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Some Regression-Based Indicators of Hospital Performance

by ADAM WAGSTAFF

DISCUSSION PAPER 45

SOME REGRESSION-BASED INDICATORS OF HOSPITAL PERFORMANCE

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Abstract

The development of performance indicators for the NHS has resulted in renewed interest in regression-based measures of hospital performance. This paper considers three regression-based measures of hospital efficiency, including the index of hospital ´costliness´ proposed by Martin Feldstein and currently used by the DHSS as a financial performance indicator. The paper begins with a critique of Feldstein´s index and then goes on to show how its defects can be overcome using stochastic frontier regression models. Two such models are considered: a cross-section model in which it is assumed that inefficiency follows a particular distribution and a panel-data model in which it is assumed that inefficiency remains constant over the sample period. All three approaches are illustrated using data from 49 acute hospitals owned and operated by the Spanish Ministry of Health. The paper is written with the non-economist in mind and is aimed primarily at statisticians and other persons in the NHS who have an interest in performance indicators. It may also be of interest, however, to persons with a general interest in the measurement of the efficiency of public sector organizations.

1. Introduction

The development of performance indicators for the NHS has resulted in renewed interest in regression-based measures of hospital performance. One measure that has proved particularly popular is the index of hospital 'costliness' proposed by Feldstein (1967). Feldstein's index - which compares a hospital's actual costs with its 'expected' costs - is, in fact, one of the variables to be found in the 'financial' indicators section of the DHSS's performance indicators. It is evident that those involved in the development of the indicators were particularly attracted by the index (see eg Smith, 1983). The reason is fairly obvious: the index claims to be able to do what might be thought impossible, namely to decide how far casemix differences between hospitals can justify cost differences.

Though Feldstein's index undoubtedly constitutes an improvement over the use of crude cost data as a measure of performance, it is not without its shortcomings. Feldstein, in fact, went to some trouble to point these out and specifically warned against using the index 'uncritically' as a measure of efficiency (see Feldstein, 1967, p50). The purpose of this paper is to examine the principal shortcomings of Feldstein's index and to show how these may be overcome - at least partially - using techniques that have been developed over the course of the last few years. Specifically, the paper considers the 'deterministic frontier' model of Aigner and Chu (1968), the 'stochastic frontier' model of Aigner, Lovell and Schmidt (1977) and the panel-data approach to the frontier model of Schmidt and Sickles (1984).

The paper is organized as follows. Section 2 examines Feldstein's index of costliness: it explains what it is, how it can be computed and what its principal limitations are. Section 3 discusses the deterministic frontier model and shows how it can overcome one of the shortcomings in Feldstein's approach, namely that it does not provide an estimate of the extent of inefficiency. Section 4 examines the stochastic frontier model of Aigner, Lovell and Schmidt: it discusses how the model seeks to overcome other problems inherent in Feldstein's approach, how it can be estimated and what its its limitations are. Section 5 examines the panel data approach to the frontier regression model developed by Schmidt and Sickles: it considers the claimed advantages of panel data over cross-section data, the different estimation methods available and the shortcomings of the panel data approach. Each section contains an empirical illustration using data from 49 acute hospitals owned and operated by the Spanish Ministry of Health. The final section contains a summary and discussion of the main conclusions to emerge from the paper.

2. Feldstein's costliness index

The early 1960s saw increasing dissatisfaction in Britain with the use of crude costs as a measure of hospital performance. Montacute (1962) in his *Costing and Efficiency in Hospitals* concluded:

> "... whilst in theory inter-hospital comparison is excellent, the use of crude costs is really a comparison of incomparables and even the enthusiast finds he is bogged down by unexpected differences. I am convinced that continuing to compare crude costs is only likely to do a disservice to costing. What is needed ... is more information about the factors which lead to differences in cost in hospitals and the relative weight of these factors." (Montacute, 1962, p209).

It was this - apparently widely-held - view that prompted Feldstein (1967) to develop his index of hospital costliness. This section examines Feldstein's index: it outlines its foundations in index number theory, considers how it can be computed using regression analysis and discusses its principal shortcomings.

It also presents an empirical illustration using data from the sample of Spanish acute hospitals.

2.1 The costliness index

The 'costliness' index proposed by Feldstein involves a comparison of a hospital's actual costs with the costs that might reasonably be expected of it, given its caseload. The index is defined as a Paasche index number: in the case when there are only two casemix categories under consideration the index can be written as

$$(1) \quad C_i^* = \frac{n_{i1}c_{i1} + n_{i2}c_{i2}}{n_{i1}c_{.1} + n_{i2}c_{.2}}$$

where

C_i^* = costliness of hospital 1,
n_{i1} = number of cases of type 1 treated by hospital i,
c_{i1} = hospital i's cost of treating a patient in casemix category 1,
$c_{.1}$ = sample average of the cost of treating a patient in casemix category 1.

The index number therefore compares a hospital's costs for specific casetypes with corresponding national average costs, where the weights used are the numbers of cases treated by the hospital in each of the casemix categories. If hospital i's costs of treating patients in both casemix categories are in line with the national average - ie $c_{i1} = c_{.1}$ and $c_{i2} = c_{.2}$ - the numerator and denominator of the costliness index will be equal and the index takes on a value of 1.0, or 100%. If the hospital's costs for the two casemix categories are above the national average, the numerator will be larger than the denominator and the index will exceed 100%. A costliness value of below 100% would be observed if hospital i's casemix-specific costs were below the national average.

The expression in eq (1) can easily be generalized to allow for more than two casemix categories. If casemix categories are indexed by j, the more general version of eq (1) is

$$(2) \quad C_i^* = \frac{\Sigma_j n_{ij} c_{ij}}{\Sigma_j n_{ij} c_{.j}}$$

where n_{ij} denotes the number of cases of type j treated by hospital i and so on. The index in eq (2) is interpreted along exactly the same lines as the two-category index in eq (1).

2.2 Computing costliness

The numerator of the costliness index is easily computed (it is simply hospital i's total cost); the denominator is less easily calculated. Feldstein suggested estimating the $c_{.j}$ - the mean casemix-specific costs - using a regression equation of the form

$$(3) \quad c_{i.} = \tau_0 + \Sigma_{j=1}^{J} \tau_j p_{ij} + u_i$$

where p_{ij} is the proportion of hospital i's patients falling into the jth casemix category, τ_0 and the τ_j are regression coefficients and u_i is an error term. Eq (3) is thus a linear regression equation relating a hospital's overall average cost to the proportions of patients falling into each of the casemix categories. Note that if there are J casemix categories in all, only J-1 ought to be entered in the estimating equation. Otherwise the variables on the right hand side of the regression equation will be perfectly collinear. For example, if there are three casemix categories and all three are included, the regression equation becomes

(5) $c_{i.} = \tau_1 p_{i1} + \tau_2 p_{i2} + \tau_3 p_{i3} + u_i$

This equation cannot be estimated as it stands because the casemix variables on the right-hand side are all exact linear functions of one another - eg $p_{i3}=1-p_{i1}-p_{i2}$. To take account of the fact that all the patients fall into one or other of the casemix categories substitute $p_{i3}=1-p_{i1}-p_{i2}$ in the equation above to obtain

(6) $c_{i.} = \tau_3 + (\tau_1-\tau_3)p_{i1} + (\tau_2-\tau_3)p_{i2} + u_i$

This equation does not suffer from perfect multicollinearity and can therefore be estimated.

The attraction of eq (3) is that if it is correctly specified, the coefficients - the τ_j - can be used to obtain estimates of the $c_{.j}$ in eq (2). To see why note that eq (3) can be converted into an equation for total costs by multiplying both sides by n_i - the total number of patients treated by hospital i. The resultant equation is

(7) $n_i c_{i.} = \tau_0 n_i + \Sigma_{j=1}^{J} \tau_j p_{ij} n_i + u_i^*$

where $u_i^* = u_i n_i$; eq (7) can be re-written

(7′) $TC_i = \tau_0 n_i + \Sigma_{j=1}^{J} \tau_j n_{ij} + u_i^*$

where TC_i denotes hospital i′s total costs. Differentiating eq (7′) with respect to n_{1i} (bearing in mind $n_i=n_{i1}+n_{i2}+...+n_{iJ}$) gives

$$\frac{\partial TC_i}{\partial n_{i1}} = \tau_0+\tau_1$$

Thus in eq (7′) $(\tau_0+\tau_1)$ can be interpreted the increase in total costs resulting from the treatment of one more patient of casetype 1. More generally, $(\tau_0+\tau_j)$ can be interpreted as the marginal costs associated with each of the casetypes.

Since eq (7′) is linear, these marginal costs are constant and equal to average costs. Note, finally, that τ_0 can be interpreted as the marginal cost of treating a patient in the omitted (ie Jth) casemix category.

In principle the estimates of the casemix-specific costs derived from eq (3) could be substituted directly in to the costliness index. There is, however, a simpler method. Dividing the top and bottom of eq (2) by n_i leaves the value of the costliness index unchanged; thus

$$\text{(2a)}\quad C_i^* = \frac{TC_i/n_i}{\Sigma_j n_{ij} c_{.j}/n_i}$$

$$= \frac{c_{i.}}{\Sigma_j c_{.j} p_{ij}}$$

Let $c_{.j}$ denote the estimate of $c_{.j}$ based on eq (3). Then the estimated version of the latter can be written

$$c_{i.} = c_J + (c_1 - c_J)p_{i1} + \ldots (c_{J-1} - c_J)p_{iJ-1}$$

$$= c_1 p_{i1} + \ldots + c_{J-1} p_{iJ-1} + c_J p_J$$

since $p_{i1}+\ldots+p_{iJ-1}=1-p_J$. C_i^* can therefore be rewritten as

$$\text{(2b)}\quad C_i^* = \frac{c_{i.}}{\hat{\tau}_0 + \Sigma_{j=1}^{J} \hat{\tau}_j p_{ij}}$$

where $\hat{\tau}_j$ denotes the estimated value of τ_j. The numerator of eq (2b) is hospital i′s overall average cost. The denominator is simply the predicted value of c_i obtained from eq (3); ie the fitted version of eq (3) can be written as

$$\text{(3a)}\quad \hat{c}_{i.} = \hat{\tau}_0 + \Sigma_{j=1}^{J} \hat{\tau}_j p_{ij}$$

Thus eq (2b) can be written as

(2c) $C_i^* = c_{i.}/\hat{c}_{i.}$

where $\hat{c}_{i.}$ is predicted average cost and, given eq (3), can be interpreted as the average cost that would be observed if hospital i's casemix-specific costs were the same as the national average.

2.3 Specification of the regression model

The regression-based method of computing costliness suggested by Feldstein is particularly attractive, in part because it can be operationalized using data that are already available, but also because it paves the way for a more general approach to the measurement of costliness. The expression in eq (2c) is more general than the Paasche indices of eq.s (1) and (2); costliness can therefore be viewed generally as a comparison of actual and 'expected' costs. Clearly it may well be desirable to entertain more complex regression equations than eq (3), thereby enabling one to arrive at a more reliable measure of 'expected' costs.

Caution needs, however, to be exercised in specifying alternative regression models. It is especially important to be clear about the theoretical status of equation being estimated and, in particular, the distinction between a cost _equation_ and a cost _function_. A cost equation is simply an accounting identity, involving a breakdown of costs into their constituent parts (eg, wage costs, laboratory costs, overheads etc). A cost function, on the other hand, derives from economic theory and expresses cost as a function of the variables that constrain an organization in its attempts to minimize its costs. These variables include input prices (not expenditure on inputs) and the level of output produced. If the relevant time horizon is the short-run (ie the organization's stock of capital is fixed), the cost function will also include the stock of capital, since a fixed stock of capital prevents the organization from reducing its costs by altering its factor mix.[1]

Regression analysis can be employed in the estimation of both types of equation. Several regression studies have been undertaken to date attempting to provide a breakdown of hospital costs.[2] Studies such as these are not, however, what is required in the present context: here a cost function is needed, since the purpose of the exercise is to determine what portion of any differences in reported costs across hospitals can legitimately be claimed to be due to differences in 'output' (eg casemix composition), differences in input prices, and so on.[3] Suggestions that researchers in this area might profit by including variables such as measures of labour input in their regression equations (see eg Straf, 1981) ought, therefore, to be firmly resisted (cf Culyer et al, 1982). There are, however, other variables that might reasonably be included. One might, for example, following Feldstein, include the stock of beds and its square.[4] One might also include caseflow and its square, though the rationale for including caseflow is not always clear. One possible rationale is that

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1. For a good discussion of the distinction between cost equations and cost functions see Knapp (1984).

2. See, for example, Coverdale et al (1980), Ashford et al (1981) and Bailey and Ashford (1984).

3. One should, of course, bear in mind that the casemix adjustment method of measuring hospital output suggested by Feldstein is highly imperfect. Its principal shortcomings are that it does not address the problem of intra-category case severity (not all patients admitted for surgery are equally ill) and that with a small number of casemix categories one runs the risk of overlooking some of the inter-hospital variation in casemix (see eg Barlow, 1968; Fuchs, 1969; Lave and Lave, 1970a). For a useful review of the various approaches to output measurement adopted in econometric work to date see Tatchell (1983).

4. There is a tendency to view the coefficients on the stock of beds and its square as indicating whether or not there are economies of scale in acute hospitals. This is, in fact, incorrect, since the the estimated partial relationship between average cost and beds does not trace out points on the long-run average cost curve (the equation from which evidence on economies of scale is obtained). On this point see Mann and Yett (1968) and Cowing et al (1983).

caseflow acts as a proxy for case complexity, with hospitals with lower caseflows (typically the larger hospitals) treating the more difficult cases within each casemix category (see eg Barlow, 1968; Fuchs, 1969; Lave and Lave, 1970a). Another obvious candidate for inclusion is teaching status (cf eg Culyer et al, op cit).

2.4 Empirical illustration on Spanish data

The data used to illustrate Feldstein's costliness index and the other measures of inefficiency considered in this paper relate to 49 acute hospitals owned and operated by the Spanish Ministry of Health (Insalud) and are for the fiscal year 1979. The sample includes both teaching and non-teaching hospitals (51% are teaching hospitals) but excludes some of the larger public hospitals in Spain (the largest hospital in the sample has 655 beds). A detailed description of the data is to be found in Lopez i Casasnovas (1984).

The equation estimated is basically the same as that settled on by Feldstein in chapter 3 of his *Economic Analysis for Health Service Efficiency*: the equation includes casemix variables, as well as the stock of beds, its square, caseflow, caseflow squared and teaching status. Table 1 presents some descriptive statistics for the sample.

Table 1
Descriptive statistics for Spanish hospitals

Variable	Mean	SD	Min	Max
Av cost[1]	51.92	12.38	33.28	88.75
Beds	337.37	152.07	101	655
Teach[2]	0.51	0.50	0.00	1.00
Caseflow[3]	33.52	6.67	20.41	48.70
Int Med	0.20	0.07	0.09	0.40
Surgery	0.32	0.09	0.10	0.52
Gynaecol	0.30	0.08	0.07	0.48
Paediatr	0.12	0.04	0.00	0.21
Inten Care	0.02	0.02	0.00	0.06

Notes: (1) Overall cost per case in Pta ´000.
(2) Teach = 1 if teaching hospital.
(3) Caseflow = cases per bed per year.
(4) Omitted casemix category was ´other´.

Table 2 presents the OLS estimates of the coefficients.

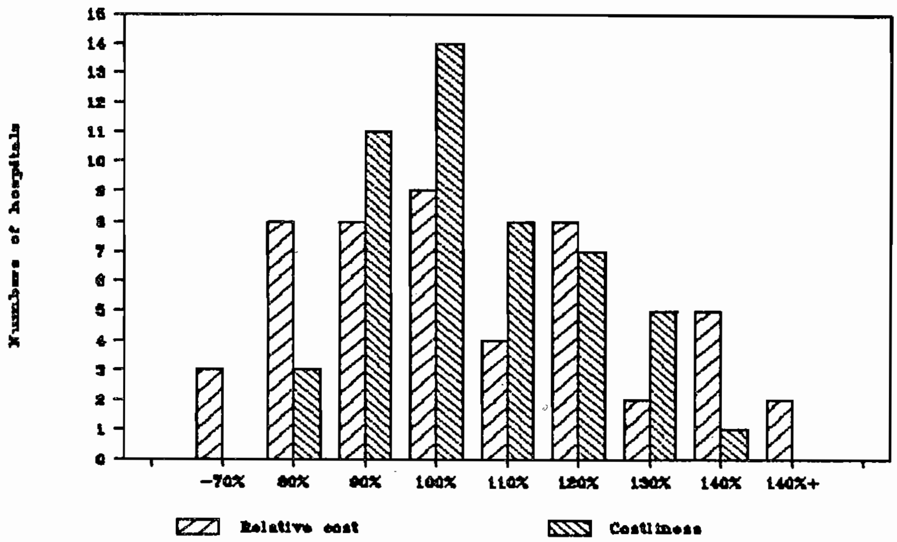
Table 2:
OLS estimates of Feldstein-type cost function

Variable	Coefficient	t-statistic
Constant	160.1430	4.295
Beds	-0.0381	0.863
$Beds^2$	0.0004	0.741
Caseflow	-5.9236	3.273
$Caseflow^2$	0.0691	2.600
Teaching	1.0752	0.336
Int Med	-11.2806	0.395
Surgery	3.2587	0.157
Gynaecol	59.3522	2.366
Paediatr	3.8436	0.114
Inten Care	0.0195	0.000
Adj R^2	0.5223	
F(10,38)	6.2479	

The coefficients on the beds and caseflow variables all have the same signs as those reported by Feldstein. The coefficients on the two bed variables indicate a U-shaped short-run average cost curve; the minimum point occurs at 47.5 beds, indicating that average costs tend to be increasing with the stock of beds over the sample range. The t-statistics on beds and beds squared indicate, however, that one cannot exclude the possibility that the partial relationship between average cost and beds is actually flat. The coefficients on caseflow and caseflow squared indicate that average cost falls with higher caseflows until a caseflow of 38 cases per bed per year is reached; thereafter average cost begins rising. The coefficient and the standard error on the teaching variable indicates that teaching hospitals have, on average, higher average costs than non-teaching hospitals, but that the effect is not significantly different from zero. As indicated in section 2.2 above, the coefficients on the casemix variables can be used to derive estimates of casemix-specific marginal costs. The implied estimates are: internal medicine 148.85; surgery 163.39; gynaecology 219.49; paediatrics 163.98; intensive care 160.16. These are not all together plausible: the low intensive care estimate is particularly implausible. In the event only the gynaecology coefficient is significantly different from zero, so that only the gynaecology marginal cost estimate differs significantly from the marginal cost of the omitted casemix category (160.14).

The regression results in table 2 can be used to compute predicted (or 'expected') costs and therefore costliness. These costliness figures can then be compared with the crude unadjusted costs. Fig 1 shows the distribution of hospitals by relative cost (ie cost per case as a percentage of the sample mean) and costliness.

Fig.1 Relative cost and costliness



As one would expect, there is far greater dispersion in the case of relative costs than in the case of costliness; crude relative costs therefore overstate the true variation in hospital cost performance. This ought also to be reflected in a low correlation between the two measures. The correlation for the present sample is indeed low (0.558). It is, in fact, a good deal lower than that reported by Feldstein (0.729), though one should bear in mind that both his sample and his number of casemix categories were both a good deal larger (n=177, J=28). A regression of costliness on relative cost for the present sample produced the following result

$$(8)\quad C_i^* = 0.653 + \underset{(0.076)}{0.349}\, [c_{i.}/c_{..}]$$

where the number in parentheses is the standard error of the coefficient. The t-statistic relevant for testing the hypothesis that the coefficient is not significantly different from unity is -8.566, indicating that there is a clear difference, even on average, between costliness and relative cost.

Possibly of more interest, however, is how close the rankings of the hospitals are on the two measures. One measure of this is the rank correlation coefficient: for this sample the coefficient was only 0.592, indicating that the ordering of hospitals on the two measures is substantially different. This is reflected in the cross-tabulation in table 3 below.

Table 3
Cross-tabulation of relative cost against costliness

Rel Cost	Feldstein Below av.	Above av.	TOTAL
Below av.	22	6	28
Above av	6	15	21
TOTAL	28	21	49

The first row of the table indicates that of the 28 hospitals that were below average efficiency on relative cost measure, 6 (21%) were actually above average on the costliness index. The second row indicates that of the 21 hospitals that were above average on the relative cost measure, 6 (28%) were actually below average on the costliness index.

2.5 Shortcomings of Feldstein's approach

Feldstein's costliness index is undoubtedly a more satisfactory measure of hospital performance than relative cost. It does, however, suffer from several shortcomings. One of these is that it provides no information on how far a hospital's costs exceed their feasible minimum. The next section discusses how this shortcoming can be overcome using the 'deterministic cost frontier' model.

3. The deterministic frontier model

Though Feldstein's index provides no indication of how far a hospital's costs exceed their feasible minimum, it can easily be modified to do so.

3.1 Costliness and the deterministic frontier model

It is useful to consider the relationship between costliness and efficiency. From eq (3) one gets

(3b) $c_{i.} = \hat{\tau}_0 + \Sigma_{j=1}^{J} \hat{\tau}_j p_{ij} + \hat{u}_i$

where $\hat{u}_i$ denotes the ordinary least squares (OLS) residual from eq (3). Combining (3a) and (3b) gives

(3c) $\hat{c}_{i.} = c_{i.} - \hat{u}_i$

and therefore eq (2b) can be written as

(2d) $C_i^* = c_{i.}/(c_{i.} - \hat{u}_i)$.

The denominator of the costliness index can therefore be interpreted as the difference between actual average costs and the 'residual' or 'unexplained' portion of average costs. Since only that portion of average costs that can be attributed to casemix is included in Feldstein's estimate of 'expected' costs, this unexplained part of average costs is implicitly being viewed by him as inefficiency. In other words, the residual in his cost function serves as a measure of efficiency: hospitals with positive residuals are therefore viewed as being of below-average efficiency (ie have actual costs that are in excess of 'expected' costs), whilst those with negative residuals are viewed as being of therefore above-average efficiency (ie have actual costs that are smaller than 'expected' costs).

That the residual in a cost function might be viewed as a measure of efficiency was assumed explicitly by Aigner and Chu (1968) in their 'deterministic frontier'. In the context of the hospital sector their argument would be as follows. Each hospital is viewed as having a minimum possible average cost, the level of which depends on factors such as its casemix, its caseflow and its stock of beds. The locus of points tracing out this minimum is the 'cost frontier'. If the hospital is both 'technically' efficient (ie produces the maximum attainable output from each bundle of inputs) and 'allocatively' efficient (ie employs inputs so that the ratios of their 'marginal products' equal the ratios of their factor prices), then it will be observed to be operating on its cost frontier. Any inefficiency - whether of the technical variety or the allocative variety - will result in it operating above the cost frontier (ie costs will exceed their feasible minimum. The extent of inefficiency is indicated by the residual of the cost function, but because inefficiency must be cost-increasing, the residual of the cost equation must be non-negative. The one-sided nature of the error term presents some statistical problems, but once these are overcome it becomes possible to obtain an estimate of inefficiency for each observation in the sample. One can then infer how far each hospital's costs exceed their feasible minimum.

3.2 Estimation of the deterministic frontier model

The statistical problems posed by the one-sided error of the cost function are discussed by Försund et al (1980) and Schmidt (1986). One particularly attractive estimation method is Greene's (1980) variant of the method proposed by Richmond (1974). This involves transforming the regression equation by adding the (unknown) mean level of inefficiency to the intercept and subtracting mean inefficiency from the error term.[5] The overall right-hand side of the regression equation is left unchanged by this transformation, but the error term term of the new equation has a zero mean and therefore estimates can be obtained by using OLS. This gives 'consistent' estimates of all coefficients of the original

5. If there is no intercept in the equation, the intercept in the transformed equation can be interpreted as mean inefficiency.

equation, except the intercept.[6] The estimate of the intercept can then be 'corrected' by shifting it up until no residual is negative and one is positive; the corrected estimate of the intercept is therefore equal to the original estimate plus the value of the smallest of the residuals. This gives a consistent estimate of the intercept of the original equation. Inefficiency can then be computed from the 'corrected' residuals, defined as the original residual less the value of the smallest of the residuals. This procedure amounts to counting the most efficient hospital as being 100% efficient.

3.3 Illustration using the Spanish data

The parameter estimates of the more general cost function of table 2 can be used to compute the implied level of inefficiency for each hospital along the lines indicated in the previous section. Table 4 presents various descriptive statistics for the estimates of inefficiency.

Table 4:
Estimated inefficiency based on regression results in Table 2
(Pta thousands)

Mean inefficiency	14.74
as % 1979 av cost	28.39%
Minimum inefficiency	0.00
Maximum inefficiency	30.52
Standard deviation	7.53
Mean costliness	143.6%

The results indicate that hospitals' costs per case are, on average, Pta 14,740 (or 28.4%) higher than they need be. Estimated mean inefficiency is equivalent to 28% of mean cost per case.

6. A 'consistent' estimate is one whose variance diminishes as the sample size increases and approaches the true value of the parameter.

3.4 Shortcomings of the deterministic frontier model

The 'deterministic frontier' model and Feldstein's costliness index both suffer from a major shortcoming, namely that they confound inefficiency with statistical 'noise' and random 'shocks' (see eg Försund et al, 1980; Schmidt, 1986). Statistical 'noise' covers things like measurement error (hopefully only in the dependent variable) and omitted (independent) variables; random 'shocks' cover unpredictable events which influence a hospital's costs but which are genuinely outside its control. That both statistical noise and random shocks are counted as inefficiency can be seen clearly from eq (3b) above: the entire residual $\hat{u}$ is classed as inefficiency or excess cost. This is really rather unsatisfactory: there are no obvious reasons why hospitals ought to be any less prone to random shocks than any other organization or why a hospital cost function is any less likely to suffer from statistical noise than any other type of regression model (cf Schmidt, 1986). Feldstein was quick to acknowledge this shortcoming and emphasized that his costliness index and the other measures of performance he proposed "should not ... be interpreted uncritically as measures of the efficiency of each hospital's management" (Feldstein, op cit, p50). The remainder of the paper is devoted to a discussion of other regression-based approaches to efficiency measurement that do not suffer from this shortcoming.

4. The stochastic frontier model

Over the course of the last decade or so a substantial amount of research has been undertaken on regression-based measures of efficiency. Surveys of this literature are to be found in Försund et al (1980) and Schmidt (1986). The great majority of the more recent research in the area has been directed at the problem of estimating inefficiency in a way that does not result in the researcher confounding inefficiency with random 'shocks'. One of the more popular of the models to have emerged to date addressing this issue is the so-called 'stochastic frontier' model of Aigner, Lovell and Schmidt (1977). It is this model that is the subject of discussion in this section. The organization of the discussion parallels that of the previous section.

4.1 The ALS model

The stochastic frontier regression model of Aigner, Lovell and Schmidt (1977) - hereafter ALS - and the regression model of Feldstein differ from one another in the assumptions they make about the error term of the regression equation. In Feldstein's model, as in the deterministic frontier model, the error term is assumed to reflect only inefficiency; in the ALS model, by contrast, it is assumed to reflect both inefficiency and random 'shocks'.

In common with the model discussed in the next section, the model of ALS is built around the observation that whilst random 'shocks' can be cost-reducing as well as cost-increasing, inefficiency must necessarily be cost-increasing. It is this latter aspect of the model that makes it a 'frontier' model: an efficient hospital operates on the frontier, whilst an inefficient hospital operates above the frontier. The model is a 'stochastic' frontier model because it allows for the possibility that the estimated frontier may not be fixed, but rather may depend on random 'shocks' and statistical 'noise'. The model of ALS thus differs from that of Feldstein in that (i) it allows for the possibility that observed costs may reflect random influences outside the hospital's control and (ii) it acknowledges the fact that inefficiency must be cost-increasing.

4.2 Estimation of the ALS model

As indicated above the error term in the ALS model is composed of two parts: (i) a symmetric term capturing statistical 'noise' and random 'shocks' and (ii) a non-negative component capturing inefficiency. The cost function in eq (3) would therefore become

$$(9) \quad c_{i.} = \tau_0 + \Sigma_{j=1}^{J} \tau_j p_{ij} + v_i + u_i$$

where the v_i denote random 'shocks' and statistical 'noise', and the u_i represent inefficiency. To render the model estimable assumptions need to be made about the distributions of the two components of the error term. ALS assume that the v_i are normally distributed (the assumption that is usually made in regression analysis) and that the u_i follow a half-normal distribution. The composite error term, unlike the error term in traditional regression models, is therefore positively skewed and has a non-zero mean.

Because of this estimation of the model becomes somewhat complicated. One possibility is to transform the estimating equation along the lines discussed in section 3.2 and estimate the transformed equation by OLS. The variances of the two components of the error term, the intercept and the mean level of inefficiency can then be estimated using the OLS estimates of the coefficients, coupled with the estimated variance and skewness of the residuals. This method - suggested by Schmidt and Lovell (1979) - is known as the OLS/moments estimation method. A more reliable - albeit more complicated - method is the maximum likelihood (ML) procedure proposed by ALS: the ML estimates have a smaller sampling variance in large samples than the 'corrected' OLS estimates. Greene (1982) has proposed an algorithm for computing the ML estimates which uses OLS/moments estimates as starting values.

The output from this estimation procedure includes the estimated mean of the u_i - ie the estimated mean level of inefficiency. One can also obtain the overall residuals for each hospital; these can be viewed as estimates of the composite error term. From these residuals an estimate of inefficiency for each hospital can be derived, though this estimate is conditional on the residuals (see Jondrow et al, 1982). Clearly it would also be desirable to be able to test for variation in inefficiency across the sample. In the ALS model inefficiency is reflected in skewness in the OLS residuals, with absence of skewness being taken to mean absence of inefficiency. Schmidt and Lin (1984) therefore suggest testing for cross-sample variation in inefficiency by testing for skewness in the OLS residuals.

4.3 Empirical illustration of the ALS approach

The ALS stochastic frontier version of the cost function of section 2 was estimated using the ML algorithm proposed by Greene (op cit). The OLS/moments estimates - used by Greene's algorithm as starting values - are reported in table 5.

Table 5:
OLS/moments estimates of the stochastic cost frontier model

$\hat{\sigma}_u^2$	6.77
$\hat{\sigma}_v^2$	55.47
$\hat{\sigma}^2$	62.24
$\hat{\sigma}_u/\hat{\sigma}_v$	0.12
Intercept	158.47
$\sqrt{b_1}$ statistic	0.03

The estimates in table 5 indicate that the majority (roughly 90%) of the variation in the residual of the cost function is attributable to variation in random 'shocks' and statistical 'noise'; only 10% of the variation can be attributed to variation in inefficiency. This is reflected in the fact that the adjusted intercept is only marginally smaller than the original estimate (158.47 compared to 160.14).

With such a small estimated variance for the efficiency term, the question arises as to whether the variance is significantly different from zero; in other words, is there any statistically significant cross-sample variation in efficiency? The simplest test way of testing for skewness is to use the skewness statistic, defined as $\sqrt{b_1}=\hat{\mu}_3/\hat{\mu}_2^{3/2}$, where $\hat{\mu}_3$ is the skewness (ie the third moment) of the OLS residuals and $\hat{\mu}_2$ is the variance of the residuals. The value of $\sqrt{b_1}$ for the present model is 0.028; this compares with a 1% critical value of $\sqrt{b_1}$ for a one-tailed test of 0.787. Thus, although the residuals are skewed in the 'correct' direction for a stochastic cost frontier, the skewness test does not allow the null hypothesis of zero cross-sample variation in efficiency to be rejected.[7] From the point of view of the economics this means that none of the variation in costliness and excess cost detected in sections 2 and 3 can be attributed to variation in inefficiency; instead, all the variation must be attributed either to statistical 'noise' or random 'shocks'. From a statistical point of view the result means that there is no need to proceed beyond the OLS estimates; the absence of any inefficiency term in the error term means that OLS is maximum likelihood.

4.4 Shortcomings of ALS model

Interpreted literally the result of the skewness test reported above means that none of the variation in estimated costliness of section 2 can be attributed to inefficiency; instead it must all be attributed to statistical 'noise' or random influences that lie outside hospitals' control. Whilst this result serves as a useful reminder of the dangers of automatically inferring inefficiency from above-average costliness, it ought not to be accepted uncritically; like Feldstein's method, the ALS approach is not problem-free.

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7. It ought to be noted that the skewness test statistic can occasionally give the 'wrong' result: there do exist asymmetrical distributions with zero values of $\sqrt{b_1}$.

Perhaps its most obvious shortcoming (see eg Schmidt, 1986) is that both the estimation of the model and the subsequent separation of inefficiency from random 'shocks' hinges on specific and somewhat arbitrary assumptions about the distribution of random 'shocks and inefficiency. Inefficiency is reflected in, and only in, skewness in the OLS residuals. Absence of skewness - as in the example above - is assumed to reflect absence of inefficiency. The assumptions regarding the distributions of the two components of the error term are very strong and have to 'work hard': eg non-normality of random 'shocks' might well be consistent with inefficiency, even if the composite error term is not skewed.

There are other problems with the ALS formulation (see Schmidt, op cit). One is that the inefficiency of a particular hospital cannot be estimated 'consistently' - ie the variance of the distribution of estimated inefficiency does not diminish as the sample size increases. Another is the implicit assumption that inefficiency is uncorrelated with any of the variables in the cost function. In reality inefficiency may be correlated with certain 'arguments' of the cost function, such as hospital size. If so the ALS method will produce unreliable estimates

5. The stochastic frontier model and panel data

In response to the limitations of the ALS stochastic frontier model several authors have recently attempted to improve on it using longitudinal or 'panel' data. In contrast to cross-section data which provide only a 'snapshot' at a particular moment in time, panel data provide observations on a sample of hospitals at several different points in time. Various writers - notably Schmidt and Sickles (1984) and Schmidt (1986) - have argued that with panel data it is possible to overcome the more serious of the limitations of the ALS approach.

5.1 The attractions of panel data

Perhaps the most significant of the claimed advantages of panel data is that the strong distributional assumptions that need to be made in the ALS model are no longer necessary. There is, however, a 'price' to pay for avoiding distributional assumptions, namely that one has to be prepared to assume that inefficiency is constant over time. A second advantage that is claimed for panel data is that inefficiency can be estimated consistently as the length of time covered by the panel increases. A third advantage of panel data is that they allow the stochastic frontier model to be estimated even if inefficiency is correlated with some of the variables in the cost function.[8]

5.2 Estimation of the stochastic frontier on panel data

Suppose that there each of the n hospitals in the sample are observed over a period of T years. The cost function of eq (9) could then be written

(10) $c_{i.t} = \tau_0 + \Sigma_{j=1}^{J} \tau_j p_{ijt} + v_{it} + u_i$

or

(10') $c_{i.t} = \tau_0 + \Sigma_{j=1}^{J} \tau_j p_{ijt} + e_{it}$

where a subscript t indicates reference to time period t and $e_{it}=v_{it}+u_i$ is the composite error term. Note that the inefficiency term has no t subscript; this reflects the assumption that inefficiency varies across hospitals but is the same in a given hospital in each year. Eq (10), like eq (9), has an error term which is skewed (the u_i are all non-negative) and has a non-zero mean. Following Schmidt and Sickles (op cit), however, one can transform the equation into one that has an error with a zero mean by adding the (unknown) mean level of inefficiency to the intercept and subtracting it from the error term (cf section

8. This possibility is not explored, however, in the present paper.

3.2 above). The resultant equation looks just like any other panel data model with an individual-specific effect (see eg Judge et al, 1982).

The literature on panel data models distinguishes between two types of individual effect model. In the first the individual-specific effect - inefficiency in the case of the hospital cost function - is viewed as being fixed; in the present context this amounts to saying that inefficiency is entirely systematic. In the second type of model the individual-specific effect is treated as random; in the context of hospital efficiency this amounts to saying that the level of inefficiency may be partly determined by chance. In neither case need any assumptions be made about the precise form of the distribution of the random shock component of the error term; moreover, in the case when inefficiency is assumed to be random, no assumption need be made about the form of the distribution of the inefficiency term. Thus the fact that the composite error term of the cost function may still be skewed even after the above transformation presents no problems from the point of view of estimation on panel data. The choice between the two characterizations of inefficiency will, in practice, be constrained by circumstances. In particular, it is not possible to treat inefficiency as a fixed effect if the cost function includes variables that remain constant over time (eg teaching status, geographical location etc). In this case the random inefficiency characterization must be adopted and the model is estimated by generalized least squares (GLS) along the lines suggested by Hausman and Taylor (1981).[9]

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9. The reason for this is as follows. In the case when inefficiency is fixed estimates are made using the dummy variable or 'within' estimator which involves transforming the equation into one that is expressed in terms of deviations from means over time. The problem with this transformation is that it 'sweeps out' not only hospital-specific effects but also time-invariant hospital-specific variables. This is not a problem in the random effects model because estimates of the coefficients for the hospital-specific variables can be arrived at via the 'between' estimator - ie estimating the model on data expressed in terms of means over time.

The output of both types of estimation includes estimates of the coefficients of the cost function. These can be used to recover estimates of the level of inefficiency of each hospital along the lines suggested by Schmidt and Sickles (op cit); their method amounts to counting the most efficient hospital in the sample as 100% efficient and measuring the degree of inefficiency of the other hospitals relative to the most efficient hospital. One can also test for cross-sample variation in inefficiency using a LaGrange multiplier test (see Judge et al, 1982, p495); under the null hypothesis of no variation in efficiency the test statistic has a chi-squared distribution with one degree of freedom.

5.3 Empirical illustration on the Spanish data

Data on average cost, the stock of beds and caseflow were available for each of the 49 hospitals for the five years 1977-1981. Data on average cost were converted to 1977 prices using the implicit health care sector deflator calculated by Lopez-Casasnovas (op cit). Unfortunately, data on casemix were available only for 1979. In estimating the panel-data version of the frontier regression model it was necessary, therefore, to assume that casemix remained unchanged over the five year period. Though this assumption has often been made in American cost function studies (see eg Lave and Lave, 1970b), evidence from Canada (see Barer, 1982) suggests that it is probably untenable. In the circumstances, though, there was no alternative but to assume constant casemix. With teaching status also remaining constant over time, there are six variables in the cost function that are time-invariant. The presence of these time-invariant variables in the cost function means that inefficiency has to be treated as random and the coefficients estimated by GLS.

GLS estimates of the coefficients of the cost frontier are reproduced in table 6.

Table 6:
GLS estimates of stochastic cost frontier on panel data for period 1977-81

Variable	Coefficient	t-statistic
Constant	105.9970	7.789
Beds	-0.1078	2.250
$Beds^2$	0.0011	2.143
Caseflow	-7.4264	16.521
$Caseflow^2$	0.0772	12.554
Teaching	4.0678	1.164
Int Med	1.3442	0.042
Surgery	7.4564	0.329
Gynaecol	76.5410	2.746
Paediatr	30.9471	0.808
Inten Care	118.7820	1.234
Adj R^2	0.6125	
F(10,234)	39.5638	

The coefficients on the beds and caseflow variables have the same sign as before, though the coefficients on the beds variables now imply a minimum point on the average cost curve of 540 beds. The coefficient on the internal medicine casemix variable is now positive and the coefficients on the remaining casemix variables are generally a good deal larger in panel data model than in the cross-section equation. The constant is, however, smaller so that the GLS estimates of the casemix-specific marginal costs are generally smaller. The GLS estimates are: internal medicine 107.34; surgery 113.45; gynaecology 182.53; paediatrics 136.94; intensive care 224.78. These seem more plausible than the OLS estimates (the intensive care estimate is a good deal larger is now the largest); again, however, only the gynaecology coefficient is significantly different from zero.

The estimates in table 6 can be used to recover estimates of inefficiency for each hospital. Table 7 reports the mean estimated level of inefficiency for the sample, together with various other statistics.

Table 7:
GLS estimates of inefficiency
(Pta thousand)

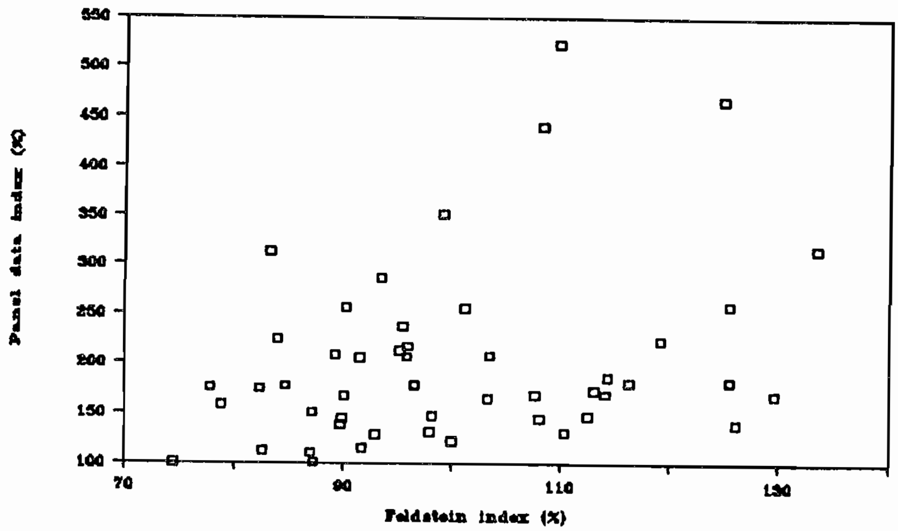
Mean inefficiency	21.82
as % 1979 av cost	42.02%
Mean expected cost	30.10
LM test statistic	28.81
$\hat{\sigma}_v^2$	123.30
$\hat{\sigma}_u^2$	62.07

The estimated mean value of inefficiency is Pta 21,820, equivalent to 42% of mean average cost in 1979. This is clearly very high, indeed possibly implausibly high. Some possible reasons for this are offered in section 5.4.

As indicated in section 5.2, it is possible to conduct a test to determine whether there is any significant variation across the sample in the level of inefficiency. The LaGrange multiplier statistic for testing this hypothesis is 28.81; the tabular value of the chi-squared distribution with one degree of freedom at the 1% level of significance is 6.635. The test suggests, therefore, that there is significant cross-sample variation in inefficiency. This result stands in stark contrast to the result obtained from the ALS model which suggested no significant variation in inefficiency across hospitals. The bottom two lines of table 7 indicate the estimated variances of the v_{it} and u_i: their values suggest that roughly one third of the variation in the overall residual can be attributed to variation in inefficiency. This is to be compared with the assumption implicit in Feldstein's approach - namely that all the variation in the residual of the cost function is to be attributed to cross-sample variation in efficiency - and the result obtained in the analysis of the ALS model - namely that none of the variation in the residual for the present sample could be attributed to variation in inefficiency.

Using the estimated value of inefficiency obtained from the estimates in table 6 it is possible to compute an index of costliness along the lines proposed by Feldstein. With the panel data results, however, it is possible to separate out inefficiency from statistical 'noise' and random 'shocks'; for the panel data version of the costliness index, therefore, the denominator of the index has been defined as reported cost less inefficiency, rather than reported cost less inefficiency and random 'shocks' combined (cf eq (2d) in section 3.1). One obvious issue of interest is the relationship between the panel data index and Feldstein's index. Fig 2 plots Feldstein's index against the panel data index.

Fig.2 Feldstein and panel data indices



The lack of relationship between the two indices is reflected in a very low correlation coefficient (r^2 = 0.077). This suggests that using an index that views all cross-sample variation in the residual of the cost function as being attributable to variations in inefficiency is probably not to be recommended.

Not surprisingly in view of the above results, the rank correlation between the two costliness indices was also very low; the correlation was only 0.274, indicating that the ranking of hospitals on the two measures is substantially different. This is illustrated dramatically in the cross-tabulation in table 8 below.

Table 8
Cross-tabulation of Feldstein and panel-data measures of costliness

Panel data	Feldstein Below av.	Feldstein Above av.	TOTAL
Below av.	17	13	30
Above av	11	8	19
TOTAL	28	21	49

The first column of the table indicates that of the 28 hospitals that were below average efficiency according to the Feldstein index, 11 (39%) were actually above average efficiency according to the panel data version of the index. The second column indicates that of the 21 hospitals that scored above average on the Feldstein measure, 13 (62%) were actually below average on the panel data index.

5.4 Shortcomings of panel data approach

Though undoubtedly an improvement on Feldstein's method, the panel data model of Schmidt and Sickles is not without its shortcomings. Perhaps its most important drawback is the assumption that inefficiency is assumed to be constant over time. This is a strong assumption and some (see eg Greene, 1986) have suggested that it is too high a price to have to pay for not having to make assumptions about the distributions of inefficiency and random 'shocks'.

Especially for long panels the assumption is likely to prove at best heroic. This makes the claim that panel data enable inefficiency to be estimated consistently as the panel gets longer look rather lame. Clearly what is required is a method for estimating inefficiency in way that permits inefficiency to change over time but does not require the imposition of strong and arbitrary assumptions about the distributions of the two components of the error term. If inefficiency changes in a broadly systematic way over time, this may not be impossible.

5. Summary and conclusions

Feldstein's index of hospital costliness was developed in response to an apparently widespread concern amongst hospital administrators that crude cost data were entirely inadequate for performance evaluation purposes. The basic idea underlying the index of costliness proposed by Feldstein was to establish how far cost differences across hospitals could be justified by casemix differences. The index was defined as a Paasche index number taking a value of 100 when a hospital's costs per case in each casemix category are the same as the corresponding national averages. The latter were estimated by a linear regression equation relating a hospital's overall average cost to the proportions of its patients falling into each of the casemix categories. From the results of the regression analysis it is possible to derive an expected' cost per case for each hospital; this expected cost is the cost per case that would be observed if the hospital's costs in each of the casemix categories are in line with the national average.

One shortcoming of Feldstein's index is that it provides no indication of how far a hospital's costs exceed their feasible minimum. This defect can be remedied using the deterministic frontier regression model in which hospitals are constrained to operate on or above, but not below, the cost frontier. The model is estimated in a way that amounts to counting the most efficient hospital as 100% efficient, so that the most efficient hospital operates on the frontier.

There is, however, another shortcoming in Feldstein's approach that is not overcome by the deterministic frontier model. Feldstein's costliness index is equivalent to expressing a hospital's reported cost per case as a proportion of the difference between its reported costs and that portion of its costs that cannot be attributed to casemix. This unattributable portion is equal to the residual of the regression equation. It is this implicit assumption - namely that costs which cannot be explained by casemix must represent inefficiency - that is the main shortcoming of Feldstein's index: in reality the residual is likely to reflect not only inefficiency but also statistical 'noise' (eg measurement errors and omitted variables) and random 'shocks' (unpredictable events that lie outside the hospital's control). With the recent research on stochastic frontier regression models this defect can be remedied and it is possible to develop an index of hospital costliness which recognizes that above-average costs not caused by an unusually costly casemix may reflect either statistical noise or random shocks.

In the paper Feldstein's index, the deterministic frontier model and two versions of the stochastic frontier model were estimated on data from 49 acute hospitals owned and run by the Spanish Ministry of Health. The results can briefly be summarized as follows. The correlation between Feldstein's index and relative cost (ie cost as a proportion of the sample average) was only 0.558. More significantly, perhaps, the rank correlation between relative cost and costliness was only 0.592, indicating that the ordering of the hospitals on the two measures is substantially different. The deterministic frontier version of Feldstein's cost function implied a mean level of inefficiency equivalent to 28% of the mean cost per case in 1979; according to this model, therefore, costs were, on average, 28% above their feasible minimum.

The first version of the stochastic frontier model to be estimated was the cross-section model of Aigner, Lovell and Schmidt (1977). The results from this model suggested that only 10% of the variation in the residual of the hospital's cost function could be attributed to variation in inefficiency, the implication being that 90% of the variation must be attributed to statistical noise and random shocks. In the event, however, the variance of the inefficiency term was found not to be significantly different from zero, suggesting that none of the variation in the residual of the cost function ought to be attributed to inefficiency. The results from the second of the frontier models - the panel data model of Schmidt and Sickles (1984) - were less optimistic, suggesting that roughly a third of the variation in the residual could be attributed to variation in inefficiency. The estimates implied a mean level of inefficiency of the order of 42% of average cost, so that costs were, on average, 42% above their feasible minimum. A comparison of Feldstein's costliness index with an index of costliness based on the panel data model revealed that both the Pearson and rank coefficients of correlation between the two indices were extremely low ($r = 0.277$ and 0.274 respectively).

There can be little doubt that the stochastic frontier model does represent an improvement over Feldstein's model. It is, however, somewhat disconcerting to find that the results can be so sensitive to the assumptions made about the nature of inefficiency. Since neither set of assumptions made in the models used in the paper is at all satisfactory, it is clearly desirable that attempts be made to try to develop a frontier model that exploits the advantages of panel data but is not based on the somewhat heroic assumption that inefficiency remains unchanged over time.

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