Analyzing Differences in Rural Hospital Efficiency: A Data Envelopment Analysis Approach

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Abstract

This study analyzes difference in efficiency among the U.S. rural hospitals using a two-stage, semi-parametric approach. Data Envelopment Analysis is used in the first stage to calculate cost, technical and allocative efficiencies of Critical Access Hospitals (CAH) and non-CAH rural hospitals. Following Simar and Wilson (2007), bootstrapped truncated regressions are used in the second stage to infer on relationship between the cost, technical and allocative inefficiencies of hospitals and some environmental variables. The estimated results show that CAHs are less cost, technical and allocative efficient than non-CAH rural hospitals. The results also show that Medicare cost-based reimbursement for CAHs has a negative effect on the efficiency of these hospitals while Medicare prospective payment system for non-CAH rural hospitals has a positive effect on hospital efficiency.

Introduction

One of the most important changes in rural health care policy was the creation of Critical Access Hospital (CAH) program which was introduced as part of the Balanced Budget Act (BBA) of 1997. The objective of the CAH program has been to protect small, financially vulnerable rural hospitals that might be essential for access to health care services by granting them Medicare cost-based reimbursement, rather than to seek ways in which their costs might be reduced (Dalton et al. 2003). A hospital that converts to CAH status has the advantage of receiving reasonable cost-based reimbursement for inpatient and outpatient service delivered to Medicare beneficiaries. However, the hospital must meet several requirements before conversion. 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; use no more than 25 acute care beds at any one time; the annual average length of stay cannot be greater than four days; and provide 24-hour emergency care services.

Prior to 1983, the Federal Government provided payments to hospitals, under its Title XVIII Program (Medicare), in the form of cost-based reimbursement. This cost-based reimbursement gave hospitals few incentives to contain their costs and operate efficiently (Gianfrancesco 1990, Morey and Dittman 1996). The rationale is that under cost-based reimbursement a hospital has an incentive to increase costs in order to receive higher revenues because Medicare pays for services on a cost basis (McKay et al., 2002/2003). In 1983, Medicare replaced cost-based reimbursement with the prospective payment system[1] (PPS). The PPS system was designed to promote efficiency in hospital operation by rewarding hospitals that are able to keep their costs below PPS rates and penalizing hospitals with higher costs[2]. The PPS system relies on the assumption that if a hospital can increase its net revenue by reducing costs, it will seek ways to increase the efficiency with which it uses its resources (Sexton et al. 1989). The CAH program has been designed to support small, isolated rural hospitals that face the threat of closure because of reduced patient volumes and rising costs. CAHs receive cost-based reimbursement[3] for inpatient and outpatient services delivered to Medicare beneficiaries and are designed to address the needs of rural communities where full service hospitals are not financially viable (Capalbo et al. 2002). However, there are some concerns that Medicare cost-based reimbursement for CAHs might have a negative impact on the efficiency with which these hospitals operate. In the 2005 Report to Congress, Medicare Payment Advisory Commission

[1] The PPS system paid a fixed fee based on the diagnosis related group (DRG) allowing variations only for very serious cases that might require additional care and resources.
[2] Under PPS system, hospitals are allowed to keep the surplus between the PPS rate and actual cost of providing services. Conversely, hospitals can lose money if their costs exceed the PPS rate.
[3] Under cost-based reimbursement, hospitals were paid an interim rate throughout the year, receiving retrospective payments from Medicare for the difference between interim payments and total allowable cost at the end of their fiscal year.

(MedPAC) states: “Although the CAH program has helped preserve access to emergency and inpatient care in isolated areas, it may not have accomplished this goal in an efficient manner” (MedPAC 2005: 167). This study contributes to the research on hospital efficiency by analyzing differences in efficiency between CAHs and prospectively paid rural hospitals using a two-stage, semi-parametric model with a bootstrap procedure suggested by Simar and Wilson (2007).

In this study, we try to answer the following two questions. First, are CAHs less efficient than the rural hospitals that did not convert to the CAH status? Second, is Medicare cost-based reimbursement one of the main causes of CAHs’ higher inefficiency? Specifically, we calculate cost, technical, and allocative efficiencies of CAHs and compare them with those of nonconverting, non-CAH rural hospitals. In addition, we try to identify the factors that might affect performance of CAHs and check whether these factors have a similar effect on non-CAH rural hospitals.

We hypothesize that CAHs are, on average, less efficient than nonconverting, non-CAH rural hospitals because of the differences in Medicare reimbursement facing these hospitals. While CAHs receive Medicare cost-based reimbursement, non-CAH rural hospitals are paid under the Medicare prospective payment system. Past evidence showed that cost-based reimbursement gave hospitals few incentives to control their costs and encouraged inefficiently produced services (Gianfrancesco 1990). On the other hand, the PPS system was designed to promote efficiency in hospital operation. Consequently, we expect that the mean inefficiency of CAHs to be higher than that of non-CAH rural hospitals.

Literature Review

The theoretical foundations of efficiency measurement are based on the seminal work of Farrell (1957) and include the measurement of technical and allocative efficiency using radial measures of distance to the production or cost frontier. Technical efficiency refers to the use of the least resources to produce a given level of output. Alternatively, technical efficiency may be defined in terms of maximizing output for a given level of input. Allocative efficiency involves selecting combinations of inputs which produce a given amount of output at minimum cost, given input prices (Hollingsworth and Peacock 2008).

The empirical measurement of economic efficiency is based on the underlying idea of defining an efficient frontier against which to measure the performance of an economic organization. Murilo-Zamorano (2004) and Worthington (2004) distinguish between parametric and non-parametric methods that have been used to estimate the efficient frontier. While in the parametric methods a functional form of the efficient frontier is predefined or imposed a priori, the non-parametric methods assume no functional form. Alternatively, Jacobs (2001) classifies these methods as statistical or non-statistical, where statistical methods are based on assumptions about the stochastic nature of the data. Non-statistical methods tend to be non-parametric and deterministic (no statistical noise), whereas statistical methods tend to be parametric and stochastic.

The parametric approach to efficiency measurement has been associated with Stochastic Frontier Analysis (SFA), which was developed independently by Aigner, Lovell, and Schmidt (1977), and Meeusen and van den Broeck (1977). SFA allows the decomposition of deviations from the efficient frontier into a random error term, that embodies statistical noise and measurement error, and a one-sided error term that acts as a measure of inefficiency (Worthington 2004, Greene 2008). However, SFA requires the specification of a functional form for the technology and an assumption about the distribution of the inefficiency error term which may be inappropriate or very restrictive. Hollingsworth and Peacock (2008) argue that SFA approach to efficiency measurement can lead to two significant problems. First, as a parametric method, SFA places restrictive assumptions on the functional form. This causes both specification and estimation problems given that little is known a priory about what functional form should be used. Second, the choice of the distribution for the inefficiency term is arbitrary, and is a potential source of model misspecification (Newhouse 1994).

The majority of health care researchers have analyzed the effect of regulatory changes on the efficiency of health care facilities using a nonparametric method called Data Envelopment Analysis (DEA). Hollingsworth and Peacock (2008) state that DEA is by far the most common method for analyzing efficiency in health care. DEA, developed by Charnes, Cooper and Rhodes (1978), is a linear programming approach that measures the economic efficiency of a firm relative to a piece-wise linear-segmented efficiency frontier constructed from the most efficient firms (Hollingsworth et al. 1999, Worthington 2004). Being nonparametric, DEA has the advantage of requiring neither the assumption of a particular functional form for technology nor assumptions regarding how inefficiency error is distributed. The drawback is that DEA assumes that any deviation of a firm from the efficient frontier is attributed to inefficiency. Therefore, DEA makes no allowance for external shocks, statistical noise, measurement error, or omitted variables in the model (Greene 2008).

Many of the studies of efficiency analysis have used a two-stage approach. In the first stage, DEA is solved and efficiency scores are calculated using only the traditional inputs and outputs. Then, in the second stage, the efficiency scores are regressed on some environmental variables thought to influence efficiency. This approach has been advocated by Coelli et al. (2005), Ray (2004), Chilingerian and Sherman (2004) among others. Important applications of the two-stage approach in health care industry include Sexton et al. (1989), Nyman and Bricker

(1989), Kooreman (1994), Ozcan et al. (1998), and Rosko et al. (1995) analyzing efficiency in nursing homes, Chang (1998) and Chu et al. (2003) analyzing efficiency in Taiwan hospitals, Ferrier and Valdmanis (1996) analyzing the efficiency of rural hospitals in the U.S., Chirikos and Sear (2000) analyzing efficiency in Florida acute care hospitals.

Methodology

Building on the previous literature, we use a two-stage, semi-parametric approach to examine the efficiency of rural hospitals in the U.S. and disentangle the effect of reimbursement mechanism on CAHs and non-CAH rural hospitals. In the first-stage, DEA is employed to estimate cost, technical, and allocative efficiencies for both CAHs and non-CAH rural hospitals. In the second stage, a measure of hospital inefficiency, obtained from DEA in the first stage, is regressed against a set of variables that are expected to influence hospital performance. One important factor to consider is how Medicare reimbursement policies affect hospital efficiency. CAHs receive Medicare cost-based reimbursement which is expected to be inversely related with hospital efficiency. On the other hand, non-CAH rural hospitals are reimbursed under the Medicare prospective payment system which is expected to be directly associated with hospital efficiency.

In DEA, the efficiency of an organization or decision making unit (DMU) can be measured using either an input or an output orientation. Input-oriented measures keep output fixed and assess the proportional reduction in input usage which is possible, while output-oriented measures keep input levels fixed and explore the proportional expansion in output quantities that is possible (Coelli et al. 2005, Jacobs et al. 2006). Following Ferrier and Valdmanis (1996), we adopt an input-oriented DEA approach based on the assumption that cost containment is a primary goal of hospital administrators and policy makers. Indeed, a hospital does not select the number of patients treated and, therefore, the output level is exogenously determined. However, the hospital still has to select the inputs so as to provide the output at the minimum cost (Ray 2004). When input prices are available in addition to output and input data and a behavioral objective such as cost minimization is appropriate, a measure of cost efficiency can be computed and decomposed into allocative and technical components (Coelli et al. 2005, Thanassoulis et al. 2008). All the efficiency measures derived below are based on the assumption of variable returns to scale (VRS) for all hospitals.

DEA measures cost efficiency in two steps. First, given input prices and output levels, the cost-minimizing input vector for the *i*-th DMU is calculated using linear programming (LP). Then cost efficiency is measured as the ratio of minimum cost to observed cost. A formal representation of cost minimization DEA is based on Ferrier and Valdmanis (1996), Ray (2004), Coelli et al. (2005), and Thanassoulis et al. (2008). We start with the observed input-output data from *n* hospitals or DMUs. Let $\mathrm{y}^{\mathrm{j}} = (\mathrm{y}_{1\mathrm{j},}\ \mathrm{y}_{2\mathrm{j}}, \ldots \ldots \ldots \mathrm{y}_{\mathrm{mj}})$ be the *m*-element output vector of hospital *j* while $\mathrm{x}^{\mathrm{j}} = (\mathrm{x}_{1\mathrm{j},}\ \mathrm{x}_{2\mathrm{j}}, \ldots \ldots \ldots \mathrm{x}_{\mathrm{kj}})$ is the corresponding *k*-element input vector. The input requirement set (i.e., the set of all input vectors that can produce a given output vector, *y*) can be represented as:

$$V(y) = \left\{x: x \geq \lambda X;\ y \leq \lambda Y;\ \sum_{j=1}^{n} \lambda_j \ = 1;\ \lambda_j \geq 0\ (j = 1,2, \ldots \ldots \ldots, N)\right\} \tag{1}$$

where *X* is an *n* x *k* matrix of *k* observed inputs, *Y* is an *n* x *m* matrix of *m* observed outputs for each of the *n* hospitals, and λ is 1 x *n* vector of weights. The summation restriction on the elements of vector λ allows for VRS. For a target output level y^o and a given input price vector w^o, the minimum cost under the assumption of VRS is:

$$C^* = \min w^{0\prime}\, x: x \in V(y^0). \tag{2}$$

The minimum cost of operation for a particular hospital is obtained by solving the DEA linear programming (LP) problem:

$$\text{Min} \quad \sum_{i=1}^{k} w_i^0 \, x_i$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j \; x_{ij} \; \leq x_i \quad (i = 1, 2, \ldots\ldots, k)$$

$$\sum_{j=1}^{n} \lambda_j \; y_{rj} \; \geq y_{r0} \quad (r = 1, 2, \ldots.., m) \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j \; = 1$$

$$\lambda_j \geq 0 \qquad (j = 1, 2, \ldots\ldots., n)$$

The optimal solution to this problem is the input vector, x_i^*, that minimizes the cost of producing the observed level of outputs given technology and input prices. The LP problem in (3) takes the *i*-th hospital and seeks to radially contract the input vector, x_i, as much as possible, while still remaining within the input requirement set. The inner boundary of this set is a piece-wise linear frontier determined by the observed data points. The radial contraction of the input vector, x_i, produces a projected point on the frontier which is a linear combination of the observed data points. The constraints in the DEA LP problem ensure that this projected point cannot lie outside the input requirement set (Coelli et al. 2005). In the LP problem in (3), all input inequality constraints are binding at the optimal solution, implying that there cannot be any input slack at the optimal bundle. In other words, when any slack is present in any input, it is possible to reduce the relevant input by the amount of the slack without reducing any output (Ray 2004).

The cost minimizing input vector, x_i^*, can be used to calculate the cost efficiency of the *i*-th hospital, CE_i, as:

$$CE_i = \; w^{0\prime} x_i^* / w^{0\prime} x_i \tag{4}$$

That is, CE_i is the ratio of minimum cost to observed cost for the *i*-th hospital. In other words, the cost efficiency measures the factor by which the observed cost can be reduced if the *i*-th hospital selects the optimal input bundle, x_i^*, and operate at a technically efficient point. Failure to achieve cost efficiency may be due to (a) technical inefficiency in the form of wasteful use of inputs, and (b) allocative inefficiency due to the incorrect mix of inputs (Ferrier and Valdmanis 1996, Ray 2004).

The input-oriented measure of technical efficiency (*TE*) of the *i*-th hospital under VRS can be calculated by solving the following DEA LP problem:

$$\begin{aligned}
&\text{Min } \theta \\
&\text{Subject to:} \\
&\sum_{j=1}^{n} \lambda_j \, x_j \le \theta x_i \\
&\sum_{j=1}^{n} \lambda_j \, y_j \ge y_i \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0 \quad (j = 1, 2, \ldots\ldots, n)
\end{aligned} \tag{5}$$

The objective of the LP problem in (5) is to find the minimum θ that reduces the input vector x_i to θx_i while guaranteeing at least the output level y_i. The optimal solution to this LP problem gives $TE = \theta^* \le 1$, where $\theta^*=1$ indicates a point on the efficient frontier and hence a technically efficient hospital. $TE<1$ indicates that it is possible to produce the observed level of outputs using less of all inputs. The LP problem must be solved separately for each DMU in the sample in order to obtain a value of θ for each DMU (Coelli et al. 2005).

Once measures of cost and technical efficiencies are derived, the allocative efficiency (*AE*) can be easily calculated as:

$$AE = CE/TE \tag{6}$$

The allocative efficiency shows by how much the cost of the hospital can be reduced if it selects the input mix that is the most appropriate given the input price ratio faced by the hospital (Ray 2004).

Most of the two-stage studies that have regressed a measure of inefficiency on environmental variables $\boldsymbol{z_i}$ have used tobit (censored) regression. However, Simar and Wilson (2007) have shown that tobit regression for the second stage is inappropriate. Instead, they suggest an approach based on truncated regression with a bootstrap approach to provide valid inferences in the second stage. Simar and Wilson (2007) argue that DEA efficiency estimates which are used as a dependent variable in the second stage regression are serially correlated in a complicated, unknown way leading to invalid inference in the conventional two-stage DEA procedure. The truncated maximum likelihood regression used in the second stage is represented as:

$$\hat{\delta}_i = \boldsymbol{z_i}\boldsymbol{\beta} + \varepsilon_i, \quad i = 1, 2, \ldots, n \tag{7}$$

where $\hat{\delta}_i = 1/DEA\ score$ such that $\hat{\delta}_i \geq 1$; $\boldsymbol{z_i}$ is a vector of k environmental variables which are thought to have an effect on the inefficiency scores $\hat{\delta}_i$; $\boldsymbol{\beta}$ is a vector of parameters to be estimated; and ε_i is distributed $N(0, \sigma^2)$ with left truncation at $1-\boldsymbol{z_i}\boldsymbol{\beta}$ for each i. To provide valid inference in the second stage analysis, Simar and Wilson (2007) suggest bootstrap procedures. In this paper, we use the bootstrap procedure referred to as Algorithm 1 by Simar and Wilson (2007).

Data

The data used for this study come from the 2006 American Hospital Association Annual Survey of Hospitals and the 2006 Medicare Hospital Cost Report. The unit of observation for the analysis is the hospital. The market area is defined as the county, a definition used consistently in hospital efficiency studies (Rosko 1999, 2001, Rosko and Mutter 2008). This study focuses on the set of CAHs as well as a comparison group of nonconverting rural hospitals. Following Rosko and Mutter (2010), the comparison group is restricted to rural hospitals with no more than seventy-five beds, allowing us to have two groups of hospitals of similar size (i.e., the average number of beds for CAH facilities was 39.01[4] while for the comparison group was 43.82). After excluding observations with incomplete information and outliers[5], a final data set of 1,310 hospitals (out of which 915 were classified as CAHs) was used in the analysis.

DEA cost-minimization model used in this study requires information on hospital outputs, inputs, and input prices. In their excellent review of hospital efficiency studies, Rosko and Mutter (2008) emphasize that virtually all of the hospital efficiency studies included both inpatient and outpatient outputs. In this study, the number of outpatient visits was included as a measure of hospital's outpatient output. This measure has been consistently used in all of the hospital efficiency studies. In addition, both the number of admissions and the number of inpatient days were included as measures of hospital's inpatient output. Following Ferrier and Valdmanis (1996), Valdmanis et al. (2008) and Harrison et al. (2009), we also included the number of surgeries performed as a hospital output. However, we disaggregated surgeries into outpatient surgeries and inpatient surgeries.

The inputs used in this analysis consist of full time equivalent (FTE) facility personnel and staffed and licensed facility beds (Ferrier and Valdmanis 1996, Harrison et al. 2009). Rosko and Mutter (2008) point out that, due to data constraints, the input price variables were similar in each national study of hospital efficiency. Following these past practices, two input prices were used in the analysis: the price of labor, approximated by the sum of payroll expenses and employee benefits divided by the full-time equivalent facility personnel; and the price of capital

[4] While CAHs are restricted to 25 acute care beds, they have no restrictions on nonacute beds.

[5] For outlier detection, methods suggested by Coelli et al. (2005) were used. In addition, the method suggested by Wilson (1993) for outlier detection for non-parametric frontier models was used. Wilson (1993) states that the efficiency scores produced by DEA may be severely influenced by the presence of outliers in the data.

which was approximated by the sum of depreciation expenses and interest expenses (obtained from Medicare Hospital Cost Report) divided by the number of facility beds. Summary statistics of the output, input, and input price variables for both CAHs and non-CAH rural hospitals are presented in Table 1.

The primary variables used in the second stage to explain hospital performance are those associated with the type of hospital reimbursement policies, ownership status, and the degree of competition in a hospital's market. Medicare reimbursement policies have an impact on hospital profits and can create incentives for hospitals to operate more efficiently. For example, reimbursement policies under Medicare PPS create incentives for reducing inefficiency while cost-based reimbursement gives hospitals few incentives to control their costs. We follow previous literature (Rosko and Mutter 2008, 2010; Mutter and Rosko 2008), and use two variables to reflect the regulatory pressure of public payers: percent of Medicare admissions ((Medicare admissions / total admissions) × 100) and percent of Medicaid admissions ((Medicaid admissions / total admissions) × 100). Under PPS system, Medicare reimbursement policies place fiscal pressure on hospitals. Therefore, the variable representing Medicare percent of admissions is expected to be inversely related with inefficiency when hospitals receive PPS reimbursement, as is the case with non-CAH rural hospitals. On the other hand, CAHs receive Medicare cost-based reimbursement and have few incentives to control their costs. As a result, we expect that Medicare percent of admissions to be directly associated with CAH inefficiency. Similarly, Medicaid percent of admissions is expected to have similar implications as the variable representing Medicare percent of admissions (Ozcan et al. 1998).

The effect of ownership on hospital efficiency should be consistent with Property Rights Theory (PRT) which suggests that for-profit hospitals pursue profit maximization (Rosko 1999).

One way in which for-profit hospitals increase their profits is by reducing inefficiency. PRT argues that when property rights are not clearly specified, incentives to promote efficient behavior decline. Therefore, we expect that for-profit hospitals will place a greater emphasis on earning profits and increasing efficiency than non-profit hospitals. The ownership status in this analysis is introduced by using dummy variables that define public/government owned hospitals, private nonprofit hospitals and for-profit hospitals.

Following previous literature on hospital efficiency, a Herfindahl-Hirschman index (HHI) is used to measure competitive pressure in the hospital market. HHI is a standard economic measure of industry concentration and was calculated by summing the squares of the market shares of admissions for all of the hospitals in the county. This index equals one in monopolistic markets and approaches zero in markets with high competition. Higher HHI values reflect less competitive pressure, and hence increased efficiency should be inversely related to HHI.

An important variable that is used to explain hospital inefficiency is the hospital occupancy rate, which is included as a measure of the demand for hospital services (Ferrier and Valdmanis 1996). It is defined as the number of inpatient days divided by the cumulative number of beds maintained during the year (number of hospital beds ×365 days). Ferrier and Valdmanis (1996) found that higher occupancy rates in rural hospitals helped enhance efficiency. Similarly, Nyman and Bricker (1989) and Ozcan et al. (1998) found a positive impact of occupancy rate on efficiency because higher occupancy allows the firm to staff more efficiently.

Other variables included in the second stage model to explain efficiency are Medicare HMO penetration used as a proxy for general HMO penetration (Rosko and Mutter 2010), a dummy variable to represent whether the hospital participates in a network, and a variable to control for differences in the quality of health services provided by hospitals. When a hospital participates in a network, it has an agreement with one or more hospitals for transfer of patients and sharing of resources and personnel. This allows hospital to provide services at lower costs by allocating the treatment of patients across network members. Thus, it is expected that hospitals that participate in a network to be more efficient than the ones that do not. Hospital accreditation status, as represented by accreditation by the Joint Commission on Accreditation of Health Care Organizations (JCAHO), is a quality measure commonly used in the literature (see for example McKay and Deily 2008). Table 1 presents definitions and summary statistics for all variables used in the analysis for the set of CAHs as well as for the comparing group of nonconverting, non-CAH rural hospitals.

Results

Table 2 shows the summary statistics of efficiency measures from three different DEA runs. Column 2 presents mean cost, technical, and allocative efficiencies from DEA with pooled data for CAHs and non-CAH rural hospitals. Columns 3 and 4 show the average efficiency levels from separate DEA models for CAHs and non-CAH rural hospitals. The average level of cost efficiency is 60% for CAHs and 70.7% for non-CAH rural hospitals. Column 5 presents the results from Banker and Natarajan (2004) DEA-based tests of efficiency differences. The null hypothesis is that there is no difference in inefficiency between CAHs and non-CAH rural hospitals. The alternative hypothesis is that the hospitals that converted to CAH status are less efficient than the comparison group of non-CAH rural hospitals. Based on this test, the null hypothesis of no difference in cost inefficiency between CAHs and non-CAH rural hospitals is rejected under the half-normal distributional assumption for efficiency scores. The result is consistent with our hypothesis that the hospitals that converted to CAH status are less cost efficient than the nonconverting, non-CAH rural hospitals. The higher level of cost inefficiency for CAHs is due to the excessive use of inputs (technical inefficiency) and non-optimal mix of inputs (allocative inefficiency). The mean technical efficiency for CAHs is 72.5%, lower than the mean technical efficiency of non-CAH rural hospitals of 79.6%, and the difference is statistically significant. This indicates that CAHs, on average, use more inputs to produce their output levels than non-CAH rural hospitals. In other words, CAHs over-consume 38% (i.e., 1/0.725 – 1) more inputs to produce their output levels, while non-CAH rural hospitals consume only 25.6% more inputs to produce their output levels than necessary. CAHs also have lower mean allocative efficiency (82.9%) than non-CAH rural hospitals (88.6%), and, again, the difference is statistically significant. These translate into a mean allocative inefficiency of 20.6% for CAHs while the mean allocative inefficiency of non-CAH rural hospitals is approximately 13%.

Determinants of efficiencies: parametric bootstrap of truncated regressions.

Tables 3, 4 and 5 present the results of bootstrapped truncated regressions in which measures of cost, technical and allocative inefficiencies are regressed against variables that are expected to influence hospital performance. Column 2 in these tables shows the results from estimation with pooled data (i.e., combined data of CAHs and non-CAH rural hospitals). Among the variables used to explain hospital inefficiency, we include a dummy variable *cah* = 1 if the hospital is classified as CAH and *cah* = 0 if it is nonconverting, non-CAH rural hospital. For comparition purposes, separate models for CAHs and non-CAH rural hospitals are also estimated and the results are presented in Columns 3 and 4. A positive sign on the coefficient of an explanatory variable implies a negative effect on efficiency while a negative sign indicates a positive effect on efficiency.

Table 3 summarizes the results from the bootstrapped truncated regressions of hospital cost inefficiency on explanatory variables. In the model with pooled data, the primary variable of interest is the *cah* dummy variable which was found positive and statistically significant. This implies that CAHs are less cost efficient than non-CAH rural hospitals. To separate the effects of explanatory variables on the cost efficiency of the two groups of hospitals, separate models for CAHs and non-CAH rural hospitals were also estimated.

The coefficients of the ownership variables measure whether for-profit and government hospitals are more or less efficient than nonprofit hospitals. The coefficient of the government ownership variable for CAHs was found positive and significant, indicating that government owned CAHs were less cost efficient relative to nonprofit CAHs. A similar effect of government ownership on cost inefficiency was also found for the group of non-CAH rural hospitals. A negative and significant effect of for-profit ownership on cost inefficiency was found for both CAHs and non-CAH rural hospitals. This negative coefficient suggests that for-profit CAHs (or non-CAH rural hospitals) are more cost efficient than nonprofit CAHs (or non-CAH rural hospitals), a result that is consistent with Property Rights Theory (PRT). According to PRT, for-profit hospitals are more efficient relative to non-profit counterparts because the profit motive creates a strong incentive to reduce costs and increase efficiency (Rosko 1996).

It is widely recognized that hospitals respond to Medicare and Medicaid payment mechanisms (McKay et al. 2002/2003, Rosko and Mutter 2008). A large number of studies have shown that Medicare PPS places fiscal pressure on hospitals. In these studies Medicare is inversely related to inefficiency (Rosko 1999). CAHs receive Medicare cost-based reimbursement and this provides few incentives for hospital cost containment. One of our hypotheses was that Medicare cost-based reimbursement for CAHs might lead to an increase in the inefficiency of these hospitals. The estimated results show that *mcrpct* (a proxy for the type of Medicare reimbursement) has a positive and significant effect on CAH cost inefficiency while it has a negative and significant effect on the cost inefficiency of non-CAH rural hospitals. Also, notice that the absolute value of the coefficient of *mcrpct* for non-CAH rural hospitals is twice as large as that for CAHs. As expected, the positive coefficient of *mcrpct* for CAHs indicates that Medicare cost-based reimbursement for CAHs leads to an increase in the cost inefficiency of these hospitals while the negative coefficient of *mcrpct* for non-CAH rural hospitals implies that Medicare PPS has a positive effect on the cost efficiency of these hospitals. The insignificant coefficient of *mcrpct* in the model with pooled data comes to confirm the opposite and offsetting effects *mcrpct* has on the two groups of hospitals. The coefficient of *mcdpct* variable was found positive and significant for CAHs; however, it was insignificant for non-CAH rural hospitals.

The coefficient of occupancy rate variable was negative and significant for both CAHs and non-CAH rural hospitals, as well as when the two groups were pooled together. The results indicate that an increase in the occupancy rate leads to a significant decrease in the cost inefficiency of analyzed hospitals. The results are consistent with Ferrier and Valdmanis (1996), who found that occupancy rate in rural hospitals, was strong, positively correlated with cost, technical and scale efficiencies. Similar to Rosko and Mutter (2010), the coefficient of Medicare HMO penetration was negative and significant for CAHs as well as when the two groups were pooled together.

Table 4 shows the estimated results from the bootstrapped truncated regressions of technical inefficiency on environmental variables. In the model with pooled data, the *cah* dummy variable was positive and statistically significant indicating that CAHs were less technical efficient than nonconverting, non-CAH rural hospitals. The effect of ownership variables on technical efficiency was similar to the case when cost efficiency was analyzed. Specifically, the coefficient of government ownership was positive and significant indicating that government hospitals were less technical efficient than nonprofit hospitals, while the coefficient of for-profit ownership was significant only for CAHs indicating that for-profit CAHs were more technical efficient than nonprofit CAHs. While the coefficient of *mcrpct* was insignificant, the coefficient of *mcdpct* was positive and significant indicating that Medicaid is a source of technical inefficiency for both CAHs and non-CAH rural hospitals. The coefficient of occupancy rate was negative, significant and large in magnitude for both groups of hospitals indicating that an increase in occupancy rate leads to a large decrease in technical inefficiency. A negative and significant (at the 10% level of significance) coefficient for both groups of hospitals was also found for Medicare HMO penetration. The coefficient of *jcaho* was positive and significant for both CAHs and non-CAH rural hospitals indicating that hospitals that offer higher levels of quality tend to be more technical inefficient. Finally, the negative coefficient of *hhi,* implying that as market competition is decreased technical efficiency of CAHs increases, is consistent with the practice of service-based competition (Robinson and Luft 1985, Noether 1988, Rosko 1996).

The results from the bootstrap truncated regressions of allocative inefficiency on environmental variables are summarized in Table 5. Again, in the model with pooled data, the *cah* dummy variable was positive and significant indicating that CAHs were less allocatively efficient than non-CAH rural hospitals. The estimated coefficients of ownership variables indicate that government CAHs were less efficient than nonprofit CAHs while for-profit non-CAH rural hospitals were more efficient than nonprofit non-CAH rural hospitals. Similar to the case when cost inefficiency was analyzed, *mcrpct* has a positive and significant effect on CAH allocative inefficiency while it has a negative and significant effect on the allocative inefficiency of non-CAH rural hospitals. The effect of occupancy rate on allocative inefficiency was positive and significant, a result consistent with Ferrier and Valdmanis (1996). Two unexpected results were that the coefficient of *netwrk* was positive and significant for non-CAH rural hospitals while the coefficient of *jcaho* was negative and significant for CAHs.

Conclusions

An important objective of this paper was to determine whether CAHs are less efficient than prospectively paid non-CAH rural hospitals. Using DEA, efficiency measures for both CAHs and non-CAH rural hospitals were calculated and compared. The results showed that CAHs were less cost, technical and allocatively efficient than non-CAH rural hospitals and the difference was statistical significant for all three measures of efficiency. In the second stage, bootstrapped truncated regressions were estimated in which measures of cost, technical and allocative inefficiencies were regressed against a set of environmental variables. The results from the models with pooled data for CAHs and non-CAH rural hospitals also showed that CAHs were more cost, technical and allocative inefficient than non-CAH rural hospitals. Therefore, the results from DEA models in conjunction with the results from the bootstrapped truncated regressions show that CAHs tend to be less efficient than non-CAH rural hospitals. It might be the case that these differences in efficiency could be a consequence of less efficient hospitals choosing to convert to CAH status (Rosko and Mutter 2010).

Another objective of this study was to identify the factors that might affect the performance of CAHs and check whether these factors have a similar effect on non-CAH rural hospitals. The results from the second stage bootstrapped truncated regressions showed that the effect of ownership status on efficiency was similar for both groups of hospitals. Specifically, government hospitals were less efficient than nonprofit hospitals while for-profit hospitals were more efficient than nonprofit counterparts. A similar effect on the efficiency of hospitals had occupancy rate and Medicare HMO penetration, both contributing to increases in the cost and technical efficiencies of hospitals. Medicare percent of admissions (a proxy for the type of Medicare reimbursement) had an opposite but expected effect on the efficiency of hospitals. The positive effect of Medicare percent of admissions on CAH cost and allocative inefficiencies indicates that Medicare cost-based reimbursement for CAHs leads to an increase in the inefficiency of these hospitals while the negative effect of Medicare percent of admissions on the cost and allocative inefficiencies of non-CAH rural hospitals implies that Medicare PPS leads to improvements in hospital efficiency.

While this study found that CAHs were less cost, technical and allocative efficient than non-CAH rural hospitals, a complete assessment of the CAH program needs to go beyond inefficiency and take into account issues such as equitable access to high-quality care. Small rural hospitals depend heavily on Medicare patients and their financial conditions can be heavily influenced by Medicare reimbursement (Dalton et al. 2003). Policy changes in health care market since the 1980s (specifically, the reimbursement changes from cost-based to PPS) have resulted in the deterioration of financial conditions and, ultimately, in the closure of many small rural hospitals (Capalbo et al. 2002). The rationale for the Medicare cost-based reimbursement of CAHs has been to protect these small, financially vulnerable rural hospitals that are essential for access to health care services in rural communities.

In rural areas, alternative sources of health care are limited and rural residents sometimes travel long distances to health care providers. CAHs appear to reduce the cost of emergency and primary care for rural residents and to increase access to health care services in rural communities. In addition, small rural hospitals like CAHs are sometimes the only entities that bring outside money into the communities, provide jobs, and attract new residents and businesses, thus playing an important role in the local economies (Doeksen et al. 1997).

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Table 1. Summary statistics and variable definitions.

DEA Variables		CAH (n=915)		Non-CAH (n=395)	
Outputs		Mean	Std. Dev.	Mean	Std. Dev.
admtot	Total hospital admissions	729.64	462.82	1,877.15	984.94
ipdtot	Total inpatient days	8,113.37	9,406.10	7,466.44	4,064.02
vtot	Total outpatient visits	28,513.82	23,596.37	50,059.19	35,285.00
suropop	Outpatient surgeries	548.14	621.26	1,313.90	1,104.07
suropip	Inpatient surgeries	104.63	142.56	421.11	363.32
Inputs					
bdtot	# hospital beds	39.01	29.32	43.82	16.48
fte	FTE employee	148.90	85.55	246.63	122.17
Input Prices					
pk	Price of capital($)	27,782.95	28,915.50	36,242.26	28,137.17
w	Price of labor($)	49,110.00	13,812.23	50,562.96	14,636.56
Second Stage Variables					
gov	Government hospital	0.45	0.50	0.40	0.49
fprofit	For-profit hospital	0.04	0.20	0.10	0.30
nprofit	Non-profit hospital	0.51	0.50	0.50	0.50
mcrpct	% Medicare admissions	60.82	14.64	52.31	12.77
mcdpct	% Medicaid admissions	11.41	9.05	18.23	9.89
occup	Occupancy rate	0.46	0.23	0.45	0.16
hhi	Herfindahl index	0.56	0.35	0.56	0.34
netwrk	1 if participate in a network	0.42	0.49	0.31	0.46
mhmo	% Medicare HMO penetration	3.80	6.92	2.90	5.58
jcaho	1 if accredited by JCAHO	0.25	0.43	0.52	0.50

Table 2. Summary statistics and tests of efficiency measures.

	Pool	CAH	Non-CAH	F-Test
Efficiency Measure	Mean (St.Dv.)	Mean (St.Dv.)	Mean (St.Dv.)	Eff. Diff.
Cost Efficiency	0.595	0.600	0.707	1.935*
	(0.165)	(0.169)	(0.165)	
Technical Efficiency	0.726	0.725	0.796	1.794*
	(0.155)	(0.158)	(0.143)	
Allocative Efficiency	0.821	0.829	0.886	2.206*
	(0.132)	(0.137)	(0.108)	

* p<0.01; Standard deviations in parenthesis.

Table 3. Truncated regression results: cost inefficiency.

	Pool	CAH	Non-CAH
cons	1.5998***	1.7321***	2.0343***
gov	0.1529***	0.1406***	0.1777***
fprofit	-0.2619***	-0.2545**	-0.2625***
mcrpct	0.0017	0.0028*	-0.0060**
mcdpct	0.0067***	0.0061**	0.0011
occup	-0.6354***	-0.5746***	-0.8448***
hhi	-0.0611	-0.029	-0.0671
netwrk	-0.0184	0.0117	0.0073
mhmo	-0.0055**	-0.0068**	-0.0034
jcaho	0.036	0.003	0.0863*
cah	0.3392***		
sigma	0.5349***	0.5661***	0.4143***

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

Notes: (1) Estimation based on Algorithm 1 of Simar and Wilson (2007), with 2000 bootstrap replications for confidence intervals of the estimated coefficients. (2) The standard errors were corrected for possible heteroskedasticity using White method.

Table 4. Truncated regression results: technical inefficiency.

	Pool	CAH	Non-CAH
cons	1.9515***	2.0060***	1.8285***
gov	0.0853***	0.0722***	0.1465***
fprofit	-0.1602***	-0.1683***	-0.0686
mcrpct	0.0003	0.0006	-0.0002
mcdpct	0.0035***	0.0036**	0.0041*
occup	-1.6326***	-1.6362***	-1.7889***
hhi	-0.0515*	-0.0467*	-0.0215
netwrk	0.0094	0.0308	0.0153
mhmo	-0.0035**	-0.0029*	-0.0070*
jcaho	0.0560***	0.0755***	0.0885**
cah	0.1195***		
sigma	0.2983***	0.3110***	0.2906***

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

Notes: (1) Estimation based on Algorithm 1 of Simar and Wilson (2007), with 2000 bootstrap replications for confidence intervals of the estimated coefficients. (2) The standard errors were corrected for possible heteroskedasticity using White method.

Table 5. Truncated regression results: allocative inefficiency.

	Pool	CAH	Non-CAH
cons	-0.4200***	-1.2261***	0.2537
gov	0.0706**	0.0837*	0.0394
fprofit	-0.1997**	-0.2389	-0.6878***
mcrpct	0.0028**	0.0056**	-0.0099***
mcdpct	0.0045**	0.0062*	-0.0042
occup	1.8197***	2.7652***	1.9946***
hhi	-0.0225	0.0372	-0.0851
netwrk	-0.0396	-0.0554	0.1167*
mhmo	-0.0003	-0.0039	0.0066
jcaho	-0.0056	-0.1223*	0.0393
cah	0.2704***		
sigma	0.3636***	0.4525***	0.3120***

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

Notes: (1) Estimation based on Algorithm 1 of Simar and Wilson (2007), with 2000 bootstrap replications for confidence intervals of the estimated coefficients. (2) The standard errors were corrected for possible heteroskedasticity using White method.