Are Critical Access Hospitals Less Efficient than Non-Converting, Prospectively Paid Rural Hospitals?

Iustin Cristian Nedelea and James Matthew Fannin

Department of Agricultural Economics and Agribusiness, Louisiana State University
Agricultural Center, 101 Martin D. Woodin Hall, Baton Rouge, LA 70803
E-mail: inedel1@lsu.edu, mfannin@agcenter.lsu.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012.

INTRODUCTION

The Medicare Rural Hospital Flexibility Program – also known as the Critical Access Hospital (CAH) Program – was established by the Balanced Budget Act of 1997. The goal of the CAH Program has been to preserve access to health care services in isolated rural areas by improving the financial conditions of small rural hospitals and potentially preventing their closure. A hospital that converts to CAH status receives Medicare cost-based reimbursement, providing that it meets several requirements. Most importantly, the hospital must be located at least 35 miles by primary road, or 15 miles by secondary road, from the nearest full service hospital, must have 25 or fewer acute care beds, annual average length of stay cannot be greater than four days, and the hospital must provide 24 hours emergency care services.

Rural hospitals that converted to CAH status have generally experienced significant improvements in their finances due to Medicare cost-based reimbursement (Medicare Payment Advisory Commission MedPAC 2005). This reimbursement method, however, has been historically associated with inefficiency in hospital operations. The rationale is that under cost-based reimbursement a hospital has an incentive to oversupply services in order to receive higher revenue because Medicare pays for services on a cost basis (McKay, Deily, and Dorner 2002/2003). The Medicare Prospective Payment System (PPS), on the other hand, has been designed to motivate hospitals to keep their costs below PPS reimbursement rates and operate more efficiently (Sexton et al. 1989). Since CAH hospitals receive Medicare cost-based reimbursement, there have been concerns that they will have a disincentive to operate efficiently (MedPAC 2005).

The goal of this study is to compare the technical efficiency of cost-based reimbursed CAHs with that of non-converting, PPS rural hospitals using recent methodological advancements in efficiency analysis. The non-converting rural hospitals tend to be larger and may experience economies of scale not available to CAHs. For this reason, we compare CAHs with two different groups of non-converting rural hospitals restricted by bed size. We use a two-stage approach, where data envelopment analysis (DEA) is used in the first stage to estimate technical efficiency of each hospital in the sample. The densities of efficiency scores of CAHs and non-converting rural hospitals are estimated and compared using a nonparametric kernel density estimator and a bootstrapped-based test proposed by Simar and Zelenyuk (2006). In the second stage, we estimate the effects of environmental variables (CAH status, ownership, Medicare and Medicaid) on hospital efficiency using a truncated regression and bootstrap procedures proposed by Simar and Wilson (2007).

DATA

For this study, two years of data are used (2005 and 2006) from the American Hospital Association (AHA) Annual Survey of Hospitals, the Area Resource File, and the Centers for Medicare and Medicaid Services (CMS) Hospital Compare public reporting database for hospital quality measures. The sample of analyzed hospitals consists of CAH-designated rural hospitals as well as a comparison group of non-converting, prospectively paid rural hospitals. Consistent with Rosko and Mutter (2010), the comparison group is restricted to rural hospitals with no more than seventy-five beds. For sensitivity analysis, another specification for the comparison group is used and includes non-converting rural hospitals with no more than fifty beds (Stensland, Davidson, and Moscovice 2003).

For the specification of hospital outputs and inputs used in the DEA model, we follow previous literature (Rosko and Mutter 2008; 2010). Hospital outputs include outpatient visits, admissions, post-admission days (inpatient days – admissions), emergency room visits, outpatient surgeries, and births. The inputs used in the DEA model consist of full time equivalent (FTE) personnel (labor input) and total staffed and licensed hospital beds (a proxy for capital input) (Ferrier and Valdmanis 1996).

To control for the quality of care, we also follow previous literature and use quality measures (from the CMS Hospital Compare database) as additional outputs in the DEA model (Nayar and Ozcan 2008). The quality measures used in this study are: (1) percent of patients given pneumococcal vaccination, i.e., pneumonia patients age 65 and older who were screened for pneumococcal vaccine status and were administered the vaccine prior to discharge, if indicated; (2) percent of patients given initial antibiotic timing, i.e., pneumonia patients given initial antibiotic within four hours after arrival; (3) percent of patients given the most appropriate initial antibiotic. Casey et al. (2012) found these to be relevant quality measures for CAHs. A particular challenge in this study is the lack of a Medicare case-mix index (usually used to adjust outputs for hospital case-mix complexity) for CAHs as these hospitals are exempted from the PPS reimbursement. However, 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.

Table 1 presents summary statistics for hospital outputs and inputs used in the DEA model for CAHs as well as the two specifications of the control group of non-converting rural hospitals.

Environmental Variables

The specification of environmental variables used in the second stage truncated regression follows Rosko and Mutter (2010) specification of inefficiency effects variables. The key variable is a CAH binary variable which is used to estimate the marginal effect of CAH status on hospital technical efficiency. Previous studies showed that the external financial pressures from Medicare and Medicaid can affect hospital efficiency. We follow Rosko and Mutter (2010; 2011) and use two variables 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).

A Herfindahl-Hirschman index (HHI) is used to control for the external 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 it takes a value between 0 and 1, with values approaching 1 indicating less competitive pressures. Another source of external pressure associated with hospital 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).

Binary variables that define government (GOV) and for-profit hospitals (FP), with non-profit hospitals as the reference category, are used to control for the internal pressure for efficiency associated with ownership (Rosko and Mutter 2011). Another internal factor, directly associated with hospital efficiency, is membership in a multihospital system which is also introduced as a binary variable (SYSTEM). Additionally, we include two control variables in the second stage regression: a binary variable for 2006, and median household income of the county (INCOME).

Variable definitions and summary statistics for the second stage model are presented in Table 1 (bottom), for CAHs and the two specifications of the comparison group of non-converting rural hospitals. As expected, CAHs have, on average, a higher percentage of Medicare admissions and a lower rate of for-profits than non-converting rural hospitals.

METHODOLOGY

The theoretical foundation of efficiency measurement is based on the work of Farrell (1957) who applied radial measures of distance to the production frontier to measure technical efficiency. In simple terms, technical efficiency is defined as the proportionate (i.e., radial) reduction in inputs that is feasible given a certain level of outputs.

In this section, we outline an economic model of efficiency measurement that is based on Simar and Wilson (2007). In economic theory, the production process can be defined in terms of a production set:

$$P = \{(x,y) \in R_{+}^{p+q} | x \text{ can produce } y\} \quad (1)$$

where $x \in R_{+}^{p}$ is an input vector and $y \in R_{+}^{q}$ is an output vector. The upper boundary of the production set, which represents the technology or production frontier, is of interest for efficiency measurement. Inefficient firms operate at points in the interior of the production set, with the distance from each interior point to the frontier representing inefficiency, while those that are efficient operate on the frontier. In this study, an input-oriented, variable returns to scale approach to efficiency measurement is used based on the assumption that hospitals have more control over the inputs used in production than over the outputs. DEA uses linear programing to define a convex set and obtain an estimate of the efficient frontier enveloping all the data. Efficiency of a firm (hospital in our case) is measured as the distance to this efficient frontier.

The input-oriented measure of technical efficiency of the *i*-th hospital assuming variable returns to scale can be estimated by solving the following DEA linear programming problem:

$$\hat{\theta}_i = \min \left\{ \theta \mid \sum_j \lambda_j y_j \geq y_i; \sum_j \lambda_j x_j \leq \theta x_i; \sum_j \lambda_j = 1; \lambda_j \geq 0, j = 1,\ldots,n \right\} \quad (2)$$

where $\hat{\theta} \leq 1$ and λ_j (j=1, 2,…., n) are the intensity variables over which optimization in (3) is made. While $\hat{\theta}$ is, by construction, an upward-biased estimator, Kneip et al. (1998) proved the consistency of the DEA efficiency estimator. $\hat{\theta} = 1$ suggests a technically efficient hospitals, while $\hat{\theta} < 1$ indicates the proportionate reduction in inputs the firm should achieve to become technically efficient.

Density Analysis of Efficiency Scores

Comparing the sample means of efficiency scores of two or more groups of firms may not provide a complete picture. An alternative way is to use a nonparametric kernel density estimator to estimate the densities of efficiency scores of these groups. Based on the estimated densities, we test the null hypothesis of equality between the densities of efficiency scores of CAHs and non-converting rural hospitals against the alternative of different densities. There are, however, at least two important problems with this approach: (1) some of the DEA efficiency scores equal to 1, by construction, violating the continuity assumption required for consistency of the density estimation, and (2) in finite samples, the estimated efficiency scores are biased and not independent (however both these problems vanish asymptotically) (Simar and Zelenyuk, 2006). To address these problems, Simar and Zelenyuk (2006) proposed a bootstrapped-based test for testing equality of densities of DEA estimated efficiency scores. In this paper, we use Simar-Zelenyuk statistics to test whether CAHs are more or less efficient than non-converting rural hospitals.

Second Stage Truncated Regression

In the two-stage approach, efficiency scores, estimated in the first stage using DEA, are regressed, in the second stage, on environmental variables using a bootstrapped truncated regression. The specification of the second-stage truncated regression used in this study is:

$$0 < \hat{\theta}_i = z_i\beta + \varepsilon_i \leq 1, \; i = 1, 2, \ldots, n \tag{3}$$

where $\hat{\theta}_i$'s are the DEA estimated technical efficiency scores, z_i is a vector of environmental variables, β is a vector of parameters to be estimated, and ε_i is assumed to be normally distributed N(0, σ^2) with left truncation at $-z_i\beta$ and right truncation at $1-z_i\beta$. The implicit assumption is that the environmental variables only affect the efficiency scores and have no effect on the frontier (Simar and Wilson 2007). Unfortunately, Simar and Wilson showed that $\hat{\theta}_i$ is a biased estimator, and efficiency scores $\hat{\theta}_i$'s (i = 1, 2,…, n) in (3) are serially correlated in a complicated, unknown way. While the correlations among $\hat{\theta}_i$'s disappear asymptotically, standard methods for inference are invalid. To provide valid inference in the second stage analysis, Simar and Wilson (2007) suggested the use of: (1) a bootstrap procedure to obtain bias-corrected DEA estimates of technical efficiency, and (2) a parametric bootstrap of the truncated regression in the second stage. Using biased efficiency estimates as the dependent variable in (3) may lead to biasness and statistical inefficiency in the estimation of β. These problems might be mitigated by using bias-corrected efficiency estimates. The second stage truncated regression may be rewritten as:

$$0 < \hat{\hat{\theta}}_i = z_i\beta + \varepsilon_i \leq 1, \ \ i = 1, 2, \ldots, n \tag{4}$$

where $\hat{\hat{\theta}}_i = \hat{\theta}_i - bias(\hat{\theta}_i)$ is the bias-corrected estimator of technical efficiency and $bias(\hat{\theta}_i)$ is the bootstrap bias estimate of $\hat{\theta}_i$. However, valid inference about β can be obtained only by using a parametric bootstrap procedure applied to the truncated regression in (4) (Simar and Wilson 2007).

RESULTS

To estimate hospital technical efficiency, we use DEA with the two years of data jointly to construct one frontier for all of the observations and measure efficiency of each hospital in the sample relative to this "best-practice" or efficient frontier. Table 2 presents the mean efficiency scores of the two groups of rural hospitals by year as well as with pooled data for two different specifications: Model 1 in which the group of non-converters is restricted to rural hospitals with ≤ 75 beds, and Model 2 in which the group of non-converters is restricted to ≤ 50 beds. The following statistics are reported for each group in each model: original mean group efficiency (Eff), bias-corrected mean group efficiency (BCEff), and standard deviation (SD).

The results in Table 2 show that the mean bias-corrected group efficiency scores are smaller than the original (uncorrected) mean group estimates, with an estimated bias of approximately 10% for both model specifications. Based on the original mean group estimates, CAHs are 3% more efficient than non-converters in Model 1 (84% for CAHs vs. 81% for non-converters) and 2% more efficient in Model 2 (84% vs. 82%). The mean bias-corrected group efficiencies indicate that CAHs are 5% more efficient than non-converters in 2005 under both model specifications. In 2006, CAHs are 4% more efficient than non-converters in Model 1 and 3% more efficient in Model 2.

Analysis of Inefficiency Densities

Figure 1 shows the densities of inefficiency scores[1] of CAHs and non-converting rural hospitals in each year as well as with the two years jointly used. Two separate specifications are used: (a) Model 1 in which the comparison group is restricted to non-converting rural hospitals with ≤ 75 beds, and (b) Model 2 in which the comparison group is restricted to ≤ 50 beds. The yearly densities of inefficiency scores of CAHs and non-converting rural hospitals in Model1 appear to be tightly grouped. However, we can notice a leftward shift of the densities of CAHs in 2005 and 2006 relative to those of non-converting rural hospitals and that the groups of CAHs have more of their distributional mass close to unity than the corresponding groups of non-converting rural hospitals, suggesting that CAHs in 2005 and 2006 are more technically efficient

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[1] We use reciprocal of original efficiency scores (inefficiency scores) in kernel density estimation.

than non-converting rural hospitals. These findings are supported by Simar-Zelenyuk test (Table 3, Model 1) which rejected the null hypothesis of equality between densities of CAHs and non-converting rural hospitals in 2005 and 2006.

An even clearer picture is provided when the two years of data are jointly used to estimate inefficiency densities of CAHs and non-converting rural hospitals in Model 1. Figure 1 (Model 1) shows that the estimated mode of density of CAHs is around 1.1 while for non-converting rural hospitals the estimated mode of density is around 1.3 suggesting that CAHs are more technically efficient than non-converting rural hospitals. This result is also supported by Simar-Zelenyuk test (Table 3) which strongly rejected the null hypothesis of equality between densities of CAHs and non-converting rural hospitals.

Figure 1 (Model 2) shows that the yearly densities of inefficiency scores of CAHs and non-converting rural hospitals appear to be more tightly grouped and Simar-Zelenyuk test failed to reject the null hypotheses on equalities of 2005 and 2006 inefficiency densities of CAHs and the corresponding densities of non-converting rural hospitals (Table 3, Model 2). A comparison of inefficiency densities of CAHs and non-converting rural hospitals (pooled data) shows that CAHs appear to be slightly more technically efficient than non-converting rural hospitals and Simar-Zelenyk test rejected the null hypothesis on equality of densities only with a bootstrap p-value = 0.08.

Analysis of Efficiency Determinants

Here, we present the results of the second stage analysis where bias-corrected efficiency scores, estimated in the first stage using DEA with a bootstrap procedure, are regressed, in the second stage, on environmental variables using a bootstrapped truncated regression model. To check the robustness of our results, we estimate separate bootstrapped truncated regressions for each year as well as with pooled data, for each of the two models. Again, in Model 1 the group of non-converters is restricted to rural hospitals with ≤ 75 beds, and in Model 2 the group of non-converters is restricted to ≤ 50 beds.

The results in Table 4 show that the CAH dummy, which is the primary variable of interest, has a positive and statistically significant (at the 1% level) coefficient in both models. In Model 1, the estimated parameters of CAH dummy suggest that CAHs are 6% in 2006, and 7% in 2005 (6.3% with pool data) more technically efficient than non-converting rural hospitals. In Model 2, the estimated results suggest that CAHs are 3.5% in 2006, and 4.7% in 2005 (6% with pool data) more efficient than non-converting rural hospitals. These results are consistent with our group efficiency analysis where we find similar differences between mean bias-corrected group efficiencies of CAHs and non-converting rural hospitals.

The second stage estimated results also indicate that system membership has a positive and highly significant effect on hospital efficiency in all model specifications suggesting that rural hospitals that are members in a multihospital system are more efficient than the ones that are not (Rosko and Mutter 2010). We find a negative and significant coefficient for government dummy only in Model 1 with 2006 and pool data suggesting that government rural hospitals are less efficient than their non-profit counterparts. The coefficient of for-profit ownership is positive and significant in both models with 2006 and pool data suggesting that for-profit rural hospitals are more efficient than non-profit and government hospitals in our sample. This is consistent with previous literature and property rights theory which suggest that one way for-profit hospitals increase their profits is by reducing inefficiency (Rosko and Mutter 2011).

Medicare and Medicaid share of admissions have positive and significant coefficients in Model 1 with 2005 data. The coefficient on Medicaid is especially highly significant and indicative of the efficiency improvement impact that reduced Medicaid reimbursement has on hospital efficiency (Rosko and Mutter 2011). A negative and significant coefficient is found for Herfindahl-Hirschman Index in Model 2 with 2005 and 2006 data suggesting that an increase in HHI (or a decrease in hospital competition) leads to a decrease in efficiency, a result consistent with other findings in the literature (Rosko and Mutter 2010; 2011).

CONCLUSION

In this study, we statistically tested for technical efficiency differences between cost-based reimbursed CAHs and non-converting, PPS rural hospitals. CAHs were compared with two different groups of non-converting rural hospitals restricted by the number of beds. Bias-corrected efficiency scores were estimated and indicate that CAHs are, on average, more technically efficient than both groups of non-converting, PPS rural hospitals. We estimated and compared the densities of efficiency scores of CAHs and PPS rural hospitals using a kernel density estimator and a bootstrap-based test proposed by Simar and Zelenyuk (2006). Density analysis suggested that CAHs are more technically efficient than non-converting rural hospitals, a result supported by Simar-Zelenyuk tests which rejected the null hypotheses of equality between the densities of efficiency scores of CAHs and non-converting rural hospitals. We also estimated bootstrapped truncated regressions (Simar and Wilson 2007) where bias-corrected efficiency scores were regressed on explanatory variables. The estimated results showed a positive and significant marginal effect of CAH status suggesting that CAHs are more technically efficient than non-converting, PPS rural hospitals. This study has an important policy implication. It shows that the CAH program has achieved its objective – it has increased access to health care services in isolated rural areas without decreasing technical efficiency of those rural hospitals that converted to CAH status.

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Table 1. Variable definitions and summary statistics

		CAH		Rural (≤ 75beds)		Rural (≤ 50beds)	
Variables		Mean	SD	Mean	SD	Mean	SD
Outputs							
Admissions		1,074.72	424.19	2,288.59	962.15	1,798.38	737.36
Post-admission days		6,123.91	6,519.39	6,428.79	2,995.17	4,609.00	1,986.34
Outpatient visits		42,111.84	30,452.84	58,845.55	38,733.99	47,727.91	33,938.45
Emergency room visits		7,116.85	4,503.27	12,426.49	6,229.05	9,905.49	4,950.65
Outpatient surgeries		911.95	725.12	1,654.33	1,090.56	1,268.85	885.42
Births		96.89	108.09	278.09	231.69	221.84	215.79
Quality Measures							
Patients given pneumococcal vaccination (%)		62.28	23.58	63.17	21.96	64.24	21.95
Patients given initial antibiotic timing (%)		84.97	8.73	81.99	9.39	82.05	9.43
Patients given the most appropriate initial antibiotic (%)		76.98	13.89	75.11	13.48	75.07	13.67
Inputs							
Total staffed and licensed hospital beds		35.44	20.85	50.25	14.63	38.46	9.26
Full time equivalent (FTE) employees		194.70	77.49	287.35	125.60	231.89	109.83
Environmental Variables							
GOV	Government hospital (1 or 0)	0.31	-	0.31	-	0.32	-
FP	For-profit hospital (1 or 0)	0.03	-	0.17	-	0.15	-
MEDICARE%	Medicare admissions (%)	59.96	12.70	50.91	10.46	51.49	11.60
MEDICAID%	Medicaid admissions (%)	12.85	7.94	18.14	9.10	17.17	8.92
HHI	Herfindahl-Hirschman index	0.49	0.35	0.56	0.33	0.55	0.33
SYSTEM	Multihospital system (1 or 0)	0.42	-	0.56	-	0.57	-
MHMO%	Medicare HMO penetration (%)	3.35	5.27	3.33	6.08	3.15	5.36
INCOME	Median household income	38,488.14	6,223.04	38,103.89	8,470.14	38,486.29	8,803.04

Table 2. Summary statistics of technical efficiency scores

	Model 1				Model 2			
	N	Eff	BCEff	SD	N	Eff	BCEff	SD
CAH06	219	0.85	0.75	0.02	219	0.85	0.76	0.02
CAH05	164	0.83	0.74	0.02	164	0.83	0.74	0.02
RUR06	298	0.82	0.71	0.02	161	0.83	0.73	0.02
RUR05	229	0.80	0.69	0.02	111	0.80	0.69	0.03
CAH	383	0.84	0.74	0.01	383	0.84	0.74	0.02
RUR	527	0.81	0.69	0.02	272	0.82	0.70	0.02
ALL	910	0.82	0.71	0.01	655	0.83	0.73	0.01

Notes. Eff is the mean of original efficiency scores; BCEff is the mean of bias-corrected efficiency scores; SD is standard deviation. In Model 1, the comparison group is restricted to non-converting rural hospitals ≤ 75 beds (or ≤ 50 beds for Model 2).

Table 3. Simar-Zelenyuk test for equality of inefficiency distributions

	Model 1		Model 2	
Null Hypothesis	Li test	p-value*	Li test	p-value*
f(CAH06)=f(RUR06)	2.43	0.012	-0.37	0.625
f(CAH05)=f(RUR05)	1.38	0.059	0.42	0.595
f(CAH06)=f(CAH05)	-0.36	0.652	-0.76	0.259
f(RUR06)=f(RUR05)	-0.65	0.387	-0.37	0.631
f(CAH)=f(RUR)	2.830	0.009	1.194	0.075

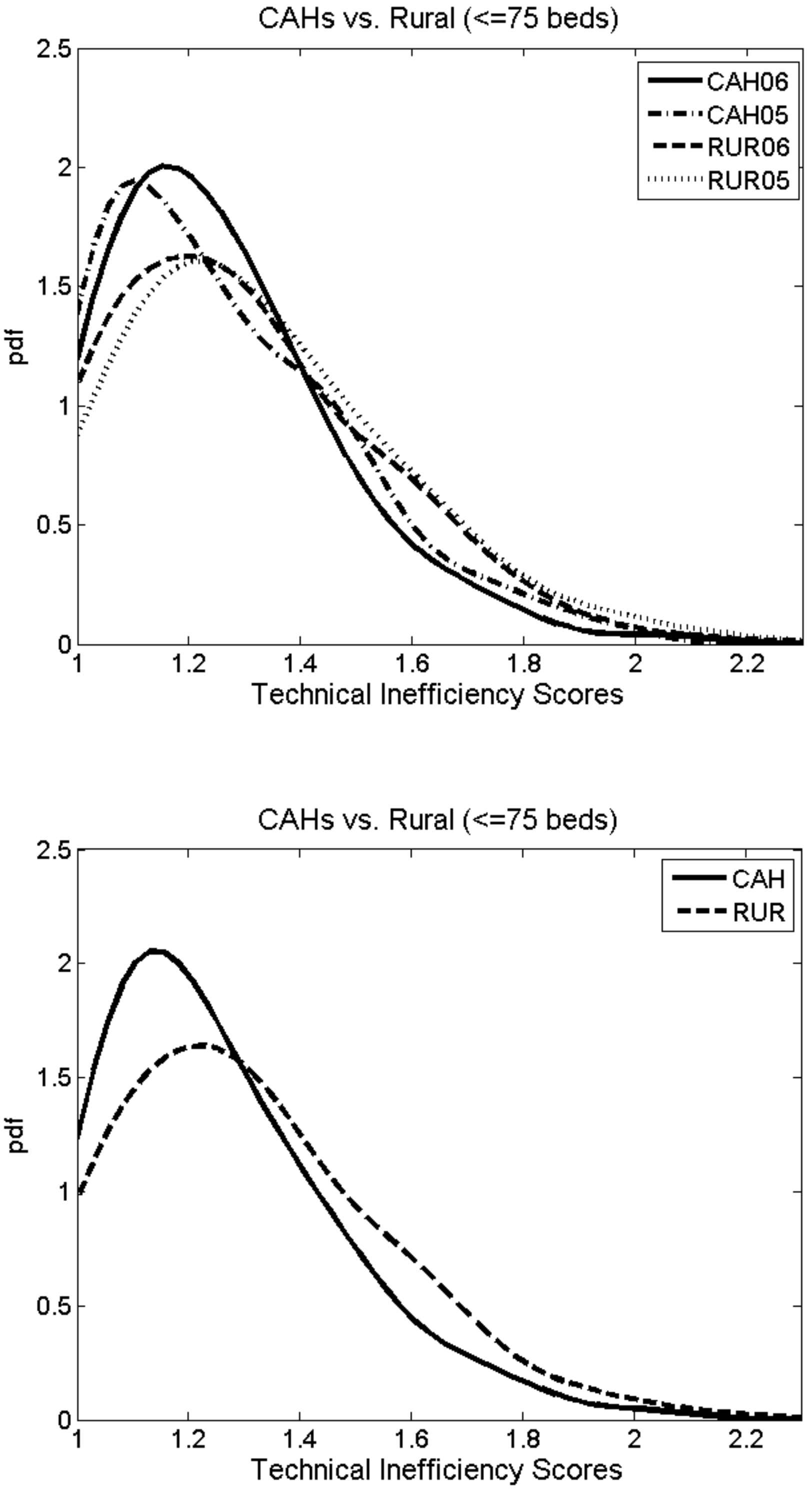
Notes. *Bootstrap p-value from 2000 iterations. Estimation by authors in Matlab after adopting from code used for Simar and Zelenyuk (2006). In Model 1, the comparison group is restricted to non-converting rural hospitals ≤ 75 beds (or ≤ 50 beds for Model 2).

Table 4. Bootstrapped truncated regression results

	Model 1			Model 2		
Variable	2005	2006	Pool	2005	2006	Pool
Constant	0.5799***	0.6809***	0.6261***	0.6397***	0.7510***	0.6980***
GOV	-0.0117	-0.0157*	-0.0147**	0.0130	0.0009	0.0046
FP	0.0303*	0.0355**	0.0343***	0.0334	0.0334*	0.0334**
MEDICARE%	0.0007	-0.0001	0.0003	0.0002	-0.0009*	-0.0004
MEDICAID%	0.0018***	-0.0005	0.0006	0.0017**	-0.0007	0.0003
HHI	-0.0122	-0.0048	-0.0079	-0.0372**	-0.0257*	-0.0299***
SYSTEM	0.0335***	0.0255***	0.0280***	0.0446***	0.0336***	0.0373***
CAH	0.0656***	0.0577***	0.0610***	0.0437***	0.0340***	0.0376***
INCOME	-2.16E-07	-4.59E-07	-3.66E-07	-7.02E-07	-3.24E-07	-5.20E-07
MHMO%	0.0004	0.0007	0.0005	0.0010	0.0010	0.0010
Y2006			0.0091			0.0154*
σ	0.0971***	0.0946***	0.0961***	0.0958***	0.0924***	0.0944***

***, **, and * denote significance at 0.01, 0.05, and 0.10 levels based on percentile bootstrap confidence intervals.

In Model 1, the comparison group is restricted to non-converting rural hospitals ≤ 75 beds (or ≤ 50 beds for Model 2). Separate bootstrapped truncated regressions were estimated for 2005, 2006, and with pooled data.


CAHs vs. Rural (<=75 beds)
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Technical Inefficiency Scores
CAH06
CAH05
RUR06
RUR05
CAHs vs. Rural (<=75 beds)
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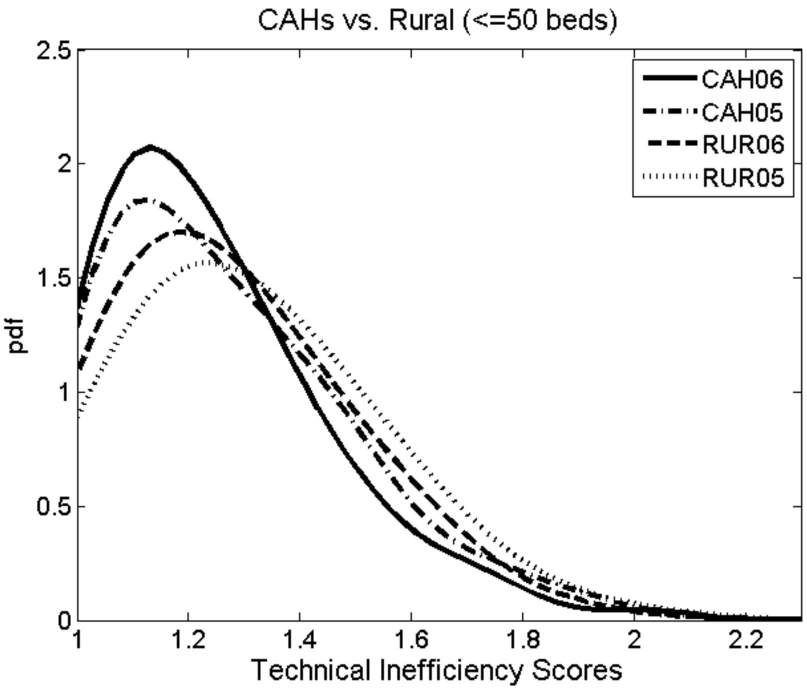
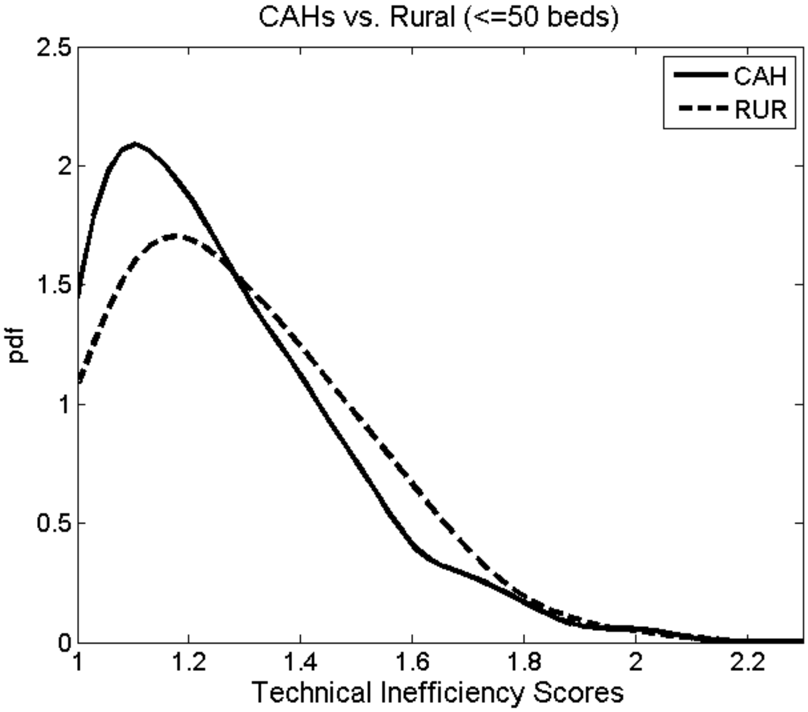
Technical Inefficiency Scores
CAH
RUR

(a) Model 1





(b) Model 2

Figure 1: Kernel estimated densities of inefficiency scores: CAHs vs. non-converting rural hospitals (2005 – 2006 as well as with pooled data)