ARE FOR-PROFIT NURSING HOMES MORE EFFICIENT?
DATA ENVELOPMENT ANALYSIS WITH A CASE-MIX CONSTRAINT

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INTRODUCTION

Public alarm over the rapid increase in overall health expenditures is widespread, yet certain categories of health care spending have increased even more rapidly than the total. National health care expenditures in the U.S. increased more than eight-fold from 1970 to 1990. During the same period, expenditures on nursing home services increased nearly eleven-fold, from $4.9 to $53.1 billion. A variety of factors have contributed to the growth in nursing home expenditures, including increases in the absolute and relative size of the population aged 65 and above, input price increases, and expanded public funding of long-term care, primarily through Medicaid. Prior to the introduction of Medicaid in the mid-1960s, government funding of long-term care was minimal. Governments at all levels now pay more than half of the national bill for nursing home services, up from about 34 percent in 1970.

Federal and state officials worry about the rising cost of nursing home care. At the state level, this concern has led to direct attempts to regulate nursing home prices and capacity. Policymakers at all levels have questioned whether nursing homes are efficient and public funds are well spent. Some states, such as Connecticut, even have incorporated efficiency incentives in the formula for Medicaid payments to individual nursing homes. Efficiency comparisons needed to implement such plans typically involve some measure of average cost, but cost differences across nursing homes may reflect input price variations as well as efficiency differences. Consequently, development of an efficiency measure that is independent of input prices is important for Medicaid reimbursement policy, as well as for informing particular homes about how to improve efficiency. One measure, technical efficiency, focuses only on the conversion of inputs to outputs and requires no price information, but conventional econometric estimates of technical efficiency have some limitations.
The standard econometric approach to measuring technical efficiency compares a firm's actual performance with its predicted performance based on a line of best fit for a sample of comparable firms. For example, in production function studies of technical efficiency, a firm is labeled inefficient if its output falls short of the predicted output of a firm with that input mix. Results, however, depend on the assumed forms of the production function and the error distribution. Also, in practice, no existing firm may lie on the line of best fit. Hypothetical role models of this sort are not always helpful to inefficient firms seeking to improve their performance or to policymakers interested in rewarding such improvements. Finally, although econometric approaches can be modified to estimate production or cost frontiers, most estimated relationships reflect average rather than potential behavior. Thus, conventional econometric approaches may systematically overestimate the degree of efficiency.

Estimated cost and profit functions also have been used to assess efficiency, but such estimations additionally require knowledge of input and possibly output prices. These prices are not always available, and for some public institutions (e.g., education, fire protection, education, etc.) explicit prices may not exist. In the health sector, especially for hospitals and nursing homes, regulated prices may inaccurately reflect true valuations. Because of these problems, efficiency measures that are independent of specific functional forms, error term assumptions, and the prices of inputs and outputs are potentially important to policymakers and firms.

Data envelopment analysis (DEA) is a nonparametric method of efficiency measurement that uses mathematical programming rather than estimating assumed cost or production functions. In its initial form, DEA compares the relative technical efficiency of a firm with all other firms in a group producing the same set of outputs from a common set of inputs. The procedure maximizes the ratio of average productivity for the firm, a ratio of weighted outputs to weighted inputs. The index is constructed in a way that "favors" the firm, subject to certain constraints.1 Charman, Cooper and Rhodes [1976] show that this fractional, nonconvex programming problem can be replaced by a simpler linear program. The linear program essentially poses and answers the following question. Given the observed behavior of the firm, does there exist a subset of sample firms whose linear combination of outputs exceeds the firm's output bundle, and whose linear combination of inputs is no greater than the firm's input bundle? If so, by what multiple could the firm's output be expanded if it adopted this linear combination of other observed production processes?

Several recent studies have used DEA to evaluate the technical efficiency of nursing homes [Fiszel and Nunnikhoven, 1992; Kleinsorge and Korney, 1992; Nyman, Bricker and Link, 1996; Nyman and Bricker, 1989; and Sexton et al., 1989]. In most of these studies, efficiency scores are then regressed on characteristics of the firm or market area that might partially explain the variation in scores. Of particular interest to economists and policymakers is the finding that for-profit homes tend to have higher scores than otherwise similar non-profit homes. Such findings, however, may overstate or understate efficiency differences between the two types of homes if controls for the nature or quality of inputs and outputs are inadequate. For example,
The primary contribution of this paper is the computation of efficiency scores that have been case-mix adjusted, but there are two other technical differences between this and earlier DEA studies of nursing home efficiency. These other refinements simply increase the flexibility of DEA and are most easily described in the next section, which offers an overview of the linear program and its application to the sample of Connecticut nursing homes. Results of a second-stage regression are then discussed, followed by a summary of findings.

Efficiency Analysis of Connecticut Nursing Homes

Interpretation of the DEA Program and Some Modifications

The DEA linear program for firm \( t \) is stated as

\[
\begin{align*}
\text{Maximize } & Z_t \\
\text{subject to the inequality constraints:} & \lambda_1 Y_{t1} + \ldots + \lambda_i Y_{t1} + \ldots + \lambda_m Y_{tm} \geq Z_t Y_{tm} & r = 1, \ldots, b; \\
(2) & \lambda_1 X_{i1} + \ldots + \lambda_i X_{i1} + \ldots + \lambda_m X_{im} \leq X_{im} & i = 1, \ldots, m; \\
\text{and the nonnegativity conditions:} & \lambda_1, \ldots, \lambda_m \geq 0.
\end{align*}
\]

The interpretation of this program is straightforward. Subscripted values of \( Y \) and \( X \) denote the \( s \) outputs and \( m \) inputs, respectively, of \( n \) firms. \( Z_t \) is an output expansion factor. We maximize \( Z_t \) by constructing a synthetic firm in equation (2), assigning weights \( \lambda \) (perhaps zero) to the outputs of each firm \( j \) with the stipulation in equation (3) that this synthetic firm should not use more of any input than firm \( t \). In effect, we ask: What is the maximum value of \( Z_t \) a common factor by which all outputs of firm \( t \) can be increased by this synthetic firm? While not necessarily optimal, \( Z_t = 1 \) (i.e., no expansion) is always possible, because \( \lambda_j = 0 \) if \( j \neq t \) and \( \lambda_j = 1 \) for \( j = t \) provides a feasible solution. When \( Z_t^* \), the optimal value of equation (1), exceeds unity, the synthetic firm (representing the weighted behavior of a "reference set" of firms for which \( \lambda > 0 \)) could at least match firm \( t \)'s outputs without using more inputs than firm \( t \). The measured efficiency of firm \( t \) is defined as \( h_t^* = 1/Z_t^* \). If \( Z_t^* > 1 \), then \( h_t^* < 1 \) and firm \( t \) is technically inefficient relative to other firms in the sample. If \( Z_t^* = 1 \), then \( h_t^* = 1 \) and firm \( t \) is technically efficient, but again only in a relative sense. This linear program must be solved for each of the \( n \) firms in the sample. Only efficient firms (\( h_t^* = 1 \)) will enter into the reference set of an inefficient firm.

The measure of technical efficiency that emerges from equations (1-4) is not fully consistent with the notion of Pareto-Koopmans efficiency. Beyond the common rate of output expansion, there may exist further opportunities to increase some outputs or to conserve some inputs. Unlike earlier nursing home studies that have been limited to measures of "radial technical efficiency" (based on common output expansion), we employ a procedure, outlined by Chernoff, Cooper and Rhodes [1985], that assigns surplus penalties for outputs and slack penalties for inputs. For example, suppose that the common rate of output expansion by the synthetic firm is two, but some outputs can be more than doubled or some inputs can be reduced below the levels observed in firm \( t \). Any such output surpluses or input slacks indicate even greater disparities between the efficiency of the synthetic firm and firm \( t \). Firm \( t \)'s efficiency score is adjusted for such surpluses or slacks by incorporating a penalty term in the objective function. When penalties are included, the maximum in equation (1) becomes:

\[
\text{Maximize } Z_t + \delta \left( \sum_{i=1}^{m} S_{it}^+ + \sum_{i=1}^{m} S_{it}^- \right)
\]

where \( S_{it}^+ \geq 0 \) and \( S_{it}^- \geq 0 \) are the surplus in output \( r \) and the slack in input \( i \) when firm \( t \) is compared to the synthetic firm, and \( \delta \) is an arbitrarily small positive value. Firm \( t \)'s efficiency score (\( h_t^* \)) is the reciprocal of the optimal value of equation (5), so the larger the penalty term in equation (5), the lower the efficiency rating. Also, both sets of constraints are converted to equalities by subtracting \( S_{it}^* \) from the left-hand side of equation (2) and adding \( S_{it}^- \) to the left-hand side of equation (3).

Previous DEA studies of nursing homes also have not allowed for variable returns to scale (VRS). Following the procedure of Banker, Chernoff, and Cooper [1984], this can be done by appending a constraint that requires the sum of weights \( \lambda_j \) for reference set firms to equal one:

\[
\sum_{j=1}^{n} \lambda_j = 1.
\]

This constraint allows for more flexible production relationships and potentially benefits the firm being evaluated [Seiford and Thrall, 1990], as illustrated in Figure 1.

Consider the simplest case in which each firm uses one input (X) to produce a single output (Y). Points A, B, C, D, and E represent firms in a given sample. Without the VRS constraint, the efficiency of firm X is compared to a synthetic firm G, constructed by simply expanding the present scale of B, the firm with the highest average product. Incorporating the VRS constraint restricts the synthetic firm to be a convex combination of firms A, B, C, and D. Note that average product, the slope of a ray from the origin to a production point, increases from A to B (increasing returns
to scale) and decreases from B to C to D (decreasing returns to scale). Efficiency of firm E is compared to the synthetic firm F rather than G. This measure is preferred when simple expansion of the high productivity firm (B) is unrealistic.

In addition to the two technical modifications (surplus/slack penalties and the VRS constraint), we adjust for case-mix differences across nursing homes by appending the constraint:

\[ \lambda_1 ADL_1 + \ldots + \lambda_n ADL_n + S_{ADL} = A DL_{0}, \quad \text{where } S_{ADL} \geq 0 \]

is the additional ADL score (i.e., beyond the level in firm 0) that could be served by the synthetic firm. Subscripted values of ADL denote the total "activities of daily living" score for each home's patients, with higher scores reflecting greater dependency. This constraint ensures that the synthetic firm, to which firm 0 is compared, must have at least as large an ADL score (i.e., as severe a case-mix) as firm 0.

**Applying DEA to the Connecticut Data**

In this study, we use annual data for 140 Connecticut nursing homes to measure DEA technical efficiency for each home. This procedure entails the solution of 140 linear programs. We repeat the process several times to evaluate the marginal effects of incorporating the case-mix constraint as well as the two other technical modifications. The data allow us to specify seven labor inputs and four outputs (Medicare, Medicaid, private, and "other"
patient days). Summary statistics for outputs, inputs, and the ADL index are shown in Table 1 for the period October 1, 1982 through September 30, 1983.

For each of the 140 homes in the sample, the fully augmented linear program, i.e., equations (1-4) modified to include equations (5-7), was solved. The minimum computed efficiency score was 0.252 and the mean score was 0.50, with a coefficient of variation of 17.2%. Of the 140 homes, 73 had a maximum score of one. Figure 2 shows the frequency distribution of scores (0.25 \leq h^*_s < 0.26; 0.26 \leq h^*_s < 0.3; \ldots; 0.95 \leq h^*_s < 1.00; and h^*_s = 1.00).

We believe that the results summarized in Figure 2 represent "best available method" estimates of technical efficiency for the homes in this sample. In addition to allowing for surplus/slack penalties and more flexible production relationships, the scores reflect a "front-end" control for differences in case-mix across firms in the sample. Given the lack of data required to control similarly for quality differences, this is about the best we can do to compare technical efficiency across homes. Obviously there may be other factors which help to explain the observed differences in efficiency scores, which we address in the next section, but it is of some interest to see how the inclusion of the case-mix constraint and the other two modifications affect the computed scores. If the marginal effects of these changes are small, even unrefined DEA models may offer useful information about the relative technical efficiency of nursing homes. If the marginal effects are large, policymakers should be cautious about using efficiency scores to compare performance unless such modifications have been made.

**Table 1**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (n = 140)</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outputs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medicare patient days (Y1)</td>
<td>473.78</td>
<td>624.81</td>
<td>126.92</td>
</tr>
<tr>
<td>Medicaid patient days (Y2)</td>
<td>2944.88</td>
<td>2024.88</td>
<td>72.65</td>
</tr>
<tr>
<td>Private patient days (Y3)</td>
<td>1726.65</td>
<td>10299.41</td>
<td>70.70</td>
</tr>
<tr>
<td>Other patient days (Y4)</td>
<td>392.63</td>
<td>630.65</td>
<td>159.29</td>
</tr>
<tr>
<td>Case-mix control</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADL index (ADL)</td>
<td>855.92</td>
<td>495.19</td>
<td>57.85</td>
</tr>
<tr>
<td>Labor inputs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dietary hours (XL)</td>
<td>2365.94</td>
<td>15972.94</td>
<td>67.54</td>
</tr>
<tr>
<td>Housekeeping hours (X2)</td>
<td>1850.64</td>
<td>17439.00</td>
<td>125.84</td>
</tr>
<tr>
<td>Laundry hours (X3)</td>
<td>7412.15</td>
<td>6628.15</td>
<td>86.92</td>
</tr>
<tr>
<td>Director of nursing hours (X4)</td>
<td>2592.87</td>
<td>592.94</td>
<td>28.12</td>
</tr>
<tr>
<td>RN hours (X5)</td>
<td>21332.03</td>
<td>16309.70</td>
<td>76.15</td>
</tr>
<tr>
<td>LPN hours (X6)</td>
<td>10283.29</td>
<td>19600.44</td>
<td>90.85</td>
</tr>
<tr>
<td>Nurse's aide hours (X7)</td>
<td>75056.83</td>
<td>50994.12</td>
<td>79.13</td>
</tr>
</tbody>
</table>

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To determine the effects of the three modifications, we recompute efficiency scores for several variants of the model. In addition to the full model (F), cited above, a basic model (B) with none of the three modifications, a model with only the addition of the VRS constraint (C), and a model with the addition of the VRS constraint and the ADL constraint were used to compute efficiency scores for the same sample. Table 2 compares the mean score, standard deviation, minimum score, and maximum score for each of 140 linear programs.

From Table 2, the separate and combined effects of the three modifications do not appear to be large. Reading down the table, the inclusion of the VRS constraint (B to C) increases the mean efficiency score by 4.65 percent and reduces the standard deviation by 0.66 percent; however, the large range of scores is essentially unaffected. Additionally controlling for case-mix (C to D), in the form of the ADL constraint, further increases the mean score but slightly increases the standard deviation, leaving the range unchanged. In the final step to the full model (D to F), the further addition of surplus/short penalties reduces the mean score and increases both the standard deviation and the range, but each of these changes is quite small.

Based on Table 2, one might conclude that such modifications to the DEA procedure, including the addition of the case-mix constraint, have only a modest impact. There are, however, several reasons still to make these modifications. First, in other samples, such modifications might be quantitatively more important. Second, if these modifications have theoretical or practical justifications, as we believe they do, they ought to be included as a matter of good practice, provided that the costs of doing so are not large. Finally, and perhaps most importantly, the relatively small differences in summary statistics shown in Table 2 may mask significant differences in computed scores for individual firms. For example, in adding the VRS constraint to the basic model (B to C), the efficiency score of one nursing home increased by 0.253, an increase of more than 50 percent. Thus, failing to modify the DEA procedure may distort assessments of individual firms, even if it does not greatly affect the sample mean or range.

REGRESSION ANALYSIS OF EFFICIENCY SCORES

Earlier analyses of nursing homes have used second-stage regressions to evaluate the sources of variation in computed efficiency scores. Scores lie within the [0,1] interval and, although the continuity of $h_i^*$ reduces the heteroscedasticity problem that accompanies the discrete linear probability model, multiple linear regression does not ensure that predicted efficiency values will lie within the unit interval. Consequently, in addition to the standard linear regression, a nonlinear estimation procedure is applied. In the nonlinear case, firm's efficiency index ($h_i^*$) is assumed to be logistically related to the $p$ explanatory factors ($f_{i0}^0, f_{i-1}^0, . . . , f_{i-N}^0$), or $h_i^* = 1/(1 + e^{-\beta f_i}) + \mu_i$, where $\mu_i$ is an additive disturbance term. This form ensures that predicted values of $h_i^*$ will lie within the unit interval. However, the logistic regression coefficients ($\beta$) do not have the usual slope interpretation that they do in the linear case, since $\beta f_i / (1 + e^{-\beta f_i}) = \beta h_i^*(1 - h_i^*) \alpha_i$. In each model, linear and logistic, the estimated sign and statistical significance of the coefficients are noteworthy, but these values cannot be directly compared between models.

Efficiency scores computed in the full DEA model (incorporating ADL, VRS, and penalties) constitute the dependent variable in the regressions shown in Table 3. Explanatory variables are divided into two groups. Beds (and beds squared), for-profit or non-profit status (for = 0; non = 1), median age of patients, certification status (ICF only = 0; joint ICF/SNF = 1), and percent Medicare patient days are facility-specific characteristics. Market area (town) characteristics that might affect
efficiency include the number of people aged 65 and over, percent of people below the poverty line, median gross rent of specified renter-occupied housing units, and the number of nursing homes per capita. Also included are dummy variables for Litchfield and Middlesex counties, which have significantly lower population densities and percentages of population living in urban areas than the other counties where sample homes are located.\textsuperscript{9} In addition to the sample mean and standard deviation of each regressor, Table 3 also lists the estimated coefficients and t-statistics for the linear and logistic regressions.

The explanatory variables jointly account for about 46.5 percent and 61.5 percent of the variation in scores in the linear and logistic models. Adjusted for degrees of freedom, these values fall to about 41.5 percent and 57.8 percent, respectively.

Number of beds is used to test for the presence of economies of scale. A squared bed variable also is included to allow for the existence of a hump-shaped efficiency function (an "ideal" size for maximum technical efficiency). In the linear model, both variables are significant and results are consistent with a hump-shaped efficiency function. Signs change and only the squared term is significant in the logistic regression, but it can be shown that in the logistic function this sign pattern is again consistent with the notion of an optimal size for technical efficiency, given other characteristics of the home and its market setting.\textsuperscript{5}

Non-profit homes appear to have significantly lower efficiency scores than otherwise similar for-profit homes. These results reinforce the findings of Nyman and Bricker (1989), Nyman, Bricker and Lin (1990), and Figel and Nunnikhoven (1992). Critics of such findings claim that apparent differences in the efficiency of for-profit and non-profit institutions may reflect systematic differences in case-mix or quality that are not captured by standard DEA approaches. However, in addition to disaggregating output by payment source, we also have introduced a front-end control for case-mix differences by including an ADL constraint (7) in the linear program. Estimated coefficients in Table 3 show that this effect remains highly significant even after an attempt is made to purge efficiency scores of case-mix bias. The mean score for non-profit homes in the sample is 0.71 with a coefficient of variation of 36.04; comparable figures for the for-profit homes are 0.92 and 12.00.

Before discussing other regressors, it is important to note that estimates of the non-profit dummy coefficient in both the linear and nonlinear models will be affected by the choice of DEA model used to generate the dependent variable (i.e., the efficiency scores). Earlier, in Table 2, we reported results for four different models: a basic model (B), a model which incorporates only the VRS constraint (C), a model with both VRS and ADL constraints (D) and a full model (F) which imposes surplus slack penalties in addition to the VRS and ADL constraints. Two-stage regressions reported in Table 3 used the efficiency scores computed in the full model, but we have run similar regressions using the scores computed by the other three DEA models. Full results are available upon request, but the effects on the estimated coefficient of the non-profit dummy variable are listed in Table 4.

The regression results for the non-profit dummy variable (and for the other independent variables) are quite robust to the particular model used to generate the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (n = 146)</th>
<th>Standard Error</th>
<th>Linear Regression</th>
<th>Logistic Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.37097</td>
<td>(0.32)</td>
<td>-1.57441</td>
<td>(6.40)</td>
</tr>
<tr>
<td>Facility characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beds</td>
<td>110.21</td>
<td>71.23</td>
<td>0.00296</td>
<td>-0.0161</td>
</tr>
<tr>
<td>Bed-squared</td>
<td>3854.22</td>
<td>8695.49</td>
<td>-0.000063</td>
<td>0.000212</td>
</tr>
<tr>
<td>Non-profit dummy</td>
<td>0.13</td>
<td>0.24</td>
<td>-0.24613</td>
<td>-1.00213</td>
</tr>
<tr>
<td>Patient median age</td>
<td>82.77</td>
<td>57.0</td>
<td>0.000074</td>
<td>-0.00249</td>
</tr>
<tr>
<td>Certification dummy</td>
<td>0.74</td>
<td>0.44</td>
<td>-0.07991</td>
<td>-0.94782</td>
</tr>
<tr>
<td>% Medicaid patients</td>
<td>64.83</td>
<td>20.40</td>
<td>-0.00216</td>
<td>-0.00595</td>
</tr>
<tr>
<td>Age 65+ population</td>
<td>6214.95</td>
<td>547.21</td>
<td>0.0000058</td>
<td>0.00013</td>
</tr>
<tr>
<td>% below poverty line</td>
<td>5.23</td>
<td>6.00</td>
<td>-0.00077</td>
<td>-0.01484</td>
</tr>
<tr>
<td>Median gross rent</td>
<td>3270.35</td>
<td>366.51</td>
<td>-0.00046</td>
<td>-0.00568</td>
</tr>
<tr>
<td>Nursing home/adv</td>
<td>0.0032</td>
<td>0.0022</td>
<td>-0.00216</td>
<td>-0.00595</td>
</tr>
<tr>
<td>Litchfield dummy</td>
<td>0.05</td>
<td>0.22</td>
<td>-0.07385</td>
<td>-1.16665</td>
</tr>
<tr>
<td>Middlesex dummy</td>
<td>0.10</td>
<td>0.30</td>
<td>-0.02266</td>
<td>-0.00209</td>
</tr>
<tr>
<td>R²</td>
<td>0.452</td>
<td>0.157</td>
<td>0.457</td>
<td>0.578</td>
</tr>
</tbody>
</table>

t-ratios in parentheses; *p<.05 for logistic regression.

efficiency score. In general, the non-profit coefficient tends to increase in absolute value as we move from the basic to the full model, especially in the nonlinear regressions. In both linear and nonlinear cases, statistical significance also increases. This pattern of increasing magnitude and statistical significance tends to further support the addition of case-mix constraints and other refinements in comparing the efficiency of for-profit and non-profit nursing homes. Note, however, that significant performance differences remain even after these refinements have been made. Whether such differences persist after front-end controls for quality remain an important question that will require better empirical measures of output quality than are commonly available.
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|**ARE FOR-PROFIT NURSING HOMES MORE EFFICIENT?**|

Market area (town) characteristics tend to perform best in the logistic model. A priori expectations about the relationship between the local "pool" of older people and the measure of efficiency are unclear. Facing greater demand for care, the home might increase its occupancy rate and improve its labor use efficiency, especially if capacity expansion is hindered by Certificate of Need (CON) restrictions. On the other hand, greater demand for care may require less vigorous competition for patients and give the home more discretion in admissions, allowing it to reserve some beds for "high revenue" private patients. The positive coefficient for the 65 years and above variable in both regressions suggests that the first effect may dominate.

Nursing home markets are somewhat localized, and poverty among the local population has two effects which could reduce efficiency. Poor living conditions outside the nursing home may reduce the likelihood of questions or complaints about performance from patients or relatives, allowing the home to be less than fully efficient. In addition, patients from a low-income environment may require more inputs per patient day to cope with previously neglected health problems. In both regressions, efficiency scores are negatively related to the percent of the local population with incomes below the poverty line, significantly so in the nonlinear model.

We focus on technical efficiency of labor use not only because labor constitutes the major resource used by nursing homes, but also because reliable data on Connecticut nursing homes' use of nonlabor inputs are difficult to construct. The principal nonlabor inputs are land and structure. Lacking direct information about these inputs for homes in our sample, we use a proxy variable that embodies the value of both inputs: median gross rent for specified renter-occupied housing units in the town where the nursing home is located. This proxy may be justified by noting that, if their highly specialized labor were removed, most nursing homes would resemble multi-family rental housing units. The significant negative coefficient of the rent variable in each regression suggests that more costly nonlabor inputs (land and structure) may force administrators to economize on these factors, impairing the labor efficiency of the nursing home, perhaps due to problems associated with more crowded conditions for patients and staff.

An increase in the number of nursing homes per capita ought to increase competitiveness and provide incentives to reduce waste and improve technical efficiency. Estimation of the two models, however, yields signs that differ from one another but do not differ significantly from zero. The lack of a "competition effect" may be attributable to the excess demand faced by most homes in Connecticut. In states with less binding rate restrictions, where market conditions are more slack, local competition may provide stronger incentives to improve efficiency.

**FINAL REMARKS**

This study of 140 Connecticut homes finds that two-thirds of the homes have efficiency scores greater than or equal to the sample mean of 0.90, and only 13 homes score below 0.65. These results are broadly comparable with results in Nyman and Bricker (1986) (mean = 0.69) and in Nyman, Bricker and Link (1993) (mean = 0.93).
but more encouraging than results reported by Sexton et al. [1989] (mean scores of 0.70 to 0.75, depending on reimbursement method and year) or Fiod and Nunnikhoven [1992] (overall efficiency score of 0.57). Keeping in mind that much of the variation in efficiency scores can be explained in the second-stage regressions with relatively few independent variables, some of which lie beyond the control of the home, it is tempting to conclude that technical inefficiency is not a pervasive problem in Connecticut nursing homes. However, several limitations of this analysis must be recognized.

First, like all DEA studies, the scores computed are relative technical efficiency scores. By construction, there always will be some units in the sample with perfect scores. Performance of other units is measured against the observed performance of this reference set, but there is no assurance that any reference set member is fully efficient in some absolute sense. Even reference set firms, then, may be able to increase technical efficiency beyond levels observed within the sample. Second, as in previous studies of nursing home efficiency, inputs have been restricted to various types of labor. While the technical efficiency of labor use is an important matter in a labor-intensive industry, questions regarding the efficient use of nonlabor inputs and full efficiency still need to be addressed. Some homes that appear to be inefficient in DEA studies of labor-use may prove to be more efficient when their use of all factors is considered. Finally, even if nonlabor factors are included, technically efficient firms may be able to reduce further the cost of producing a particular mix of inputs by adopting a different input mix to improve allocative efficiency. Such an analysis requires detailed information about input prices that can be difficult to obtain, especially for durable non-labor inputs.

In comparing the performance of for-profit versus non-profit nursing homes, this study, like several earlier ones, suggests that for-profit homes tend to exhibit greater technical efficiency than otherwise comparable non-profit homes. Moreover, this performance gap persists, even after modifying the procedure to account for potential case-mix differences between homes, and after incorporating two other technical modifications of the standard DEA approach. Remaining doubt about the difference in technical efficiency between for-profit and non-profit homes arises largely because the calculation of the technical efficiency scores. Because the calculation of the technical efficiency scores, there is some statistical evidence that the property rights structure. The next logical step, it would seem, is to develop and incorporate better measures of quality in the first-stage computation of efficiency scores, as we have done for case-mix in the present study. Our data set did not permit this extension, but given appropriate and reliable measures of quality it should not be difficult to generate efficiency scores that consider both the severity of patient needs and the quality of the services they receive.

NOTES

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1. The weights (variables in the program) are chosen to give the firm the highest possible efficiency rating, subject to conditions that these weights be non-negative and that no other efficiency firm, using the same weights, exceed the maximum value of zero.

2. The ALD Index quantifies the ability of residents to function in eating, dressing, moving in and out of a chair or bed, and moving about with a cane or wheel chair, if needed. In Connecticut, each home rates each resident numerically from 4-12, with a higher score reflecting greater dependency.

3. Alternatively, the problem can be constrained to find the maximum rate of input contraction, subject to the constraint that the synthetic firm produces an output bundle no smaller that that produced by firm 1.

4. This formulation of the penalty function is not problem free, since outputs and inputs are measured differently and resulting efficiency scores may depend on measurement units. One could adopt the "Russell measure," an alternative non-equal measures of efficiency proposed by Ford and Lowell [1978], but Bunnell [1989] notes that there are also problems with this approach. In the present study, the addition of the penalty function has rather marginal effects (see Table 2).

5. Previous DEA studies of nursing homes differ in their methods of disaggregating output. Some restrict their analysis to a single output (Nyma, Brickner and Link, 1996). Others define multiple outputs (based on the distinctions between skilled nursing facility (SNF) patients, intermediate care facility (ICF) patients, or other categories reflecting potential differences in care requirements) (Nymann and Brickner, 1996; Fiod and Nunnikhoven, 1992). At least one other DEA study (Sexton et al., 1995), categorizes output by payment source (Medicaid and non-Medicaid patient days), a practice that is more common in cost studies of nursing homes (Dor, 1998). If costs do not differ by payment class, this approach may be less useful than disaggregating the SNF/ICF distinction. McKee's [1989] estimated cost function for a sample of 81 Texas homes suggests that costs for Medicaid and private patients do not differ. However, Chatterjee and Green [1996] (tolling cost function estimates for the present sample of 169 Connecticut homes finds significantly higher marginal labor costs per day for private patients than for Medicaid patients. Medicaid authorities and relative of Medicaid patients have long worried about such differentials, but the issue has not been resolved and it is unclear whether intra- or inter-homes differences in the level of care are involved in such cost differences. In any event, Connecticut reimbursement rules hinged on this distinction; thus, we adopt the payment score approach in this study.


7. To verify the need to correct for case-mix bias in the computation of DEA scores, we also used an unadjusted DEA score, computed without the ADM constraint, in second-stage regressions that contained ADM as an explanatory variable. Those regressions confirm that unadjusted efficiency scores are negatively related to ADM scores.

8. Some variables included in earlier DEA studies of nursing homes are absent, either because they did not apply to homes in our sample (e.g., hospital affiliation) or were unavailable.

9. Consider the logistic function, \[ h = \left(1 + e^{-\beta x}ight)^{-1}, \] where \( \beta \) is an explanatory factor that appears both linearly and quadratically (e.g., number of beds), and \( C \) is the sum of other explanatory factors. It can be shown that \[ \frac{\partial^2 h}{\partial x^2} \leq \frac{4}{3 (1 + e^{-\beta x})^2} = \beta^2. \] For \( \beta \gg 1, \) this expression will be positive. For \( \beta \ll 0, \) the function is quadratic and negative if the term in square brackets is negative. From the log-linear regression results, \( \beta = 0.01487 \) and \( \beta = 0.00021. \) Using these values in the preceding condition implies that \( \frac{\partial^2 h}{\partial x^2} < 0 \) if \( x > 36.4. \) All values of \( x \) in the sample satisfy this condition. Thus, \( h^{-1} \) is a concave function of nursing home size.
FIVE SOURCES OF PRICE STICKINESS: AN EMPIRICAL INVESTIGATION

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INTRODUCTION

Over the past few years the focus of many studies of price stickiness has shifted from an imperfectly competitive factor market to an imperfectly competitive product market. This new perspective is typified by the works of Rotemberg and Woodford (1991) and Carlton (1988) which assert that frequent price adjustments can alienate customers, break down collective marketing agreements and/or induce inventory speculation. When the cost associated with these conjectured responses exceeds the second-order gains identified with conventional short-run profit maximizing price adjustments, the supplier decides against any price change. In these circumstances sticky price behavior is clearly optimal, and may even result in an optimizing framework. Not everyone shares this exclusive product market focus. Recent work by Blinder (1991) and Gordon (1996) is more eclectic and argues that imperfectly competitive factor markets together with the firm’s input-output structure can also contribute to price stickiness.

In this study, we test the relative merits of the competing product/output factor market arguments by examining empirically the comparative contributions of five narrow definitions of price stickiness hypotheses associated with Okun, Hicks, Schultze, Shupp, and Leonieff. The first three of these five hypotheses are consistent with the new product market focus. The latter two are more congruent with an older focus on factor markets and on input-output structure. The acronym OHSSHL is used to refer to these five hypotheses.

In the next section we define the five price stickiness hypotheses and outline an optimizing model incorporating the same. In the subsequent section we test the hypotheses using data from 22 three-digit and 9 two-digit SIC industries.

THE FIVE HYPOTHESES AND AN OPTIMIZING MODEL

In this section a formal model incorporating the defining elements of the five OHSSHL hypotheses is developed. Each sector or industry is modeled as a profit-maximizing representative firm competing in an imperfectly competitive market and facing a demand schedule given by

\[ x_p = \sigma_p - b \cdot p \]

where \( x_p \), \( \sigma_p \), and \( p \) denote respectively the outside demand, the degree of market penetration, and the price level of the \( p \) firm (industry) in period \( t \). The coefficient \( b \) measures demand response to a price change. Outside demand in equation (1) above is