How Reliable Are Hospital Efficiency Estimates?:

Exploiting the Dual to Homothetic Production

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Abstract

For scientific use, stochastic frontier estimates of hospital efficiency must be robust to plausible departures from the assumptions made by the investigator. Comparisons of alternative study designs, each well within the "accepted" range according to current practice, generate similar mean inefficiencies but substantially different hospital rankings. The three alternative study contrasts feature 1) pooling vs. partitioned estimates, 2) a cost function dual to a homothetic production process vs. the translog, and 3) two conceptually valid but empirically different cost of capital measures. The results suggest caution regarding the use of frontier methods to rank individual hospitals, a use that seems required for reimbursement incentives, but they are robust when generating comparisons of hospital group mean inefficiencies, such as testing models that compare nonprofits and for-profits by economic inefficiency. Demonstrations find little or no efficiency differences between these paired groups: nonprofit vs. for-profit, teaching vs. nonteaching, urban vs. rural, high percent of Medicare reliant vs. low percent, and chain vs. independent hospitals.

Frontier cost analysis of hospital inefficiency has become a minor industry, one where data envelopment analysis (DEA) (1,2,3,4,5,6) dominated in earlier research publications, and the stochastic frontier method is now also attracting many applications (7,8,9,10,11). Despite the enthusiasm evidenced by the number of these studies, many questions about validity and robustness have been raised.

When the paper by Zuckerman, Hadley and Iezzoni (ZHI) brought the stochastic method to the fore in the health economics literature (October, 1994), it presented mean hospital inefficiency estimates for the United States by pairs of hospital groups, and it pursued several methodological issues by investigating possible departures from the standard econometric assumptions. Like our own initial efforts (12), their work seemed to find the stochastic frontier approach to hospital costs to be ready for use. But in the same issue of the *Journal of Health Economics,* Newhouse (13) and Skinner (14) each took opposition to hospital frontier applications, with Hadley and Zuckerman (15) strongly defending. Elsewhere, and since that time, questions raised about non-frontier cost studies have come to be even more worrisome when applied to frontier versions.

We propose that among these questions four issues are primary, and they are addressed in the paper. First, as Newhouse (13) argued, the heterogeneity of hospital outputs may be difficult or impossible to capture in frontier analysis. Second, there is a potential for misspecification due to structural differences between the cost functions of groups of hospitals. Third, the choice between theoretically acceptable cost function forms may arbitrarily affect the estimated efficiencies; and, fourth, the inevitable choices when operationally defining input variables, especially the difficulties of measuring input prices, may affect the estimated efficiencies.

Three of these four issues are addressed empirically in this study. The omitted issue in the empirical analyses, the potential problem of output heterogeneity, has a large philosophical dimension not very amenable to empirical testing. While the question of output heterogeneity is a serious concern, the complaint itself has two flaws. First, if it is meant that frontier analysis can never be safely applied due to possible omitted output variables, then the complaint itself cannot be tested satisfactorily inasmuch as unknown and omitted variables might always exist. Second, like econometric analysis generally, the proof will probably lie in future practical applications or in unanticipated side discoveries of scientific applications of frontier measurement techniques. Even at this stage of progress, extensive multi-product cost functions have been applied (10,12,16), which seem to account for much of output heterogeneity (see also ZHI), though quality measurements remain difficult.

The remaining empirical issues form the analyses of this paper. We find that specification error that arises through applying an “incorrect" cost function to a group of hospitals, disturbs the individual inefficiency estimates and their rankings; nevertheless, estimated mean inefficiencies between groups are little affected by our tests. The paired groups whose means we compare are: teaching/nonteaching, urban/rural, for-profit/nonprofit, hiMedicare/loMedicare, and chain/independent.

We also find that the analyst's choice between two widely accepted cost function forms disturbs the individual inefficiency estimates and their rankings. Again, these changes as tested do not materially affect the estimated mean inefficiencies between groups of hospitals. The functional forms compared are the popular translog and a generalization of the still popular Cobb-Douglas form.

Finally, two alternative measures of the capital cost input price are compared. Each approximates the Jorgenson capital cost under frequently invoked assumptions. One is the commonly employed approach of measuring interest and depreciation charges per bed, while the other approaches the Jorgenson capital cost more directly but with greater practical, data-gathering difficulties. We find that the resultant two measures generate substantially different estimates of individual inefficiencies and their rankings, but the estimated group mean inefficiencies are nearly the same.

We conclude that the stochastic frontier analysis, as we have tested it, does not produce robust estimates of individual hospital inefficiencies. Conversely, the estimates of mean inefficiencies between groups of hospitals, including pairs of groups with substantial policy interest, are very stable.

The paper proceeds in four sections. Section I states the default assumptions, the homothetic cost function, and the baseline results. Section II addresses the specification bias caused by pooling disparate subgroups of hospitals. Section III assesses alternative specifications for the form of the cost function. Section IV investigates the effect of choosing between alternative measures of the cost of capital. The paper concludes that the stochastic frontier group mean inefficiencies are robust to these variations in method considered but that the correlations of individual hospital estimates and their rankings are not.

I. The Homothetic Cost Function

Approaching hospital efficiency via a closed form, homothetic cost function has distinctive advantages; one can estimate simultaneously the allocative and technical components of total inefficiency. A hospital may be inefficient because it fails to obtain the maximum output from a set of inputs, technical inefficiency; for example, Magnussen (1) estimates technical efficiency via a production function describing this alternatively as "output increasing" or "input saving". However, a hospital is also inefficient when it fails to combine inputs appropriately given input prices and productivities: allocative inefficiency.   A cost function derived as dual to a closed form production function can be applied to simultaneously measure both forms of inefficiency.

Let the multi-product production function be a homothetic closed form as in Equation (1), which is a generalization of the Cobb-Douglas homogeneous function. Thus it is a more flexible version of perhaps the most popular functional form in economic analysis generally. The existence of the dual cost function requires a closed form production function and firm goals that imply cost-minimizing behavior. The fact that most hospitals in the United States are nonprofit firms thus raises an additional question: Are nonprofit hospitals cost minimizers? Theoretically, nonprofit hospitals will seek technical efficiency provided that hospital goals are advanced by cost reduction. Allocative efficiency conditions are met in cases where hospital goals consist of only profits and outputs (“output” may encompass several definitions of quality as well). Then the cost-minimization criteria are met regardless of what marginal utility weights are applied to those utility arguments. Ellis (17) describes the variety of efficiency definitions, including social efficiency, and demonstrates the degree to which hospitals of various theoretical forms achieve the efficiencies. Lakdwalla and Philipson (18) provide an example of a hospital model that meets these conditions, inasmuch as the hospital values only profits and outputs, calling it the "profit deviating hospital." Their approach places nonprofit and for-profit hospitals on common ground both as to the utility function and the cost-minimizing behavior.

It is also possible to the contrary that nonprofit hospitals seek goals that are not adequately measured or subsumed by standard measured outputs. For example, charity care, community education, screening, preventive care are not included. Beyond this, nonprofits may expend resources on community-minded goals that are difficult to quantify in practice or even in principle. Omitted output thus could bias the case against nonprofits. While the empirical literature, which often reports very similar behaviors between nonprofit and for-profit hospitals, makes this concern unlikely in our view, it should be recognized that the nature of ownership type is not yet fully understood and this suggests caution.

Third party payment, which can include complex and even "uneconomic" selections over which procedures third parties will cover, raises concern about social efficiency; however, it need not inhibit or distract from cost minimizing behavior by the hospital. For example, were insurance coverage to consist solely of a coinsurance rate with zero deductible, an increase in coverage is effectively a rotating shift in demand; it does not eliminate the hospital's cost control incentives any more than other shifts in demand. The social inefficiency caused by moral hazard is a result of downward sloping demand, and it occurs whether or not hospitals minimize their costs of production. It is not one of the inefficiencies addressed in the paper.

Given these considerations, the underlying production function chosen is the following multi-product homothetic frontier form generalized from Fox and Hofler (19):

$$(1) \quad y_1 e^{\Theta_1 y_1} \prod_{j=2}^{m} (y_j e^{\Theta_j y_j})^{\lambda} \quad = \quad a\left(\prod_{i=1}^{n} x_i^{\alpha_i}\right)^{\delta} e^{v-u}$$

where y_j is the jth output, x_i is the ith input, and the parameters to be estimated are $\Theta_j, \alpha_i, \delta, a, and\ \lambda$. The error term is composed of two parts, *v* and *u*, which include the usual, symmetric error term, v, representing random disturbances to output and the nonnegative error term, u, representing technical inefficiency. We assume that v is normally distributed with a mean of zero and that u is a truncated normal. It is clear that only the extent of technical inefficiency can be measured from (1). The extent of both types of inefficiency and the costs of each can be measured by using the cost frontier dual to (1).

An intermediate step in deriving the dual cost function is to calculate the set of allocative efficiency conditions, which require that the ratio of marginal products equals the ratio of input prices. In Equation (2) we have chosen output one as the example case and set MP_{11}, the marginal product of output one with respect to input one, in the denominator. The marginal product of output one with respect to input i, where i is chosen other than input one, in the numerator. The remaining assumption is that the hospital errs from attaining equality of marginal product ratios to input price ratios, but it errs according to a known distribution of the allocative inefficiency error term ε_i.

$$(2) \quad \frac{MP_{1i}}{MP_{11}} = \frac{\alpha_i \delta y_1}{x_i(1+\Theta_1 y_1)} \div \frac{\alpha_1 \delta y_1}{x_1(1+\Theta_1 y_1)} = \frac{\alpha_i x_1}{\alpha_1 x_i} = \frac{p_i}{p_1} e^{\varepsilon_i} \quad i = 1,...,n.$$

That is, $\varepsilon_i = 0$ means allocative efficiency and $\varepsilon_i \neq 0$ means allocative inefficiency. A positive value for ε_i reflects underutilization of input i. We assume that (each observation's) $\varepsilon = (\varepsilon_2, ..., \varepsilon_n)$ has a multivariate normal distribution with mean zero and covariance matrix ∑, and that the ε_i are independent of v and u.

The assumption of independence between the allocative and technical inefficiencies, ε_i *and* u, while strong, is commonly made in the stochastic frontier literature. This practice may arise because of the complexity of the alternative assumption but perhaps also from the question of whether the cost in added complexity is rewarded by sufficiently better estimates. Schmidt and Lovell (20) developed and estimated a model in which the two terms are correlated and compared the results with the version where they were assumed to be uncorrelated. They conclude that the "... strong similarity in the two sets of estimates of frontier technology suggests ... that the way in which we model inefficiency relative to a stochastic frontier, and the nature of the inefficiency we find, has no appreciable effect on our inferences concerning the shape and placement of the frontier."

We also assume that v and u are independent. This assumption is natural when the frontier shift term, v, represents a random shock to the hospital, such as a damaging storm, a suddenly interrupted source of supply, or unexpected personnel problems. In contrast, independence of the two errors is not so clear in cases where the two share the same generating source. For example, were researchers to incorrectly pool groups of teaching and nonteaching hospitals, this would cause specification errors that in turn would make the observed v and u interdependent should teaching status also affect the hospital's ability to generate patient care efficiently while also teaching. Likewise, were inefficient management to induce the "unexpected shock" on the v term, such as when poor management decisions led to "unexpected" labor strife, then the two error terms would be interdependent. The assumptions of independence, both between ε_i and *u* and between *v* and *u* are made throughout.

The dual total cost function (with a frontier embedded within it) expressed in logarithms is as follows:

$$(3)\ \ln C = K + \sum_{j=1}^{m} \frac{\lambda_j}{r\delta} \ln y_j + \sum_{j=1}^{m} \frac{\Theta_j \lambda_j}{r\delta} y_j + \sum_{i=1}^{n} \frac{\alpha_i}{r} \ln p_i - \frac{1}{r\delta}(v-u) + E$$

where $K = -\frac{1}{r}(\frac{1}{\delta}\ln a + \ln(\prod_{i=1}^{n} \alpha_i^{\alpha_i}))$

and where $E = \sum_{i=2}^{n} \frac{\alpha_i}{r} \varepsilon_i + \ln(\alpha_1 + \sum_{i=2}^{n} \alpha_i e^{-\varepsilon_i});\ \sum_{i=1}^{n} \alpha_i = r \equiv 1;\ \lambda_1 \equiv 1.$

This cost function is well-behaved, linearly homogeneous in prices, non-decreasing in output, and it possesses the several desirable properties suggested by Baumol, Panzar, and Willig (21) for multi-product cost functions.

In summary, the cost function stems from a production function that generalizes the Cobb-Douglas, which is a familiar cost function in the economics literature. It can be applied to measure both technical and allocative inefficiency. The technical inefficiency is measured by u, which can be estimated for each firm; its contribution to costs becomes (1/rδ)u. Each input's allocative inefficiency for a given hospital is captured by the ε_i, its contribution to total costs is given by the term E – lnr, which is zero in perfect efficiency but adds to the costs when allocative inefficiency occurs.

For example, a technically and allocatively efficient hospital has: each u=0; each ε_i also equal to zero; and zero excess costs. Conversely, inefficiency is captured by u not equal to zero and/or one or more nonzero ε_i. In such cases, the particular hospital will have excess costs due to that inefficiency. It bears stressing that each hospital has different extents and costs of inefficiency and that this frontier function approach measures each hospital's performance on the different dimensions.

The Data

A merger of the American Hospital Association Survey (AHA Survey) for 1985 with the Medicare case mix index for the same year forms the main sample. We combined the two files by matching identifying variables across the samples via the AHA "Crosswalk" program. Data items vary somewhat from year to year, and the 1985 survey was chosen because it contains one of the better sets of financial data of the type required. The sample is also very close in time to the comparison sample of ZHI, which draws from 1988. The aim of the investigation does not require an assessment of present day inefficiency at a national level; however, we required national inefficiency estimates based on the 1985 data.

In addition, financial data for hospitals in 1985 were matched with the Marshall and Swift Index of construction costs by locality for that year. Most of the financial data were obtained from the Medicare Capital Cost data set obtained from the Health Care Financing and Administration agency. These Medicare data enable the further investigation into the quality and significance of alternative measures of the capital cost input price. These richer financial data are applied only to the analysis that focuses on capital cost; the requisite cross-matching of data sets of different size results in too substantial a reduction in sample size to warrant their application to all investigations. The total number of matches generated a subset of hospitals with complete capital cost data that is approximately one third the size of the first sample: 791 compared to 2007 hospitals.

The cross-section approach is criticized by some analysts (22) who recommend panel data. Panel methods do not require assumptions about parameters of the distribution of the error terms. They also provide many observations on inefficiency for each firm. Nevertheless, we chose the cross-section approach for several reasons: 1) the primary comparison study, ZHI, was a cross-section study; and 2) the comparison sample was a national level sample; and 3) no panel data of the desired variables and universe were available in that era.

Outputs

Five outputs were selected and in most cases measured by annual inpatient days: general medical surgical, pediatrics, obstetrics/gynecology, all other inpatient, and outpatient visits. To further capture output heterogeneity, the number of medical/surgical inpatient days was multiplied by the Medicare Case-Mix Index for 1985.

Input Prices

Average wages for two types of labor were calculated: nurses, and all other. The wage variables were calculated by dividing total payroll in the category by the corresponding full time equivalent personnel. An "FTE" is calculated as the sum of full time personnel plus one half the part time personnel. FTE Nurses are the weighted sum of RNs, LPNs and Aides using national relative wages as weights. The relative wage is the ratio of the LPN wage (and respectively the Aide wage) to that for RNs. Using national data for the relative wage is equivalent to the assumption that relative wages are constant across hospitals. Thus, it is effectively assumed that average nurse wages differ between hospitals only for two reasons: the number of nurses of various types differs, and the overall level of wages, whether "generous" or "tight", differs. The assumption of fixed relative wages is of course not literally true, for example, there will be variations in quality and seniority among nurses at different hospitals; this introduces a fiction we think is minor but could in turn introduce biases of unknown size and sign. Furthermore, the hospital labor market may be monopsonistic to some degree and correspondingly the nurse wages may become endogenous to the hospital's quality and output decisions. In all of these cases, the wage and other coefficients would be affected.

Capital costs also raise measurement issues. The theoretical cost of capital can be approximated in practice at least two ways: 1) the ratio of interest plus depreciation to the number of staffed hospital beds, and 2) a given hospital's weighted average of debt and equity rates applied to local construction costs. The two approaches to capital costs are featured in Section IV, which addresses the empirical and policy issue of whether a seemingly arbitrary choice by the researcher has material implications for practice.

Except for this investigation, the paper applies as a default definition that of interest plus depreciation per bed (see also ZHI).

Finally, several variables are included to adjust the outputs for differences in quality of care. Applying an analysis that originated with Hill-Burton researchers (23, 24), Joskow (25) defines "reservation quality" as $\beta = (B - \mu)/\sqrt{\mu}$ where B is the number of staffed hospital beds in active use and μ is the average daily census. Assuming that the census is Poisson distributed, the mean census is approximately μ and the standard deviation is $\sqrt{\mu}$. The β is the number of standard deviations above the mean census represented by the number of beds. Given the assumptions and further assuming that the average census is large, which is typically true of the sample hospitals, the β distribution approximates the distribution of the "z" score in standard normal tables. Analogous to the z score, a higher β implies a smaller probability in the right hand tail of the distribution and thus a smaller probability of turning patients away. By choosing a large β, the hospital is setting aside staffed beds as a reserve capacity available in case of unusually strong demand, hence the term reservation quality.

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By incorporating the reservation quality into the cost function, the researcher recognizes that unused beds are not mere waste, but also provide a service to the community. Unfortunately, these data are unable to distinguish such cases from those hospitals that choose excess capacity to a degree that bears inefficiently high costs given community values. Omitting the variable would cause more serious problems by tending to overstate the inefficiencies of smaller hospitals. For a given β under these assumptions, the occupancy rate is $OR = \dfrac{1}{1+\beta/\sqrt{\mu}}$, which increases with μ; this implies that smaller hospitals will tend to have greater percentages of unused beds even when offering the same probability of a patient being turned away as a larger hospital.

Quality of output is measured in additional ways. One quality variable is the percentage of the medical staff that is Board Certified. Case-mix adjustment, which is based on cost-related factors, may also be associated with more intensive protocols that often themselves are an indication of quality, as Ellis (26) has suggested in a theoretical context. Furthermore, teaching status has been demonstrated to relate to quality (27); and, the Joint Commission for the Accreditation of Hospitals, an accreditation indicator tested in several versions, was at least ostensibly aimed at the identification of quality.

More direct measures of quality would be desirable, but they were not available for the study, nor are widely accepted measures available today. Many physicians describe the quality of care they provide solely in terms of individual patients (28). Other relationships have been detected, for example, hospital volume is a determinant of quality of care in some cases (29). However, the broader analyses, such as the application of adjusted mortality rates, remain controversial when applied to individual hospitals.

This study applies techniques that are approximately the state of the art in current frontier studies. If the present art is proven to be inadequate, it is doubtful that the conclusions of these investigations will be affected, though it is surely possible. Just as possible, improved measures of quality will add further caution to the use of frontier functions for ranking of hospitals by cost inefficiency. Throughout this study, the methods by which quality of care is addressed are held constant.

Finally, five binary criteria are used to group hospitals in the secondary analyses, each pair applies a definition from the AHA Survey. The hospital that reports it is a member of a multi-institutional organization is designated here as a chain hospital; others are called independents. A teaching hospital is one affiliated with a medical school, typically offering resident training and teaching rounds; such a hospital may cover its teaching costs in part or in whole through charging patients. The definitions of urban and rural, always somewhat arbitrary, here are defined as urban if it is located in a Metropolitan Statistical Area, and rural else. The percent of revenue generated from Medicare is applied to derive Hi Medicare when those revenues exceed 29 percent of total revenues and Lo Medicare otherwise. "Nonprofit" implies a non-government hospital incorporated under laws that prohibit net revenues from being distributed, For-Profit implies incorporation as a commercial enterprise; and Public hospitals, which include all other types, were excluded from the sample.

Table 1 restates the variables and gives extended explanations and short names. The table also reports descriptive statistics for the study variables and selected other variables; it also gives a breakdown on these variables by the five study criterion variables. Sections II, III and IV, which follow, examine the robustness of hospital stochastic frontier inefficiency estimates under three pairs of alternative choices over research methods.

Table 1 About Here

II. Specification Bias and Pooling

Pooling can generate specification bias when the true cost function differs across groups of hospitals. For example, the cost function of for-profit/rural/non-teaching/hiMedicare/Independent hospitals probably differs from nonprofit/urban/teaching/loMedicare/Chain hospitals. When these two groups are pooled, the parameter estimates and composed errors could be biased. Estimated inefficiencies undoubtedly would also be biased.

The five hospital criterion variables—for-profit/nonprofit, urban/rural, teaching/non-teaching, hiMedicare/loMedicare, and chain/independent--create 32 logically possible combinations or "cells" of hospitals. These 32 possible logical cells generated 16 cells with sufficient degrees of freedom for the maximum likelihood estimation. For example, there were too few for-profit/rural/teaching/loMedicare/chain hospitals to permit any estimation procedure. For five of the remaining cells, the cost function failed to converge, leaving a final sample of 11 cells together having a total of 1661 hospitals. A comparison of least squares regression estimates over the pooled 11 cells versus estimation by individual cell easily implied the rejection of pooling; the critical F value at $\alpha = .01$ is 1.32, while the calculated F = 4.74.

Hospital inefficiencies were estimated with the stochastic frontier procedure of LIMDEP 7.0 following the methods of Aigner, Lovell and Schmidt (30). Expectations on individual hospital error terms were made following the method of Jondrow et al. (31). Alternatively pooling and partitioning, the approach draws comparisons of sample mean inefficiencies, group means, and rankings. The cost function is as in Equation (3).

Partitioning is somewhat costly in computing time and analysis, and it can raise havoc with degrees of freedom. The situation is familiar, one of comparing the costs of bias to the benefits of a simpler and more accessible process. The answer depends on one's objectives. One objective may require data on sample mean inefficiency or means within and between groups, while another objective may require the rankings of hospitals and substantial precision in individual estimates. The degree of bias may be important for one objective but less critical for another.

Table 2 About Here.

The estimated equations for the pooled sample and for the first cell are shown in Table 2. In most cases, the coefficients of the output variables are positive, as is appropriate, and both input price coefficients are positive. The "third" input price, the wage of other personnel, *woth*, was applied to normalize the input prices the equation, and it is not shown in the table. The equations exhibit a significant *lambda* indicating skewness of the error term so as to suggest the existence of inefficiency. Table 3 presents the mean inefficiency estimates for the pooled and non-pooled samples; it also reports both the Pearson correlation coefficient and the Spearman rank order correlation coefficient. The allocative inefficiency levels (as measured by the ε_i) are nearly identical for the two samples; however, the total inefficiency is somewhat smaller in the partitioned version, reflecting its lower technical inefficiency estimate.

Recall that the values of the epsilons, the errors measuring allocative inefficiency, can take on either positive or negative values and that each represents over or under use of a specific input relative to the capital input, which was chosen as the reference input. Thus for example, positive ε_2 would suggest under use of nurses relative to capital, whereas a positive ε_3 would suggest the under use of other personnel relative to capital. Here the epsilons are very small in absolute value, and in comparison to their standard deviations cannot be confidently said to be different from zero. Thus, we cannot confidently conclude that there is either over or under use of these resources relative to capital.

Table 3 About Here.

Correlations of the technical, allocative and total inefficiencies across the alternative techniques of pooling vs. partitioning are probably too low for many purposes. Errors in published rankings of hospitals could bring high costs to the publisher or even to society at large; if substantial weight is attached to the cost of such errors, pooling may be unwise.

Nevertheless, the differences between the mean inefficiencies in these samples, though statistically significant, are very small; and the means themselves, 13 and 11 percent, are also small with relatively high standard deviations. Little may be gained even if hospitals could have eliminated all inefficiency in these data. Schwartz and Mendelson (32) reached a similar conclusion when evaluating the U.S. hospital by different methods.

These estimated mean inefficiencies corroborate ZHI (10), but these correlation data lie near or below the lower end of their range, which in contrast was between .759 and .989. The correlations of the rankings themselves, as given by the Spearman correlation statistic, are yet somewhat lower. In Table 4, the criterion group means for nonpooled inefficiencies tend to be smaller than their pooled counterparts; one conjecture might be that specification bias error is incorrectly attributed to inefficiency in the pooled sample. However, the ZHI data contain several examples with larger inefficiency estimates for the non-pooled side.

Table 4 About Here.

In summary, there are small differences between group means across the pooled and partitioned versions; similarly there are small differences between the hospital criterion groups themselves. These results suggest that mean inefficiencies are robust regarding pooling vs. partitioning, but individual hospital estimates and rankings are importantly affected.

III. The Translog vs. the Homothetic Cost Function

The multi-product homothetic cost function has advantages in that it is a closed form function and permits the exploitation of duality theory so as to provide simultaneous estimates of the technical and allocative elements of total inefficiency. In contrast, the popular translog alternative is a flexible functional form (FFF) and gains in flexibility for what it gives up in other respects. It is not a closed form and no dual cost function uniquely exists for it, furthermore, different FFFs give different results regarding economic values such as elasticity of substitution when estimated on the same sample (34). In the present context, both cost functions operate best as local approximations, the translog providing the best possible local approximation. The homothetic adds structure, which gives the advantages we described but also entails the caveat that the validity of the estimates depends on that added structure being the correct specification. While this homothetic function is new to the health literature, it has been applied elsewhere (19) and it is a generalization of one of the most popular functional forms used in economics, the Cobb-Douglas. The translog, which was the form applied in the ZHI study, has been very widely applied in recent decades and is the popular choice in cases where functional form is a focus of the research. The present claim is that each entails advantages and disadvantages, making it hard for the researcher to discriminate between them a priori. What are the differences between them empirically?

Equation (4) states the translog cost function, which was estimated on the main sample; the inefficiency estimates were compared with the pooled sample under the default assumptions.

$$(4)\qquad \ln C = \delta_o + \sum_{j=1}^{J} \delta_j \ln y_j + \sum_{k=1}^{K} \beta_k \ln p_k + ½ \sum_{j=1}^{J}\sum_{l=1}^{J} \eta_{jl} \ln y_j \ln y_l$$

$$+ ½ \sum_{k=1}^{K}\sum_{m=1}^{K} \gamma_{km} \ln p_k \ln p_m + \sum_{j=1}^{J}\sum_{k=1}^{K} \rho_{jk} \ln y_j p_k + \sum_{n=1}^{N} \theta_n X_n$$

where as before y_j are outputs, p_k are input prices, and X_n are other variables used to describe the output. For this comparison, the cost of capital is defined as the ratio of depreciation and interest per staffed bed, the default measure. Since the translog approach does not provide allocative and technical components, the basis of comparison is the total inefficiency measure. The Appendix presents the cost function estimates for the translog. Table 1 provides definitions of the variables and their short names as used in the translog.

The two forms yield very similar mean inefficiencies (12.7.0 vs. 10.1 percent). The correlation of the individual hospital measures statistically significant, but the Pearson correlation is somewhat small at 0.79, while the correlation between rankings is weaker as indicated by the Spearman correlation coefficient of 0.65. Nevertheless, there are once again only small and relatively unimportant differences between subgroup means as reported in Table 5. While comparing across methods (between columns), the different mean inefficiencies are statistically significant but trivial in a material sense; while comparing across hospital criterion groups (vertically within rows), the differences in means are miniscule, with the exception of ownership status, which suggests a materially small advantage to the nonprofits. Two additional themes appear consistently in these data: 1) the translog estimates are always lower; and 2) in four of five paired subgroups, the same subgroup is suggested to be the more efficient-- nonprofits, independents, non-teaching and high Medicare.

Table 5 About Here.

IV. Alternate Measures of the Cost of Capital

Input price measurement is a weak link in hospital cost function analysis, and the cost of capital is especially problematic. This is demonstrated through testing the reliability of estimated efficiencies across models that differ only in the respect that they apply alternative measures of the cost of capital.

Measure 1: $r_1 = (I_k + D_k)/Beds_k$ where the k subscripts indicate hospital or locality specific values, and where I_k are total interest payments during the period, D_k are depreciation charges, and $Beds_k$ are the number of short term general staffed beds. Under this alternative, which is the default in other sections, the “cost of capital” can be constructed from readily available data, and it approximates the Jorgenson (33) theory though under somewhat restrictive assumptions. It focuses on debt and depreciation, and this neglect of equity may be important inasmuch as even nonprofit hospitals maintain fund balances analogous to equity.

Measure 2: $r_2 = P_k(i_k + \delta - \rho_k)$ where $i_k = w_k d + (1 - w_k)e$.

Here P_k are the prices or costs of constructing a bed locally. These are derived in what follows by the application of the local value of the Marshall Swift Construction Cost Index for 1985 for each locality across the United States. Interest rates i_k are calculated as the weighted average of the interest rate for debt and the rate of return on equity, e. The interest rate for debt is taken as Moody's AAA corporate bond yield for for-profits and Moody's AAA municipal bond yield for nonprofits. Inflation rates are those reported in the *Statistical Abstract of the United States* for SMSAs where available or the regional rate where no SMSA rate is given.

The rate of return on equity, e, is the average cost of equity reported for four large hospital corporations in 1985. These corporations were: Hospital Corporation of America, Humana, American Medical International, and National Medical. Delta, the depreciation rate, is assumed to be common to all firms for a capital life of 30 years and straight line depreciation, that is, it is set equal to .0333 for all cases.

Measure 1, which is simple to construct and requires only readily available data, has theoretical drawbacks. Measure 2 has more stringent data requirements, but under somewhat more plausible assumptions, it is the Jorgenson (33) cost of capital. It is identical with Jorgenson's if interest and depreciation can be charged against revenues for tax purposes, or if tax rates are zero. Plus we have allowed equity and debt rates to differ and inflation to be nonzero.

The bed price, P_k, plays a weighty role in Measure 2 inasmuch as its estimated average level importantly determines the estimates of allocative inefficiency, the over or under use of an input relative to capital. It is useful to expand on the practical choices made here. The local "Bed Price" is derived by multiplying the national mean construction cost of a hospital bed in 1985 by the Marshall and Swift Construction Cost Index. The national mean cost of a bed was estimated by dividing total hospital bed construction costs ($3.9 billion, *Modern Healthcare*, 1986) for 1985 by total beds from new construction, renovation and expansion. These latter two categories include some double counting. For a given architectural or design and build firm that appeared on both lists, we took the largest of the two figures. This somewhat understates the total new beds, but it is probably the best of the options. The remaining financial data were acquired to calculate the weights over debt vs. equity by hospital; for this purpose the Medicare Capital Data Set (for 10/84 through 10/85) were merged with the main sample. The matching process entailed the loss of a large number of degrees of freedom; the resulting sample is approximately one third the size of the main sample.

Equation (3) was estimated alternatively using r_1 and r_2. Table 6 shows similar coefficients for most variables across equations including the cost of capital measures. Both equations perform well overall and exhibit the skewness associated with inefficiency.

Table 6 About Here.

The two yield similar mean efficiencies (as shown in Table 7). Mean allocative inefficiency, ostensibly the direct recipient of the impact of differences in measured capital cost, is barely affected.

Table 7 About Here.

The sample mean capital costs are $ 9693.60 and $ 9365.90 (not shown in the table) for Measures 1 and 2 respectively, however, the r_i are *uncorrelated*. The low allocative inefficiency correlation, 0.56, shows a substantial effect of the switch in measures. The allocative error terms, the epsilons, are not significantly correlated across equations.

Can one of the measures be rejected? The candidate for rejection should be Measure 1, inasmuch as Measure 2 is less susceptible to hospital accounting practices and fits theory better. However, an operational version requires more and better data as well as an important intermediate data step. Each added data step acquires more conceptual purity while at the same time introducing an additional avenue for error in practice.

V. Discussion and Conclusions

In summary, mean inefficiencies were compared across each of three selected variations in research methods: 1) two alternative methods of addressing specifications of subsample cost function, pooling vs. partitioning; 2) two alternative forms for the cost function, homothetic vs. translog; and 3) two alternative measures of the cost of capital.

Overall national estimates of mean inefficiencies are comparable to the findings of Zuckerman, Hadley and Iezzoni (10). The group mean inefficiencies were robust to each of these variations in methods, this finding tends to corroborate the view of Hadley and Zuckerman (15) that stochastic frontier analysis of hospital inefficiency would prove to be of practical use when applied to the task of comparing group means. In addition, these data suggest that the pairs of hospital criterrion groups selected for study-- nonprofits vs. for-profits; urban vs. non-urban; independent vs. chain; high Medicare vs. low; and teaching vs. non-teaching take on very similar mean inefficiency levels. The estimated differences in hospital group inefficiency means are usually miniscule; the estimated advantage to nonprofits is somewhat larger than other differences, though not large enough to appear meaningful.

However, inefficiencies estimated for individual hospitals across each of the three three paired variations in method are only weakly correlated. The Pearson correlation coefficients ranged from 0.56 to 0.90, while the Spearman rank order correlations were yet somewhat weaker, ranging from 0.46 to 0.84. Correlation coefficient values under 0.70, which is sometimes used as a rule of thumb, are common, and the lowest values tend to occur with respect to allocative inefficiency estimates. That these correlations tend often to be low across alternative methods of similar plausibility tends to corroborate the Newhouse prediciton (13) that the individual estimates would not be reliable enough for planning applications.

Several cautions are warranted in interpreting these results. This study, like that of ZHI, relied in part on American Hospital Association Annual Survey and chose all cases with complete data. Because the model entailed substantial data requirements, the approach reduced the sample size to well below the universe size, suggesting that many U.S. hospitals within the AHA universe omitted one or more items required for the equations. These data are advantageous for comparison to ZHI and offer a well-known data source; nevertheless, we cannot test the embedded assumption that responses to the survey were accurate and unbiased with respect to the items that hospital responders chose to omit. Likewise, the investigation of possible specification error here is focused on five subgroup criteria we have selected. There could be other important ones. Furthermore, while the application of a multi-product form of the cost function has greater sensitivity to the heterogeneity of output than single product forms, the degree of aggregation required to make such estimations practical is still substantial. Finally, given the results for our variations on the practical definition of an input price variable, the cost of capital, one is cautioned that errors in other input price variables could prove to be important.

Future research might investigate alternative wage variables, better capital cost measures, seek out-of-sample confirmations, apply other hypothesis-testing approaches, and study the connections of stochastic frontier methods with economic theory regarding the sources of inefficiency. It is also encouraging that studies are becoming available (35) that compare the DEA and the stochastic frontier methods on the same data. It is now more often recognized that the distance measures in DEA are by nature also estimates from a distribution (36), and this suggests that the two approaches may be tending toward convergence. Dor (22) and Kooreman (37) described the two as complementary, and a resolution, combination or dual use suggests a fruitful area for study.

Table 1A. Variables Used in the Econometric Equations

Variable Name	Additional comments	Variable symbol in translog equation
Expenses Total	Dependent Variable logged	
Log General Inpatient Days	General medical/surgical	$\ln y_1$
Log Pediatrics Days	Pediatrics	$\ln y_2$
Log Obstetrics Days	Obstetrics/gynecology	$\ln_3$
Log Other Days	All other	$\ln_4$
Log Outpatient Visits	Outpatients	$\ln_5$
General Inpatient Days	As above but not logged	
Pediatrics Days	As above but not logged	
Obstetrics Days	As above but not logged	
Other Days	As above but not logged	
Outpatient Visits	As above but not logged	
Cost of Capital, r_i	Log of alternate definitions described in the text	p_1
Nurse Wage	Log of weighted average of payments to various nurses	p_2
Percent Board Certified	Percent of medical staff	PCTBC
Reservation quality	Measure reserve capacity	Resequal

Table 1B. Descriptive Statistics on the Main Sample, n=2007

Variable Description	Mean	Standard Deviation	Minimum	Maximum
General Inpatient Days	33408	35538	330	315710
Pediatric Inpatient Days	1648	3164	1	53987
Obstetric Inpatient Days	2721	3808	1	30858
Other Inpatient Days	12213	17656	1	179280
Outpatient Visits	41138	59886	1	1284968
Cost of Capital, RKAP	12714	5926	529	24832
Nurse Wage, WNURS	20926	5971	5109	49140
All Other Personnel Wage	19857	4997	5603	46674
Joint Commission Accreditation	0.82	0.37	0.0	1.0
Percent Board Certified	65.9	17.7	7.14	100.0
Reservation Quality	6.43	3.13	-1.10	29.84
Hospital Beds	203.3	184.2	12	1455
Expenses Total	24577892	30387690	440630	276469430
Registered Nurses FTEs	141.9	169.4	3	1380
LPN Nurses FTEs	36.8	40.3	0.0	443.0
Nonprofit Hospital	0.88	0.33	0.0	1.0
Teaching	0.18	0.38	0.0	1.0
Urban Indicator	0.51	0.50	0.0	1.0
Percent Revenue from Medicare	30.38	8.58	0.0	71.0
Multi-inst Organization Chain	0.33	0.47	0.0	1.0
Case-mix index for hospital	1.10	0.122	0.59	1.95

Table 1C. Selected Means with Breakdown by Five Criteria

Category	Variable	Nonprofit (For-profit)	Teaching (Nonteach)	Urban (Rural)	Hi Medicare* (LoMedcre)	Chain (Independt)
Input prices	Wage, nurses	$20954 (20723)	$22658 (20558)	$21982 (19840)	$20553 (21366)	$21100 (20839)
	Wage,other	$20134 (17844)	$21353 (19538)	$20916 (18766)	$19661 (20087)	$19982 (19704)
	Cost capital	$12389 (15066)	$14774 (12275)	$14707 (10662)	$11940 (13624)	$14083 (12029)
Quality items	%JCAH accreditatio n	84 (73)	99 (79)	92 (73)	78 (87)	85 (82)
	%Board certified	67 (62)	73 (64)	68 (64)	66 (66)	66 (66)
	Reservation quality score	6.3 (7.5)	6.8 (6.3)	6.7 (6.1)	6.3 (6.6)	7.2 (6.0)
Size items	Beds	213 (126)	466 (147)	302 (100)	169 (243)	219 (195)
	Expenses total	$26.2 mil (12.6 mil)	$68.9 mil (15.2 mil)	$40.6 mil (8.1 mil)	$18.5 mil (31.7 mil)	$27.1 mil (23.3 mil)
Criterion variables	%Nonprofit	100 (0)	99 (85)	88 (88)	88 (88)	73 (95)
	%Teaching	20 (1)	100 (0)	33 (2)	13 (23)	21 (16)
	%Urban	51 (50)	94 (41)	100 (0)	41 (62)	54 (49)
	% Medicare	30 (31)	28 (31)	29 (32)	36 (24)	31 (30)
	%Chain	28 (74)	40 (32)	35 (31)	33 (33)	100 (0)
Ratios of interest	Exptot/Bed	$99724 (88011)	$144436 (88495)	$122860 (73032)	$87445 (111087)	$101951 (96484)
	Exptotal/ Inpat. Day	$456 (494)	$546 (443)	$517 (402)	$427 (501)	$494 (444)
	RNFTE/Bed	0.594 (0.454)	0.826 (0.525)	0.712 (0.439)	0.510 (0.657)	0.568 (0.582)
N of cases	2007	1764 (243)	352 (1655)	1018 (989)	1085 (922)	669 (1338)

Note: See Table 1A and text for extended variable definitions. The FTE or full time equivalent figures add part time personnel as ½ full time. We define HI and LO Medicare by whether the hospital acquires more (less) than 29% of its revenues from the Medicare program.

Table 2. Maximum Likelihood Estimates of Frontier Cost Equations
For Pooled Sample and First Cell (t values in parentheses)

Independent Variable	Pooled	First Cell
Constant	-2.1994 (-33.24)	-1.266 (4.25)
Log General Inpatient Days	0.72722 (99.31)	0.62250 (21.44)
Log Pediatrics Days	0.00444 (2.38)	0.01218 (1.86)
Log Obstetrics Days	0.00208 (1.14)	0.01218 (1.54)
Log Other Days	0.04577 (22.65)	0.04611 (3.57)
Log Outpatient Days	0.07853 (15.43)	0.08631 (3.57)
General Inpatient Days	-0.705E-06 (-3.72)	-0.176E-05 (-0.55)
Pediatrics Days	0.716E-05 (2.63)	0.277E-04 (0.98)
Obstetrics Days	0.165-04 (8.19)	0.349E-04 (1.35)
Other Days	0.416E-05 (15.98)	0.349E-05 (1.88)
Outpatient Visits	0.441E-07 (8.19)	0.349E-04 (1.35)
Cost of Capital, ri	0.20348 (29.03)	0.22584 (9.15)
Nurse Wage	0.34701 (31.95)	0.31016 (8.41)
Percent Board Certified	0.00052 (2.71)	0.00059 (1.04)
Reservation Quality	0.01148 (8.46)	0.00461 (0.80)
lambda	1.6391 (22.54)	0.99394 (4.51)
sigma	0.26967 (38.45)	0.21725 (8.96)
n	2007	229

Note: In both equations, the cost of capital was defined as the interest plus depreciation divided by the number of beds.

Table 3. Mean Inefficiency Measures and Their Correlations (standard deviations in parentheses) Under Pooling vs. Partitioning "Cells"

Measure	Pooled Sample	Partitioned	Correlations
$Epsilon_2$	0.20 (0.55)	0.20 (0.68)	0.82 [0.79]
$Epsilon_3$	-0.10 (0.56)	-0.02 (0.68)	0.82 [0.80]
Technical Inefficiency	8.41* (8.37)	5.29 (5.45)	0.71 [0.70]
Allocative Inefficiency	4.31* (5.11)	5.60 (6.56)	0.72 [0.61]
Total Inefficiency	12.72* (9.94)	10.88 (8.02)	0.68 [0.67]
n	1661	1661	1661

*Note: The “inefficiency” entries are the percentage increase in costs due to the specified source of inefficiency; their standard deviations appear in parentheses. An asterisk indicates that the difference in means between the pooled and partitioned samples is statistically significant at the five percent level; the t values ranged from 5 to 13 in absolute value. The last column gives the Pearson product moment [Spearman rank order] correlations of each series of inefficiency measures.

Table 4. Breakdown of Inefficiency Estimates by Hospital Category, and a Comparison with Zuckerman, Hadley, and Iezzoni, (ZHI)

	Inefficiency Estimates			ZHI’s inefficiency estimates		
Hospital Category	Pooled	Partition.	Correl.	Pooled	Partition.	Correl.
Main sample	12.9%*	10.9%	0.67	13.6%	NA	NA
Nonprofit	12.6*	11.0	0.68	12.9%	11.8%	0.95
For-Profit	16.2*	8.0	0.64	14.4	19.5	0.76
Urban	12.6*	10.7	0.78	13.2	14.5	0.95
Rural	13.4*	11.1	0.58	13.8	20.9	0.92
Chain Member	13.9	13.2	0.46	NA	NA	NA
Independent	12.5*	10.0	0.77	NA	NA	NA
Teaching	13.4	11.8	0.73	13.2	11.8	0.79
Non-teaching	13.0*	10.7	0.67	13.5	15.7	0.99
High Medicare	11.7	11.0	0.65	NA	NA	NA
Low Medicare	13.9*	10.8	0.70	NA	NA	NA

Note: Entries report the percentage increase in costs due to total inefficiency, the sum of allocative and technical inefficiency. An asterisk indicates a case where the pooled estimates and the estimate via partitioning differ significantly at the five percent level by the t test; comparable t tests were not available on the ZHI data. Pearson correlations are shown in the columns labeled Correl.

Table 5. Comparing Inefficiencies Between the Homothetic
and Translog Versions with Pearson (Spearman) Correlations.

Category of Hospital	Percent Inefficient Homothetic	Translog	Correlations
Main Sample	12.7%*	10.8%	0.79 [0.65]
Nonprofit	12.6*	10.6	0.78 [0.65]
For-profit	16.2*	12.5	0.80 [0.65]
Urban	12.6*	11.0	0.84 [0.73]
Rural	13.3*	10.6	0.75 [0.58]
Chain member	13.8*	11.2	0.81 [0.67]
Independent	12.3*	10.6	0.77 [0.63]
Teaching	13.0*	11.6	0.86 [0.81]
Non-teaching	13.0*	10.6	0.77 [0.61]
High Medicare %	11.7*	10.0	0.71 [0.57]
Low Medicare %	13.6*	11.7	0.84 [0.74]

*Note: Entries are the percentage increase in costs due to total inefficiency. An asterisk indicates that the translog estimate differs significantly from the homothetic estimate at the five percent level by the t test; t values ranged from 2.1 to 7.0. The “Correlations” are Pearson product moment [Spearman rank order] correlations of the total inefficiency estimates for each hospital for the alternative functional forms.

Table 6. Cost Equations Under Alternative Cost of Capital Measures

Variable	Measure 1 Coefficient (t value)	Measure 2 Coefficient (t value)
Constant	-1.3643 (-10.85)	-2.6656 (-21.79)
Log General InpatientDays*	0.6657 (53.02)	0.7925 (63.52)
Log Pediatrics Days	0.6991E-02 (2.29)	0.5656E-02 (1.67)
Log Obstetrics Days	0.3155E-02 (1.03)	-0.6360E-03 (-0.18)
Log Other Days	0.3460E-01 (10.20)	0.3176E-01 (7.64)
Log Outpatient Visits	0.6699E-01 (10.61)	0.7296E-01 (9.83)
General Inpatient Days*	0.1490E-06 (0.38)	-0.1161E-05 (-2.47)
Pediatrics Days	0.3732E-05 (0.90)	0.6601E-05 (1.34)
Obstetrics Days	0.1565E-04 (3.87)	0.2039E-04 (4.12)
Other Days	0.4540E-05 (9.10)	0.3230E-05 (4.69)
Outpatient Visits	0.2862E-06 (1.91)	0.4283E-06 (1.97)
Cost of Capital, r_i	0.2341 (21.71)	0.2194 (6.26)
Nurse Wage	0.3636 (18.18)	0.3700 (13.40)
Percent Board Certified	0.6332E-03 (1.83)	0.90592E-03 (2.31)
Reservation Quality	0.2314E-01 (10.79)	0.1835E-01 (7.31)
lambda	1.7714 (16.20)	1.6840 (12.14)
sigma	0.2679 (25.63)	0.3129 (23.33)
n	791	791

*Note: Fuller variable definitions given in Table 1. General inpatient days has been adjusted for case-mix using the Medicare Case-Mix Index. The input price variables are divided by a third input price, wage of other health employees, before performing the maximum likelihood procedure.

Table 7. Mean Percent Cost Increase Due to Sources of Inefficiency (standard deviations in parentheses) and Correlations Across Alternative Cost of Capital Measures

Inefficiency Measure	Capital Cost By Measure 1	Capital Cost By Measure 2	Correlations
Epsilon$_2$	-0.2655* (0.536)	-0.0092 (0.524)	0.02 [0.00]
Epsilon$_3$	-0.7332* (0.546)	-0.4738 (0.523)	0.03 [0.04]
Technical Inefficiency*	0.0676* (0.081)	0.1029 (0.103)	0.91 [0.84]
Allocative Inefficiency*	0.0758* (0.076)	0.0583 (0.055)	0.56 [0.46]
Total Inefficiency*	0.1435* (0.113)	0.1611 (0.119)	0.75 [0.52]
n	789	789	789

*Note: Entries are the percentage increase in costs due to the specified inefficiency; their standard deviations are given in parentheses. An asterisk indicates that the translog estimate differs significantly from the homothetic estimate at the five percent level by the t test. The last column gives the Pearson product moment [Spearman rank order] correlations of each measure when the estimates are based on alternative cost of capital measures.

Appendix Table 1. Maximum Likelihood Estimates of the Frontier Translog Cost Function

Variable	Coefficient	*t* value
Constant	-1.0524	-3.642
LNY1	0.4781	8.688
LNY2	0.0260	1.599
LNY3	-0.0041	-0.0254
LNY4	0.1175	5.867
LNY5	0.0089	0.178
LNP1	0.4334	6.776
LNP2	0.3731	3.423
LNY1*LNY1	0.0455	5.538
LNY1*LNY2	-0.0148	-3.389
LNY1*LNY3	-0.0062	-1.565
LNY1*LNY4	-0.0190	-3.557
LNY1*LNY5	-0.0338	-3.694
LNY2*LNY2	0.0106	3.982
LNY2*LNY3	-0.0006	-0.586
LNY2*LNY4	-0.0011	-0.727
LNY2*LNY5	0.0042	1.022
LNY3*LNY3	0.0263	10.113
LNY3*LNY4	-0.0028	-1.989
LNY3*LNY5	-0.0093	-2.568
LNY4*LNY4	0.0247	21.215
LNY4*LNY5	-0.0186	-3.978
LNY5*LNY5	0.0326	7.254
LNP1*LNP1	0.1014	8.887
LNP1*LNP2	-0.0450	-1.253
LNP2*LNP2	0.0818	2.604
LNY1*LNP1	-0.0070	-0.808
LNY1*LNP2	0.0071	0.449
LNY2*P1	-0.0010	-0.451
LNY2*P2	0.0039	0.955
LNY3*P1	-0.0047	-1.921
LNY3*P2	0.0157	3.876
LNY4*P1	0.0223	8.689
LNY4*P2	-0.0202	-3.925
LNY5*P1	-0.0193	-2.335
LNY5*P2	-0.0080	-0.598
PCTBC	0.0003	1.823
RESQUAL	0.0134	10.636
lambda	1.5030	20.924
sigma	0.2350	34.543

REFERENCES

(1) Magnussen, Jon, "Efficiency Measurement and the Operationalization of Hospital Production," *Health Services Research*, Vol. 31, No. 1, April 1996, pp. 21-37.

(2) Ozcan, Yasar A., Roice D. Luke, and Cengiz Haksever, "Ownership and Organizational Performance: A Comparison of Technical Efficiency Across Hospital Types," *Medical Care*, Vol. 30., No. 9, September 1992, pp. 781-794.

(3) Valdmanis, Vivian G., "Ownership and Technical Efficiency of Hospitals," *Medical Care*, Vol. 28, No. 6, June 1990, pp. 552-561.

(4) Grosskopf, Shawna, and Vivian Valdmanis, "Measuring Hospital Performance: A Non-parametric Approach," *Journal of Health Economics*, Vol. 6, 1987, pp. 89-107. pp. 335-340.

(5) Register, Charles A., and Edward R. Bruning, "Profit Incentives and Technical Efficiency in the Production of Health Care," *Southern Economic Journal*, Vol. 53, 1987, pp. 899-914.

(6) Sherman, H. David, "Hospital Efficiency Measurement and Evaluation," *Medical Care*, Vol. 22, No. 10, October 1984, pp. 922-935.

(7) Wagstaff, Adam, and Guillem Lopez, "Hospital Costs in Catalonia: A Stochastic Frontier Analysis," *Applied Economics*, Vol. 3., No. 7, July 1996, pp. 471-474.

(8) Mark, Tami L., "Psychiatric Hospital Ownership and Performance: Do Nonprofit Organizations Offer Advantages in Markets Characterized by Asymmetric Information?," *The Journal of Human Resources*, Vol. 31, 1996, pp. 631-669.

(9) Bosmans, Nathalie, and Fabienne Fecher, "Performance of Belgian Hospitals: A Frontier Approach," *Health Economics*, Vol. 4, 1995, pp. 389-397.

(10) Zuckerman, Stephen, Jack Hadley and Lisa Iezzoni, "Measuring Hospital Efficiency With Frontier Functions," *Journal of Health Economics*, Vol. 13, No. 3, October 1994, pp. 255-280.

(11) Wagstaff, Adam, "Estimating Efficiency in the Hospital Sector: A Comparison of Three Statistical Cost Frontier Models," *Applied Economics*, Vol. 21, 659-672.

(12) Hofler, Richard, and Sherman Folland, “Technical and Allocative Inefficiencies of United States Hospitals Under a Stochastic Frontier Approach,” Prepared for presentation at the Midwest Economics Association Fifty-fifth Annual Meeting, 1991, St. Louis, Missouri, Oakland University, Department of Economics, Working Paper No. 92-1, Rochester, Michigan.

(13) Newhouse, Joseph, “Frontier Estimation: How Useful a Tool for Health Economics?,” *Journal of Health Economics*, Vol. 13, No. 3, October 1994, pp. 323-328.

(14) Skinner, Jonathan, “What Do Stochastic Frontier Cost Functions Tell Us About Inefficiency?,” *Journal of Health Economics,* Vol. 13, No. 3, October 1994,

(15) Hadley, Jack, and Stephen Zuckerman, “The Role of Efficiency Measurement in Hospital Rate Setting,” *Journal of Health Economics*, Vol. 13, No. 3, October 1994,

(16) Granneman, Thomas W., Randall S. Brown, and Mark V. Pauly, “Estimating Hospital Costs: A Multiple-Output Analysis,” *Journal of Health Economics*, Vol. 5, 1986, pp. 107-127.

(17) Ellis, Randall P., “Hospital Cost Function Estimation When Firms May Not try To Minimize Total Costs,” mimeo, Economics Department, Boston University, MA, September, 1993.

(18) Lakdawalla, Darius, and Tomas Philipson, “Nonprofit Production and Competition,” Working Paper 6377, National Bureau of Economics Research, Cambridge, MA, January, 1998.

(19) Fox, William F. and Richard A. Hofler, "Using Homothetic Composed Error Frontiers to Measure Water Utility Efficiency," *Southern Economic Journal*, Vol. 53, No. 2, 1986, pp. 461-77.

(20) Schmidt, Peter, and C,.A. Knox Lovell, “Estimating Stochastic Production and Cost Frontiers When Technological and Allocative Inefficiency Are Correlated,” *Journal of Econometrics,* Vol. 13, May 1980, pp. 83-100.

(21) Baumol, William J., John C. Panzar, and Robert Willig, *Contestable Markets and the Theory of Industry,* (San Diego: Harcourt Brace Jovanovich, 1982).

(22) Dor, Avi, “Non-minimum Cost Functions and the Stochastic Frontier: On Applications to Health Care Providers,” *Journal of Health Economics*, Vol. 13, 1994, pp. 329-334.

(23) Joseph, Hyman, and Sherman Folland, “Uncertainty and Hospital Costs,” *Southern Economic Journal,* Vol. 39, October 1972, pp. 267-273.

(24) Carey, Kathleen, “Stochastic Demand for Hospitals and Optimizing ‘Excess’ Bed Capacity,” *Journal of Regulation Economics*, Vol. 14, 1998, pp. 165-187.

(25) Joskow, Paul L., "The Effects of Competition and Regulation on Hospital Bed Supply and the Reservation Quality of the Hospital," *Bell Journal of Economics*, Vol. 11, No. 2, 1980, pp. 421-447.

(26) Ellis, Randall P., “Creaming, Skimping and Dumping: Provider Competition on the Extensive and Intensive Margin,” *Journal of Health Economics*, Vol. 17, 1998, pp. 537-555.

(27) Taylor, Donald H., David J. Whellan, and Frank A. Sloan, “Effects of Admission to a Teaching Hospital on the Cost and Quality of Care for Medicare Beneficiaries,” *New England Journal of Medicine,* Vol. 340, 1999, pp. 293-.

(28) Casalino, Lawrence, “The Unintended Consequences of Measuring Quality of the Quality of Medical Care,” *New England Journal Medicine,* Vol. 341, 1999, pp. 1147-.

(29) Thiemann, David R., et al., “Association Between Hospital Volume and Survival After Acute Myocardial Infarction in Elderly Patients,” *New England Journal of Medicine*, Vol. 340, 1999, pp. 1640-.

(30) Aigner, Dennis J., C. A. Knox Lovell, and Peter Schmidt, "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics*, Vol. 6, No. 1, July 1977, pp. 21-37.

(31) Jondrow, J., C.A.K. Lovell, I. Materov, and P. Schmidt, "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," *Journal of Econometrics*, August 1982, pp. 233-238.

(32) Schwartz, William B., and Daniel N. Mendelson, "Eliminating Waste and Inefficiency Can Do Little to Contain Costs," *Health Affairs*, Vol. 13, No. 1, Spring, 1994, pp. 224- 238.

(33) Jorgenson, Dale W., “Capital Theory and Investment Behavior,” *American Economic Review*, Vol. 53, May, 1963, pp. 247-59.

(34) Despotakis, Kostas A., "Economic Performance of Flexible Functional Forms," *European Economic Review*, Vol. 30, 1986, pp. 1107-1143.

(35) Frech, H.E. III, and Lee Rivers Mobley, "The Demsetz Hypothesis and Hospital Markets: An Empirical Analysis," Working Papers in Economics 5-96, Department of Economics, University of California, Santa Barbara, CA 93106-9210.

(36) Burgess, James F., and Paul W. Wilson, “Variation in Inefficiency Among U.S. Hospitals,” INFOR, Vol. 36, August 1998, pp. 84-102.

(37) Kooreman, Peter, "Data Envelopment Analysis and Parametric Frontier Estimation: Complementary Tools," *Journal of Health Economics*, Vol. 13, 1994, pp. 345-346.