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Measuring Economies of Scope in Hospitals:

A Data Envelopment Analysis Approach

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Summary

This paper develops a new means of measuring economies of scope within hospitals based on production efficiency rather than cost efficiency. The method links non-parametric Data Envelopment Analysis of efficiency to an index of specialisation. We demonstrate using panel data of 44 UK hospital Trusts that there is a statistically significant negative relationship between hospital efficiency and the degree of specialisation. Multi-product hospitals operate more efficiently than hospitals which tend towards specialisation. This may have important policy implications regarding market structure and the consequences of potential mergers.

Keywords: economies of scope, efficiency, data envelopment analysis, panel data, random effects.

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1. Introduction

Much of the literature on the efficient production of health care in hospitals has focussed on their overall technical efficiency relative to their scale of operation and the issue of whether or not there are economies of scale [1]. However, the issue of economies of scope, which is concerned with the range rather than the scale of production, is also of importance because of the multi-product nature of a hospital. The existence of economies or diseconomies of scope is a key feature in determining whether it is more efficient for hospitals to specialise in particular areas or to maintain several specialties within a more general hospital.

In this paper, economies of scope are investigated by examining the relationship between hospital efficiency and the degree of specialisation. Efficiency is measured using Data Envelopment Analysis (DEA) [1], which allows the use of multiple inputs and outputs. Specialisation is measured using a new index based on the number of cases seen in different specialties. This extends existing empirical methods, adding a further dimension to the measurement of the efficiency of health care services.

The paper is structured as follows. Section 2 reviews the theory of economies of scope. Section 3 discusses the empirical method and section 4 applies this to a sample of hospitals in the Northern and Yorkshire Region in the UK. Section 5 discusses the implications of the results and further uses of the empirical method.

2. Theory of Economies of Scope

Economies of scope in health care provision exist when it costs less to produce two or more services in one hospital, rather than produce them in separate hospitals [2][3]. The concept is fundamental to the formation of multi-service hospitals, since it may be possible for inputs to be shared by different services, allowing the exploitation of spare capacity under conditions of limited demand for each service.

For the simple case of a multi-product firm producing two goods, economies of scope are defined as [4]:

$$C(q_1, q_2) < C(q_1, 0) + C(0, q_2) \quad (1)$$

where C denotes cost and q_1, q_2 are outputs of goods 1 and 2. Thus, economies of scope exist where joint production of outputs q_1 and q_2 is less costly than separate specialist production. If the inequality is reversed there are diseconomies of scope, that is joint production is more costly than separate production, or specialisation.

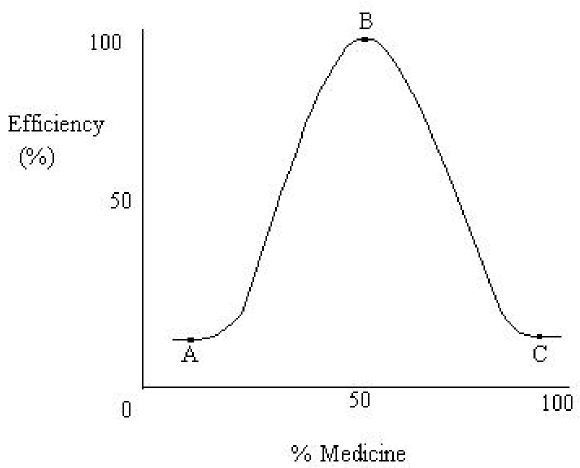
Empirical studies of economies of scope in health care have examined cost functions, in particular the issue of separable costs, those which can be attributed to specific outputs [5]. In this paper, the production function is examined rather than the cost function. The methods are, however, consistent under conditions where duality theory demonstrates the fundamental relationship between a hospital's cost function and production technology. The dual of a production function which maximises output subject to input constraints is a cost function which minimises costs subject to output constraints [6]. To our knowledge, this paper is novel in examining production efficiency, rather than cost efficiency, for the issue of economies of scope in hospitals.

3. An Empirical Method for Measuring Economies of Scope

Here, we examine the efficiency of production in terms of potential economies of scope by measuring the relationship between efficiency and specialisation. The extent to which a hospital is specialised is measured by case mix defined according to specialty. Efficiency is measured by the DEA efficiency score. DEA is a non-parametric method which measures how far inefficient hospitals are away from a best practice production frontier. The efficiency of a particular hospital is measured relative to the rest of the sample using a weighted ratio of multiple outputs and multiple inputs. DEA has been used many times in health care and is a robust technique founded in economic production theory [1].

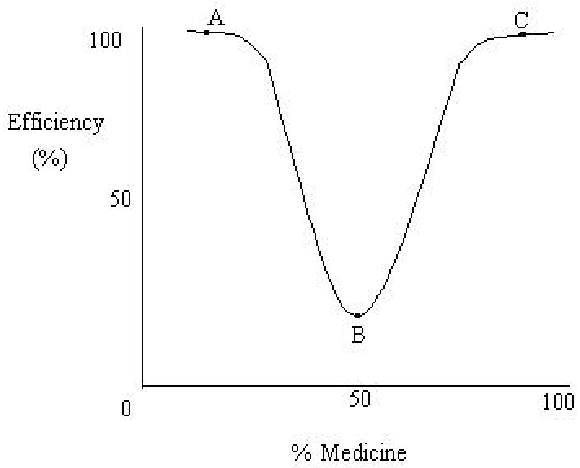
The method is illustrated using the simple example of two specialties, medicine and surgery for three hospitals, A, B and C. For each hospital, specialisation is measured by the percentage of cases seen within the two specialties.

Figure 1: Economies of Scope



Hospital A specialises in surgery and produces little general medicine; Hospital C specialises in medicine and undertakes little surgery; and Hospital B produces medicine and surgery in equal amounts. Figure 1 illustrates the case where the DEA efficiency score is higher for Hospital B than for Hospitals A and C. Hospital B is 100 per cent efficient and Hospitals A and C are 10 per cent efficient. Here, the two specialties are cost complementary; there are economies of scope for Hospital B; and joint production is more efficient than specialisation. Figure 2 shows the opposite case. The DEA efficiency scores are higher for Hospitals A and C which specialise than for Hospital B which jointly produces the two outputs; the specialties are not cost complementary; there are diseconomies of scope; and it is more efficient to specialise.

Figure 2: Diseconomies of Scope



For the more usual case where there are several specialties, a specialisation index which measures the degree of variation in production is required. To measure this variation in production the standard deviation of the number of cases seen in each specialty is calculated for each hospital, and this is standardised by dividing through by the total number of cases seen in the hospital. This index has a lower bound at zero as joint production increases. It has an upper bound which depends upon the number of specialties, given by:

$$\sqrt{\frac{1-(1/n)}{n-1}} \qquad (2)$$

where n is the number of specialties observed in the sample. (The proof for the upper bound is available from BH.) The greater the total number of specialties, the smaller is the upper bound. This is illustrated by Table 1, which shows four fictitious hospitals producing output within five specialties. Hospital A produces all outputs in equal proportions of 200 units, or 20 per cent of a total output of 1,000. The standard deviation of output is zero, and the resulting specialisation index score is zero. For Hospital B, where production levels of the five specialties vary but all are produced, the index score is 0.12. Hospitals C and D specialise in one output and both have index scores of 0.45, which is the upper bound.

Table 1: An Example of the Specialisation Index

	Hospital A	***Hospital B***	***Hospital C***	***Hospital D***
Medicine	200 (20%)	100 (20%)	700 (100%)	0 (0%)
Surgery	200 (20%)	200 (40%)	0 (0%)	0 (0%)
Mental Illness	200 (20%)	50 (10%)	0 (0%)	0 (0%)
A&E	200 (20%)	100 (20%)	0 (0%)	0 (0%)
Maternity	200 (20%)	50 (10%)	0 (0%)	1,000 (100%)
Total Output (1)	1,000 (100%)	500 (100%)	700 (100%)	1,000 (100%)
St. Dev. (2)	0	61.24	313.05	447.21
Specialisation Index (2)/(1)	0	0.12	0.45	0.45

4. Data and Results

Data used are for 44 UK hospital Trusts in the Northern and Yorkshire Region for the years 1994/5 and 1995/6. Fifteen of them are Priority Trusts which specialise in treating the long term mentally ill and those with learning disabilities. Sixteen are Acute Trusts which are on average 25 per cent larger than other Trusts in the sample, undertaking the majority of patient episodes of care, and receiving the majority of accident and emergency cases (over 60 per cent of the total in both cases). Thirteen are Combined Trusts which undertake both priority and acute services. They are on average 20 per cent smaller than Acute Trusts and 20 per cent larger than Priority Trusts [7].

Summary scores in Table 2 show the type of Trust, the number in the sample, the average DEA efficiency score, the average specialisation index score for each sub-sample, and the number of efficient hospitals that make up the production frontier. These results are shown for 1994/5 and 1995/6; a full set of results is in Appendix I.

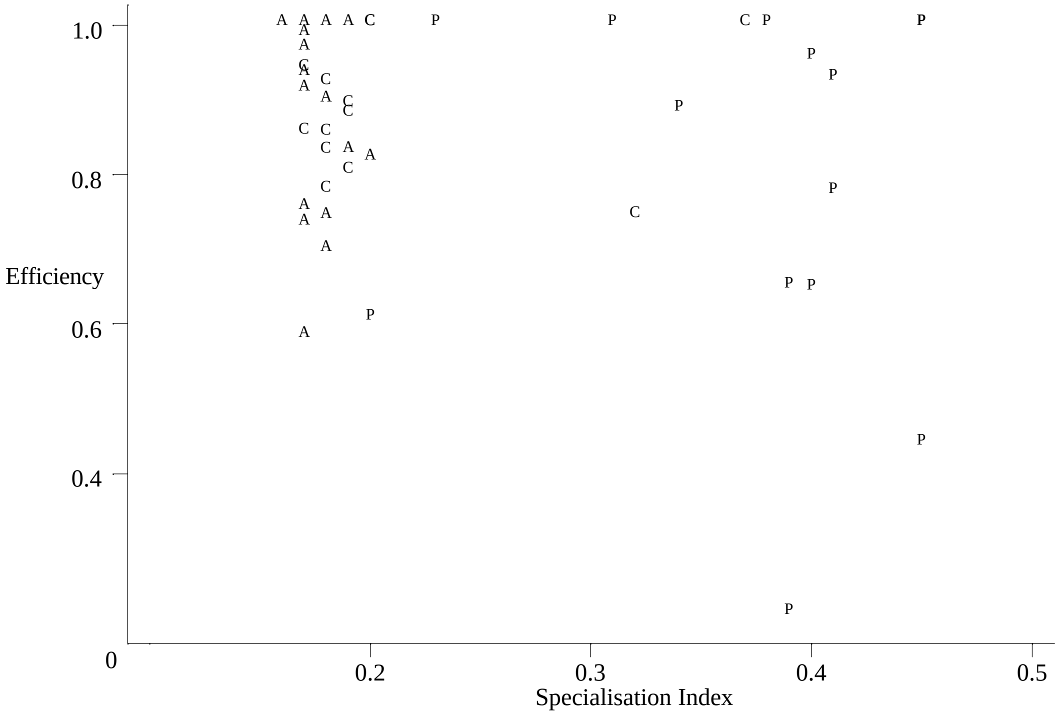
Table 2: Summary Scores

1994/5	***No.***	***DEA Efficiency***	***Specialisation Index***	***No. Efficient***
Priority	15	0.81	0.37	6
Combined	13	0.88	0.21	3
Acute	16	0.87	0.18	4
Overall	44	0.85	0.26	13

1995/6	***No.***	***DEA Efficiency***	***Specialisation Index***	***No. Efficient***
Priority	15	0.81	0.37	5
Combined	13	0.87	0.22	5
Acute	16	0.91	0.18	8
Overall	44	0.86	0.26	18

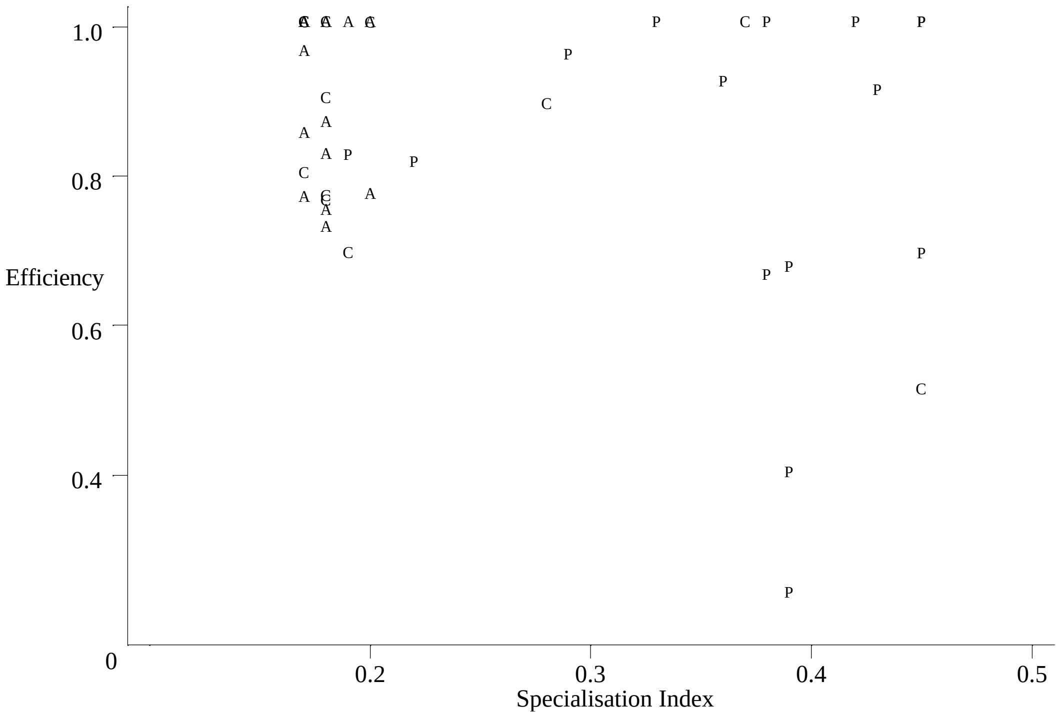
Table 2 suggests that the specialisation index is a valid measure, since it is consistent with the functional classification of the hospitals, and is robust over time. Since the specialist (Priority) hospitals are less efficient, there seems to be evidence of economies of scope. However, there could be many other reasons for this so the relationship needs to be examined at an individual hospital level.

Figure 3: Scatterplot of Efficiency and Specialisation Index Scores, 1994/5



A=Acute, C= Combined, P=Priority

Figure 4: Scatterplot of Efficiency and Specialisation Index Scores, 1995/6



A=Acute, C=Combined, P=Priority

Figures 3 and 4 show scatterplots comparing efficiency and specialisation of individual hospitals identified by type of Trust. There is some clustering within Trust types, and within types there appears to be a negative relationship between the efficiency scores and the specialisation index. This may be further investigated using a panel data regression model [8], which can be specified as:

$$Y_{it} = \alpha + \mu_i + \beta X_{it} + \varepsilon_{it} \qquad i=1,2,\ldots,n \text{ and } t=1,2,\ldots,T \qquad (3)$$

Y_{it} is the efficiency score for individual unit i at time t, X_{it} is the specialisation score for individual unit i at time t. The stochastic term, ε_{it}, is assumed to have the usual classical properties with zero mean, constant variance, σ_ε^2, and zero covariance. β is the coefficient, α is the mean intercept term and μ_i is the difference from the mean intercept term for the ith individual. If μ_i are fixed, representing parametric shifts in the regression line, (3) is a fixed effects or dummy variable model. Conversely, if μ_i are random deviations from the mean intercept, (3) is a random effects or error components model. With a random effects model, specific assumptions are made about the distribution of μ_i, which are a consequence of some random process, so unconditional inference is possible, whereas with the fixed effects model inference is conditional on the μ_i in the sample. Further, if the assumptions made by the random effects model are correct, then using this extra information will lead to an efficient estimator. Mundlak [8] states that μ_i can always be considered random as they are correlated with X_i and so $E[\mu_i]$ will not be constant, but some function of the average of X_i over time.

Table 3: Estimation Results.

Model	***Estimates***	***Specification Tests***
Fixed Effects	$\hat{Y}_{it} = \underset{(10.09)^*}{1.18} - \underset{(2.77)}{1.26}\ X_{it}$	$R^2 = 0.05$ $F_{1,43} = 7.69$ [0.01]# RESET Test: $F_{3,40} = 0.49$ [0.69] Dummy Variable: $F_{43,43} = 5.94$ [0.00]
Mundlak Random Effects	$\hat{Y}_{it} = \underset{(14.86)}{0.94} - \underset{(2.77)}{1.26}\ X_{it} + \underset{(1.83)}{0.94}\ X_1$	$R^2 = 0.06$ Wald test: $\chi^2_2 = 9.74$ [0.01] Hausman test: $\chi^2_1 = 0.00$ [0.99] Breusch-Pagan test: $\chi^2_1 = 22.04$ [0.00] $\{\hat{\sigma}_\mu^2 = 0.02$, sd = 0.14} RESET test: $\chi^2_3 = 1.86$ [0.60] rho = 0.71
Tobit Mundlak Random Effects	$\hat{Y}_{it} = \underset{(10.96)}{0.98} - \underset{(1.92)}{1.24}\ X_{it} + \underset{(1.32)}{0.96}\ X_1$	Wald test: $\chi^2_2 = 4.37$ [0.11] RESET test: $\chi^2_3 = 4.90$ [0.18] rho = 0.68

*(t values), #[p values]

Both fixed and random effects models were estimated by generalised least squares [8]. Initial random effects models were found to be mis-specified. Re-specification using a Mundlak model, where X_1 is the within group aggregate value of X_i, gave robust results. Table 3 shows that for fixed and Mundlak random effects models the coefficient for the relationship between the effect of the specialisation index on the efficiency scores is significant and negative, that is, the larger the specialisation index, the more inefficient is the Trust.

For the fixed effects model the F-test [9] rejects the null hypothesis that the model is not significant overall; and the RESET Test [10] does not reject the null hypothesis that the model is correctly specified. For the Mundlak random effects models the R^2 is larger and the Hausman specification test [9] does not reject the null that differences in fixed and random coefficients are not systematic; thus the Mundlak random effects model is consistent and correctly specified. The Breusch-Pagan LM test [8] rejects the null that the $\hat{\sigma}_{\mu}^{2} = 0$, confirming that the Mundlak random effects panel data model is appropriate, and there are effects within groups over time and between groups. The RESET test does not reject the null that the model is correctly specified, and the fraction of variance due to μ_i is significant. Given these results the Mundlak random effects model appears to be the best specification. We also tested for the significance of year and Trust functional classification using dummy variables and found these to be insignificant.

Since the dependent variable can only take values between zero and one, a limited dependent variable (LDV) Tobit Mundlak random effects panel data model was also estimated [9].

$$Y_{it} = \begin{cases} Y_{it}^{*} \text{ if } Y_{it}^{*} < 1 \\ 1 \text{ otherwise} \end{cases} \tag{4}$$

$$Y_{it} = \begin{cases} Y_{it}^{*} \text{ if } Y_{it}^{*} > 0 \\ 0 \text{ otherwise} \end{cases}$$

Equation (4) relates observed values Y_{it} to unobserved values Y_{it}^{*}. The estimated model is also in Table 3. The coefficient for X_{it} for the Tobit LDV model is statistically significant and consistent with the GLS random effects and fixed effects models. The RESET test does not reject the null that the model is correctly specified, although the Wald test [9] is insignificant.

We conclude there is a statistically significant systematic negative relationship between the efficiency scores and the specialisation index scores, whether a fixed effects, random effects or Tobit model specification is used. All imply that more specialised Trusts are more inefficient and that production therefore operates under conditions of economies of scope.

5. Summary and Conclusions

Because of the difficulty of measuring economies of scope, there are few empirical studies of them. This paper has developed a method for doing this based on analysis of production rather than cost efficiency, and therefore provides new evidence on the existence of economies of scope in UK hospitals. We develop an index to measure the degree of joint production or specialisation in hospitals. By comparing this specialisation index to DEA efficiency scores, we establish if a particular hospital demonstrates economies of scope. Moreover, while this measure can be applied to any industry, it is especially suited to health care given the multi-input, multi-output nature of production. We find a systematic negative relationship between the efficiency scores and the specialisation index, which suggests that more specialist Trusts are less efficient.

These results are exploratory but if confirmed by a larger data set over a longer time period would have important policy implications. The view that specialist units are more efficient is not substantiated by our results. These results should be of interest both to hospital managers and to policy makers in terms of their implications for the structure of the market for hospitals in the NHS. Mergers that result in multi-service hospitals would result in a more efficient delivery of health care, as specialist production is relatively inefficient. Thus, there may be a case either for a local monopolies or competing multi-product hospitals, as the most efficient market structure for the provision of hospital care for the NHS.

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Appendix I - **Full results**

		1994/5		1995/6	
Type	***Trust***	***Efficiency***	***Specialisation Index***	***Efficiency***	***Specialisation Index***
Priority	**NY18**	1.00	0.31	0.95	0.29
	NY19	1.00	0.38	1.00	0.38
	NY23	1.00	0.45	0.69	0.45
	NY25	1.00	0.45	1.00	0.45
	NY27	1.00	0.23	0.81	0.22
	NY31	1.00	0.45	1.00	0.45
	NY22	0.95	0.40	0.90	0.43
	NY26	0.92	0.41	0.92	0.36
	NY24	0.88	0.34	1.00	0.33
	NY30	0.77	0.41	1.00	0.42
	NY17	0.64	0.39	0.66	0.38
	NY20	0.64	0.40	0.67	0.39
	NY21	0.60	0.20	0.82	0.19
	NY29	0.43	0.45	0.39	0.39
	NY28	0.21	0.39	0.23	0.39
Combined	**NY41**	1.00	0.20	1.00	0.17
	NY43	1.00	0.20	0.99	0.20
	NY44	1.00	0.37	1.00	0.37
	NY38	0.94	0.17	1.00	0.17
	NY35	0.92	0.18	0.76	0.18
	NY34	0.89	0.19	0.89	0.18
	NY36	0.88	0.19	0.50	0.45
	NY32	0.85	0.17	1.00	0.17
	NY37	0.85	0.18	1.00	0.18
	NY40	0.82	0.18	0.76	0.18
	NY42	0.80	0.19	0.69	0.19
	NY33	0.77	0.18	0.79	0.17
	NY39	0.74	0.32	0.89	0.28
Acute	**NY01**	1.00	0.17	1.00	0.18
	NY03	1.00	0.19	1.00	0.20
	NY14	1.00	0.18	1.00	0.19
	NY16	1.00	0.16	1.00	0.17
	NY07	0.98	0.17	1.00	0.17
	NY10	0.96	0.17	0.85	0.17
	NY15	0.93	0.17	1.00	0.17
	NY04	0.91	0.17	0.76	0.17
	NY09	0.89	0.18	0.86	0.18
	NY13	0.83	0.19	0.82	0.18
	NY08	0.82	0.20	0.76	0.20
	NY05	0.75	0.17	0.74	0.18
	NY06	0.74	0.18	1.00	0.18
	NY11	0.73	0.17	0.96	0.17
	NY12	0.69	0.18	0.72	0.18
	NY02	0.58	0.17	1.00	0.17
	Average	***0.85***	***0.26***	***0.86***	***0.26***