 (teaching)	27	32,43
Mann-Whitney U	420,5	
p	0,56	

To analyze the existence of a relationship between the value G and managerial efficiency, we used a Kruskall-Wallis test. The null hypothesis is that the average efficiency score is the same for the 4 groups of G geographic dispersion. The table show that the 5 health centers with value G=1 (low dispersion) obtain lower efficiency scores, but the differences are not staristically significant. Thus, we cannot establish a relationship between managerial inefficiency and the value G.

Table 7. Relationship between managerial efficiency and value G

	N	Average Rank
G=1	5	25,90
G=2	22	30,30
G=3	14	34,96
G=4	20	30,28
Kruskall-Wallis H	1,28	
p	0,73	

Finally, to test the relationship between managerial efficiency and the percentage of old population we divided the sample in three efficiency groups (low, average, high). Group 1 contains the 18 health centres that score less than 91%. Group 2 contains the 17 health centres that obtain a score larger than 91% but are inefficient. Group 3 contains the 26 efficient health centres. Table 8 shows the results of the Kruskal-Wallis ranks test. We observe that group 1 (low efficiency centres) has a significantly higher percentage of old population. Thus we can establish a negative relationship between managerial inefficiency and the percentage of old population.

Table 8. Relationship between managerial efficiency and the percentage of old population

Efficiency group	N	Average rank
1 (low)	18	38,06
2 (average)	17	24,24
3 (high)	26	30,54
Kruskal-Wallis H	5,33	

P	0,07

5. Concluding remarks

This paper provides additional evidence about the deficit in the discriminating power of DEA when the number of input-output dimensions is high relative to the sample size. There are three ways to improve the discriminating power of DEA. First, the simplest procedure is to reduce the number of input-output dimensions to be considered in the model specification. The cost of this approach is that information that may be relevant to discriminate is overlooked. Second, we can increase sample size. This is the best solution (theoretically) although unfortunately it may be not feasible (in practice) when the researcher is working with complete but small populations, as it is often the case. A third approach is to improve the discriminating power of the model supplying some additional information on how the discrimination must be done. Value Efficiency Analysis (VEA) was developed to easily incorporate a piece of qualitative information in the DEA specification. This information corresponds to the identification of a Most Preferred Solution that acts as an ideal reference on the eyes of an expert. Our results show that VEA significantly increases the discriminating power of DEA.

The paper applied both DEA and VEA methodologies to a sample of 61 public health care centres in Asturias (Spain) during the year 2002. The sample includes all the public centres that satisfy some homogeneity criteria. As we use the entire population data, we cannot increase the discriminating power of DEA just increasing the sample size. The DEA scores show a very large average level of overall efficiency in the sample. Furthermore, scale inefficiency due to large production scales seems to be the main contributor to overall inefficiency. The dimension of the health centre appears as a critical factor according to our results and this factor is often overlooked in the planning of the structures of the health system.

VEA analysis also shows quite high average levels of overall efficiency, but scale and managerial inefficiencies share the responsibility evenly. Just incorporating information on an efficient health care centre that is considered as an appropriate general referent (MPS), VEA notably increases the discriminating power. From 19 DEA efficient health centres we obtain just 13 VEA efficient ones. In reality what is happening is that VEA allows a simple identification of centres which DEA efficiency score is based in unrealistic values for the shadow prices of inputs and outputs. These centres benefit from the extreme flexibility of DEA but would not resist a further analysis on their activity data. For example, one DMU may obtain a DEA score of 1 simply because it is the unit that produces the largest quantity of an output and, thus, assigns a very large weight to that variable. VEA does not allow this extreme flexibility. The productive behaviour must be globally acceptable. The MPS indicates what is considered as a globally acceptable behaviour. Our empirical application shows an average reduction of 28% in the dispersion of the shadow prices assigned by each DMU to weight inputs and outputs with respect to the DEA formulation. Thus, the improvement in the discriminating power of VEA is obtained with a better rationality in the selection of shadow prices in the mathematical programs.

With respect to contextual variables, we appreciate a significant negative relationship between managerial VEA efficiency and the percentage of old population assigned to the health centre. In turn, even though we observe some positive relationship between efficiency scores and geographical dispersion, this relationship is not statistically significant at conventional levels. Finally, we were not able to find any relationship between teaching and efficiency in Asturian health centres.

References

Allen, R., Athanassopoulos, R., Dyson, G. and Thanassoulis, E. (1997). Weights Restrictions and Value Judgements in Data Envelopment Analysis: Evolution, Development and Future Directions. Annals of Operations Research 73; 13-34.

Ali, A. (1994). Computational aspects of Data Envelopment Analysis. In: Charnes A, Cooper WW, Lewin AY, Seiford LM (Eds), DEA: Theory, Methodology and Applications, Kluwer Academic Publishers: Boston. p. 63-88.

Alonso, R.., García, R., González, J.A. (1995). The Services Portfolio in Primary Health Care. Medifam; 3; 131-136.

Banker, R., Charnes, A. and Cooper, W. (1984). Some Models for Estimating Technical and Scale Inefficiencies. Management Science; 39; 1261-1264.

Charnes, A., Cooper, W. and Rhodes, E. (1978). Measuring the Efficiency on Decision Making Units. European Journal of Operational Research; 2; 429-44.

Dyson, R., Thanassoulis, E. (1988). Reducing Weight Flexibility in Data Envelopment Analysis. Journal of Operational Research Society; 6; 563-576.

García, F., Marcuello, C., Serrano, D. and Urbina, O. (1999). Evaluation of Efficiency in Primary Health Care Centres: An application of Data Envelopment Analysis. Financial Accountability and Management; 15(1); 67-83

García, L. and Minué, S. (1998). Product Measurement in Primary Care. Cuadernos de Gestión; 4(4); 191-200.

Giuffrida, A. and Gravelle, H. (2001). Measuring Performance in Primary Care: Econometric Analysis and DEA. Applied Economics; 33(2); 163-175.

Goñi S. (1999). An Analysis of the Effectiveness of Spanish Primary Health Care Teams. Health Policy; 48; 107-117.

Halme, M., Joro, T., Korhonen, P., Salo, S. and Wallenius, J. (1999). A Value Efficiency Approach to Incorporating Preference Information in Data Envelopment Analysis. Management Science; 45(1); 103-115.

Hollingsworth, B., Dawson, P. and Maniadakis, N. (1999). Efficiency Measurement of Health Care: A Review of Nonparametric Methods and Applications. Health Care Management Science; 2; 161-172.

INSALUD. (1997). Services Portfolio in Primary Care. Definitions, Acreditarion Criteria, Coverage Indicators, and Technical Standards. Insalud: Madrid.

Juncosa, S., Bolívar, B., Roset, M. and Tomás, R. (1999). Performance of an ambulatory casemix measurement system in primary care in Spain. European Journal of Public Health; 9(1); 27-35.

Kooreman, P. (1994). Nursing Home Care in the Netherlands: A Nonparametric Efficiency Analysis. Journal of Health Economics; 13(3); 301-316.

Martí, T., Grenzner, V. (1999). Models of Primary Care in Catalonia. Cuadernos de Gestión en Atención Primaria; 5(3); 116-123.

Orueta, J., López, J., Báez, K., Aiarzaguena, J., Aranguren, J. and Pedrero, E. (1999). Application of the Ambulatory Care Groups in the primary care of a European national health care system: Does it work?. Medical Care; 37(3); 524-554

Pedraja, F., Salinas, J. and Smith, P. (1997). On the Role of Weight Restrictions in Data Envelopment Analysis. Journal of Productivity Analysis; 8; 215-230.

Pinillos, M. (2003). Efficiency in Public Primary Care. Papeles de Economía Española; 95; 213-225.

Puig, J. (2000). Efficiency in Primary Care: a Critical Review of Frontier Indicators. Revista Española de Salud Pública; 74; 483-495.

Pujol, E., Gené, J., Sans, M., Sampietro, L., Pasarín, M., Iglesias, B., Casajuana, J. and Escaramís, G. (2006). The Product of Primary Care defined by Professionals and Users. Gaceta Sanitaria; 20(3); 209-219.

Roll, Y., Cook, W. and Golany, B. (1991). Controlling Factor Weights in Data Envelopment Analysis. IIE Transactions; 23; 2-9.

Salinas, J., Smith, P. (1996). Data Envelopment Analysis Applied to Quality in Primary Health Care. Annals of Operational Research; 67; 141-161.

Sarrico, C. and Dyson, R. (2004). Restricting Virtual Weights in Data Envelopment Analysis. European Journal of Operational Research; 159; 17-34.

Thompson, R., Singleton, F., Thrall, R. and Smith, B. (1996). Comparative Site Evaluations for Locating a High Energy Physics Lab in Texas. Interfaces; 16; 35-49.

Wong, Y., Beasley, J. (1990). Restricting Weight Flexibility in Data Envelopment Analysis. Journal of Operational Research Society; 41; 829-835.

Worthington, A. (2004). Frontier Efficiency Measurement in Health Care: A Review of Empirical Techniques and Selected Applications. Medical Care Research and Review; 61(2); 135-170.