Efficiency Analysis of Rural Hospitals: Parametric and Semi-parametric Approaches

I.Cristian Nedelea
Graduate Research Assistant
Department of Agricultural Economics and Agribusiness
Louisiana State University
101 Martin D. Woodin Hall
Baton Rouge, LA 70803
Phone: 225.578.2595
Email: inedel1@lsu.edu

J. Matthew Fannin, Ph.D.
Associate Professor
Department of Agricultural Economics and Agribusiness
Louisiana State University Agricultural Center
101 Martin D. Woodin Hall
Baton Rouge, LA 70803
Phone: 225.578.0346
Email: mfannin@agcenter.lsu.edu

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Birmingham, Alabama, February 4 - 7, 2012

Introduction

The primary goal of this study is to analyze whether Critical Access Hospitals (CAHs) are less or more cost efficient than a comparison group of non-converting, prospectively paid rural hospitals. As a secondary goal, we examine the performance of the two-stage approach and stochastic frontier analysis (SFA), and how the two methods can be used to make valid inferences about the effects of environmental variables on estimated cost efficiency. In many of the efficiency analysis studies, researchers have been interested in explaining differences in estimated efficiencies across firms or decision making units (DMU). Typically, this involves inferring on the relationship between estimated efficiency scores and a set of environmental variables. From a policy perspective, hospital managers and policymakers can become more effective decision makers by understanding the relationships between efficiency and these environmental variables. Two methods have been mostly used in the literature to investigate the impact of environmental variables on estimated efficiency scores. The first method is SFA which is a parametric approach based on production or cost functions. The second method is the two-stage approach in which efficiency scores are estimated in the first stage using data envelopment analysis (DEA), and, in the second stage, the efficiency scores are regressed on environmental variables that can influence efficiency.

The CAH program (also known as the Medicare Rural Hospital Flexibility program), introduced by the Balanced Budget Act of 1997, has been created in response to the dramatic deterioration of financial conditions (and the potential threat of closure) of small rural hospitals. Hospitals participating in the CAH program receive cost-based reimbursement for services delivered to Medicare beneficiaries providing they meet certain conditions before conversion (i.e., the number of acute care beds is restricted to less than or equal to 25; annual average length of inpatient stay must be less than or equal to 4 days, etc.). In contrast, the rest of the hospitals are paid a fixed fee based on diagnosis related group (DRG) under the Medicare prospective payment system (PPS).[1] Previous research showed that Medicare cost-based reimbursement gave hospitals few incentives to control their costs and encouraged inefficiently produced services (Gianfrancesco, 1990; McKay, Deily and Dorner, 2002/2003). One of the goals of the PPS system, on the other hand, has been to promote efficiency in hospital operations by motivating hospitals to keep their costs below PPS payment rates (Sexton, Leiken, and Sleeper, 1989). Although the CAH program has helped to preserve access to health care in rural areas, there is a concern that, since CAH hospitals receive Medicare cost-based reimbursement, they will have a reduced incentive to control costs and operate efficiently (MedPAC, 2005).

In the efficiency analysis literature there has been considerable interest in reconciling SFA and DEA (Mutter et al., 2011). Two studies that compared SFA and DEA are Chiricos and Sear (2000) for US hospitals, and Jacobs (2001) for hospitals in the UK and both studies found significant differences between the results from the two approaches. Linna (1998) examined cost efficiency of Finish hospitals and found that SFA and DEA generated similar results. Our study extends previous literature by providing an empirical application of both the two-stage DEA approach and SFA in the specific context of analyzing cost efficiency differences between CAH rural hospitals and a group of non-converting, PPS rural hospitals.

Methods

DEA vs. SFA

For the efficiency analysis of DMUs, researchers have applied frontier methods such as DEA or SFA. Both methods measure inefficiency of a DMU as the distance between a best practice (or efficient) frontier and actual performance of the DMU. However, the two methods differ in some key theoretical

[1] Under cost-based reimbursement, hospitals are paid the full cost of providing services to Medicare beneficiaries, while PPS pays a fixed fee based on DRG. PPS allows hospitals to keep the difference between PPS reimbursement rate and actual hospital cost.

aspects. DEA measures efficiency relative to a nonparametric estimate of an unobserved true frontier, conditional on observed data (Simar and Wilson, 2007). As a nonparametric method, DEA requires no assumptions about the specific form of the frontier or the probability density of inputs and outputs used in the production process. However, DEA assumes no errors and deviations from the efficient frontier are entirely assumed to be due to inefficiency.

Stochastic frontier models avoid some of the limitations of the DEA. Specifically, SFA allows the decomposition of deviations from the efficient frontier into a random error term that embodies statistical noise and a one-sided error term representing inefficiency. However, SFA requires the specification of a functional form for the frontier and assumptions about the distributions of the random error and inefficiency error terms which might be very restrictive (Newhouse, 1994).

DEA measures cost efficiency in two steps. First, given input prices and output levels, the cost-minimizing input vector for each hospital is calculated using linear programming. Next, cost efficiency is measured as the ratio of minimum cost to observed cost and takes a value between 0 and 1, where a value of 1 indicates a cost efficient hospital (for technical details of cost efficiency estimation, see Coelli et al. (2005)). The cost efficiency measures the factor by which the observed cost can be reduced if the hospital selects the optimal input bundle (which minimizes the cost of producing a given level of output given input prices) and operates at a technically efficient point (where output is produced using minimum quantities of inputs).

Alternatively, cost efficiency can be estimated using SFA which, in a general form, specifies total cost as a function of outputs and input prices plus a composite error term (Coelli et al., 2005):

$$TC_i = f(Y_i, W_i) + \varepsilon_i \qquad (1)$$

where TC_i represents the total cost of the i-th hospital, Y_i is a vector of outputs, W_i is a vector of input prices, and ε_i is a composite error term which can be decomposed as

$$\varepsilon_i = v_i + u_i \tag{2}$$

where v_i captures random statistical noise, assumed normally distributed, and u_i represents cost inefficiency for which a distribution must also be assumed.[2] Given the distributional assumptions for the two error terms, the model is estimated by maximum likelihood (Coelli et al., 2005). In a cross-sectional stochastic frontier model, the cost inefficiency is observed indirectly from the estimates of the composite error and is calculated as the expected value of inefficiency, conditional upon the composite residual.

In the estimation of a stochastic frontier cost model, one must also specify a functional form for the cost equation. The most popular functional forms used in empirical research have been the translog and Cobb-Douglas cost functions. The translog function has been shown to be more flexible in the sense that it can provide a second-order differential approximation to any arbitrary function at a single point, making it the preferred functional form in empirical research. However, increased flexibility of the translog function comes at the cost of an increased number of parameters to estimate, and this may give rise to multicolinearity problems (Coelli et al., 2005).

Impact of Environmental Variables on Cost Efficiency

The focus in this research is on making valid inference about the impact of environmental variables on hospital cost efficiency. In the two-stage approach, cost efficiency scores, estimated in the first stage using DEA, are regressed, in the second stage, on some environmental variables to investigate how hospital efficiency is influenced by such explanatory variables.

The specification of the second-stage truncated regression used in this study is:

$$\hat{\delta}_i = z_i\beta + \varepsilon_i \geq 1, \quad i = 1, 2, \ldots., n \tag{3}$$

[2] Distributions assumed for the one-sided error term: half-normal, truncated-normal, exponential and gamma.

where $\hat{\delta}_i$ is the reciprocal of DEA-estimated cost efficiency scores (referred to as inefficiency scores) such that $\hat{\delta}_i \geq 1$, ε_i is assumed to be distributed N(0, σ^2) with left truncation at $1\text{-}z_i\beta$, z_i is a vector of k environmental variables which are thought to have an effect on hospital efficiency and β is a vector of parameters to be estimated. It has been shown that the DEA-efficiency estimates used as the dependent variable in the second stage are serially correlated in a complicated, unknown way (Simar and Wilson, 2007). While this correlation disappears asymptotically, Simar and Wilson (2007) showed that conventional methods for inference in the second stage regression are invalid. To provide valid inference in the second stage analysis, they suggested a bootstrap algorithm which is a parametric bootstrap of the truncated regression

In SFA, the impact of environmental variables on the cost inefficiency is specified as:

$$\hat{u}_i = z_i\beta + w_i \tag{4}$$

where $\hat{u}_i$ is the SFA estimated cost inefficiency, z_i is a vector of environmental variables, β is a vector of parameters to be estimated and w_i is a random variable defined by the truncation of the normal distribution with mean zero and variance σ^2. The stochastic frontier cost model used in this study allows cost inefficiency to be explicitly modeled as a function of environmental variables, the parameters of which are estimated simultaneously with the stochastic cost frontier in a one-stage procedure.

Data

Two years of data, 2005 and 2006, are used in this study. The data come from the American Hospital Association (AHA) Annual Survey of Hospitals, the Area Resource File, the Medicare Hospital Cost Report, and the Centers for Medicare and Medicaid Services (CMS) Hospital Compare public reporting database for hospital quality measures. We focus on the set of CAH-designated rural hospitals as well as on a comparison group of non-converting, prospectively paid rural hospitals.

Following Stensland, Davidson, and Moscovice (2003), the comparison group is restricted to rural hospitals with no more than fifty beds, allowing us to have two groups of hospitals of similar size (while CAHs are restricted to no more than 25 acute care beds, they have no restrictions on non-acute care beds; the mean for the CAH total staffed and licensed beds in our sample was 36 while for non-converting rural hospitals was 38 (Table 1)).

For the specification of the stochastic frontier cost function, we followed Rosko and Mutter (2010). Specifically, we used total hospital expenses as the dependent variable and input prices, hospital outputs and product mix descriptors as explanatory variables. Hospital outputs consist of outpatient visits (*opv*), admissions (*admtot*), and post-admission days (*postdays*) (inpatient days – admissions). Consistent with previous literature, a set of product mix descriptors is also included: percent of emergency room visits (*erv%*) ((emergency room visits / outpatient visits) × 100), percent of outpatient surgeries (*outsurg%*) ((outpatient surgeries / outpatient visits) × 100) and percent of births (*birth%*) ((births / admissions) × 100). Additionally, we control for quality using percent of patients given pneumococcal vaccination (*pneum_vac%*) and percent of patients given initial antibiotic timing (*initial_antib%*). Input prices used in the analysis are: the price of labor (sum of payroll expenses and employee benefits divided by the full-time equivalent facility personnel) and the price of capital (sum of depreciation expenses and interest expenses - from the Medicare Hospital Cost Report - divided by the number of facility beds) (Rosko and Mutter, 2010). The assumption of linear homogeneity in input prices is imposed by normalizing the cost equation by the price of labor.

The DEA-cost model requires information on hospital outputs, inputs, and input prices (Ferrier and Valdmanis, 1996). For consistency, we used the same hospital outputs and input prices as in the stochastic frontier cost function. However, the product mix descriptors used in the SFA are included as actual outputs in the DEA model. Specifically, we used the following hospital outputs in our DEA model: outpatient visits, admissions, post-admission days, emergency room visits, outpatient surgeries, and births. Consistent with previous literature, we used the two quality measures as additional outputs in the DEA model (Nayar and Ozcan, 2008). The physical inputs consist of full time equivalent (FTE) facility personnel (labor input) and total staffed and licensed hospital beds (a proxy for capital), and the input prices are identical to the ones in the SFA (the price of labor and the price of capital).

A particular challenge in this study is adjusting outputs to control for case-mix variations. Unfortunately, there is no Medicare Case-Mix Index available for CAHs as these hospitals are exempted from the PPS system. In the stochastic frontier cost function, percent of emergency room visits, percent of outpatient surgeries and percent of births can also be used as case-mix proxies (Rosko and Mutter, 2011). Ozgen and Ozcan (2004) and others noted that the lack of case-mix variables in DEA efficiency models is in part compensated by specification of multiple outputs. In the DEA model, we expand the set of outputs (beyond the ones used in SFA) in order to capture case-mix differences by including emergency room visits, outpatient surgeries and births.

The set of environmental variables used to explain cost efficiency, on which we focus in this analysis, is identical for both the stochastic frontier model and the second stage truncated regression. For the specification of environmental variables, we follow Rosko and Mutter (2010, 2011). The primary variable of interest is a CAH dummy (one if the hospital is a CAH and zero otherwise) which is used to test whether CAHs are more or less cost efficient than non-converting rural hospitals. Dummy variables that define government hospitals (*Government*), non-profit hospitals, and for-profit hospitals (*For-profit*) are included to control for internal pressure for efficiency associated with ownership (Rosko and Mutter, 2010; 2011). Non-profit ownership is the reference category. Another environmental variable, directly associated with hospital efficiency, is membership in a multihospital system which is also introduced as a dummy variable (*System*).

Two variables are used to control for the external pressure for efficiency associated with public payers: Medicare percent of admissions (*Medicare%*) ((Medicare admissions / total admissions) × 100) and Medicaid percent of admissions (*Medicaid%*) ((Medicaid admissions / total admissions) × 100). The effect of Medicare percent of admissions on hospital inefficiency is unclear, given the joint use in estimation of cost-based reimbursed CAHs and PPS-reimbursed non-converting rural hospitals. Previous literature showed that reimbursement policies under Medicare PPS create incentives for reducing inefficiency while cost-based reimbursement gives hospitals few incentives to control their costs.

A Herfindahl-Hirschman index (*HHI*) is used to control for competitive pressure in a hospital's market (which, consistent with previous studies, is defined as the county). HHI is calculated by summing the squares of the market shares of admissions for all of the hospitals in the county and takes a value between 0 and 1, with values approaching 1 indicating less competitive pressures. Another source of external pressure for efficiency is Health Maintenance Organization (HMO) penetration. We used percent of Medicare HMO penetration (*MHMO%*) from the Area Resource File as a proxy for general HMO penetration (Rosko and Mutter, 2010). Finally, median household income of the county (*Income*) and a dummy variable for 2006 to control for time effects are also included as environmental variables to explain hospital efficiency. Variable definitions for both SFA and the two-stage DEA approach are presented in Table 1. Summary statistics of these variables are presented for both CAHs and the comparison group of non-converting rural hospitals.

Results

Table 2 shows summary statistics of cost efficiency scores estimated by both DEA and SFA and using the two years of data jointly. The DEA mean cost efficiency for CAHs was 68 percent while for the comparison group of non-converting rural hospitals was 72.4 percent. The mean cost efficiency estimated using SFA was 90.6 percent for CAHs and 95 percent for non-converting rural hospitals. Both models indicate that CAHs are, on average, less cost efficient than non-converting rural hospitals and the difference in cost efficiency between CAHs and non-converting rural hospitals is 4.4 percent under both models. As expected, however, there is a significant difference in the magnitude of efficiency scores estimated by DEA and those estimated by SFA which is attributed in principal to the differences in how the two approaches measure efficiency. DEA, as a nonparametric method, assumes that deviations from the efficient frontier are entirely due to inefficiency, making no allowance for random statistical noise. SFA, on the other hand, is a parametric approach in which deviations from the efficient frontier are decomposed into a random error term representing statistical noise and a one-sided error term representing inefficiency.

Table 4 shows the results obtained from the estimation of the SFA translog cost function. The coefficient of the price of capital was found positive and significant, as expected, in contrast with the negative and significant coefficient of the same variable found by Rosko and Mutter (2010). Some of the estimated coefficients of the output variables and interaction terms were insignificant or of an unexpected sign, fact that may be due to multicolinearity problems. Similar to Rosko and Mutter (2010), we also found positive and significant coefficients for the product mix descriptors (erv%, outsurg%, and birth%). Of the two quality control variables, only one (pneum_vac%) was found positive and significant , indicating a direct relationship between quality and hospital costs (Rosko and Mutter, 2010).

Cost Efficiency Determinants

The focus of this study, however, is on using the two-stage approach and SFA to make valid inference about the impact of environmental variables on hospital cost inefficiency. Table 3 summarizes the results of the second stage bootstrapped truncated regression and SFA models in which cost inefficiency scores are regressed on environmental variables. As an interpretation rule, a positive coefficient suggests a positive effect on cost inefficiency, while a negative coefficient suggests a negative effect on inefficiency (an improvement in efficiency).

The primary variable of interest is the CAH dummy which indicates whether CAHs are more or less cost efficient than the comparison group of non-converting rural hospitals. The results in Table 3 show that the coefficient of the CAH dummy is positive and highly statistical significant (p-value < 0.01) in both the bootstrapped truncated regression model as well as the SFA model suggesting that CAHs are less cost efficient than non-converting rural hospitals. The results are consistent with previous literature (Rosko and Mutter, 2010) and with our hypothesis that CAHs are less cost efficient than non-converting rural hospitals because of the differences in Medicare reimbursement facing these hospitals.

The estimated results show a positive and significant coefficient of government ownership in both models suggesting that government rural hospitals in our sample are less cost efficient than nonprofit rural hospitals, a result that is consistent with previous literature (Rosko and Mutter, 2010). For-profit ownership, on the other hand, has an insignificant coefficient in both models.

Medicare share of admissions (*Medicare%*) has a positive and significant coefficient (p-value < 0.05) in the bootstrapped truncated regression model while the coefficient is positive but insignificant in the SFA translog model. This is in contrast with the negative coefficient of the same variable found by Rosko and Mutter (2010). Nevertheless, Rosko and Mutter (2010) as well as our research analyze a joint set of Medicare cost-based reimbursed CAHs and PPS reimbursed non-converting rural hospitals and one can expect an inconclusive effect of Medicare share of admissions on hospital efficiency in this situation. Similar to Rosko and Mutter (2010), we also found an insignificant effect of Medicaid percent of admission (*Medicaid%*) variable on hospital cost inefficiency.

The negative and significant coefficient of system membership (*System*) in both our models is consistent with previous literature and suggests that rural hospitals that are members in a multihospital system are more cost efficient than the ones that are not. Rosko and Proenca (2005) argue that hospitals participating in a multihospital system can provide services at lower costs and with greater efficiency by collaborating on service delivery. The negative and significant coefficient of Medicare HMO in our SFA model may suggest that Medicare HMO penetration creates pressure for rural hospitals to operate more cost efficiently. In particular, health maintenance organizations have contributed to health care cost containment by encouraging the use of outpatient services instead of inpatient care and by extracting large discounts from providers (Rosko, 2001). Consistent with the findings of Rosko and Mutter (2010), we also found a positive and significant coefficient of the county median household income (*Income*) on hospital cost inefficiency.

Conclusions and Discussion

In this study, we examined the impact of conversion to CAH status on hospital cost inefficiency using SFA as well as a two-stage approach. The estimated results showed a positive and highly significant coefficient of CAH dummy variable in both models suggesting that CAH rural hospitals were less cost efficient than the comparison group of non-converting rural hospitals. This conclusion is consistent with the findings of Rosko and Mutter (2010), who compared the cost inefficiency of CAHs with that of non-converting rural hospitals using SFA, and with our hypothesis that CAHs are less cost efficient than non-converting rural hospitals.

Previous research showed that hospitals that converted to CAH status increased their Medicare payments and improved their profit margins as a result of the Medicare cost-based reimbursement. MedPAC (2005) estimated that in 2003 payments per CAH were roughly $850,000 higher under

Medicare cost-based reimbursement than they would have been under PPS reimbursement. Similarly, Stensland, Davidson, and Moscovice (2003) found that hospitals that converted to CAH status significantly increased their Medicare revenue, profitability, employee salaries and capital expenditures. They estimated that, on average, inflation-adjusted revenue of hospitals that converted to CAH status increased by $518,571 per hospital, half of which was used to cover loses or retained as profits and the other half used to raise salaries and to cover other expenses. Analyzing quality improvements in CAHs, Casey and Moscovice (2004) found that Medicare cost-based reimbursement allowed CAHs to fund additional staff, staff training and equipment to improve patient care. Further, anecdotal evidence suggests that after hospitals improved their finances post-conversion, many CAHs invested in new equipment, new hospitals or major infrastructure upgrades.

While efficiency is an important factor for measuring the effectiveness of a health care policy or program, a complete assessment of the CAH program needs to go beyond efficiency and take into account issues such as equitable access to high-quality care. The rationale for the Medicare cost-based reimbursement of CAH hospitals has been to protect these small, financially vulnerable rural hospitals and prevent their potential closure. The benefits of the CAH program have been mostly associated with improvements in access to health care services in isolated rural areas. Previous literature also showed that retaining a limited hospital facility in a rural community not only reduces welfare losses relative to the hospital closure (McNamara, 1999), but also has a positive economic impact on the community as a whole (Holmes et al., 2006). The cost of the CAH program is represented by the increased Medicare payments for CAH hospitals which are borne in principal by federal taxpayers. While a complete evaluation of the CAH program requires answering the question whether the total benefits outweigh the total costs, we focused in this research on assessing the impact of conversion to CAH status on hospital cost inefficiency.

A large number of efficiency analysis studies used SFA with cross-sectional data. However, the cross-sectional stochastic frontier model has been shown to have some limitations. Schmidt and Sickles (1984) noted three limitations of SFA with cross section data. First, in cross-sectional stochastic frontier models, firm-specific efficiency is unidentified and researchers typically estimate expectations of efficiency conditional on a composite residual. Second, cross-sectional stochastic frontier models require specific distributional assumptions for each error component in order to estimate efficiency. Third, the efficiency error term is assumed to be independent of regressors (i.e., inputs and outputs), an assumption which is very restrictive.

Alternatively, one can use the two-stage approach along the line of Simar and Wilson (2007) with cross-sectional data. Using DEA to estimate efficiency scores in the first stage, one can avoid potential misspecification problems that affect SFA. In the semi-parametric model defined by Simar and Wilson (2007), the assumptions of a linear functional form and truncated normal errors in the second stage appear to be less restrictive as compared with a fully parametric approach. Further, the assumption of independent errors in SFA is avoided in the model defined by Simar and Wilson (2007) where the first stage estimation does not require independence between the efficiency scores and the inputs and outputs.

Our research suggests that SFA and the two-stage DEA approach are viable alternatives for analyzing the impact of environmental variables on hospital cost efficiency. We found that both SFA and the two-stage approach generated mostly similar and consistent results in our empirical application of the two methods to the efficiency analysis of rural hospitals. Both methods have advantages and disadvantages that one needs to be aware of. In particular, when using the two-stage DEA approach, researchers should consider using the bootstrap algorithm proposed by Simar and Wilson (2007) for making valid inference. Researchers should also consider using both methods, wherever possible, as a robustness check of the impact of environmental variables on estimated efficiency.

References

Casey, M. M., & Moscovice, I. (2004). Quality improvement strategies and best practices in Critical Access Hospitals. The Journal of Rural Health, 20, 327–334.

Chirikos, T.N., & Sear, A.M. (2000). Measuring hospital efficiency: a comparison of two approaches. Health Services Research, 34 (6), 1389-1408.

Coelli, T., Rao, D., O'Donnell, C., & Battese ,G. (2005). An introduction to efficiency and productivity analysis (2nd ed.). New York: Springer.

Ferrier, G.D., & Valdmanis, V. (1996). Rural hospital performance and its correlates. Journal of Productivity Analysis, 7, 63-80.

Gianfrancesco, F.D. (1990). The fairness of the PPS reimbursement methodology. Health Service Research, 25, 1-23.

Holmes, G. M., Slifkin, R. T., Randolph, R. K., & Poley, S. (2006). The effect of rural hospital closures on community economic health. Health Services Research, 41, 467–485.

Jacobs, R. (2001). Alternative methods to examine hospital efficiency: Data Envelopment Analysis and Stochastic Frontier Analysis. Health Care Management Science, 4, 103-115.

Linna, M. (1998). Measuring hospital cost efficiency with panel data models. Health Economics, 7, 415-427.

McKay, N.L., Deily, M.E., & Dorner, F.H. (2002/2003). Ownership and changes in hospital inefficiency, 1986-1991. Inquiry, 39, 388-399.

McNamara, P. E. (1999). Welfare effects of rural hospital closures: a nested logit analysis of the demand for rural hospital services. American Journal of Agricultural Economics, 81 (3), 686–91.

Medicare Payment Advisory Commission (MedPAC). (2005). Report to Congress: Issues in a Modernized Medicare Program. Washington, DC.

Mutter, R.L., Rosko, M.D., Greene, W.H., & Wilson, P.W. (2011). Translating frontiers into practice: taking the next steps toward improving hospital efficiency. Medical Care Research and Review, Supplement 68(1), 3S-19S.

Nayar P., & Ozcan, Y.A. (2008). Data envelopment analysis comparison of hospital efficiency and quality. J Med Syst, 32 (3), 193-199.

Newhouse, J. (1994). Frontier estimation: how useful a tool for health economics? Journal of Health Economics, 13, 317-322.

Ozgen, H., & Ozcan, Y.A. (2004). Longitudinal analysis of efficiency in multiple output dialysis markets. Health Care Management Science, 7, 253-261.

Rosko, M. D. (2001). Cost efficiency of U.S. hospitals: a stochastic frontier approach. Health Economics, 10, 539–551.

Rosko, M.D., & Mutter, R.L. (2010). Inefficiency differences between Critical Access Hospitals and prospectively paid rural hospitals. Journal of Health Politics, Policy and Law, 35(1), 95-126.

Rosko, M.D., & Mutter, R.L. (2011). What have we learned from the application of stochastic frontier analysis to U.S. hospitals? Medical Care Research and Review, Supplement 68(1), 75S-100S.

Rosko, M.D., & Proenca, J. (2005). Impact of network and system use on hospital X-efficiency. Health Care Management Review, 30, 69-79.

Schmidt, P., & Sickles, R.C. (1984). Production frontiers and panel data. Journal of Business and Economic Studies, 2, 299-326.

Sexton, T., Leiken, A.M., & Sleeper, S. (1989). The impact of prospective reimbursement on nursing home efficiency. Medical Care, 27, 154-163.

Simar, L., & Wilson, P.W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, 136, 31-64.

Stensland, J., Davidson, G., & Moskovice, I. (2003). The financial effects of Critical Access Hospital conversion. University of Minnesota Rural Health Research Center, Working Paper #44.

Table 1. Summary statistics and variable definitions

		CAH		Rural	
DEA and SFA Variables	Variable Definition	Mean	SD	Mean	SD
Outputs					
admtot	Total hospital admissions	1,072.12	427.87	1,730.83	737.84
postdays	Postadmission days	6,296.83	6,769.26	4,535.68	2,024.08
opv	Total outpatient visits	42,104.53	30,384.28	45,033.72	33,299.60
erv	Emergency room visits	6,981.46	4,516.93	9,492.27	5,194.94
outsurg	Outpatient surgeries	889.98	721.07	1,175.71	885.10
births	Total births	97.53	109.61	202.41	213.33
Quality Outputs					
pneum_vac%	%Patients given pneumococcal vaccination	62.31	23.66	59.90	24.28
initial_antib%	%Patients given initial antibiotic timing	84.74	8.75	80.87	10.40
Inputs					
bdtot	Total staffed and licensed hospital beds	35.92	22.27	37.93	9.41
fte	Full time equivalent (FTE) employee	191.95	79.35	216.16	98.51
Input Prices					
pk	$ Price of capital	36,824.86	29,993.99	35,780.83	27,633.52
w	$ Price of labor	50,747.63	13,418.28	49,177.05	12,514.33
Additional SFA Variables					
exptot	Total hospital expenditure	1.80E+07	9.31E+06	2.08E+07	1.20E+07
erv%	% Emergency room visits	20.60	13.52	26.49	16.71
outsurg%	% Outpatient Surgeries	2.60	2.41	3.41	3.59
birth%	% Admissions for birth	7.91	7.90	10.86	10.21
Environmental Variables					
Government	Government hospital (1,0)	0.32	0.47	0.34	0.47
For-profit	For-profit hospital (1,0)	0.03	0.18	0.14	0.35
Medicare%	% Medicare admissions	59.90	12.57	52.47	11.77
Medicaid%	% Medicaid admissions	13.05	7.98	17.37	9.65
HHI	Herfindahl-Hirschman index	0.50	0.35	0.56	0.33
System	Member of a multihospital system (1,0)	0.42	0.49	0.51	0.50
MHMO%	% Medicare HMO penetration	3.26	5.31	2.64	4.76
Income	Median household income	38,432.78	6,190.83	37,391.59	8,465.68

Table 2. Summary statistics of DEA and SFA estimated cost efficiency

		DEA Eff. Estimates		SFA Eff. Estimates	
Year	N	Mean	SD	Mean	SD
CAH2005	178	0.678	0.184	0.905	0.048
CAH2006	224	0.679	0.181	0.906	0.048
Rural2005	153	0.720	0.163	0.949	0.034
Rural2006	205	0.727	0.171	0.950	0.033
CAH	402	0.679	0.182	0.906	0.048
Rural	358	0.724	0.167	0.950	0.033
All	760	0.700	0.177	0.927	0.047

Table 3. Estimated effects of environmental variables on cost inefficiency

Variable	Bootstrapped Truncated Reg.	SFA Translog
Constant	1.0898***	-0.1629
Government	0.0589*	0.0431**
For-profit	-0.0885	0.0156
Medicare%	0.0036**	0.0011
Medicaid%	0.0013	-0.0013
HHI	0.0507	0.0399
System	-0.1245***	-0.0392**
CAH	0.1685***	0.0535***
Income	4.48E-06*	4.60E-06***
MHMO%	-0.0060	-0.0097***
Y2006	-0.0092	-0.0204

***p<0.01, **p<0.05, *p<0.10

Table 4. Results of the SFA estimation

Variable	Coeff.	t-stat.
cons	3.1126	1.6032
ln(admtot)	-0.4428	-1.1250
ln(postdays)	0.1101	0.4656
ln(opv)	0.1071	0.4349
ln(pk)	0.7527	3.6888
ln(admtot)-sq	-0.0500	-0.7987
ln(admtot)*ln(postdays)	-0.0440	-1.5258
ln(admtot)*ln(opv)	0.1428	4.5178
ln(postdays)-sq	0.0964	3.2159
ln(postdays)*ln(opv)	-0.0420	-2.4426
ln(opv)-sq	-0.0510	-1.8981
ln(pk)-sq	0.0955	4.9089
ln(admtot)*ln(pk)	-0.0247	-0.8433
ln(postdays)*ln(pk)	0.0396	2.2323
ln(opv)*ln(pk)	-0.0657	-4.0868
erv%	0.0029	4.4628
outsurg%	0.0176	5.6814
birth%	0.0048	4.4488
pneum_vac%	0.0007	2.1324
initial_antib%	-0.0001	-0.0719
Y2006	0.0005	0.0118
Environmental Variables		
Constant	-0.1629	-1.4734
Government	0.0431	2.2271
For-profit	0.0156	0.4211
Medicare%	0.0011	1.2682
Medicaid%	-0.0013	-0.8207
HHI	0.0399	1.5195
System	-0.0392	-2.2823
CAH	0.0535	2.8621
Income	4.60E-06	3.3379
MHMO%	-0.0097	-21.0912
Y2006	-0.0204	-0.3924