A PANEL DATA DESIGN FOR ESTIMATION OF HOSPITAL COST FUNCTIONS

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Abstract—This paper estimates a multiple-output hospital cost function using a panel data technique that allows for correlation between unobservable individual effects and observable determinants of behavior. Analysis of 1733 facilities for the period of 1987–1991 yields estimates that differ widely from those obtained from a more standard cross-sectional procedure. While the latter method results in negative and stable measures of ray economies of scale, the panel model indicates positive economies of scale that fall slightly over time.

I. Introduction

THE MAJORITY of hospital cost function estimations have relied on single-year cross-sectional data. Yet researchers are aware that there likely exist unobservable systematic differences among hospitals. These individual hospital effects include quality of services, severity of illness, and managerial ability. It is therefore probable that cross-sectional behavioral equations suffer from omitted-variables bias. By estimation using panel data methodology it is possible to purge behavioral parameters of some of this bias.

Some recently developed econometric models are designed to accommodate data sets that provide a short time series on a large number of individuals. Such models are well suited for estimation of hospital cost functions. This paper uses panel data methodology to estimate a multiproduct hospital total variable cost function on a sample of 1733 nonfederal hospitals for the years of 1987–1991. The technique allows for correlation between the unobservable differences among hospitals and their observable determinants of behavior. The next section reviews the hospital cost function literature in the context of individual hospital differences. Section III describes the empirical model and the estimation technique. The sources of data and the variable definitions are contained in section IV. Section V presents the panel estimation results and contrasts them with those of the cross-sectional single equations. Measures of scale economies using both approaches are discussed in section VI. The final section summarizes and concludes.

II. Background

Previous work in determining hospital cost functions econometrically is extensive. Surveys of important issues underlying this research are contained in Cowing et al. (1983) and, more recently, in Ellis (1991). From a methodological perspective, the multiproduct nature of the hospital constitutes the largest problem for these analyses. Researchers have taken a variety of approaches to capturing the relationship between hospital costs and the many services offered while keeping the number of explanatory variables manageable. Earlier models estimated average cost as a function of various determinants. This widely used set of "behavioral" cost functions is often accused of being ad hoc and lacking foundation in the usual assumptions of production technology.

A later group of models, following the work of McFadden (1978), employs "flexible" functional forms. Because these forms regress total costs on output quantities and input prices, they are more consistent with the economic theory of production than the earlier ad hoc cost functions. Notable within this literature are the papers by Cowing and Holtmann (1983) and Conrad and Strauss (1983). Both reject the concept of a single aggregate measure of output.

The trend in recent work is toward "hybrid" flexible forms that include explanatory variables in addition to output quantities and input prices. These efforts strike some balance between the previous two groups of models and retain a number of desirable features from each. Leading in this approach is the study by Grannemann et al. (1986), which separates inpatient discharges (by type) from patient days and emergency department visits from other outpatient visits. They found distinct measures of marginal cost for the two dimensions of inpatient care. They also showed strong emergency department scale economies, unlike other outpatient visits for which marginal and average incremental costs were roughly equivalent. Vita (1990) continued this line of inquiry using data on a sample of California hospitals for five outputs. The results of this translog function indicated ray scale diseconomies. Breyer (1987) was critical of rudimentary classification of patients in most output measures. He proposed a specification in which the flexibility of the functional form is applied to the three global output categories of cases, patient days, and staffed beds. This approach, while not tested, offers potential for reducing the number of parameters to be estimated without sacrificing detailed measurement of case mix. Thus far a consensus has not been reached on the appropriate form of the hospital cost function.

Nearly all existing cost-function estimations utilize data drawn from a single year. Such analyses are not equipped to control for individual hospital differences that cause variation in costs. One exception is the study of hospital competition by Zwanziger and Melnick (1988), which draws on California data for the years of 1980–1985. These authors tested for the presence of hospital-specific effects in the residual. Finding a very high degree of intrahospital correlation, they used a variance components model in their study. Gaynor and Anderson (1995), in an analysis of the cost of

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empty hospital beds, also used panel data in a fixed-effects model, which they applied to American Hospital Association (AHA) data for 1983–1987.

With the growing movement toward hospital cost containment of the last decade, considerable concern has arisen over the relationship between cost and quality of care. While there is some evidence that quality improvement is consistent with lower costs (Fleming (1991), Binns (1991)), the underlying relationship between the quality and cost factors is unclear. Despite the interest in the quality variable, very few cost function estimations include measures of quality as an explanatory variable. Quality of hospital service is an elusive characteristic that is very difficult to define, yet alone quantify. Inclusion of a quality variable has been attempted by Fleming (1991), who found mortality and readmission indexes to be significant determinants of cost. Gertler and Waldman (1992) developed an empirical model in which costs are adjusted for unobserved endogenous quality and applied it to a sample of long-term care facilities. The parameter estimates differed significantly from those in which quality was treated as an unobserved factor subsumed in the error term. If quality is an important determinant of hospital costs, routinely ignoring it in cost function estimation can be a serious problem. Yet reliable measures of quality may be generally unavailable. Incorporating an individual hospital effect through estimation of a panel data model is an alternative approach that may capture variation in cost due to quality or other unobservable differences among hospitals. The next section describes an estimation methodology designed to that end.

III. Empirical Methodology

A variety of models has been developed to capture the heterogeneity among individuals that is contained in combined time-series and cross-sectional data sets. A traditional method is that of the fixed-effects estimator, which treats the individual-specific effect as a fixed parameter. This technique (also known as the within-groups estimator or the least-squares dummy variable model) transforms the data into deviations from individual means. It is appropriate when the focus of interest is on the particular cross-sectional units used to estimate the model. Fixed-effects models perform best on data sets containing a reasonably lengthy time series, since it is required for consistent estimation of the fixed effects that both time-series and cross-sectional dimensions go to infinity. The drawbacks are that time-invariant effects cannot be estimated, and that it is not possible to make predictions for "average" hospitals or for those out of the sample.

The class of models better suited to data sets containing large numbers of individuals and a short time series are the random-effects (or error components) models that treat the individual effect as a random component of the error term. An error structure is assumed, and the parameters are estimated by (feasible) general least squares (GLS). Because the individual effect is estimated as a distribution, predictions can be made for out-of-sample individuals. Consistent estimation of these models requires only that the cross-sectional dimension go to infinity. The disadvantage of this approach is the commonly made assumption that the unobservable individual effect is uncorrelated with the observable determinants of behavior. In most empirical models, market behavior theory suggests that this assumption is questionable. In the case of hospitals, for example, it would be preferable to allow for output to be related to managerial ability and quality to be affected by length of stay.

Hausman and Taylor (1981) proposed a random-effects model that addresses the potential correlation between the individual effect and the observable explanatory variables. The latter variables are partitioned into individual and time varying (X columns) and individual varying only (Z columns) with assumptions about which columns are correlated with the individual effects. The individual means of the uncorrelated X's are used as instrumental variables in estimating the correlated Z's. The Hausman and Taylor estimator improves on the fixed-effects estimator in that it produces coefficients for time-invariant variables. However, a necessary condition in practice is that the number of uncorrelated X's be greater than the number of correlated Z's.

Chamberlain (1982, 1984) has also proposed a correlated random-effects model that accounts for the relationship between the individual-effects and the explanatory variables. In particular, he estimates each period in a multivariate framework as a separate equation, thus transforming a single-equation model in two dimensions into T equations in one cross-sectional dimension, where T is the number of time periods. No specific assumptions about the error structure are required. Because this model, described below, contains one equation for each year in the sample, the panel data results are easily contrasted with those of single-equation cross-sectional estimations. One disadvantage is the large number of parameters to be estimated. In addition, a functional form must be assumed for the distribution of the individual effect. This will require that the unobservable individual effects vary linearly with the explanatory variables. The method also requires that the individual effects be invariant over the time period of study. (For an empirical application of this model, refer to Jakubson (1988).)

Consider the model

$$y_{it} = \beta x_{it} + a_i + \mu_{it} \tag{1}$$

where y_{it} are total costs of hospital i ($i = 1, 2, \ldots, N$) in time period t ($t = 1, 2, \ldots, T$), x_{it} are observable characteristics of hospital i in period t, a_i represents unobservable effects that vary by hospital, and μ_{it} is a random disturbance term. Assume further that $\mu_i = (\mu_{i1}, \mu_{i2}, \ldots, \mu_{iT})$ is independent of $x_i = (x_{i1}, x_{i2}, \ldots, x_{iT})$ and a_i, and has a normal distribution with zero mean and variance Σ. Two approaches to estimate equation (1) are taken. The first is to treat each year as a separate cross section and proceed with single-year estimations, as has commonly been done with hospital cost functions. This procedure fails to consider the individual effect as a distinct component of the error term. Alternatively, a random-effects approach is taken in which a_i is a separate part of the disturbance that varies by hospital, and in which a_i is correlated with the observables x_{it}. The steps in the former approach are well known; the discussion proceeds now to a description of the correlated random-effects model.

The following expression formalizes the correlation between the individual effect and the observable explanatory variables,

$$a_i = \lambda_1 x_{i1} + \lambda_2 x_{i2} + \cdots + \lambda_T x_{iT} + \omega_i . \tag{2}$$

It is assumed that ω_i is normally distributed and independent of x_i and μ_i. In the event that a_i is uncorrelated with x_{it}, the parameters $\lambda_1, \ldots, \lambda_T$ will be equal to zero. Substitute equation (2) into equation (1) to obtain the expression

$$y_{it} = \beta x_{it} + \lambda_1 x_{i1} + \lambda_2 x_{i2} + \cdots + \lambda_T x_{iT} + \omega_i + \mu_{it} . \tag{3}$$

In this formulation the values of x in all periods enter the cost function in time t through their correlation with the individual effect. Let the following set of T equations represent the unrestricted (reduced) form of equation (3):

$$y_{it} = \pi_{t1} x_{i1} + \pi_{t2} x_{i2} + \cdots + \pi_{tT} x_{iT} + \omega_i + \mu_{it} . \tag{4}$$

If Π is the matrix of coefficients in equation (4), then the set of restrictions implied by equation (3) requires that

$$\Pi = \beta I_T + j_T \lambda' \tag{5}$$

where I_T is a T-dimensional identity matrix and j_T is a T-vector (column) of 1's.

The minimum-distance methodology of Malinvaud (1970) is used to impose the restrictions in equation (5) on the reduced-form coefficient estimates. Utilization of the minimum-distance estimator involves minimizing a function of the distance between the vectors containing the estimated unrestricted parameters and the structural parameters implied by the restrictions. Specifically, let k_t represent the number of explanatory variables (including leads and lags) in each of the T unrestricted cross sections in equation (4) and $K = \Sigma_{t=1}^{T} k_t$. Let π be the K vector containing the rows of the reduced-form Π matrix and let $\hat{\pi}$ be its estimator. Let the $K \times K$ covariance matrix of $\hat{\pi}$ be represented by Ω, and let $\hat{\Omega}$ be its estimator. If θ is the q-vector of structural parameters ($q < K$), and $g(\theta)$ is the function that maps θ into π, then the desired estimator $\hat{\theta}$ is chosen to minimize

$$D(\theta) = [\hat{\pi} - g(\theta)]' \hat{\Omega}^{-1} [\hat{\pi} - g(\theta)]. \tag{6}$$

The value of θ that minimizes expression (6) is equal to

$$\hat{\theta} = (g' \hat{\Omega}^{-1} g)^{-1} g' \hat{\Omega}^{-1} \hat{\pi} \tag{7}$$

(Hsiao, 1986). Under the null hypothesis that the restrictions are valid, $D(\hat{\theta})$ is distributed $\chi^2_{(K-q)}$.

IV. Data Description

The majority of data used in this analysis comes from two independent sources: the AHA's *Annual Survey of Hospitals* and the Health Care Financing Administration (HCFA) Hospital Cost Reporting Information System (HCRIS) data files. The HCRIS files are cycles four through eight (1987–1991) of the prospective payment system (PPS). The sample of 1733 hospitals represents all facilities that were present in both data files after excluding specialty hospitals, hospitals subject to all-payer systems of reimbursement (for which databases were not comparable with the larger group), and hospitals having fewer than 100 beds.[1]

Having no evidence that hospitals are in long-run equilibrium,[2] the specific form of equation (1) to be estimated is (suppressing subscripts) the following short-run cost function:

$$TC = Pe^{f+a+u} \Rightarrow \ln TC - \ln P = f + a + u \tag{8}$$

where

$$\begin{aligned} f = \mathrm{A} &+ \alpha_1 DIS + \alpha_2 DIS^2 + \alpha_3 DIS^3 + \delta_1 OPV \\ &+ \delta_2 OPV^2 + \delta_3 OPV^3 + \Sigma \delta_k X_k \end{aligned} \tag{9}$$

and where

TC = total variable costs
P = input price measure
DIS = number of discharges
OPV = number of outpatient visits
X_k = a vector of other exogenous factors that affect total costs.

This formulation draws from the work of Grannemann et al. (1986).

Input price variation is a major geographic determinant of cost variation. The only input price measure available for nonfederal hospitals was the index of local-area wage rates that has been produced by HCFA for use in determining prospective payments to hospitals. This is an index that

[1] The period studied here is part of an eight-year panel beginning in 1984. (For more detail refer to Management Science Group (1993, chap. 3).) This study was limited to the most recent five years, given the rapid increase in the number of parameters in this model brought about by lengthening the panel. Evidence that hospitals with fewer than 100 beds exhibit cost structures that are distinctly different from larger hospitals comes from Carey and Stefos (1992).

[2] Cowing and Holtmann (1983) make this assertion as well, and results of a Hausman test supporting this premise for these data are found in Carey and Stefos (1992).

reflects average hospital wages in each metropolitan (or nonmetropolitan) statistical area as a percentage of the national average hospital wage.[3] In order to maintain the assumption of linear homogeneity in input prices, the logarithm of the price measure is subtracted from the logarithm of total costs in the equation to be estimated. Since local wages and other inputs are probably highly correlated, restricting the coefficient on the wage index to be 1 in this way is likely to ensure near homogeneity.

The remaining vector of variables includes factors found by previous researchers to be significant in explaining cost variation. Total fixed assets is used as a measure of fixed capital. This measure includes building, land, and equipment after allowance for depreciation. Two variables are included to control for output variation among inpatients not captured by the discharge variable: average length of stay and case mix index. The latter is measured using the Medicare DRG (diagnosis-related groups) case mix index. As assumed by most previous researchers, this variable is treated as exogenous.

A substantial list of recent works examines the relationship between market concentration and costs. The general result that greater competition is associated with higher costs has been attributed to nonprice competition through quality or other demand-inducing characteristic rather than technical efficiency (Joskow (1980), Robinson and Luft (1985), White (1987), Hadley and Swartz (1989)). However, Zwanziger and Melnick (1988) and Melnick et al. (1992) claim that this effect is changing in California hospitals. A recent review of this literature by Dranove and White (1994) discusses the rapid changes in market structure and the associated cost consequences. A Herfindahl index is included as a measure of market structure. This was constructed using the county as a market and the number of discharges as a measure of output from which to determine market shares. Garnick et al. (1987) found that the county is a useful measure of market area for this purpose.

Dummy variables are also used to control for other factors deemed important in explaining variation in cost due to differences in teaching status, population size, and ownership. Conventional wisdom attributes higher teaching hospital costs to the cost of "medical education," which is thought to involve extra procedures and consultations as well as an intrinsically more complex case mix structure. Population size is included since urban hospitals in general are more costly (Thorpe (1988)). Finally, theory suggests that investor-owned hospitals operate more efficiently than nonprofits since they must earn a rate of return for their investors. The level of teaching activity is classified into three groups: heavy (affiliation with a medical school and membership in the Council of Teaching Hospitals), light (medical school affiliation only), and nonteaching (neither affiliation nor Council of Teaching Hospitals membership).

[3] Because the index was rebased in four of the five years of the sample, the time dimension of this variable was lost. To capture cross-sectional variation, each hospital's 1991 wage index value was used in calculations.

TABLE 1.—DESCRIPTIVE STATISTICS OF REGRESSION VARIABLES

Variable	1987	1988	1989	1990	1991
Facility operating expenditures (000); 1987 dollars	41,022[a] (38,904)[b]	43,254 (41,183)	45,169 (42,845)	47,987 (45,564)	50,553 (48,447)
Wage index	1.02 (0.16)	0.96 (0.15)	0.96 (0.15)	0.96 (0.15)	0.95 (0.15)
Discharges (0000)	0.984 (0.694)	0.985 (0.702)	0.980 (0.710)	0.989 (0.720)	0.986 (0.722)
Outpatient visits (0000)	6.900 (7.962)	7.529 (8.092)	7.995 (8.328)	8.476 (8.934)	9.003 (9.438)
Fixed assets (0,000,000); 1987 dollars	2.854 (3.131)	2.908 (3.241)	2.923 (3.193)	3.009 (3.282)	3.080 (3.329)
Average length of stay (0)	0.813 (0.616)	0.815 (0.640)	0.825 (0.657)	0.835 (0.703)	0.833 (0.762)
Case mix index	1.22 (.14)	1.25 (.15)	1.28 (.16)	1.29 (.17)	1.32 (.19)
Herfindahl index	.38 (.32)	.38 (.32)	.39 (.32)	.39 (.32)	.39 (.32)
Heavy teaching dummy	.10 (.30)	.10 (.30)	.10 (.30)	.10 (.30)	.10 (.30)
Light teaching dummy	.17 (.38)	.17 (.38)	.17 (.38)	.17 (.38)	.17 (.38)
Large urban dummy	.32 (.47)	.32 (.47)	.32 (.47)	.32 (.47)	.32 (.47)
Small urban dummy	.42 (.49)	.42 (.49)	.42 (.49)	.42 (.49)	.42 (.49)
Nonprofit dummy	.74 (.44)	.74 (.44)	.74 (.44)	.74 (.44)	.74 (.44)
For-profit dummy	.11 (.31)	.11 (.31)	.11 (.31)	.11 (.31)	.11 (.31)
$N = 1733$					

[a] Mean.
[b] Standard deviation in parentheses.

The population of a hospital's surrounding community was coded by collapsing the metropolitan statistical area size (MSAS) into three groups: large urban (over 1 million), small urban (100,000 to 1 million), and rural. Ownership is categorized as nonprofit, profit, and other (city, county, or state facility). Summary statistics describing the sample of hospitals are listed in table 1. Expenditures and fixed assets are deflated to 1987 dollars using the Medicare PPS input price index.

V. Estimation Results

It was shown in section III from a theoretical perspective that the individual hospital effects are likely to be correlated with the observable determinants of hospital costs. Statistical evidence of the orthogonality of these effects can be obtained from the specification test devised by Hausman (1978). Under the hypothesis of no correlation between the individual effects and the regressors, both the commonly applied models of ordinary least squares (OLS) in the fixed-effects case and GLS in the random-effects case are consistent, while under the alternative hypothesis the fixed-effects approach is consistent but the random-effects is not. Therefore under the null hypothesis, the two estimates should not differ systematically. The specification is based on the statistic

$$m = (\hat{\beta}_1 - \hat{\beta}_2)'(M_1 - M_2)^{-1}(\hat{\beta}_1 - \hat{\beta}_2)$$

where $\hat{\beta}_1$ are the parameter estimates, M_1 is the covariance matrix from the fixed-effects estimation, and $\hat{\beta}_2$ and M_2 are the corresponding estimates from the random-effects model excluding dummy variables. The m-statistic has a $\chi^2(K)$ distribution, where K is the number of unknown parameters. The value of m exceeds 2022, and the critical value at the 1% level is 27.7. The null hypothesis of no correlation between the individual hospital effects and the regressors is therefore rejected.

The cross-sectional regression technique applied to the data is OLS, as is common in most hospital cost function estimations. Table 2 contains the results of these estimations. This case in which each year is treated separately will be used as a benchmark for comparison to the panel results listed below. For comparison, the parameter estimates of the fixed-effects model are also listed in table 2. The coefficient on discharges is much lower in the fixed-effects model, consistent with the presumption of omitted-variable bias. Both models yield similar estimates on outpatient visits.

The unrestricted estimates corresponding to the π's of equation (4) are estimated using the GLS technique of seemingly unrelated regression (SUR). If the individual hospital disturbances are correlated across equations (time), this method of estimation is more efficient than OLS. (The OLS cross-equation estimated covariances are used in the construction of the GLS estimator.) The results of these estimations are listed in table 3. In these equations the individual hospital effect enters through the coefficients on the discharge, outpatient visit, average length of stay, and case mix variables. This is a reflection of the expected correlation of these variables with unobservables such as quality and managerial effort. Preliminary analysis indicated that the leads and lags on the remaining variables were insignificant in explaining cost variation.

In order to isolate the individual effect (i.e., to separate the β's from the λ's), a set of restrictions is placed on the discharge and outpatient visit variables in the π matrix using the minimum-distance methodology. Although the model allows restrictions on coefficients of all the correlated variables, this set of structural restrictions is chosen because these are the two variables of interest in the construction of scale economy measures in the next section. (That is, separation of the β's from the λ's on the length of stay and case mix variables is of little value at a cost of reducing the precision on the discharge and outpatient coefficients, which are key to evaluating scale economies below.) The β's are allowed to vary over time. This allows for comparability with cross-sectional model results. The minimum-distance estimates are listed in table 4. These estimates are derived from the parameters and covariance matrix of the SUR estimator. The completed set of panel estimates consists of the parameters contained in table 4 for discharges and outpatient visits (including leads and lags) and the SUR estimates of table 3 for the remaining variables.[4]

Most results are similar in both the OLS and the SUR estimates. The parameters on the discharge, outpatient visit, and average length of stay variables exhibit the expected signs. Most of the signs on the coefficients for the remaining variables also behave as anticipated. The case mix index is highly significant (positively) in the OLS regressions. In the SUR regressions, however, it is the 1988 and 1991 case mix measures that are significant in each year. The lower precision of the case mix measure in the SUR regressions may be reflective of "DRG creep." This is an increase in case mix resulting from hospitals' upcoding efforts rather than real, cost-bearing increases in resource intensiveness. The level of fixed assets is very significant in explaining cost variation, and the negative coefficient on the Herfindahl index supports the theory of nonprice competition.

The effect of teaching is as anticipated. Hospitals with heavy teaching missions have higher costs. The coefficients on the dummy variables representing large urban hospitals are not significantly positive, as was found previously (Thorpe (1988)). A possible explanation for this is correlation between the urban dummy and the Herfindahl index. The latter variable may be capturing the cost variation due to surrounding population density. Finally the profit versus nonprofit status does not appear to have an effect on cost, all else being equal. This result is consistent with the bulk of previous research findings.

The results of the restrictions imposed on the discharge and outpatient visit variables using the minimum-distance estimator (listed in table 4) can be contrasted with the cross-sectional estimates contained in table 2. The output variables account for much less of the variation in total cost in the panel data model. The structure imposed on the model by the restrictions separates the individual effect (which enters through the λ's) from the output effect (that of the β's). The χ^2 statistic takes the value of 110.0. Since the critical value for 30 degrees of freedom ($K - q = 50 - 20$) at the 5% level is 43.8, we fail to accept the null hypothesis that the set of restrictions fully characterizes the reduced form. However, given the large number of hospitals in the sample, it should be noted that because the standard errors of the unrestricted estimates become smaller as N increases, a rejection is difficult to interpret.

A different assumption permitted by the model restricts the β's to single values, that is, it does not allow the coefficients on discharges and outpatient visits to vary over time. To test whether the β's are time invariant, the

[4] The computation for these estimates was an author-written routine based on PROC SYSLIN in SAS.

TABLE 2.—CROSS-SECTION (OLS) AND FIXED-EFFECTS RESULTS

	OLS					
Variable	1987	1988	1989	1990	1991	Fixed Effects
Intercept	14.60[a]	14.62	14.70	14.81	14.95	—
	(0.063)[b]	(0.060)	(0.057)	(0.057)	(0.055)	—
Discharges	2.21	2.38	2.20	2.20	2.27	1.29
	(0.047)	(0.052)	(0.047)	(0.050)	(0.053)	(0.036)
Discharges squared	−0.761	−0.889	−0.767	−0.780	−0.826	−0.389
	(0.026)	(0.031)	(0.027)	(0.028)	(0.031)	(0.017)
Discharges cubed	9.29 E-2	0.117	9.52 E-2	9.49 E-2	0.102	4.09 E-2
	(4.21 E-3)	(5.24 E-3)	(4.44 E-3)	(4.51 E-3)	(4.88 E-3)	(2.49 E-3)
Outpatient visits	2.32 E-2	2.09 E-2	2.34 E-2	2.13 E-2	1.66 E-2	2.24 E-2
	(2.33 E-3)	(2.30 E-3)	(2.19 E-3)	(2.15 E-3)	(2.06 E-3)	(1.02 E-3)
Outpatient visits squared	−1.60 E-4	−2.22 E-4	−2.79 E-4	−3.39 E-4	−2.35 E-4	−3.35 E-4
	(8.51 E-5)	(8.17 E-5)	(8.42 E-5)	(7.63 E-5)	(7.24 E-5)	(3.15 E-5)
Outpatient visits cubed	9.00 E-7	1.06 E-6	1.37 E-6	1.33 E-6	8.40 E-7	9.74 E-7
	(3.4 E-7)	(3.4 E-7)	(3.3 E-7)	(2.7 E-7)	(2.4 E-7)	(0.009 E-5)
Discharges × outpatient visits	−6.42 E-3	−3.45 E-3	−4.92 E-3	−2.13 E-3	−1.07 E-3	−1.89 E-3
	(1.32 E-3)	(1.34 E-3)	(1.28 E-3)	(1.17 E-3)	(1.30 E-3)	(5.20 E-4)
Fixed assets	3.25 E-2	2.67 E-2	3.16 E-2	3.15 E-2	2.91 E-2	1.31 E-2
	(2.49 E-3)	(2.44 E-3)	(2.55 E-3)	(2.66 E-3)	(2.75 E-3)	(1.33 E-3)
Average length of stay	0.639	0.463	0.546	0.418	0.343	0.337
	(0.046)	(0.038)	(0.041)	(0.038)	(0.035)	(0.019)
Average length of stay squared	−0.260	−1.77	−0.221	−0.161	−0.131	−6.24 E-2
	(0.019)	(0.013)	(0.016)	(0.013)	(0.011)	(5.47 E-3)
Average length of stay cubed	2.30 E-2	1.33 E-2	1.90 E-2	1.24 E-2	9.61 E-3	3.64 E-3
	(1.95 E-3)	(1.11 E-3)	(1.53 E-3)	(1.09 E-3)	(8.94 E-4)	(4.06 E-4)
Case mix index	0.741	0.747	0.715	0.707	0.665	0.794
	(0.044)	(0.041)	(0.037)	(0.037)	(0.034)	(0.017)
Herfindahl index	−0.150	−0.128	−0.111	−9.20 E-2	−7.35 E-2	0.440
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.046)
Heavy teaching dummy	0.141	0.149	0.143	0.139	0.125	—
	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)	—
Light teaching dummy	4.17 E-2	3.99 E-2	4.36 E-2	3.16 E-2	2.20 E-2	—
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	—
Large urban dummy	−2.90 E-2	−3.05 E-2	−5.54 E-2	−5.65 E-2	−8.24 E-2	—
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	—
Small urban dummy	−3.26 E-2	−2.52 E-2	−2.80 E-2	−1.60 E-2	−3.26 E-2	—
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	—
Nonprofit dummy	−2.83 E-2	−1.98 E-2	−1.06 E-2	−1.56 E-2	−1.95 E-2	—
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	—
For-profit dummy	−2.75 E-2	−2.00 E-2	5.52 E-3	1.98 E-2	−9.00 E-3	—
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	—
R^2	0.9458	0.9458	0.9479	0.9429	0.9448	0.4189

[a] Coefficients.
[b] Standard error in parentheses.

minimum-distance estimator was also obtained under this alternative set of restrictions. Under the null hypothesis of constant β's, the difference in the distance statistics is distributed according to the difference in degrees of freedom under the alternative assumptions [(50 − 12) − (50 − 20)] (Jakubson (1988)). Since the distance statistic goes to 127.3 and the critical value for $\chi^2(8)$ is 15.5, the hypothesis of common β's is rejected.

VI. Measuring Scale Economies

It is difficult to evaluate the significance of the difference in the results of each model judging only from the regression coefficients. Hence this section considers scale economy and marginal cost values that follow from the results derived above. Evidence from hospital cost functions on the existence of economies of scale is mixed. Alexander and

Morrisey (1988) and Friedman and Shortell (1988) demonstrate scale economies obtained from behavioral-type cost function estimations. Vitaliano (1987) concludes that either result is attainable, depending on the functional form applied to 166 New York State acute-care hospitals. A quadratic form yielded a shallow U-shaped average cost curve, whereas a logarithmic form indicated significant economies of scale. The hybrid (translog) approach of Vita (1990) found diseconomies of scale for a sample of 296 California hospitals.

Given the multiproduct nature of the cost function, two different scale economies concepts emerge. One measures product-specific economies of scale. This characterizes the cost effects of expanding each output separately, while holding production levels of other outputs constant. This approach is attractive when substitution of one output for the other is of interest (outpatient care for inpatient, for example). However, separation of the individual output effects is based on the calculation of incremental costs, which underestimate the total cost of each output, and which also requires evaluation of the function far from the sample mean and possibly outside the range of the data. (For a discussion of these problems see Baumol et al. (1988) and Vita (1990).) Alternatively, the concept of ray scale economies can be utilized. This is a measure of the proportional increase in costs resulting from a simultaneous proportional increase in all outputs. Since the object of this section is a basic comparison of panel data methodology with standard cross-sectional estimation, the latter less problematic approach is deemed more appropriate.

The formula for ray scale economies arising from the variable cost function is

$$S = (1 - \epsilon_K)/\Sigma\epsilon_i \qquad (10)$$

where ϵ_K is the elasticity of the fixed factor, beds, and ϵ_i are the output elasticities.[5] A value of S greater than 1 indicates the presence of scale economies. Table 5 presents the ray scale economy values measured according to equation (10) and evaluated at the sample means. While the cross-sectional model shows diseconomies of scale, the panel model indicates significant scale economies. There is virtually no change in the cross-sectional model over the period of study. In the panel model, however, the scale economies fall by about 8% over the five years. Table 5 also contains measures of marginal cost for each individual output evaluated at the mean for each model. The panel model estimates are much lower than those of the cross-sectional estimates, reflecting the difference in economies of scale observed using that technique. The scale economy and marginal cost estimates differ from those most recently reported in the published literature. Vita (1990), for example, reports ray scale diseconomies for California hospitals for 1983. His estimate for medical–surgical discharge marginal cost is \$2043, which is not inconsistent with the panel data trend observed here. However, his marginal cost estimate for outpatient visits is higher (\$74). The estimate of Grannemann et al. (1986) for the marginal cost of an outpatient visit in 1981 (\$83) is comparable in magnitude to Vita's. A slightly higher measure of this variable is reported by Koop and Carey (1994)—\$122 for the period of 1985–1988. Their pooled data (which did not utilize panel techniques) found the marginal cost of a discharge to be \$3246, which falls between the panel and cross-sectional estimates of the current study.

VII. Discussion

The five-year data series of this study allows for observing how scale economies are changing over time as well as for comparing panel techniques with the more commonly used cross-sectional techniques. The 8% fall in the ray scale economy measure reported above is not surprising, given the movement of output during this time. The number of outpatient visits increased by 30%, representing a vast expansion of outpatient service aimed at reducing the cost of health care. Much of this larger volume is associated with technological advances that made procedures formerly requiring an overnight stay possible on an outpatient basis. Examples of these technologies include imaging procedures such as CT scans and MRI, less invasive surgical procedures, such as arthroscopes and laparoscopes, improved cataract surgical techniques, and shorter acting anesthetics.

Differences between the two models in cost estimates and overall scale economies have implications for hospital payment systems. In contrast to the cross-sectional model, the panel data technique yields measures of economies of scale. These are associated with marginal costs that are much lower than those of the former model. These results follow from the elimination of upward bias in the output (discharge and outpatient visit) variable estimates in the cross-sectional case. Failure to control for quality or other hospital individual differences can result in serious overestimates of the marginal cost of hospital output. This has particular policy relevance for Medicare PPS, given recent concerns over declining operating margins under this system and possible inadequacy of payment rates (Sheingold and Richter (1992)).

While estimates at the mean illustrate the differences between the panel technique and the traditional model and demonstrate changes over time, it is also useful for policy purposes to observe how scale economy measures vary across hospital size. To that end panel model ray scale

[5] It should be noted that equation (10) uses the actual value of beds rather than its optimal level. The difference in these procedures is that the former is a measure of returns to scale at the actual level of capital whereas the latter measure lies along the firm's efficient expansion path (long-run economies of scale). The long-run cost function can be obtained from estimation of a variable cost function only by mathematical derivation that requires price data on the fixed factor. Calculation at the actual level of beds is a feasible alternative. If adjustment to the efficient path is likely to be slow, as expected in this case, the former approach is the superior one. For a detailed discussion of these two methods, refer to Braeutigam and Daughety (1983).

TABLE 3.—UNRESTRICTED (SEEMINGLY UNRELATED REGRESSION) PANEL RESULTS

Variable	1987	1988	1989	1990	1991
Intercept	14.83[a]	14.84	14.87	14.89	14.97
	(0.056)[b]	(0.056)	(0.055)	(0.058)	(0.059)
Discharges					
1987	1.76	0.254	0.217	0.179	0.153
	(0.051)	(0.041)	(0.040)	(0.042)	(0.042)
1988	0.116	1.61	8.46 E-2	8.22	3.63 E-2
	(0.048)	(0.058)	(4.67 E-2)	(4.89 E-2)	(4.86 E-2)
1989	−8.81 E-2	−9.34 E-3	1.51	2.95 E-2	−4.22 E-2
	(4.78 E-2)	(4.80 E-2)	(0.055)	(4.94 E-2)	(4.93 E-2)
1990	5.70 E-2	6.10 E-2	4.54 E-2	1.57	8.13 E-2
	(4.50 E-2)	(4.53 E-2)	(4.43 E-2)	(0.056)	(4.65 E-2)
1991	−6.17 E-2	−5.14 E-2	−2.53 E-2	2.44 E-2	1.70
	(3.69 E-2)	(3.70 E-2)	(3.64 E-2)	(3.81 E-2)	(0.052)
Discharges squared	−0.535	−0.574	−0.547	−565	−592
	(0.017)	(0.019)	(0.016)	(0.017)	(0.020)
Discharges cubed	6.14 E-2	6.89 E-2	6.36 E-2	6.45 E-2	6.73 E-2
	(2.68 E-3)	(3.07 E-3)	(2.56 E-3)	(2.59 E-3)	(3.11 E-3)
Outpatient visits					
1987	1.39 E-2	2.92 E-3	1.57 E-3	9.51 E-4	5.78 E-4
	(2.55 E-3)	(2.20 E-3)	(2.16 E-3)	(2.26 E-3)	(2.26 E-3)
1988	3.47 E-3	1.25 E-2	5.01 E-3	5.50 E-3	5.03 E-3
	(2.66 E-3)	(2.96 E-3)	(2.61 E-3)	(2.74 E-3)	(2.74 E-3)
1989	1.18 E-3	1.59 E-3	8.32 E-3	−2.20 E-3	−1.56 E-3
	(2.51 E-3)	(2.52 E-3)	(2.68 E-3)	(2.59 E-3)	(2.58 E-3)
1990	−2.26 E-3	−1.55 E-3	4.01 E-4	8.97 E-3	4.50 E-4
	(2.38 E-3)	(2.39 E-3)	(2.34 E-3)	(2.71 E-3)	(2.46 E-3)
1991	2.78 E-3	2.55 E-3	2.33 E-3	3.05 E-3	1.05 E-2
	(1.97 E-3)	(1.98 E-3)	(1.94 E-3)	(2.04 E-3)	(2.33 E-3)
Outpatient visits squared	−8.93 E-5	−7.21 E-5	−1.11 E-4	−1.40 E-4	−1.42 E-4
	(5.01 E-5)	(4.71 E-5)	(4.36 E-5)	(4.30 E-5)	(4.60 E-5)
Outpatient visits cubed	4.41 E-7	3.49 E-7	5.18 E-7	5.31 E-7	4.89 E-7
	(2.09 E-7)	(2.05 E-7)	(1.83 E-7)	(1.55 E-7)	(1.54 E-7)
Discharges × Outpatient Visits	−3.94 E-3	−3.55 E-3	−3.16 E-3	−1.75 E-3	−9.31 E-4
	(7.62 E-4)	(7.49 E-4)	(6.59 E-4)	(6.28 E-4)	(7.95 E-4)
Fixed assets	1.41 E-2	1.10 E-2	1.14 E-2	1.11 E-2	1.27 E-2
	(1.60 E-3)	(1.47 E-3)	(1.51 E-3)	(1.59 E-3)	(1.79 E-3)
Average length of stay					
1987	0.447	1.20 E-2	−4.43 E-3	(−3.75 E-2)	−5.04 E-2
	(0.036)	(2.56 E-2)	(−2.43 E-2)	(2.55 E-2)	(2.57 E-2)
1988	1.22 E-2	0.362	−3.72 E-2	−3.19 E-2	−4.90 E-2
	(2.14 E-2)	(0.030)	(2.11 E-2)	(2.20 E-2)	(2.21 E-2)
1989	−3.65 E-2	−1.18 E-2	0.386	1.70 E-2	9.82 E-3
	(2.61 E-2)	(2.63 E-2)	(0.033)	(2.69 E-2)	(2.71 E-2)
1990	−5.77 E-2	−5.61 E-2	−5.68 E-2	0.322	−2.07 E-2
	(2.94 E-2)	(2.98 E-2)	(2.89 E-2)	(0.035)	(3.02 E-2)
1991	−8.10 E-2	−7.77 E-2	−4.44 E-2	−6.92 E-2	0.276
	(2.42 E-2)	(2.43 E-2)	(2.39 E-2)	(2.50 E-2)	(0.033)
Average length of stay squared	−0.120	−0.100	−0.108	−8.61 E-2	−7.17 E-2
	(0.010)	(0.008)	(0.008)	(6.90 E-3)	(6.72 E-3)
Average length of stay cubed	8.79 E-3	6.77 E-3	7.90 E-3	5.49 E-3	4.03 E-3
	(1.03 E-3)	(6.13 E-4)	(7.11 E-4)	(5.46 E-4)	(5.17 E-4)

TABLE 3.—(CONTINUED)

Variable	1987	1988	1989	1990	1991
Case mix index					
1987	0.129	6.31 E-2	3.61 E-2	9.77 E-2	−6.61 E-3
	(0.106)	(0.107)	(0.105)	(0.110)	(0.110)
1988	0.387	0.472	0.308	0.269	0.329
	(0.131)	(0.132)	(0.129)	(0.135)	(0.136)
1989	4.15 E-2	−1.47 E-2	0.198	6.29 E-2	7.43 E-2
	(0.128)	(0.128)	(0.126)	(0.132)	(0.132)
1990	−9.70 E-2	−9.80 E-2	−6.65 E-2	8.17 E-2	−6.66 E-2
	(0.123)	(0.124)	(0.121)	(0.127)	(0.127)
1991	0.347	0.401	0.359	0.350	0.510
	(0.085)	(0.085)	(0.084)	(0.088)	(0.088)
Herfindahl index	−0.135	−0.115	−0.106	−7.72 E-2	−6.65 E-2
	(0.018)	(0.018)	(0.018)	(1.88 E-2)	(1.90 E-2)
Heavy teaching dummy	0.143	0.131	0.118	0.113	0.101
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Light teaching dummy	6.01 E-2	4.66 E-2	4.50 E-2	3.60 E-2	2.73 E-2
	(1.34 E-2)	(1.35 E-2)	(1.32 E-2)	(1.38 E-2)	(1.38 E-2)
Large urban dummy	4.31 E-3	2.04 E-3	−2.05 E-2	−1.53 E-2	−4.81 E-2
	(1.59 E-2)	(1.60 E-2)	(1.56 E-2)	(1.64 E-2)	(1.65 E-2)
Small urban dummy	−1.06 E-2	−6.59 E-3	−5.88 E-3	7.25 E-3	−1.11 E-2
	(1.36 E-2)	(1.37 E-2)	(1.34 E-2)	(1.40 E-2)	(1.41 E-2)
Nonprofit dummy	−1.01 E-2	−5.68 E-3	−4.02 E-3	−8.30 E-3	−1.13 E-2
	(1.27 E-2)	(1.26 E-2)	(1.24 E-2)	(1.30 E-2)	(1.30 E-2)
For profit dummy	−6.18 E-2	−4.95 E-2	−2.43 E-2	6.11 E-3	−1.68 E-2
	(1.79 E-2)	(1.80 E-2)	(1.76 E-2)	(1.84 E-2)	(1.84 E-2)
R^2 (system weighted) = 0.8430					

[a] Coefficient.
[b] Standard error in parentheses.

TABLE 4.—RESTRICTED (MINIMUM-DISTANCE ESTIMATED) PANEL RESULTS

	Coefficient	Standard Error
β		
Discharges		
1987	1.50	0.033
1988	1.58	0.034
1989	1.54	0.031
1990	1.57	0.032
1991	1.63	0.036
Outpatient visits		
1987	1.12 E-2	1.44 E-3
1988	9.99 E-3	1.38 E-3
1989	1.00 E-2	1.24 E-3
1990	9.15 E-3	1.25 E-3
1991	7.93 E-3	1.34 E-3
λ		
Discharges		
1987	0.219	3.77 E-2
1988	6.66 E-2	4.34 E-2
1989	−5.39 E-2	4.41 E-2
1990	6.90 E-2	4.15 E-2
1991	−2.13 E-2	3.42 E-2
Outpatient visits		
1987	1.77 E-3	2.01 E-3
1988	4.08 E-3	2.45 E-3
1989	−1.13 E-4	2.31 E-3
1990	−7.34 E-4	2.19 E-3
1991	2.67 E-3	1.83 E-3
	$\chi^2(30) = 110.0$	

economies were calculated at quartile values of the output variables of discharges and outpatient visits (and at the means of the other variables). For 1991 these measures were 1.74, 1.42, and 1.64 for the first quartile, median, and third quartile of output, respectively. That scale economies persist even in large facilities is an important finding, relevant to the issue of hospital size efficiency. The implication is that cost savings are possible from the consolidation of smaller facilities, which would reduce duplication of expensive high-technology services.[6]

Comparison of results by hospital size also has implications for the Medicare PPS. The current method sets "prices" that are established by averaging historic costs across hospitals. Costs are adjusted for differences in case mix, teaching, wages, and low-income share. This standardization procedure is designed to prevent hospitals from becoming "winners and losers" under PPS for reasons other than efficiency of operation. Various proposals for improving the standardization procedure have been put forward,

[6] A possible explanation for the unexpected rise in moving from the median to the third quartile is unobserved interaction between quality and output. Since the costs of some quality measures (e.g., good food or nursing care) are proportional to the number of patients, increases in output may be correlated with increases in quality costs. If output is initially picking up improvements in quality that eventually are satiated, the measure of marginal costs at lower output levels may be overestimated.

TABLE 5.—RAY SCALE ECONOMIES AND MARGINAL COSTS (EVALUATED AT MEAN)

	Output Level		Cross-Sectional Model / Panel Model		
Year	Discharges	Outpatient Visits	Ray Scale Economy	Discharge Marginal Cost	Outpatient Visit Marginal Cost
1987	9840	68,996	0.887/1.53	3542/2051	56/21
1988	9852	75,293	0.892/1.49	3760/2260	57/20
1989	9804	79,952	0.887/1.47	3875/2402	60/20
1990	9894	84,765	0.887/1.45	4054/2579	61/21
1991	9857	90,029	0.890/1.41	4361/2811	54/20

including an adjustment for hospital size (Sheingold (1990)). The finding that economies of scale are not flat across output levels suggests that size is a factor that should be considered in future refinements of the payment system.

Quality differences are assumed to exist among hospitals, are unobservable and unmeasured in cost functions, and are reasonably assumed to remain constant over a time period of only five years. It is therefore likely that the diversity in levels of hospital quality comprises a portion of the hospital-specific effect. By applying structure to the unobservables, the panel data methodology is an alternative approach to capturing variation in hospital costs due to quality differences. What appears in cross-sectional analysis as diseconomies of scale may be the higher costs of producing a superior level of unmeasured quality in larger hospitals.

Although quality is obviously a critical unobservable difference between hospitals, it is not necessarily the only one. Managerial disparities also exist among hospitals, are largely unmeasurable, and have potentially large cost implications. Another possibility is unmeasured change in case mix complexity. As more services are shifted to outpatient departments, the average complexity as well as the costliness of both inpatient and outpatient cases rise. If this is not fully captured by the Medicare DRG case mix index, it would be contained in the individual hospital effect, giving the appearance of falling economies of scale (or amplifying the effect of truly declining scale economies).

VIII. Conclusion

This paper has estimated a multiple-output hospital cost function for a sample of 1733 nonfederal hospitals. It differs from most previous hospital cost function analyses in that it uses panel data methodology which is applied to the period of 1987–1991. This allows for more information to be gained from the five-year data set than if five separate cross-sectional estimations were made. In the panel model, an unobservable hospital-specific effect that is otherwise subsumed in the error is identified and isolated. In this process, omitted-variables bias is removed from the parameter estimates. Because the particular panel data methodology chosen here does not make the assumption that the unobservable effect is uncorrelated with the observable explanatory variables, it is an improvement over commonly used random-effects models.

Comparison of the panel to cross-sectional results for the same model illustrates the importance of separating the individual effects from the cost function parameters. This is seen in a comparison of the measures of scale economies that arise from each model. The cross-sectional estimates result in negative ray scale economy measures that remain stable over the five years. The panel estimation, in contrast, yields a result of positive scale economies that fall gradually during the study period. This application is of considerable importance in the case of hospitals, given the significant recent movement in the industry toward greater consolidation and the changing environment of hospital payment. The conclusions of this paper underscore the seriousness of omitted-variables bias in the econometric estimation of hospital cost functions.

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