RESOURCE SUBSTITUTION IN TEXAS NURSING FACILITIES

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ABSTRACT

As demand for long-term care in the United States outpaces public and private funding, it is increasingly important that geriatric are facilities be managed efficiently and that productivity gains be achieved. These goals require a detailed understanding of resource demand and utilization in nursing homes. This paper draws on a panel of Texas nursing homes to estimate substitution elasticities in a translog cost model. We find that many resource pairs are weak substitutes and that significant automation is unlikely to occur unless wage rates rise in relation to the cost of capital prevailing in the sample period.

INTRODUCTION

As the U. S. population ages, care for the elderly becomes an increasingly urgent issue. Private and public resources to meet this need are already severely strained although the large baby-boom cohort has not yet reached its years of peak demand for long-term care. Many state Medicaid budgets are stagnant or shrinking, and benefits are consequently being curtailed [Caffrey (2001), Greene (2005), Lueck (2005a, 2005b), Sandberg (2005), Silverman (2006)]. These developments increase the importance of efficient operations in geriatric facilities, of which the traditional nursing home is still the prototype. It is therefore relevant to examine actual and potential resource utilization in the nation's nursing facilities. How do firms combine human resources with plant and equipment to provide long-term care? What is the scope for substitution among inputs in the provision of services? How are these features of the production process reflected in the typical firm's demand for various kinds of resources?

Econometric research on production, cost and demand in the U. S. markets for long-term care began about thirty years ago. As the references cited in the next section indicate, there is now an extensive literature that has strengthened our understanding of the processes and the problems of this service industry. However, several important issues remain unresolved, among them the questions raised in the previous paragraph. As best we can discern, the modeling of production functions and cost functions for nursing facilities has not focused in detail on the resource mix and the scope for substitution among inputs; but these issues are critical for assessing the industry's efficiency and its ability to increase productivity as demand continues to outpace public and private funding.

In this paper, therefore, we draw on a panel of Texas nursing facilities in 1999 and 2002 to estimate resource demand and substitution elasticities for plant and equipment ("capital") and seven categories of human resources. Using a conceptually correct substitution elasticity, we report estimates based on least squares, robust regression, and bootstrap confidence intervals. The next section summarizes the relevant literature, and section three provides a concise survey of the long-term care industry in Texas. A translog cost function is specified in section four, the elasticity parameters are discussed in section five, and the data set is described in section six. In section seven, we discuss the resource demand elasticities and the Morishima substitution elasticities estimated by least squares and by robust regression. The final section contains a summary, conclusions, and conjectures.

MODELING EFFICIENCY IN NURSING FACILITIES

A non-parametric approach to modeling efficiency of resource utilization is data envelope analysis (DEA), which has been applied to the nursing home industry by Nyman and Bricker (1989), Fizel and Nunnikhoven (1992), Duffy et al. (1994), Erlandsen and Forsund (1999), Kooreman (1994), and SOA Associates (2003). The latter authors use DEA to evaluate a nation-wide sample of skilled nursing facilities. Inputs include the number of beds in each facility and the utilization of nurses, aides, and other employees. Among the output measures are resident days and indicators of the clinical or functional changes experienced by residents. The average inefficiency is estimated to be 36 percent. For skilled nursing facilities unaffiliated with hospitals, "the correlations between quality of care and the nursing home cost indicated that quality can improve without a corresponding increase in expenditures on patient care. For non-profit nursing homes, quality scores rose with increased expenditures on nurses" (SOA 2003).

Parametric stochastic frontier production and cost functions have been applied to nursing-home data sets by Vitaliano and Torren (1994), Anderson et al. (1999), Filippini (1999), Farsi et al. (2005), and Knox et al. (2007). For example, Farsi et al. (2005) examine a panel of 36 Swiss nursing facilities during the period 1993-2001. The authors address the choice of random effects or fixed effects to model unobserved heterogeneity among the facilities. If the random effects are correlated with the regressors included explicitly in the model, inconsistent estimators will be produced (e. g., Greene 2003, p. 301). On the other hand, the fixed-effects approach, while consistent, may be statistically inefficient when there is substantial unobserved heterogeneity. Using a latent-correlation method of Mundlak (1978), Farsi et al. show how inconsistency in the random effects might be avoided. The authors report that "our individual inefficiency estimates appear rather sensitive to the econometric specification. These differences are partly due to different specifications of inefficiency and heterogeneity across the models and partly due to the large sampling errors incurred at the individual level" (Farsi et al. 2005, p. 2139).

Using a panel of Texas nursing facilities, Knox et al. (2007) estimate the stochastic production frontier by the methods of maximum likelihood and quantile regression and infer that the average avoidable productivity shortfall is at least 8 percent and perhaps as large as 20 percent. Moreover, non-profit facilities are notably less productive than comparable facilities operated for profit; and the industry is characterized by constant returns to scale.

Castle (2001) examines nursing homes that are pioneer users of new processes and technology since "identifying characteristics associated with this early adoption process could be useful in further facilitating the diffusion of innovations" (Castle 2001, 161). From a sample of more than 13,000 US facilities between 1992 and 1997, the author identifies the first 20 percent of firms to adopt any of 13 innovations, including for example special care units for Alzheimer's disease, AIDS, head trauma or Huntingdon's disease as well as subacute care for physical therapy, cardiac treatment, and dialysis. Castle finds that the early innovators are characterized by larger bed size, chain membership, a large proportion of private-pay residents, retrospective Medicaid reimbursement, and location in a county having high average income and significant competition from other nursing facilities.

This overview of the literature, while by no means exhaustive, indicates the range of methodologies, data sets, and issues that nursing home researchers have explored in recent decades as they try to assess the industry's performance with respect to innovation and resource utilization. However, it appears that none of these studies has produced direct estimates of the substitution elasticities or the resource-demand elasticities in the provision of nursing-home services.

AN OVERVIEW OF TEXAS NURSING FACILITIES

Giacalone (2001, chapters 1, 4) provides a general quantitative description of nursing facilities in the United States during the late 1990s. Some 17,000 nursing homes served 1.6 million residents and employed almost 1.8 million workers. About two thirds of the facilities were proprietary (profit-seeking), and 56 percent were members of a multifacility organization (a "chain"). Giacalone (2001, p. 63) remarks, "Despite the wave of mergers that the nursing home industry experienced in the 1990s, the industry cannot be said to be highly concentrated. . . . Based on number of facilities, the four-firm and eight-firm concentration ratios for 1998 were 10.3 percent and 16.4 percent respectively. Based on number of beds, the comparable ratios were 11.0 and 19.0 percent. Though industry concentration was slightly higher based on bed capacity, these are low concentration ratios."

Table 1 provides an overview of licensed Texas nursing facilities that participated in the Medicaid program in 2002. Although its nursing home industry conforms to the national pattern in many respects, Texas is a rich source of information and experience because of the state's size, geographic and ethnic diversity, and regulatory environment. Moreover, Texas has more nursing home beds than any other state and is second only to California in number of nursing facilities. Compared to the national average, the industry in Texas has a smaller proportion of non-profit facilities (only 17 percent of licensed home in 2002) and a much larger proportion of chain members (79 percent of licensed homes in 2002). The latter statistic reflects merger and consolidation throughout the 1990s.

In general, the complex policy issues that the Texas industry and its regulators must address include accessibility to long-term care, the amount and quality of the care provided, and compensation to providers of care. Since 1989, Medicaid reimbursement has been based on a prospective fixed-rate, case-mix system. According to the Texas Department of Human Services (1990), this system has three objectives: (1) to encourage the delivery of quality services, (2) to improve access for patients requiring extra assistance, and (3) to increase payment equity among facilities. In pursuit of these goals, the state repealed its Certificate of Need legislation in September 1986, a step that led to facility expansion, new construction, and an excess supply of beds. In this respect also, Texas differs from many other states whose occupancy rates exceed 90 percent. For Texas in 2002, the average occupancy rate in for-profit nursing facilities was 69 percent; in nonprofit facilities, it was 80 percent.

Table 1
Texas Nursing Facility Profile, 2002

	For-profit facilities		Non-profit facilities	
Facility characteristics	**Chain**	**Independent**	**Chain**	**Independent**
Number of facilities	709	135	94	79
Average no. of beds	114	103	109	102
Average occupancy %	68	71	76	84
Sources of revenue				
Medicaid %	61.7	69.0	58.7	59.3
Medicare %	19.2	9.5	14.9	5.8
Private pay %	13.9	15.9	17.3	20.5
Other %	5.2	5.6	9.1	14.4
Average case mix				
index (scaled 1 – 12)	7.4	7.6	7.6	7.7

Texas nursing homes appear to be labor intensive, relying on low-wage employees and eschewing automation and advanced technology [e. g., Flood (1999, 2000); Francis (2006)]. Some data support this impression. At the national level in 2002, there was $34,188 worth of private fixed assets per full-time equivalent employee in facilities for nursing and residential care, compared to $100,908 in hospitals, $41,676 in ambulatory health care, $106,319 in manufacturing, and $27,436 in the construction industry [BEA (2004)]. Long-term care in the U. S. is therefore fairly labor intensive [Burkins (1997), Karr (2006)]. While a strictly comparable capital-labor ratio for Texas nursing facilities is not available, our data indicate that the industry's median appraised value of land and improvements was about $17,000 per employee in 2002 [Texas Health and Human Services Commission (2002)]. Even after generous allowance for the tendency of tax appraisals to undervalue business assets, this datum reinforces the impression that nursing facilities in Texas are labor intensive relative to their peers nationally and certainly compared to other health care services and to private enterprise in general.

With this précis of the industry in hand, we turn to the formulation of a cost function for Texas nursing homes.

SPECIFICATION OF A TRANSLOG MODEL

Our model is the canonical translog cost function [Berndt and Christensen (1973); Greene (2003), pp. 366-369], which has been widely used to represent the cost structure of a firm behaving as a price taker in the markets where it purchases resources. According to the translog specification, the cost share of each resource, s_i, is a log-linear combination of all the resource prices, p_j , j = 1, … , M :

$$s_i = \beta_i + \delta_{i1}\log p_1 + \delta_{i2}\log p_2 + \ldots + \delta_{iM}\log p_M . \qquad (1)$$

Microeconomic theory proposes the symmetry of the cross partial derivatives, so we require that $\delta_{ij} = \delta_{ji}$ in this set of M equations. In addition, the sum of the cost shares must be one, so $\Sigma\beta_i = 1$, $\Sigma\delta_{ij} = 0$ for each column j, and $\Sigma\delta_{ij} = 0$ for each row i. To incorporate the latter restrictions, we select resource M as the numeraire and transform the prices of the other resources:

$$s_i = \beta_i + \delta_{i1}\log(p_1/p_M) + \delta_{i2}\log(p_2/p_M) + \ldots + \delta_{i\,M-1}\log(p_{M-1}/p_M)\ . \qquad (2)$$

Then equation M becomes redundant and is not estimated explicitly.

In model (2), linear homogeneity is a maintained hypothesis. The assumption is supported by Knox et al. (2001, 2003, 2007), who find constant returns or modestly increasing returns to scale in Texas nursing homes based on econometric models of cost, production, and profit functions. We complete the specification of the translog function by augmenting equation (2) with variables that classify each nursing facility as to form of ownership (for-profit = 1, nonprofit = 0) and affiliation (chain membership = 1, independent = 0). There is also a variable to indicate whether each observation is from 1999 (= 0) or 2002 (= 1). These dummy variables are included to control for possible differences in the average cost shares between groups and over time. In the context of this paper, their regression coefficients are of secondary interest and are not reported below.

The set of M-1 equations (2) is a reduced form because individual nursing facilities are assumed to be price takers in resource markets. This assumption seems reasonable for most Texas nursing facilities; significant monopsony power is unlikely since at several levels there is vigorous competition for human resources. In the first place, the Department of Health and Human Services licenses about a thousand nursing facilities, including more than 200 independent firms and many small chains; no nursing home chain owns more than ten percent of the facilities. Practically all the nursing homes, whether independent or chain members, must recruit registered nurses, licensed vocational nurses, nurses aides, custodial and maintenance staff, food-preparation personnel, and other workers. In these labor markets, each firm competes with other nursing facilities and with hospitals, clinics, doctors' offices, and –for non-nursing functions like maintenance and food preparation— with a vast range of enterprises throughout the Texas economy.

On the other hand, it seems plausible that the largest Texas nursing home chains can negotiate volume discounts for some types of plant and equipment; and they may sometimes be able to exercise market power when they lease or buy real estate. According to the theory of a monopsonistic firm, these exceptions to price-taking behavior would alter model (2) because each input's marginal revenue product would be equated not to a given input price but to a marginal factor cost that varies with the amount of input purchased. Compared to price takers, nursing homes with buying power would tend to purchase smaller amounts of resources and would presumably provide a reduced volume of long-term care. Subject to the availability of data, an examination of the cost behavior of the largest chains would be a worthwhile direction for additional research.

A related question is whether Texas nursing facilities are price takers in their "product" markets; if they have market power as providers of long-term care, their resource demand functions would tend to be less elastic than estimates based on model (2). However, Table 1 shows that Medicaid and Medicare patients generate most of the industry's revenue; and the firms are essentially price takers vis-a-vis these third-party payers, who set uniform per-diem rates based on the type of care provided. If the nursing homes practice monopolistic competition in pursuit of federal and state funds, they do so by varying their case mix of Medicaid residents and the kinds of therapy offered to Medicare patients. These strategies probably do not give typical Texas nursing facilities much selling power. For example, Medicaid evaluates the case mix on a scale from 1 to 12 in order to reward firms that care for many residents with serious physical or cognitive disabilities; but Table 1 shows that the actual average case mix is tightly clustered between 7 and 8 across all major categories of facilities --hardly an indication of aggressive product differentiation.

While private-pay patients account for a relatively small share of the industry's revenue, this market segment might seem to be the most suitable for product differentiation since third-party payers are not involved; instead, the residents or their families assume the expense. In their study of private-pay demand in Texas nursing facilities, Knox et al. (2006) indeed find a preference for non-profit homes and also for larger homes (perhaps because they could offer more amenities). Moreover, demand is estimated to be inelastic (about 0.7), an indication of market power. However, there is evidence that price-taking behavior tends to prevail even in the private-pay segment. For example, the median private-pay per diem is virtually identical to the median Medicaid per diem. This may reflect awareness on the part of nursing home managers that many private-pay patients will soon exhaust their assets and become Medicaid beneficiaries. In addition, Table 1 shows that excess capacity prevails in most nursing facilities; the relatively low occupancy rates presumably constrain the manager's ability to set prices. On balance, the assumption of price-taking behavior for the firms in model (2) does not seem to be at variance with what the industry-level data indicate about competitiveness in resource and product markets.

ELASTICITIES OF SUBSTITUTION AND RESOURCE DEMAND

While it is straightforward to define asubstitution elasticity for a cost function with just two resources, the concept is problematic when there are three or more resources. The translog cost model assumes that, as input prices vary, product managers make cost-minimizing adjustments to the entire input mix; and there are several definitions of the net substitution between any pair of resources. Perhaps the most widely-cited formula is the Allen (1938) partial elasticity of substitution between resources i and j:

$$A_{ij} = (\delta_{ij} + s_i s_j) / s_i s_j \quad . \tag{3}$$

However, Blackorby and Russell (1981, 1989) argue compellingly to replace A_{ij} by an asymmetric formula due to Morishima (1967):

$$M_{ij} = (A_{ji} – A_{ii})\, s_i \; . \tag{4}$$

The authors show that M_{ij}, unlike A_{ij},"(i) *is* a measure of curvature or substitution, (ii) *is* a sufficient statistic for assessing –quantitatively as well as qualitatively—the effects of changes in price or quantity ratios on relative factor shares, and (iii) *is* a logarithmic derivative of a quantity ratio with respect to a marginal rate of substitution or a price ratio" [Blackorby and Russell (1989), p. 883]. The logarithmic partial derivative "requires that only the i-th price, in the ratio p_i / p_j, should vary. Allowing p_j as well as p_i to vary would entail variation in all other price ratios, p_k / p_j, $k \neq i$, contrary to the definition of partial differentiation…Thus, asymmetry of partial elasticities of substitution is natural" [Blackorby and Russell (1989), p. 885].

In addition to the Morishima elasticities, we estimate the price elasticity of demand for each resource,

$$\eta_{ii} = [\delta_{ii} + s_i (s_i - 1)] / s_i \,. \qquad (5)$$

It is evident that expressions (4) and (5) are non-constant functions of the cost shares; accordingly, the sample means of the cost shares are used to evaluate the estimates of (4) and (5). Moreover, the elasticities are non-linear functions of the cost shares, so the point estimates and confidence intervals for M_{ij} and η_{ii} are computed using 5,000 replications of the bootstrap [Efron and Tibshirani (1993); Greene (2003), pp. 924-925].

It is clear that many nursing homes in Texas have fewer residents than their staff and facilities could accommodate. Table 1 documents low occupancy rates, and Knox et al (2007) find that the average technical inefficiency relative to the production frontier is between 8 and 20 percent. Can meaningful substitution elasticities be estimated using equations (2), (4) and (5) when many firms are operating at suboptimal levels while a few firms are on the cost frontier or even below it temporarily?

Evidently the model must have an asymmetric error distribution with a non-zero mean; but as Greene (2003, pp. 502-503) remarks, these features do "not negate our basic results for least squares in this classical regression model. The [stochastic frontier] model satisfies the assumptions of the Gauss-Markov theorem, so least squares is unbiased and consistent (save for the constant term), and efficient among linear unbiased estimators." In other words, least squares adequately estimates the *slope* coefficients of the cost function, and these determine the elasticities of substitution and resource demand.

This econometric result is based on the standard theory of the competitive firm, in which profit maximization can be seen as a two-stage process (conceptually, not sequentially in time). First the manager identifies the cost-minimizing combination of resources for any given level of production: equal marginal product per additional dollar spent on each resource. Then the manager selects the most profitable level of production based on the prevailing product prices: for each resource, the marginal revenue product equals the price of the resource. A stylized interpretation of the situation in Texas nursing facilities is that managers are performing the first task correctly but are in many cases failing at the second task. Given resource prices, managers are providing certain amounts of long-term care efficiently; but given Medicaid and Medicare per diems, most managers should be providing more long-term care than they do provide. Estimation of the elasticity parameters relates only to the first stage of the profit-maximization process and is unaffected by inefficiencies in the second stage.

Of course, this is not the only possible interpretation of the industry's situation; however, no model can capture all the different ways in which firms could be inefficient, so some premise about the manager's behavior is required. The assumption outlined in the previous paragraph is consistent with our model and estimation strategy, and it might be motivated as follows. Nursing home managers and their staff often have enough knowledge and experience to get the resource mix approximately right at the first stage of the profit-maximization process. For many reasons, however, managers may not provide the optimal amount of long-term care at the second stage of the process. After all, the current operating environment is fraught with uncertainties including sudden, significant changes in reimbursement polices for Medicaid and Medicare, the emergence of alternative long-term care arrangements such as assisted living, the vagaries of litigation when patients or their families allege malpractice and negligence, the labyrinth of the bankruptcy process (many facilities were reorganized under Chapter 11 during our sample period), and the complexities of obtaining financing for operations and capital improvements. Moreover, non-profit nursing facilities are presumably pursuing goals other than profit maximization (although the first stage is still relevant for these firms since, whatever their goals, it makes sense to try to achieve them at the least cost per unit of service provided.)

Having formulated the translog cost model, we now describe the data used to estimate it.

DATA SET AND DEFINITION OF VARIABLES

The source of our data is the cost reports of Texas nursing facilities participating in Medicaid [Texas Department of Human Services (1999), Texas Health and Human Services Commission (2002)]. The 1999 cross section contains 977 facilities, and the 2002 cross section contains 975 facilities; so the sample size is 1,952. In addition to the dummy variables mentioned above, the reports provide cost shares and prices for nine resource categories: registered nurses (rn); licensed vocational nurses (lvn); medication aides, restorative aides and nurse aides (aide); social workers, activity directors, and other resident care staff (orc); central supply, laundry and housekeeping staff (cslh); food-preparation personnel (food); maintenance workers (maint); the senior administrator (admin); and plant and equipment or "capital" (cap). The cost shares range from 2% for maint to 29% for aide. Choosing admin as the numeraire, we examine resource demand and utilization among the other eight categories. [Knox et al. (2001, 2005) explore the determinants of compensation for senior administrators in Texas nursing homes.]

The price variable for each human resource is an average hourly wage rate, specifically the ratio of wages and salaries to total hours worked during 1999 and 2002. Payroll taxes and employee benefits are excluded since the cost reports do not record those outlays in detail for our human-resource groups. Of course, the social security tax is a fixed fraction of salary so its omission does not affect the elasticity estimates in our model. The price for the capital resource is the facility cost per square foot of property in 1999 and 2002. Facility cost includes outlays for leasing, insurance, and interest as well as provisions for depreciation and amortization of plant and equipment. There is no apparent problem of multicollinearity since the correlation matrix of the eight resource prices has a condition number of 6.58, well below the threshold value of 20 that has been mentioned in the econometric literature as an indicator of a badly-conditioned set of regressors [Greene (2003), pp. 56-58].

DISCUSSION OF ELASTICITY ESTIMATES

The left half of Table 2 displays least-squares estimates of the price elasticity of demand (η_{ii}) for each resource. All the price elasticities are negative, as economic theory predicts; and according to the 90% confidence intervals computed by the bootstrap, all the elasticities are significantly different from zero with the exception of orc, whose elasticity is essentially zero (perfectly inelastic). The confidence intervals indicate that the other seven resource demands are either inelastic or approximately unit elastic.

Table 2
Resource Price Elasticities of Demand
(5,000 bootstrap samples)

	Least Squares Estimates n=1,952			Robust Regression Estimates n = 1,905		
Resource	**demand price elasticity**	**5% lower bound**	**95% upper bound**	**demand price elasticity**	**5% lower bound**	**95% upper bound**
rn	-0.898	-1.043	-0.751	-0.883	-1.031	-0.735
lvn	-0.490	-0.572	-0.411	-0.473	-0.555	-0.394
aide	-0.359	-0.430	-0.286	-0.317	-0.388	-0.246
orc	-0.049	-0.133	0.035	-0.037	-0.125	0.048
cslh	-0.840	-0.984	-0.697	-0.541	-0.658	-0.419
food	-0.806	-0.980	-0.606	-0.499	-0.584	-0.397
maint	-0.656	-0.767	-0.545	-0.641	-0.733	-0.545
cap	-0.382	-0.406	-0.357	-0.364	-0.386	-0.342

It is well known that least-squares estimation is vulnerable to outlying observations; therefore, the right-hand section of Table 2 displays the results of robust regression. Each equation (2) was estimated by the high-breakdown, high-efficiency algorithm of Yohai, Maronna, and Zamar [Insightful Corporation (2002)]. This exercise produced eight sets of residuals whose covariance matrix was computed using the Minimum Covariance Determinant (MCD) algorithm of Rousseeuw and van Driessen (1999) as implemented in S-plus [Insightful Corporation (2002)]. The MCD estimates a consistent covariance matrix that is minimally affected by stray data. The inverse of the matrix was then used to calculate a Mahalanobis-type distance for each sample observation --in other words, a multivariate measure of outlyingness. Observations whose distances exceeded a cut-off value were dropped from the sample. Our conservative cut-off value was the 99.9 percentile of the chi-square distribution with eight degrees of freedom, and it identified 47 data as probable outliers. [Detailed treatments of MCD and related methods are provided by Rousseeuw and Leroy (1987), Rousseeuw and van Zomeren (1990), Rocke and Woodruff (1996), and Maronna and Zamar (2002)].

For the most part, the robust estimates in Table 2 are close to the least-squares results. The exceptions are the demand elasticities for cslh and food, where the least-squares point estimates are notably larger in absolute value than their robust counterparts; and the respective confidence intervals do not overlap. In fact, all the robustly estimated elasticities are closer to zero than are the least-squares versions, so the elimination of outliers reinforces the impression that the eight demand functions are fairly inelastic over the price ranges in our data set.

Underlying these resource demand curves are the Morishima partial elasticities of substitution in equation (4), for which least-squares point estimates and 90% confidence intervals are displayed in Table 3. For each resource pair, the left-hand section of Table 3 shows the elasticity M_{ij} when the price of the first resource varies; and the right-hand section shows the elasticity M_{ji} when the price of the second resource varies. Evidently, there are some considerable asymmetries, as in the case of rn and aide. If the only change in resource prices is a 10% increase in the hourly wage of registered nurses, then the optimal ratio of aide to rn rises by 8.45%. If, however, it is the hourly wage of aides that increases by 10%, the optimal ratio of aide to rn drops by only 1.73%. Similar patterns exist for rn and orc and for lvn and orc, suggesting that nursing-home managers tend to use skilled nursing personnel only where they are indispensable, relying on aides, therapists, and activity directors to perform more general resident-care assignments.

Table 3
Morishima subsitution elasticities in the translog cost function
(least-squares estimates; n = 1,952; 5,000 bootstrap samples)

	Elasticity when the price of resource i varies			Elasticity when the price of resource j varies		
Resource pair (i,j)	**estimate of Mi,j**	**5% lower bound**	**95% upper bound**	**estimate of Mj,i**	**5% lower bound**	**95% upper bound**
rn,lvn	1.014	0.841	1.194	0.807	0.626	0.992
rn,aide	0.845	0.687	1.006	0.173	0.013	0.337
rn,orc	0.849	0.679	1.021	0.022	-0.068	0.112
rn,cslh	1.052	0.868	1.235	0.977	0.793	1.152
rn,food	1.014	0.857	1.179	0.921	0.699	1.114
rn,maint	1.145	0.932	1.356	0.721	0.608	0.840
rn,cap	0.971	0.822	1.124	0.502	0.464	0.537
lvn,aide	0.633	0.527	0.737	0.541	0.431	0.650
lvn,orc	0.619	0.477	0.760	0.073	0.018	0.164
lvn,cslh	0.640	0.518	0.757	0.890	0.732	1.043
lvn,food	0.575	0.442	0.703	0.834	0.607	1.032
lvn,maint	0.676	0.483	0.870	0.675	0.561	0.789
lvn,cap	0.589	0.505	0.675	0.441	0.411	0.471
aide,orc	0.376	0.221	0.529	0.051	-0.038	0.140
aide,cslh	0.692	0.561	0.821	0.925	0.771	1.076
aide,food	0.811	0.654	0.961	0.934	0.704	1.133
aide,maint	0.374	0.183	0.563	0.659	0.544	0.772
aide,cap	0.472	0.391	0.555	0.435	0.406	0.463
orc,cslh	0.016	-0.085	0.116	0.789	0.612	0.967
orc,food	0.019	-0.084	0.123	0.749	0.480	0.976
orc,maint	0.103	-0.030	0.240	0.685	0.553	0.817
orc,cap	0.065	-0.022	0.151	0.435	0.404	0.467
cslh,food	0.912	0.744	1.078	0.887	0.670	1.093
cslh,maint	1.041	0.860	1.226	0.717	0.592	0.845
cslh,cap	0.874	0.728	1.017	0.446	0.415	0.475
food,maint	0.769	0.535	0.972	0.648	0.538	0.758
food,cap	0.839	0.635	1.014	0.439	0.410	0.469
maint,cap	0.663	0.556	0.776	0.421	0.384	0.456

Another set of notably asymmetric Morishima elasticities involves orc vis-à-vis cslh, food, and maint. According to the left-hand section of Table 3, the latter three human resources are not substitutes for orc; however, the right-hand section of the table shows that orc can be partial substitutes for cslh, food, and maint. This is plausible if the orc personnel are "jack of all trades," assisting as needed for inventory management, housekeeping, food preparation, and light maintenance such as cleaning and painting.

For all the substitution elasticities in Table 3, the point estimates are inelastic or barely unit elastic; the largest 95% bound is just 1.356; and the M_{ij} for the pairs orc,cslh, orc,food, and orc,maint do not differ significantly from zero. In other words, many resources employed in nursing facilities are more nearly complements than substitutes. This also seems plausible since, apart from the aide and orc categories, other personnel and equipment appear to be specialized. With respect to cap (plant and equipment), the largest substitution elasticities are rn,cap, cslh,cap, and food,cap; but even these are barely unit elastic according to the confidence intervals. Such patterns suggest that the scope for automation is rather limited under the typical resource usage observed in 1999 and 2002.

Table 4
Morishima subsitution elasticities in the translog cost function
(robust regression estimates; n = 1,905; 5,000 bootstrap samples)

	Elasticity when the price of resource i varies			Elasticity when the price of resource j varies		
Resource pair (i,j)	**estimate of M(i,j)**	**5% lower bound**	**95% upper bound**	**estimate of M(i,j)**	**5% lower bound**	**95% upper bound**
rn,lvn	1.005	0.832	1.179	0.812	0.625	0.994
rn,aide	0.826	0.663	0.986	0.124	0.040	0.292
rn,orc	0.844	0.676	1.019	0.018	0.074	0.112
rn,cslh	0.961	0.780	1.142	0.612	0.457	0.757
rn,food	0.999	0.836	1.164	0.619	0.507	0.715
rn,maint	1.171	0.977	1.368	0.716	0.618	0.816
rn,cap	0.957	0.807	1.108	0.491	0.456	0.526
lvn,aide	0.624	0.520	0.732	0.511	0.404	0.618
lvn,orc	0.656	0.511	0.804	0.074	-0.020	0.166
lvn,cslh	0.555	0.437	0.673	0.568	0.433	0.692
lvn,food	0.500	0.380	0.617	0.512	0.398	0.611
lvn,maint	0.711	0.525	0.895	0.664	0.567	0.760
lvn,cap	0.566	0.484	0.651	0.422	0.393	0.449
aide,orc	0.414	0.262	0.564	0.053	-0.039	0.144
aide,cslh	0.593	0.465	0.722	0.612	0.479	0.729
aide,food	0.648	0.530	0.770	0.596	0.489	0.683
aide,maint	0.284	0.084	0.474	0.639	0.543	0.737
aide,cap	0.421	0.341	0.501	0.413	0.386	0.441
orc,cslh	0.000	-0.099	0.098	0.481	0.340	0.614
orc,food	-0.044	-0.151	0.060	0.350	0.189	0.494
orc,maint	0.065	-0.064	0.201	0.655	0.548	0.763
orc,cap	0.056	-0.036	0.146	0.424	0.390	0.457
cslh,food	0.594	0.453	0.724	0.561	0.453	0.662
cslh,maint	0.649	0.497	0.791	0.673	0.575	0.772
cslh,cap	0.565	0.441	0.681	0.410	0.381	0.439
food,maint	0.433	0.315	0.537	0.624	0.531	0.720
food,cap	0.532	0.432	0.619	0.417	0.389	0.445
maint,cap	0.651	0.558	0.744	0.426	0.392	0.460

Of the 56 substitution elasticities in Table 3, only 18 have confidence intervals that include 1, the Cobb-Douglas elasticity. In other words, for the purpose of modeling the typical resource mix in Texas nursing homes, a Cobb-Douglas hypothesis is unlikely to be satisfactory.

All the estimates in Table 3 were repeated with the data set from which 47 outliers were deleted. The robust results, displayed in Table 4, are broadly similar to the least-squares estimates. As with the resource demand elasticities, the robust Morishima elasticities tend to be even less elastic than their least-squares counterparts; for example, only six robust confidence intervals include 1.

SUMMARY, CONCLUSIONS, AND CONJECTURES

Subject to the limitations inherent in our data, model and methodologies, we conclude that the demand for resources in Texas nursing facilities is inelastic or at most unit elastic. Of the resource pairs examined in this paper, many are virtually complementary in production. This comment applies in particular to the relationship between most human resources and the typical nursing home's plant and equipment. Cost-effective automation in Texas nursing facilities is likely to be limited unless wage rates increase substantially in relation to the cost of capital. This kind of change in relative resource costs might, for example, result from large-scale retirements of nursing personnel in the baby-boom cohort and from restrictions on immigration that reduce the supply of nurses' aides, food-preparation employees, and custodial workers.

We have proposed an interpretation of our translog cost model in which many nursing home managers choose a cost-minimizing combination of resources but nevertheless operate inefficiently because they accept too few residents. In other words, managers may achieve technical efficiency but not allocative efficiency. What are the obstacles to higher average occupancy rates in Texas nursing facilities, and which of these obstacles might be reduced by appropriate public policies?

First, federal and state reimbursement arrangements could be more stable and transparent. We have mentioned that Medicaid reimbursement in Texas is based on a prospective fixed-rate, case-mix system. But is the application of this system reliable and predictable in practice? As recently as 1998, the robustly-computed cross-sectional correlation between a facility's case mix and its Medicaid per diem was 0.92; by 2002, however, the correlation was only 0.04! Another example of unstable payment policy is the Congress' abrupt decision in 1998 to slash the Medicare per diem, which is believed to have precipitated or accelerated widespread Chapter 11 bankruptcy filings by Texas nursing home chains in recent years (Guerra 2002, Lagnado 2002, Barr 2005). Yet another instance is the Medicaid crisis that arose when public-sector budgets in Texas and other states moved sharply into deficit during the growth recession of 2001-2003.

In the second place, state regulators could be more proactive in helping to match supply and demand for long-term care. We have mentioned that the 1986 repeal of the Certificate of Need law was followed by a large expansion of capacity in Texas nursing facilities. As it happened, this growth coincided with the emergence of alternative long-term care arrangements like assisted living, which probably exacerbated the excess supply of beds. Given the virtual certainty of a rapidly aging population, average occupancy rates in nursing homes may well rise from now on. Nevertheless, government agencies should try to anticipate institutional, technological, and demographic trends in elder care so that regulatory changes have positive impacts on the industry's development. For example, regulations that impede the introduction of new technology need to be scrutinized (Flood 1999, 2000). Moreover, the granting of tax-exempt status requires careful monitoring to guarantee that the operations of non-profit nursing facilities in fact contribute to accessible, high-quality long-term care.

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