TECHNICAL EFFICIENCY IN TEXAS NURSING FACILITIES: A STOCHASTIC PRODUCTION FRONTIER APPROACH

*By Kris Joseph Knox, Eric C. Blankmeyer, and J. R. Stutzman**

Abstract

A rapidly aging U. S. population is straining the resources available for long term care and increasing the urgency of efficient operations in nursing homes. The scope for productivity improvements can be examined by estimating a stochastic frontier production function. We apply the methods of maximum likelihood and quantile regression to a panel of Texas nursing facilities and infer that the average productivity shortfall due to avoidable technical inefficiency is at least 8 percent and perhaps as large as 20 percent. Non-profit facilities are notably less productive than comparable facilities operated for profit, and the industry has constant returns to scale (JEL I11, L89, D12).

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, Lueck 2005a, 2005b). These developments increase the importance of efficient operations in geriatric facilities, of which the traditional nursing home is still the prototype. It is therefore important to discover whether there is scope for substantial productivity improvement in the nation's nursing facilities. How do best-practice firms use their resources? How large is the output gap between these firms and their counterparts who achieve only average productivity? Should regulators promote mergers to exploit scale economies or should they encourage competition among independent enterprises? Do for-profit nursing homes employ their resources more effectively than comparable non-profit facilities?

This paper examines technical efficiency in the Texas nursing home industry, one of the largest in the nation. The microeconomic production function is an appropriate model for exploring the issues mentioned above, especially when econometric methods are used to estimate the stochastic frontier –the production function of the firms that achieve technical efficiency, within the limits of sampling error. Using a panel of facilities from 1999 and 2002, we estimate the 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. The remainder of the paper includes an overview of nursing facilities in Texas, a concise survey of data envelope analysis and the stochastic production frontier as frameworks for modeling technical efficiency, a proposal that quantile regression could be used to complement maximum likelihood estimation for stochastic production frontiers, the specification and estimation of a production function for Texas nursing homes, and a discussion of the implications for technical efficiency, scale economies, and overall economic efficiency.

---

* Kris Joseph Knox, Department of Maritime Administration, Texas A&M University at Galveston, Galveston, TX 77552; Eric C. Blankmeyer and J. R. Stutzman, Department of Finance and Economics, Texas State University, San Marcos, TX 78666, eb01@txstate.edu.

An Overview of Texas Nursing Facilities

Before formulating an operational model of production and technical efficiency in Texas nursing homes, we offer an overview of the industry. 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: 2002 Texas Nursing Facility Industry Profile

Facility & Characteristics	Profit Seeking		Nonprofit	
	Chain	Independent	Chain	Independent
Number of facilities	709	135	94	79
Average number of beds	113.56	102.93	109.32	101.72
Average occupancy rate (%)	68.43	71.10	76.45	83.53
Sources of revenue:				
Medicaid (%)	61.74	69.04	58.71	59.31
Medicare (%)	19.16	9.46	14.94	5.75
Private Pay (%)	13.89	15.86	17.33	20.48
Other (%)	5.21	5.64	9.02	14.46
Average case-mix index (on a scale of 1-12)	7.35	7.58	7.62	7.74

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. Table 1 provides an overview of licensed Texas nursing facilities participating in the Medicaid program in 2002. 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 vigorous merger and consolidation throughout the 1990s. More recently, Texas nursing homes have experienced a rash of bankruptcies. It appears that these insolvencies are attributable in part to the industry's heavy reliance on Medicare reimbursements for patients receiving short-term therapy following surgery or other medical intervention. In Texas, the median 1999 Medicare per diem was about three times larger than for Medicaid or private-pay residents. Concerns about excessive payments led the

Congress to curtail Medicare funding, and nursing homes nationwide incurred big losses. However, few of the bankrupt facilities in Texas closed their doors; many were salvaged by merger and acquisition.

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 average 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.

Modeling Technical Efficiency

Economists make extensive use of parametric production functions, which they often estimate by ordinary least squares (OLS) or one of its variants. However, many researchers believe that parametric models are unduly restrictive and prefer to study the structure of production via data envelope analysis (DEA). Unfortunately, DEA results are not robust against outliers because they are based on the data forming part of the convex hull of the sample, precisely those observations that statisticians often consider unreliable and choose to discard using "convex peeling" [Rousseeuw and Leroy (1987, pp. 253-254); Greene (1999, pp. 97-99); SOA Associates (2003)].

Despite these problems, there are several applications of DEA to the nursing home industry, including Fizel and Nunnikhoven (1992), Duffy et al. (1994), Erlandsen and Forsund (1999), Kooreman (1994), Nyman and Bricker (1989) and SOA Associates (2003). In particular, Nyman and Bricker (1989) use DEA to calculate efficiency scores for184 nursing facilities in Wisconsin in 1979. There are five output measures ranging from patients in skilled nursing facilities (SNF) to those requiring only assisted living; and there are four inputs measuring the average daily hours of nurses, social workers, therapists and other employees. The mean inefficiency is estimated to be 10.8 percent. Using the DEA scores as the dependent variable in a regression model, the authors find that for-profit nursing homes have significantly higher technical efficiency than their nonprofit counterparts. The proportion of SNF residents, the wage rates paid to employees, and an urban location are also statistically significant determinants of efficiency. Less successful are variables measuring the size of the nursing facility, hospital affiliation, and quality of care.

SOA Associates (2003) use DEA to evaluate a nation-wide sample of SNFs. 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 authors screen for outlying data by peeling off a number of extreme observations as mentioned above. The average inefficiency is estimated to be 36 percent. For SNFs 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).

The principal alternative to DEA is the stochastic production frontier (SPF). Debreu (1951) and Farrell (1957) raise the conceptual issue that led to the development of SPF methods: the OLS stochastic model is incompatible with the microeconomic theory of a production function. The latter is supposed to be a technological relationship that shows the maximum output achievable with a given combination of resources. While particular firms may fall short of the optimal outcome, they cannot exceed it, logically speaking. Therefore, the sample observations cannot be scattered randomly and symmetrically around the production function as the OLS model requires. To address this problem, the SPF estimates a parametric production function that includes a compound random error reflecting productivity variations due to (1) avoidable mistakes in a firm's organization, management, and technology; and (2) effects beyond a firm's control such as macroeconomic shocks. The former variations are efficiency shortfalls that enter the production function with a negative sign, while the latter can have either sign.

Aigner et al. (1977) propose a maximum likelihood estimator (MLE) for the SPF. They consider a Cobb-Douglas production function in which the output y is produced by k resources x_k :

$$\ln y = \beta_0 + \Sigma \beta_k \ln x_k - u + v \ . \tag{1}$$

The random error is composed of two terms: v represents shocks that a firm cannot avoid; these can be positive or negative and are assumed to have a normal distribution centered at zero. The efficiency shortfall that a firm can potentially avoid or rectify is represented by u. Aigner et al. examine two alternative distributions for u: the absolute value of a normal variable or an exponential variable. The corresponding nonlinear log-likelihood functions are maximized by numerical methods [e.g., Greene (1999, pp. 100-102; 2003, pp. 502-504)]. An important parameter is E(u), in percentage terms the average avoidable inefficiency or productivity shortfall, which is estimated as the average residual in MLE and quantile regression.

Dor (1994) and Newhouse (1994) discuss applications of stochastic frontier production and cost models to the health care industry. Several papers bring the methodology to bear on nursing homes. In particular, Vitaliano and Toren (1994) apply a stochastic frontier cost function to a biannual panel of 607 nursing facilities in New York and estimate the average cost inefficiency at 29 percent. This shortfall is associated with excessive overhead cost and diseconomies of scale in both for-profit and non-profit firms. Using a sample of 653 nursing facilities from a national survey in 1995, Anderson et al. (1999) construct a Bayesian SPF model to compute average inefficiency, which they estimate to be 37 percent. The authors find that non-profit homes are almost always less efficient than their for-profit counterparts. More surprisingly, perhaps, the model shows that members of nursing home chains are very likely to be less efficient than independent facilities.

Filippini (1999) examines a panel of 36 Swiss nursing facilities during the period 1993-1995. His translog stochastic cost frontier model, which controls for differences in quality and institutional organization, indicates that facilities operated by the government incur higher costs than other nonprofit homes, other things equal. Moreover, scale economies are found at most output levels. Farsi et al. (2005) study the same Swiss nursing homes, extending the panel to 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. (2005) 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).

In this paper, we use the SPF rather than DEA because our interest is in parametric models that provide a concise representation of the industry's productive structure, making due allowance for random variation among firms and offering general policy guidance. With respect to the choice of modeling a production function or a cost function, the well-known theorem of Shephard (1970) shows that the two forms provide equivalent information for firms that are price takers in their resource markets. However, estimation of the cost function requires data on the resource prices.

To avoid spurious regression, those prices should be constructed independently of the cost data, the dependent variable; in other words, resource prices computed as unit values (e. g., average cost per worker-year) seem problematic. Lacking independent measurements of the resource prices paid by Texas nursing facilities, we proceed to model the stochastic production frontier.

Quantile Regression

As a complement to MLE, we propose to estimate the SPF model using the quantile regression (QR) of Koenker and Bassett (1978). According to Koenker and Hallock (2000, p. 19), "There is often a compelling substantive case for focusing attention on the behavior of conditional extreme values...in production-cost models where they represent firms near the technological frontier." We argue that the top quantiles (percentiles) of the production function are intuitively appealing estimators of the SPF; moreover, QR has a useful property of monotonicity and is more robust than the half-normal MLE when there are outliers in the measurements of output, the dependent variable in the production function.

Just as OLS estimates the conditional mean of the dependent variable in a linear model, the conditional median (the fiftieth percentile) can be estimated by minimizing the sum of the absolute residuals, often called the L_1 norm. Generalizing this idea, Koenker and Bassett define the quantile regression for the kth conditional percentile, QR(k), as the vector b of linear regression coefficients that minimizes

$$\Sigma\, k|y_i - x_i b| + \Sigma\, (1\text{-}k)|y_i - x_i b| \qquad (2)$$

where $0 < k < 1$, y_i is an observation on the dependent variable, x_i is an observation on a vector of independent variables, the first summation runs over the positive residuals ($y_i > x_i b$), and the second summation runs over the negative residuals ($y_i < x_i b$). Thus, QR(0.50) is the median or the L_1 norm, where positive and negative residuals receive equal weight since $k = 1 - k$.

However, our interest focuses on the top quantiles, for example QR(0.90). In the context of a production function for nursing homes, QR(0.90) estimates the 90th percentile of output conditional on the resources employed and on other relevant regressors. Positive residuals are heavily penalized in the minimand, so the regression plane closely approximates the theoretical production function but still makes allowance for random variation. In this sense, QR(0.85), QR(0.90), QR(0.95) and other percentiles in the upper tail of the conditional distribution represent the production frontier where best-practice firms are operating.

It may be helpful to visualize the QR process for bivariate linear regression, with the dependent variable on the vertical axis and the independent variable on the horizontal axis as usual. If the model's random errors are homoscedastic, the regression lines for QR(0.85), QR(0.90), and QR(0.95) will be almost parallel to one another; any differences in their slopes are due merely to sampling error. However, the intercepts of the lines will tend to be different: QR(0.85) lies below QR(0.90), which is underneath QR(0.95). On the other hand, it is possible that the various quantiles will have different slopes due to heteroscedasticity or because a single parametric model cannot adequately represent the bivariate relationship over the entire conditional distribution. The latter situation is obviously of considerable importance in the exploration of technical efficiency.

There is of course the question which of the top quantiles should represent the SPF. The accuracy with which those percentiles can be differentiated obviously depends on the size of the sample and the amount of information it contains about the upper tail of the conditional distribution (Koenker 2005, pp. 130-131). In their study of medfly longevity, for example, Koenker and Geling (2001) compute regression quantiles over intervals like (0.9991, 0.9992...0.9999); but then their sample contains almost 20,000 observations. Koenker and Bassett (1978) advocate linear combinations of adjacent quantiles. As a practical matter, it seems evident that nursing facilities whose productivity --output conditional on given levels of resource utilization-- is at the 90th percentile are among the best-practice firms in the industry. Accordingly, we focus on the production function at QR(0.90); however, we also report the average avoidable productivity shortfalls at QR(0.85) and QR(0.95).

The half-normal MLE is quite vulnerable to outlying data in the dependent variable because it maximizes a function involving squared errors; anomalous observations can have a drastic impact on the estimates of coefficients and average inefficiency. On the other hand, QR is much less susceptible to outliers since it minimizes the absolute values of the errors instead of their quadratic values. However, both methods are vulnerable to bad leverage points among the regressors, an issue that we address below.

The conditional linear quantile function has a useful property of monotonicity: Koenker and Hallock (2000, p. 18) remark that "the quantiles are equivariant with respect to any monotone increasing transformation, so the transformed random variable h(Y) has conditional quantile functions $Q_{h(Y)}(\tau) = h(Q_Y(\tau))$, a fact that considerably simplifies the interpretation of a wide variety of transformation models." (Here τ stands for any percentile.) Additional discussion of the homothetic properties of quantile regression and related methods is provided by Rousseeuw and Hubert (1999), which includes a comment by Roger Koenker and a rejoinder by P. J. Rousseeuw et al.

For the linear model with independent and identically distributed disturbances, Bassett and Koenker (1978) show that QR is $\sqrt{n}$-consistent and asymptotically normal with a large-sample covariance matrix proportional to $(X'X)^{-1}$. In the case of panel data like ours, heteroscedasticity needs to be taken into account. Koenker and Zhao (1994) demonstrate that QR is $\sqrt{n}$-consistent and asymptotically normal for conventional heteroscedastic linear models. The precision of the regression coefficients can be estimated by the inversion of a rank test that "offers a reliable method of constructing confidence intervals in the non-iid error context. These intervals are constructed to find a set of hypothetical values of the parameter that would not lead to rejection at the prescribed level. The test, in turn, is based on a fundamental link between the formal linear programming dual of the quantile regression optimization problem and the theory of rank statistics, introduced in Gutenbrunner and Jureckova (1992)" [Koenker and Hallock (2000), pp. 13-14]. We use the S-plus function "rq" (Insightful Corporation, 2002) to compute these robust confidence intervals.

Koenker (2005) and Koenker and Hallock (2000, 2001) provide accessible surveys of QR; among other topics, they discuss robustness, computation, software availability, inferential procedures, caveats in the use of QR, and applications in areas like prenatal care, education policy, labor market discrimination, demand analysis, and value at risk in financial markets. Koenker and Machado (1999) propose a goodness-of-fit statistic for quantile regression analogous to R-squared in OLS regression.

Specification and Estimation of a Production Function

In view of the low utilization rates observed in many Texas nursing facilities, we turn to the specification of a production function model that can characterize the behavior of firms achieving various levels of technical efficiency. Interest naturally centers on the nursing homes that, within the limits of sampling error, appear to be the most productive. From the cost reports for 1999 and 2002 (Texas Department of Human Services 1999, Texas Health and Human Services Commission 2002), we constructed a panel of nursing facilities participating in the Medicaid program. We define a facility's output – the dependent variable -- as the number of resident days it provided in 1999 or 2002. Because this might be considered an unduly restrictive measure of long-term care, indexes of quality and case mix were included as controls in some exploratory regressions. Specifically, the Texas Department of Human Services (2000) uses a Quality Reporting System (QRS) to summarize information about the health and capabilities of each facility's residents as well as deficiencies, complaints and violations documented by regulators. The case mix is quantified in the Texas Index of Level of Effort (TILE), in which every resident of a facility is assigned to one of eleven categories based on the amount of supervision and assistance that the person requires. However, the QRS and the TILE were not statistically significant in any regressions and have not been retained in the model.

As for the model's regressors, the inputs to the production function include the number of beds (BEDS, a proxy for the capital stock) and the annual hours worked by six groups of employees: registered nurses (RN), licensed vocational nurses (LVN), nurses' aides (AIDE), other resident care staff including social workers and activity directors (ORCS), laundry and housekeeping personnel (L&H), and food preparation staff (FOODPREP). In addition, there are dummy variables representing ownership (for-profit = 1, nonprofit = 0) and time (1999 = 1, 2002 = 0).

With respect to data preparation, it bears repeating that our estimation methods are not robust against bad leverage observations among the continuous-valued regressors. We screen for these bad leverage points using the Minimum Covariance Determinant (MCD) algorithm of Rousseeuw and van Driessen (1999) as implemented in S-plus (Insightful Corporation, 2002). For our seven resource inputs, the algorithm estimates a consistent correlation matrix that is minimally affected by stray observations. The inverse of the correlation matrix is then used to compute a Mahalanobis-type distance for each sample observation, a multivariate measure of outlyingness. Observations whose distances exceed a cut-off value, the 97.5 percentile of the chi square distribution with seven degrees of freedom, are dropped from the sample. 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). This data cleaning eliminated 157 observations, so our panel contains 1,833 observations, of which 910 are from 1999 and 923 are from 2002. In each year, the sample covers more than eighty percent of all the licensed nursing homes in Texas.

Initially we considered a translog production function as the model for Texas nursing facilities [Berndt and Christensen (1973)], but collinearity among the regressors precluded its use. The condition number of their correlation matrix --including linear, quadratic and interaction terms in the logarithms of the resources-- is 2,133.7, much higher than the value of about 20 mentioned in the literature as a threshold indicator of multicollinearity [Greene (2003, 56-59)]. However, the Cobb-Douglas model, a special case of the translog function, has a condition number of 8.0, which is acceptable. Accordingly, we adopt the Cobb-Douglas functional form.

The production function is a structural relationship, part of a theoretical framework in which for-profit nursing homes are trying to maximize profits and non-profit facilities are pursuing other objectives, for example maximum "service" subject to a budgetary constraint. Therefore, the production function's identification status has to be examined, at least to the extent of verifying the "order condition" [Greene (2003, pp. 389-394)]. Among the regressors, some of the human-resource inputs are likely to be endogenous variables; for example, a decision on the utilization of nurses' aides probably depends of the volume of resident days to be provided. On the other hand, the excluded variables that appear to be exogenous to the facility include the seven resource prices, the Medicaid reimbursement rate, and various determinants of the demand for long-term care such as the size and income of the elderly population and the availability of alternatives to nursing-home care like assisted living facilities. From the standpoint of these exclusions, therefore, the production function is in fact overidentified. A related issue is the possibility of simultaneous-equation bias. Unfortunately, the question is moot because our data set does not provide enough valid instrumental variables for the human-resource inputs. For example, suitable estimates of the resource prices paid by each facility are not available.

Discussion of Estimation Results

Table 2 shows estimates for the Texas nursing home production function based on the half-normal MLE model; the coefficients for the exponential model are very similar. The MLE standard errors have been corrected for heteroscedasticity using White's consistent estimator of the covariance matrix (e. g., Greene 2003, pp. 220-221); and all the MLE coefficients are statistically significant at the 1% level. A typical nursing home operated for profit provides 9.8% more resident days than a non-profit home using the same resources. A nursing home whose aides work 10% more hours provides 3.3% more resident days, other things equal. The mean MLE residual, an estimate of the typical shortfall from technical efficiency due to avoidable errors, is -11.4%; and its standard deviation is 0.3%, indicating a high level of statistical significance. In the exponential MLE model, the average technical inefficiency is estimated to be -8.0%.

Table 2 also shows the QR(0.90) version of the SPF. The Koenker-Machado analogue of R-squared is 0.75. The estimate of average technical inefficiency, -14.9% with a standard deviation of 0.3%, is larger in absolute value than its MLE counterparts. The QR(0.90) slope coefficients generally agree in sign and order of magnitude with the corresponding MLE results. Two exceptions are ln LVN, whose QR(0.90) coefficient is half as large as the MLE estimate, and ln BEDS, whose QR(0.90) coefficient is twice that of the MLE estimate. The Spearman rank correlation between the half-normal MLE residuals and the QR(0.90) residuals is 0.94 ($p = 0.000$), so the two regression methods are in excellent agreement when it comes to scoring the inefficiency of individual nursing facilities in the sample. All the QR(0.90) coefficients are statistically significant at the 5% level or better. As previously explained, these significance levels are based on confidence intervals that allow for the possibility of heteroscedasticity. As an additional point of comparison, the estimates for QR(0.85) and QR(0.95) are displayed in Table 3, where the average efficiency shortfalls are respectively -11.9% and -18.3%, each with a standard deviation of about 0.3%.

Table 2: Estimates of a Texas Nursing Home Production Function

	Half-normal MLE	QR(0.90)
Intercept	0.810**	1.648**
For-profit dummy variable	0.098**	0.077**
1999 dummy variable	0.084**	0.062**
ln RN	0.035**	0.021*
ln LVN	0.123**	0.060**
ln AIDE	0.334**	0.264**
ln ORCS	0.054**	0.046**
ln L&H	0.164**	0.168**
ln FOODPREP	0.168**	0.181**
ln BEDS	0.120**	0.257**
Average residual	-0.114**	-0.149**

Note: ** statistically significant at 1 % level; and * statistically significant at 5 % level. n = 1,833 nursing facilities; dependent variable = ln resident days.

In Tables 2 and 3, the estimated coefficient for the 1999 dummy variable is positive and statistically significant at the 1% level; its value ranges from 5.3% to 8.4%. Why did best-practice nursing facilities experience this deterioration in performance between 1999 and 2002 ? Among the possible explanations, two in particular deserve to be mentioned. In the first place, Texas did not escape the recession that afflicted the U. S. economy at the start of the 21st century; the state incurred a large fiscal deficit, and the Medicaid budget which is crucial to nursing facilities came under severe pressure. Secondly, Congress tinkered extensively with Medicare reimbursement during this period, legislating in 1997 some large, unanticipated cuts that contributed to a rash of nursing-home bankruptcies nationwide. Congress then responded by providing stopgap supplemental funding for Medicare in 1999 and 2000. It seems evident that the impacts of these policy shifts extended to 2002 and beyond, making it very difficult for the industry to manage its operations efficiently.

In any case, our regression results suggest that the typical technical efficiency of nursing homes in Texas is at least 8% -- and perhaps as much as 20% -- below that of the best-practice facilities. If indeed the average avoidable inefficiency approaches 20%, then managers and regulators of Texas nursing facilities should find it well worthwhile to explore policies and practices that could reduce such a large productivity gap. These measures might include improved arbitration of liability claims and more consistent reimbursement rules for Medicaid and Medicare. In addition, regulations that impede the introduction of new technology may need to be reviewed (Flood, 1999 and 2000). Moreover, the granting of tax-exempt status requires careful monitoring since Tables 2 and 3 show that non-profit nursing homes are notably less efficient than comparable facilities operated for profit. This is, of course, a well-known empirical result; in particular, it supports the findings of Anderson et al. (1999), who apply a Bayesian SPF to a national sample of nursing facilities.

Table 3: Additional Quantile Regression Estimates of a Production Function

	QR(0.85)	QR(0.95)
Intercept	1.317**	1.982**
For-profit dummy variable	0.081**	0.048*
1999 dummy variable	0.073**	0.053**
ln RN	0.027**	0.014*
ln LVN	0.082**	0.069*
ln AIDE	0.293**	0.259**
ln ORCS	0.044**	0.047**
ln L&H	0.175**	0.155**
ln FOODPREP	0.171**	0.160**
ln BEDS	0.202**	0.271**
Average residual	-0.119**	-0.183**

Note: ** statistically significant at 1 % level; and * statistically significant at 5 % level. n = 1,833 nursing facilities; dependent variable = ln resident days.

We have already noted that, after years of consolidation and acquisition, only 20% of Texas nursing homes remain independent; it seems relevant to ask whether this merger activity may now have exhausted its usefulness. After all, microeconomic theory indicates that one symptom of insufficient competition is the existence of pervasive excess capacity and the concomitant technical inefficiency. An examination of the SPF's returns to scale may provide further insight on this issue since scale economies provide a rationale for chain membership and for consolidation in general. In Table 2, the returns to scale are estimated by summing the coefficients of the seven resources. For the half-normal MLE, this sum is 0.998; and a chi-square test of constant returns has a significance level of 0.796. For the exponential MLE, the resource coefficients sum to 0.996; and the significance of the chi-square test is 0.525. In the case of QR(0.90), the sum of the resource coefficients is 0.997; and the significance level of an F-test is 0.848. In other words, the hypothesis of constant returns to scale is very credible, a conclusion that reinforces our skepticism about the economic value of additional consolidation among Texas nursing facilities.

The inferences drawn from Tables 2 and 3 demonstrate the usefulness of QR as a complement to the widely used MLE method. Specifically, QR provides a second opinion about the average avoidable productivity shortfall, the size and statistical stability of regression coefficients, and the extent of scale economies.

Finally, it seems worthwhile to comment on the scope and relevance of technical efficiency. This goal, which has been the focus of the paper, is evidently desirable from society's viewpoint and also from the perspective of any enterprise that does not exercise much market power, even if the enterprise is not devoted to maximizing profit. After all, technical efficiency is basically a strategy to avoid wasting scarce resources. Microeconomic theory emphasizes, however, that technical efficiency is only a necessary condition for the achievement of overall economic efficiency. Managers of nursing homes must also take into account the demand side of their market, primarily the structure of Medicaid reimbursement but also income from Medicare, private patients, and charitable contributions.

For this purpose, the examination of a production function will often be complementary to a study of the profit function that characterizes a group of nursing facilities. The latter is a reduced-form model in which a firm's profit is explained by the enterprise's organizational objectives and operating characteristics, the prices of its products or services, the prices of its variable resources, its capital stock and other relevant variables. In principle, the profit function reflects both technical and allocative efficiency [Lau and Yotopoulos (1971), Greene (1999, pp. 114, 120-125), Kumbhakar and Tsionas (2005)]. Profit functions for Texas nursing facilities are estimated and analyzed in Knox et al. (2001, 2003). With respect to the higher technical efficiency of for-profit homes and the prevalence of constant returns to scale, their results are consistent with the estimates reported in this paper.

References

Aigner, D. J., C. A. K. Lovell, and P. Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Models." *Journal of Econometrics* 6: 21-27.

Anderson, R. L., D. Lewis, and J. R. Webb. 1999. "The Efficiency of Nursing Home Chains and the Implications of Non-profit Status." *Journal of Real Estate Portfolio Management* 5: 235-245.

Berndt, E., and L. Christensen. 1973. "The Translog Function and the Substitution of Equipment, Structures, and Labor in U. S. Manufacturing, 1929-1968." *Journal of Econometrics* 1: 81-114.

Caffrey, A. 2001. "States Seek to Curb Medicaid Costs." *Wall Street Journal*, February 7, B13.

Debreu, G. 1951. "The Coefficient of Resource Utilization." *Econometrica* 19: 273-292.

Dor, A. 1994. "Non-minimum Cost Functions and the Stochastic Frontier: On Applications to Health Care Providers." *Journal of Health Economics* 13: 329-334.

Duffy, J. A. M., J. A. Fitzsimmons, and N. Jain. 1994. "Analysis of Nursing Home Care Using

DEA." *Proceedings of the Decision Sciences Institute* 3: 1870-1872.

Erlandsen, E., and F. R. Forsund. 1999. "Efficiency in the Provision of Municipal Nursing- and Home-Care Services: The Norwegian Experience." Oslo, Norway: University of Oslo Department of Economics memorandum No. 32/99.

Farrell, M. J. 1957. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society* A120: 253-290.

Farsi, M., M. Filippini, and M. Kuenzle. 2005. "Unobserved Heterogeneity in Stochastic Cost Frontier Models: An Application to Swiss Nursing Homes." *Applied Economics* 37: 2127-2141.

Filippini, M. 1999. "Cost and Scale Efficiency in the Nursing Home Sector: Evidence from Switzerland," Quaderno N. 99-02, Lugano, Switzerland: Universita della Svizzera Italiana.

Fizel, J. L., and T. S. Nunnikhoven. 1992. "Technical Efficiency of For-Profit and Non-Profit Nursing Homes." *Managerial and Decision Economics* 13: 429-439.

Flood, M. 1999. "Use of Machines to Dispense Drugs To Nursing-Home Patients Is Debated," *Wall Street Journal*, December 1, T4.

Flood, M. 2000. "Blow Dealt To Pharmacy Machines," *Wall Street Journal*, March 8, TX1.

Giacalone, J. A. 2001. *The U. S. Nursing Home Industry*. Armonk, NY: M.E. Sharp.

Greene, W. H. 1999. "Frontier Production Functions" in *The Handbook of Applied Econometrics*, Volume II, 81-166, edited by M. H. Pesaran and P. Schmidt. Oxford, UK: Blackwell.

Greene, W. H. 2003. *Econometric Analysis*. Fifth Edition. Upper Saddle River, NJ: Prentice Hall.

Gutenbrunner, C., and J. Jureckova. 1992. "Regression Quantile and Regression Rank Score Process in the Linear Model and Derived Statistics." *Annals of Statistics* 20: 305-330.

Insightful Corporation. 2002. *S-Plus 6 Robust Library User's Guide Version 1.0*. Seattle, WA: Insightful Corporation.

Koenker, R. 2005. *Quantile Regression*. New York, NY: Cambridge University Press.

Koenker, R., and G. Bassett Jr. 1978. "Regression Quantiles." *Econometrica* 46: 33-50.

Koenker, R., and J. Machado. 1999. "Goodness of Fit and Related Inference Processes for Quantile Regression." *Journal of the American Statistical Association* 94: 1296-1310.

Koenker, R., and O. Geling. 2001. "Reappraising Medfly Longevity: A Quantile Regression Survival Analysis." *Journal of the American Statistical Association* 96: 458-468.

Koenker, R., and K. F. Hallock. 2000. Quantile Regression: An Introduction. www.econ.uiuc.edu/~roger/research/home.html.

Koenker, R., and K. F. Hallock. 2001. "Quantile Regression: An Introduction." *Journal of Economic Perspectives* 15: 143-156.

Koenker, R., and Q. Zhao. 1994. "L-estimation for Linear Heteroscedastic Models." *Journal of Nonparametric Statistics* 3: 223-235.

Knox, K. J., E. Blankmeyer, and J. R. Stutzman. 2001. "The Efficiency of Nursing Home Chains and the Implications on Nonprofit Status: A Comment." *Journal of Real Estate Portfolio Management* 7: 177-182.

Knox, K. J., E. Blankmeyer and J. R. Stutzman. 2003. "Organizational Efficiency and Quality in Texas Nursing Facilities." *Health Care Management Science* 6: 175-188.

Kooreman, P. 1994. "Nursing Home Care in The Netherlands: A Nonparametric Efficiency Analysis." *Journal of Health Economics* 13: 301-316.

Kumbhakar, S. C. and E. G. Tsionas. 2005. "The Joint Measurement of Technical and Allocative Inefficiencies: An Application of Bayesian Inference in Nonlinear Random-Effects Models." *Journal of the American Statistical Association* 100: 736-747.

Lau, L., and P. Yotopoulos. 1971. "A Test for Relative Efficiency and Application to Indian Agriculture." *American Economic Review* 61: 94-109.

Lueck, S. 2005a. "Soaring Costs for Medicaid Ravage State, Federal Budgets." *Wall Street Journal*, February 7, A1.

Lueck, S. 2005b. "Creative Accounting for Medicaid." *Wall Street Journal*, February 24, A4.

Maronna, R. A., and R. H. Zamar. 2002. "Robust Estimates of Location and Dispersion for High-Dimensional Datasets." *Technometrics* 44: 307-317.

Mundalk, Y. .1978. "On the Pooling of Time Series and Cross Section Data," *Econometrica* 64: 69-85.

Newhouse, J. P. 1994. "Frontier Estimation: How Useful a Tool for Health Economics?" *Journal of Health Economics* 13: 317-322.

Nyman, J., and D. Bricker. 1989. "Profit Incentives and Technical Efficiency in the Production of Nursing Homes Care." *Review of Economics and Statistics* 71: 586-594.

Rocke, D. M., and D. L. Woodruff. 1996. "Identification of Outliers in Multivariate Data." *Journal of the American Statistical Association* 91: 1047-1061.

Rousseeuw, P. J., and A. M. Leroy. 1987. *Robust Regression and Outlier Detection.* New York: Wiley.

Rousseeuw, P. J., and M. Hubert. 1999. "Regression Depth." *Journal of the American Statistical Association* 94: 388-402.

Rousseeuw, P. J., and K. Van Driessen. 1999. "A Fast Algorithm for the Minimum Covariance Determinant Estimator." *Technometrics* 41: 212-223.

Rousseeuw, P. J., and B. C. Van Zomeren. 1990. "Unmasking Multivariate Outliers and Leverage Points." *Journal of the American Statistical Association* 85: 633-651.

Shephard, R. W. 1970. The Theory of Cost and Production. Princeton, NJ: Princeton University Press.

SOA Associates. 2003. "Access to Long-Term Care: Why Are Some Skilled Nursing Homes Closing Down?" Upper Marlboro, MD: SOA Associates.

Texas Department of Human Services. 1990. *Reimbursement Methodology for Nursing Facilities.* Austin, TX.

Texas Department of Human Services. 2000. *How QRS Rates Nursing Homes.* Austin, TX.

Texas Department of Human Services. 1999. *1999 Cost Report: Texas Nursing Facility* (paper form and spreadsheet). Austin, TX.

Texas Health and Human Services Commission. 2002. *2002 Cost Report: Texas Nursing Facility* (paper form and spreadsheet). Austin, TX

Vitaliano, D.. F., and M. Toren. 1994. "Cost and Efficiency in Nursing Homes: A Stochastic Frontier Approach." *Journal of Health Economics* 13: 281-300.