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Three essays on the efficiency of rural hospitals in the United States

Iustin Cristian Nedelea
Louisiana State University and Agricultural and Mechanical College, inedel1@lsu.edu

THREE ESSAYS ON THE EFFICIENCY OF RURAL HOSPITALS IN THE UNITED STATES

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Iustin Cristian Nedelea
B.A., University of Bucharest, 1997
M.S., Louisiana State University, 2007
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ABSTRACT

The Critical Access Hospital (CAH) Program was created in response to the dramatic deterioration of financial conditions and the potential threat of closure of small rural hospitals under the Prospective Payment System (PPS). CAHs receive cost-based reimbursement for services provided to Medicare patients in exchange for accepting a number of restrictions. In the first essay, I examine the impact of conversion to CAH status on hospital efficiency. The estimated results show that CAHs are less cost and allocatively efficient than non-converting, PPS rural hospitals, without being less technically efficient. Relative to their pre-conversion selves, CAHs appear to be slightly less allocatively efficient, while they are slightly more technically efficient, and no less cost efficient. The second essay examines cost efficiency differences between CAHs and non-converting, PPS rural hospitals using quality controls and alternative methods of efficiency analysis. The results show that CAHs are, on average, less cost efficient than non-converting, PPS rural hospitals. The third essay estimates the marginal effects of environmental variables on the technical efficiency of CAHs. The results suggest that enhanced Medicare reimbursement may not have had a detrimental effect on the technical efficiency of CAHs. Overall, the results of this dissertation have important policy implications. First, they show that cost-based reimbursed CAHs are, on average, between 4.5 and 6.7 percentage points less cost efficient than non-converting, PPS rural hospitals. This can be translated in a cost per CAH between $751,000 and $1.12 million (in 2005 dollars) higher than the cost that would have been under the PPS. Second, the results show that the technical efficiency of CAHs improved relative to the pre-conversion period and that CAHs are as technically efficient as non-converting, PPS rural hospitals. Third, improved technical efficiency of CAHs in conjunction with their decreased cost efficiency suggest that reductions in CAHs'

cost efficiency may not be a function of direct overconsumption of physical inputs. Rather, decreased cost efficiency of CAHs may be driven by allocative inefficiency generated by the inability of these hospitals to substitute to lower input cost combinations in the production process.

CHAPTER 1

INTRODUCTION

1.1 Introduction and Background Information

Rural hospitals in the U.S. have plaid a critical role in the delivery of health care services in rural communities. Their major goal has been to increase health care access for individuals living in rural areas [1]. However, due to their relatively small size, rural hospitals have been vulnerable to policy changes. Medicare has been the most important source of revenue for rural hospitals because rural communities have a disproportionately larger proportion of the elderly than their urban hospital counterparts [2]. Relying heavily on Medicare, small rural hospitals have been largely affected by the Medicare reimbursement policies. The increased dependence on Medicare has been even more significant starting with the Social Security Amendments of 1983 when Medicare replaced the retrospective cost-based reimbursement with the Prospective Payment System (PPS). While under the cost-based reimbursement hospitals are reimbursed total allowable costs for providing services to Medicare beneficiaries, the PPS system pays a fixed fee per case depending on the diagnosis-related group (DRG). The PPS system has been designed to promote efficiency in hospital operations by encouraging the use of outpatient services, instead of inpatient care, and reduced length of stay [3].

Rural hospitals (especially small ones) were particularly vulnerable to the financial pressures resulting from the PPS reimbursement [3]. Under the PPS, Medicare paid rural hospitals at a lower rate than their urban counterparts for the same services because of the lower labor costs in rural areas. This, combined with a general decline in non-Medicare admissions and occupancy rates and with increased dependence of rural hospitals on Medicare reimbursement, undermined the general financial viability of rural hospitals in the 1980s and

1990s. One consequence of this financial stress was an increase in the closure of rural hospitals. In response to the financial problems of small rural hospitals, Congress created special Medicare payment policies.

One of the most important changes in rural health care policy that has impacted rural hospitals dramatically has been the creation of Critical Access Hospital (CAH) program which was introduced by the Balanced Budget Act (BBA) of 1997. A hospital that converts to CAH status has the advantage of receiving Medicare cost-based reimbursement for inpatient and outpatient services, post-acute (swing-bed) care, and laboratory services delivered to Medicare beneficiaries. Under the BBA of 1997, however, a rural hospital had to meet several requirements before being considered eligible for CAH designation. Most importantly, to qualify for CAH status a hospital needed to be classified as non-metropolitan, be under government or non-profit ownership, be located at least 15 miles by secondary road or 35 miles by primary road from the nearest short-term general hospital, or be declared by the state as a “necessary provider”. Under the “necessary provider” provision, states could waive the distance requirement for hospitals that were considered important for the delivery of health care services and qualify them for CAH conversion. Many hospitals failed to meet the 35-mile criterion for being considered isolated hospitals and entered the program based on state criteria that declared them necessary providers. Hospitals that converted to CAH status were also required to use no more than 15 acute care beds at any one time plus an additional of 10 beds to be used only as swing beds for long-term care patients, limit the length of stay to 96 hours or less for acute care patients, and provide 24-hour emergency care services.

The Balanced Budget Refinement Act (BBRA) of 1999 subsequently expanded CAH eligibility by allowing for-profit hospitals to participate, and by including facilities that were located in counties contained in Metropolitan Statistical Areas but identified as rural by their own state regulations. The BBRA also replaced the 96-hour length of stay limit with the less restrictive requirement that the annual average length of stay could not be greater than four days.

The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (MMA) eliminated states' ability to declare a hospital as a "necessary provider" starting in January 2006 and states could no longer waive the distance requirement. As a result, few additional hospitals met the criteria and entered the CAH program after January 2006. In addition, MMA increased the reimbursement for CAHs to 101 percent of reasonable costs for inpatient, outpatient and post-acute care, the number of acute care beds increased from 15 to 25, and allowed CAHs to have PPS reimbursed skilled nursing facilities, psychiatric units, rehabilitation units, and home health agencies.

Since 1999, the CAH program has grown rapidly from 41 hospitals in 1999 to 1,055 hospitals in 2005 and to 1,327 CAHs in 2011. A large number of hospitals converted to CAH status between 2001 and 2005, with the largest number of hospitals joining to CAH program in 2005 because of the intention of the federal government to stop allowing states to waive the distance requirement with "necessary provider" criteria [4]. Medicare Payment Advisory Commission (MedPAC) [5] estimated that, due to flexibility in the "necessary provider" criteria, only 17 percent of CAHs are more than 35 road miles from another provider, 67 percent are 15 to 35 miles, and 16 percent of CAHs are less than 15 miles from another hospital.

The CAH program has been created to preserve access to primary and emergency care services in isolated rural areas by improving the financial conditions of small rural hospitals and preventing closure. Rural hospitals that converted to CAH status have generally experienced significant improvements in their finances due to Medicare cost-based reimbursement. MedPAC

[5] estimated hospitals that converted to CAH status have dramatically increased their Medicare payments and improved their all-payer profit margins from -1.2 percent in 1998 to 2.2 percent in 2003. For similar rural hospitals that did not convert to CAH status and remained on PPS all-payer profit margins declined from 2.2 percent in 1998 to -0.2 percent in 2003. Additionally, Medicare payments to CAHs rose, on average, by 9.5 percent per year during the period 1998-2003, compared with a 3.3 percent rise for similar rural hospitals that did not convert to CAH status.

Medicare cost-based payments for CAH hospitals were over $3 million per hospital in 2003, roughly $850,000 more per hospital than if CAHs would have received PPS payment rates. MedPAC [5] estimated that the $850,000 represented increased Medicare payment rates rather than volume increases. The increase in the volume of outpatient services and post-acute (swing-bed) days at CAHs was roughly offset by the decrease in inpatient volume. MedPAC [5] also predicted that, in 2006, Medicare payments per CAH were roughly $1 million higher under cost-based reimbursement than they would have been under PPS rates. Recent data from MedPAC indicate that payments for CAHs are roughly $2 billion higher than they would have been under PPS. While part of this increase in Medicare spending can be explained by improvements in quality and access since quality and access improvements have been the goals of the CAH program [6], part of it might represent inefficiency.

The PPS system has been designed to promote efficiency in hospital operations by motivating hospitals to keep their costs below the PPS reimbursement rates [7]. Under the PPS system, hospitals are allowed to keep the difference between the PPS rate and actual cost of providing services. Conversely, hospitals can lose money if their costs exceed the PPS rates. Cost-based reimbursement, on the other hand, 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 (and increase costs) in order to receive higher revenues because Medicare pays on a cost basis [8-9]. Since CAH hospitals receive Medicare cost-based reimbursement, there have been concerns that they will have a disincentive to control costs and operate efficiently. In the 2005 Report to Congress, the Medicare Payment Advisory Commission 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.”

1.2 Framing the Policy Question

One of the most important challenges regarding rural health care policy changes is to determine whether the benefits outweigh the costs. The CAH program has been designed 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 prospective payments [10]. The benefits of the CAH program have been mostly associated with improvements in access to health care services in isolated rural areas. Previous research has shown that an increase in travel time both discourages the demand for health care and reduces the probability of seeking health care [11]. Because CAHs decrease the travel time by maintaining hospital services in isolated areas, it is expected that the demand for health care services (and, consequently, health status) will increase in rural areas [12]. In addition, retaining a limited hospital facility in a rural community not only reduces welfare losses relative to the hospital closure [13], but also has a positive economic impact on the community as a whole [14].

The cost of the CAH program is represented by increased Medicare payments for CAH hospitals which are borne in principal by taxpayers. As previously mentioned, MedPAC [5] estimated that in 2003 payments per CAH were roughly $850,000 higher under cost-based reimbursement than they would have been under the PPS system. The total costs of the CAH program under Medicare cost-based reimbursement may consist of two parts: costs associated with optimal use of resources in health care production and costs associated with inefficiency. While a complete evaluation of the CAH program requires answering the question whether the total benefits outweigh the total costs, I focus in this research on assessing the efficiency / inefficiency of CAH hospitals. The question I seek to answer in this research is: does the CAH program have created a disincentive for the efficient operation of hospitals that converted to CAH status? Alternatively, does enhanced Medicare reimbursement have a negative effect on the efficiency of CAHs?

1.3 Study Objectives

Cost containment in the health care industry is one of the issues at the forefront of the present health care debate. With health care costs rising at a rapid rate, an analysis of the efficiency of CAH program is important as Congress weighs the tradeoff of increased Medicare costs versus rural health care access.

The primary objective of this research is to analyze the impact of the CAH program on hospital efficiency. Specific objectives are:

1. Analyze the impact of conversion to CAH status on hospital efficiency by comparing the cost, technical, and allocative efficiencies of a sample of rural hospitals before and after the conversion to CAH status as well as by comparing the efficiency of CAHs with that of a group of non-converting, PPS rural hospitals.
2. Examine cost efficiency differences between CAHs and non-converting, PPS rural hospitals using quality controls and alternative methods of efficiency analysis.

3. Estimate the (marginal) effects of environmental variables (especially of Medicare and Medicaid financing) on the technical efficiency of CAH hospitals.

1.4 Contributions to Literature

Previous research focused almost exclusively on evaluating financial performance and quality of care of CAH hospitals. Using a panel data set of 89 rural hospitals in Iowa, Li et al. [15] found that hospitals that converted to CAH status significantly increased their operating revenues, expenses, and margins. MedPAC [5] estimated hospitals that converted to CAH status have dramatically increased their Medicare payments and improved their all-payer profit margins between 1998 and 2003. Li et al. [16] examined the impact of CAH conversion on hospital patient safety and found that CAH conversion was associated with improved performance of certain Patient Safety Indicators. In a recent study, Rosko and Mutter [17] compared the cost inefficiency of CAHs with that of prospectively paid rural hospitals using stochastic frontier analysis and found that CAHs were, on average, less cost efficient than PPS rural hospitals.[1]

The overall contribution of this study to the literature is twofold. The first is treating efficiency as a metric that should be considered in the policy analysis of the CAH program that has a focus on access and quality. The second is the application of improved techniques to hospital efficiency analysis. Specifically, a nonparametric kernel density estimator is used to estimate and visualize the efficiency distributions of a sample of hospitals before and after the conversion to CAH status as well as of a comparison group of non-converting, prospectively paid rural hospitals. The null hypotheses on equality between these efficiency distributions are tested using a bootstrap-based test proposed by Simar and Zelenyuk [18]. Further, a two-stage, semi-parametric approach with the single and double bootstrap procedures proposed by Simar

[1] No published articles on the efficiency of CAHs existed when I started this research.

and Wilson [19] is used for making valid inferences about the impact of environmental variables on hospital efficiency.

1.5 Outline

In Chapter 2, the impact of conversion to CAH status on hospital efficiency is examined (Objective 1) using a two-stage approach and recent methodological advancements of Simar and Zelenyuk [18] and Simar and Wilson [19]. In the first stage, data envelopment analysis (DEA) is used to estimate cost, technical, and allocative efficiency scores of each hospital in the sample. I estimate and compare the densities of efficiency scores of CAHs, before and after conversion, and PPS rural hospitals using a nonparametric kernel density estimator and a bootstrap-based test proposed by Simar and Zelenyuk [18]. In the second stage, a truncated regression with a bootstrap procedure suggested by Simar and Wilson [19] is used to investigate how the conditional mean of efficiency scores is influenced by environmental variables such as CAH status, Medicare and Medicaid reimbursement, hospital ownership, etc.

Density analysis and results from bootstrapped truncated regressions show that CAHs are less cost and allocatively efficient than prospectively paid rural hospitals, without being less technically efficient. Relative to their pre-conversion selves, CAHs appear to be slightly less allocatively efficient, while they are slightly more technically efficient and no less cost efficient. Overall, the results suggest that the CAH program may have decreased allocative and cost efficiencies of rural hospitals that converted to CAH status relative to prospectively paid rural hospitals, without significantly increasing their technical efficiency.

In Chapter 3, I examine cost efficiency differences between cost-based reimbursed CAHs and non-converting, PPS rural hospitals using quality controls and alternative methods of efficiency analysis (Objective 2). The first method is DEA which is a nonparametric approach that uses linear programming to estimate cost efficiency scores. A nonparametric kernel density estimator is used to estimate the densities of cost efficiency scores of CAH and PPS rural hospitals, and the null hypothesis on equality between these densities is tested using a bootstrap-based test suggested by Simar and Zelenyuk [18]. The second method is the two-stage, semi-parametric approach in which cost efficiency scores, estimated in the first stage using DEA, are regressed, in the second stage, on explanatory variables expected to influence hospital cost efficiency. In the second stage, both a tobit model (which has been traditionally used in the literature) and a truncated regression with a bootstrap procedure suggested by Simar and Wilson [19] are used to estimate the marginal effects of environmental variables (in particular, CAH status) on hospital cost efficiency. Although tobit has been historically used in the two-stage approach applications, Simar and Wilson [19] indicate that tobit is a misspecification under their statistical model. The third method is stochastic frontier analysis (SFA) which is a parametric approach based on a cost function.

DEA and SFA were both used to estimate hospital cost efficiency. CAHs were, on average, 4.5% using DEA and 6.7% using SFA less cost efficient than non-converting rural hospitals. Density analysis of cost efficiency scores indicated that CAHs were more cost inefficient than non-converting, PPS rural hospitals and the difference was found statistically significant based on Simar-Zelenyuk test. Marginal effects of environmental variables were estimated using SFA and the two-stage DEA approach with both the tobit and truncated regression. The estimated results showed that the CAH dummy was statistically significant in SFA and the bootstrap truncated regression models and insignificant in the tobit model. Specifically, I found that CAHs were 5.2% less cost efficient using bootstrapped truncated regression, and 7.3% less cost efficient using SFA than non-converting, PPS rural hospitals.

While these results support our prior findings, they also show how the tobit model in this case may lead to an alternative interpretation.

In Chapter 4, the research question I seek to answer is: if cost-based reimbursement creates disincentives for hospitals to operate efficiently, does an increase in Medicare patient mix have a negative effect on CAHs' technical efficiency? I use the two-stage approach with single and double bootstrap procedures suggested by Simar and Wilson [19] to estimate the marginal effects of environmental variables (in particular, Medicare reimbursement) on CAHs' technical efficiency (Objective 3). Simar and Wilson [19] showed that the DEA efficiency scores are serially correlated and inference in the second stage regression is invalid based on standard methods. They defined a statistical model where a truncated regression with a (single) parametric bootstrap procedure allows for valid inference in the second stage. An additional problem is that the DEA efficiency estimator, although consistent, is biased. In order to address both the bias and serial correlation of efficiency scores, Simar and Wilson [19] developed a double bootstrap procedure, where bias-corrected efficiency estimates are obtained in the first stage using a specific bootstrap procedure. In the second stage, the marginal effects of environmental variables on (bias-corrected) efficiency scores are estimated using a second, parametric bootstrap procedure applied to the truncated regression.

An important finding was that the performance of the double bootstrap procedure in explaining hospital efficiency significantly improved when quality was accounted for in efficiency estimation relative to a similar model without quality. I also compared the performance of the double bootstrap procedure with that of the single bootstrap procedure of Simar and Wilson [19]. While both bootstrap procedures were created to provide valid inference, the double bootstrap procedure clearly improved statistical efficiency in the second stage truncated regression relative to the single bootstrap procedure. The key finding of this study was that the Medicare percent of admissions variable had an insignificant effect on CAHs' technical efficiency, suggesting that Medicare cost-based reimbursement may not have created a disincentive for these hospitals to operate in a less technically efficient manner.

Chapter 5 of this dissertation provides conclusions and examines some policy implications. In particular, my findings of improved technical efficiency of CAHs in conjunction with decreased cost efficiency might suggest that the reduction in CAHs' cost efficiency may not be a function of direct overconsumption of physical inputs. Rather, decreased cost efficiency of CAHs may be driven by allocative inefficiency generated by the inability of these hospitals to quickly substitute to lower input cost combinations in the production process.

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CHAPTER 2

IMPACT OF CONVERSION TO CRITICAL ACCESS HOSPITAL STATUS ON HOSPITAL EFFICIENCY[1]

2.1 Introduction

The Critical Access Hospital (CAH) Program, introduced by the Balanced Budget Act of 1997, has been created to protect small, financially vulnerable rural hospitals that might be important for access to health care services in isolated rural areas in the U.S. [1]. A hospital that converts to CAH status receives Medicare cost-based reimbursement provided it meets requirements such as restrictions on the maximum number of acute care beds and average length of inpatient stay. Under cost-based reimbursement, hospitals are reimbursed for the total costs of providing health care services. This reimbursement method was used by Medicare to pay for hospital services before 1983. Although access to health care services and hospital finances improved significantly, cost-based reimbursement led to a rapid increase in health care costs. Furthermore, historical evidence suggested that it was associated with inefficiency in hospital operations. Under cost-based reimbursement, payment levels equaled hospitals' costs. Thus, it provided incentives for hospitals to oversupply services, overuse resources, and increase costs in order to increase their revenues since Medicare paid for services on a cost basis [2-3].

In 1983, Medicare introduced a new payment method known as the Prospective Payment System (PPS). Medicare classified all illnesses into diagnosis-related groups (DRGs) and estimated the average cost per case for each group. Under the PPS, hospitals are paid fixed prices based on the DRGs and are allowed to keep the difference between these

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fixed DRG prices and their costs. Thus, the PPS has provided an incentive for hospitals to reduce costs and increase their efficiency by motivating hospitals to keep their costs below the PPS rates in order to make profits [4]. Small rural hospitals, however, were particularly vulnerable to the financial pressures of the PPS and commonly failed to cover costs on Medicare patients [5].

The CAH Program has been created to preserve access to health care services in isolated rural communities by improving the financial conditions of small rural hospitals and preventing their closure. However, there have been concerns that Medicare cost-based reimbursement has provided a disincentive for CAHs to control costs and operate efficiently. In the 2005 Report to Congress, the Medicare Payment Advisory Commission (MedPAC) [6] 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."

The objective of this paper is to determine the impact (if any) of CAH conversion on hospital efficiency. To achieve this objective, we use recent developments in the area of efficiency analysis implemented using a two-stage approach. In the first stage, data envelopment analysis (DEA) is used to estimate hospital cost, technical, and allocative efficiency scores [7]. In simple terms, a firm is technically efficient if it uses the minimum quantities of inputs to produce a given level of outputs. For the hospital sector, technical efficiency refers to the relationship between inputs used (i.e., capital and labor) and outputs produced (i.e., outpatient visits, inpatient days, surgeries, etc.). Allocative efficiency reflects the ability of a hospital to produce a given level of outputs using the optimal combination of inputs (i.e., cost-minimizing), given input prices. A hospital is (overall) cost efficient when it

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is both technically and allocatively efficient. Cost efficiency indicates the extent to which the hospital minimizes the cost of producing a specific level of outputs, given input prices.

Further, the densities of efficiency scores of CAHs and PPS (non-CAH) rural hospitals (which include hospitals prior to CAH conversion as well as non-converting, PPS rural hospitals) are estimated and compared using a nonparametric kernel density estimator and a bootstrap-based test proposed by Simar and Zelenyuk [8]. In the second stage, we use truncated regressions with bootstrap suggested by Simar and Wilson [9] to investigate how the conditional mean of efficiency scores is influenced by environmental variables such as CAH status, Medicare and Medicaid reimbursement, and hospital ownership.

Previous studies analyzed the impact of Medicare reimbursement changes on either cost efficiency [3,10] or technical efficiency of health care facilities [4] using standard methods such as DEA or stochastic frontier analysis. To the best of our knowledge, this is the first study that examines differences in all three Farrell [11] type efficiency measures jointly between hospitals operating under different Medicare reimbursement systems, using methodological advancements proposed by Simar and Zelenyuk [8] and Simar and Wilson [9]. We hypothesize that cost-based reimbursed CAHs are more cost inefficient than PPS rural hospitals because of the differences in Medicare reimbursement methods, and thus incentives, facing these two groups of rural hospitals. Additionally, we analyze not only whether cost-based reimbursed CAHs are more cost inefficient than PPS rural hospitals but also whether this cost inefficiency increase comes more from technical inefficiency (i.e., hospitals do not use the minimum input quantities to produce their output levels) or allocative inefficiency (i.e., hospitals do not use the least-cost combination of inputs in producing their outputs).

2.2 CAH Program

The CAH Program was introduced as part of the Balanced Budget Act of 1997 and it was subsequently expanded by the Balanced Budget Refinement Act of 1999 and the Medicare Prescription Drug, Improvement, and Modernization Act of 2003. A hospital that converts to CAH status has the advantage of receiving Medicare cost-based reimbursement, equivalent to 101 percent of actual cost, for inpatient and outpatient services 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 or be declared by the state as a "necessary provider"; use no more than 25 acute care beds at any one time; annual average length of stay cannot be greater than four days, and the hospital must provide 24-hour emergency care services. Before January 2006, states could waive the distance requirement using the "necessary provider" provision. That is, a state could declare a hospital a "necessary provider" and qualify it for CAH conversion based on arbitrary criteria. Further, some CAHs were allowed to exist in Metropolitan Statistical Areas based on state regulations that declared them rural hospitals. MedPAC [6] estimated that only 17 percent of CAHs are more than 35 road miles from another provider, 67 percent are 15 to 35 miles, and 16 percent of CAHs are less than 15 miles from another hospital.

Rural hospitals that converted to CAH status have generally experienced significant improvements in their finances due to Medicare cost-based reimbursement. For example, hospitals that converted to CAH status have dramatically increased their Medicare payments and improved their all-payer profit margins from -1.2 percent in 1998 to 2.2 percent in 2003. For similar rural hospitals that did not convert to CAH status and remained on PPS all-payer profit margins declined from 2.2 percent in 1998 to -0.2 percent in 2003. Medicare payments to CAHs rose, on average, by 9.5 percent per year during the period 1998-2003, compared with a 3.3 percent rise for similar rural hospitals that did not convert to CAH status [6]. MedPAC [6] estimated that in 2003 payments per CAH were roughly $850,000 higher under cost-based reimbursement than they would have been under the PPS.

2.3 Literature Review

The impact of Medicare reimbursement changes on the efficiency of health care facilities has been an important research topic. Morey and Dittman [12] examined the effect of cost-based reimbursement on the technical efficiency of North Carolina hospitals operating in 1978. Using DEA, they found that hospitals with a higher percentage of cost-based reimbursement tended to be less technically efficient. Sexton et al. [4] analyzed the effect of the PPS on the technical efficiency of 52 nursing homes in Maine using DEA with four years of data (two years before and two years after the introduction of the PPS). An unexpected result was that the average technical efficiency fell after the introduction of the PPS. In their paper, Chern and Wan [13] analyzed the impact of the PPS on the technical efficiency of hospitals in Virginia. They used a DEA model with two years of data (1984, before, and 1993, after the PPS was implemented) lumped together and found no statistically significant differences in technical efficiency over the study period.

Evaluating the performance of the CAH Program has spurred significant interest in health services research area. Stensland, Davidson, and Moscovice [14] 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. Using a panel data set on 89 rural hospitals in Iowa, Li, Schneider, and Ward [15] found that hospitals that converted to CAH status increased their operating revenues, expenses, and profit margins. Similarly, Schoenman and

Sutton [16] also found that, after conversion to CAH status, hospitals dramatically increased their profitability due to Medicare cost-based reimbursement. Using a stochastic frontier cost function, Rosko and Mutter [10] compared the cost inefficiency of CAHs with that of prospectively paid rural hospitals and found that CAHs were, on average, more cost inefficient.

2.4 Methodology

To assess the impact of CAH status on hospital efficiency, we use a two-stage approach, where DEA is used in the first stage to estimate cost, technical, and allocative efficiency scores of each hospital in the sample. DEA uses linear programming (LP) to define a piecewise linear estimate of the efficient frontier enveloping all the data. Efficiency of a firm is measured relative to this efficient (best-practice) frontier. As a nonparametric approach, DEA does not assume a specific functional form for the frontier or probability distributions and, thus, avoids any misspecification problems. Its main drawback, however, is that it is deterministic, meaning that deviations from the efficient frontier are entirely attributed to inefficiency and no allowance is made for statistical noise, random shocks, or measurement error. The two-stage approach, however, allows us to deal with this issue in the second stage regression model. In this study, an input-oriented DEA model is used because (1) it is consistent with previous literature and with the assumption that hospitals have more control over the inputs than over the outputs, and (2) it allows a natural decomposition of cost efficiency into its technical and allocative components.

DEA measures cost efficiency in two steps. First, given input prices and output levels, the cost-minimizing input vector for each hospital is calculated by LP. Next, cost efficiency is estimated 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 our specific case, let y_{rj} be a vector of six outputs ($r = 1, \ldots, 6$) and x_{ij} a vector of two inputs ($i = 1, 2$) for each hospital j (j = 1,….., n). For a given level of outputs y_{ro} and an input price vector w_{io} (i = 1, 2) for hospital o, the minimum cost under variable returns to scale (VRS) is obtained by solving the following LP problem:

$$Min_{\lambda_j, x_{io}^*} \sum_{i=1}^{2} w_{io} x_{io}^* \ s.t.: \tag{1}$$

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, (r = 1,.....,6) \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}^*, (i = 1, 2) \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, (j = 1,......,n)
\end{aligned}$$

where λ_j and x_{io}^* are the decision variables. The optimal solution to this problem is the input vector x_{io}^* that minimizes the cost of producing the observed level of outputs given technology and input prices. The cost efficiency, CE, is:

$$CE = \sum_{i=1}^{2} w_{io} x_{io}^* \Big/ \sum_{i=1}^{2} w_{io} x_{io} \ . \tag{2}$$

That is, CE is the ratio of minimum cost to observed cost and indicates the proportion of the hospital's observed cost required to produce its observed level of outputs [17]. For example, a cost efficiency score of 0.75 indicates that the hospital is cost inefficient, with cost inefficiency measured at 33 percent (i.e., 1/0.75 - 1).

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

$$Min_{\lambda_j, \theta} \ \theta \ s.t.: \tag{3}$$

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, (r = 1,.....,6) \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, (i = 1, 2) \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, (j = 1,......,n)
\end{aligned}$$

The objective of the LP problem in (3) is to find the minimum θ that proportionally reduces the input vector to θx_{io} while guaranteeing at least the output level y_{ro}. The optimal solution to the LP problem is $TE = \theta \leq 1$, where $TE = 1$ 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 than all inputs. That is, a technical efficiency score of 0.85, for example, indicates that the hospital is technically inefficient, with technical inefficiency measured at 17.6 percent (i.e., 1/0.85 - 1).

Once cost and technical efficiency scores are derived, the allocative efficiency (*AE*) can be simply calculated as:

$$AE = CE / TE. \tag{4}$$

The allocative efficiency indicates 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. From (4), the following relationship can be defined between cost, technical, and allocative efficiencies:

$$CE = TE \times AE. \tag{5}$$

This suggests that failure to achieve cost efficiency may be due to (a) technical inefficiency in the form of wasteful use of inputs overall, and (b) allocative inefficiency due to the incorrect mix of inputs given input price levels.

2.4.1 Analysis of Efficiency Distributions

To analyze differences in efficiency between CAHs and non-CAH, PPS rural hospitals, we first estimate and visualize the densities of efficiency scores using a nonparametric kernel density estimator. Based on the estimated densities, we test the null hypothesis of equality between CAH and non-CAH efficiency distributions against the alternative that they are different. One of the major problems encountered in the analysis of distributions of efficiency scores arises from the fact that, in finite samples, the DEA efficiency estimator is biased (however, it is a consistent estimator [18]) and the estimated efficiency scores are not independent [8-9].

Building on the work of Li [19], Simar and Zelenyuk [8] proposed a bootstrapped-based test for testing equality of distributions of DEA-estimated efficiency scores. To briefly outline the test statistics, suppose group A is the group of CAHs and group Z is the group of non-CAH, PPS rural hospitals. We are interested to test the null hypothesis of equality between the efficiency distributions of the two groups against the alternative that they are different:

H_0: $f_A(u_A) = f_Z(u_Z)$

H_1: $f_A(u_A) \neq f_Z(u_Z)$

where $u_{A,i}\,(i = 1,....,n_A)$ and $u_{Z,k}\,(k = 1,....,n_Z)$ are the efficiency scores of CAHs and non-CAH, PPS rural hospitals and $f_A(u_A)$ and $f_Z(u_Z)$ are the corresponding probability distributions. The Li [19] test statistics is:

$$\hat{J}_{n_A,n_Z,h} = n_A h^{1/2} \hat{I}_{n_A,n_Z,h} / \hat{\sigma}_{\lambda,h} \xrightarrow{d} N(0,1) \tag{6}$$

where

$$\begin{aligned}\hat{I}_{n_A,n_Z,h} = {} & \frac{1}{n_A^2 h}\sum_{i=1}^{n_A}\sum_{k=1}^{n_A} K\left(\frac{u_{A,i}-u_{A,k}}{h}\right) + \frac{1}{n_Z^2 h}\sum_{i=1}^{n_Z}\sum_{k=1}^{n_Z} K\left(\frac{u_{Z,i}-u_{Z,k}}{h}\right) \\ & - \frac{1}{n_A n_Z h}\sum_{i=1}^{n_Z}\sum_{k=1}^{n_A} K\left(\frac{u_{Z,i}-u_{A,k}}{h}\right) - \frac{1}{n_Z n_A h}\sum_{i=1}^{n_A}\sum_{k=1}^{n_Z} K\left(\frac{u_{A,i}-u_{Z,k}}{h}\right)\end{aligned} \tag{7}$$

and

$$\begin{aligned}\hat{\sigma}_{\lambda,h}^2 = 2\Bigg\{ & \frac{1}{n_A^2 h}\sum_{i=1}^{n_A}\sum_{k=1}^{n_A} K\left(\frac{u_{A,i}-u_{A,k}}{h}\right) + \frac{\lambda_n^2}{n_Z^2 h}\sum_{i=1}^{n_Z}\sum_{k=1}^{n_Z} K\left(\frac{u_{Z,i}-u_{Z,k}}{h}\right) \\ & - \frac{\lambda_n}{n_A n_Z h}\sum_{i=1}^{n_Z}\sum_{k=1}^{n_A} K\left(\frac{u_{Z,i}-u_{A,k}}{h}\right) - \frac{\lambda_n}{n_Z n_A h}\sum_{i=1}^{n_A}\sum_{k=1}^{n_Z} K\left(\frac{u_{A,i}-u_{Z,k}}{h}\right)\Bigg\} \times \int K^2(u)du\end{aligned} \tag{8}$$

where K is a kernel function (assumed to be Gaussian), h is a bandwidth, $\lambda_n = n_A / n_Z$, $n = n_A + n_Z$, $\lambda_n \to \lambda$ when $n_A \to \infty$, and $\lambda \in (0,\infty)$ is a constant.

Simar and Zelenyuk [8] noted that an important problem encountered in the application of the test is the discontinuity problem. By construction, some of the DEA efficiency scores equal to 1, creating a spurious mass at unity and violating the continuity assumption required to ensure consistency of the density estimation. They suggested two approaches to deal with the discontinuity problem. The first approach is based on computation and bootstrapping the Li test using the sample of DEA efficiency scores without those equal to unity. The second approach is based on computation and bootstrapping the Li test using the sample of DEA efficiency scores where those equal to unity are "smoothed" away from the boundary by adding a small amount of noise (see Simar and Zelenyuk [8] for the bootstrap algorithm for Li statistics). We adopt the second approach with a Gaussian kernel and a bandwidth selected using Silverman [20].

2.4.2 Second Stage Truncated Regression

In the second stage, cost, technical, and allocative efficiency scores, obtained in the first stage using DEA, are regressed on a set of explanatory variables to investigate the dependency of efficiency scores on such variables. In an influential paper, Simar and Wilson [9] criticized previous two-stage studies because of the failure to define a statistical model consistent with the second stage analysis. They argue that inference in those studies is invalid because of the failure to account for the serial correlation present among efficiency estimates used in the second stage regression. Simar and Wilson [9] defined a statistical model in which a truncated regression with a bootstrap procedure allows for valid inference in the second stage analysis. Following Simar and Wilson [9], our second stage model is specified as a truncated regression:

$$\hat{u}_i = z_i\beta + \varepsilon_i \geq 1, \quad i = 1, 2, \ldots, n \tag{9}$$

where $\hat{u}_i$ is the reciprocal of efficiency scores[2] (which are referred to as inefficiency scores) such that $\hat{u}_i \geq 1$, ε_i is assumed to be distributed N(0, σ^2) with left truncation at $1 - z_i\beta$, 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. Unfortunately, in (9), $\hat{u}_i$'s are serially correlated in a complicated, unknown way. To provide valid inference in the second stage analysis, Simar and Wilson [9] suggested a parametric bootstrap of the truncated regression. In this paper, we use their Algorithm 1 bootstrap procedure whose steps are the following:

1. Use the method of maximum likelihood to obtain an estimate $\hat{\beta}$ of β in the truncated regression $\hat{u}_i = z_i\beta + \varepsilon_i > 1$, using $m < n$ observations where $\hat{u}_i > 1$ (i = 1, …, m).
2. Loop over the next three steps L = 2000 times to obtain a set of bootstrap estimates $\Delta = \left\{\hat{\beta}^*\right\}_{b=1}^{L}$:
   a. For each i = 1,…., m, draw ε_i from $N(0, \hat{\sigma}^2)$ with left truncation at $1 - z_i\hat{\beta}$.
   b. Compute $u_i^* = z_i\hat{\beta} + \varepsilon_i$, $i = 1, \ldots, m$.
   c. Estimate the truncated regression of u_i^* on z_i, yielding estimates $\hat{\beta}^*$.
3. Use the bootstrap values in Δ and the original estimates of $\hat{\beta}$ to construct percentile confidence intervals for each element of β.

Step 2 is a parametric bootstrap of a truncated regression model. The bootstrapped coefficients for each resample are estimated and placed in an $L \times k$ matrix. Once the bootstrap values in Δ are obtained, percentile bootstrap confidence intervals can be constructed for each element of β.

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[2] Such a parameterization of efficiency scores will give us a dependent variable with only a lower bound at 1 in

2.5 Data

In this study, we use four years of data (1997, 1998, 2005, and 2006) from the American Hospital Association (AHA) Annual Survey of Hospitals, the Area Resource File and the Medicare Hospital Cost Report. To assess the impact of CAH conversion on hospital efficiency, we examine changes in efficiency for a sample of rural hospitals classified as CAHs in 2005 and 2006 (post-conversion period) that were PPS hospitals in 1997 and 1998 (pre-conversion period). We also include a control group of non-converting rural hospitals with less than seventy-six beds which retained the PPS status throughout the study period [10]. Consistent with previous literature, we recognize the difficulty of creating a control group since hospitals choose to convert to CAH status and any comparison group will differ from converting hospitals [14]. However, this criterion allowed us to have two groups of hospitals of similar size (the mean for CAH total beds in our sample was 41 while for non-converting rural hospitals was 46.8) while maintaining a measurable number of observations for the comparison group. While selection issues may be of concern, Rosko and Mutter [10] indicate that an approach in which CAHs are compared not only to non-converting rural hospitals but also to pre-conversion selves may mitigate these issues. A total of 797 CAHs and 298 non-converting, PPS rural hospitals in each of the four years were included in our initial sample. For consistency, we eliminated 159 CAHs located in Metropolitan Statistical Areas.

The DEA-cost model used in this study requires information on hospital outputs, inputs, and input prices. All hospital efficiency studies included both inpatient and outpatient outputs. The number of outpatient visits has been consistently used as a measure of outpatient output. Similarly, the numbers of admissions and post-admission days (inpatient

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the second stage truncated regression, unlike the original efficiency measures that are bounded by 0 and 1.

days – admissions) have been used as measures of inpatient outputs [10,21]. Additionally, hospital outputs are heterogeneous and researchers have included variables such as emergency room visits, outpatient surgeries, and births to control for output heterogeneity. Our choice of outputs was guided by previous literature [10,21] and includes outpatient visits, admissions, post-admission days, emergency room visits, outpatient surgeries, and births (Table 2.1). Due to data constraints, input price variables were also similar in hospital efficiency studies [10,21]. Following this literature, we use two input prices: the price of labor (sum of payroll expenses and employee benefits divided by the full-time equivalent (FTE) facility personnel), and the price of capital (sum of depreciation expenses and interest expenses − obtained from the Medicare Hospital Cost Report – divided by the number of facility beds). The corresponding physical inputs used in this analysis consist of FTE personnel and total staffed and licensed facility beds (a proxy for capital) [17].

For the choice of variables used in the second stage (Table 2.1), we followed recent literature on hospital efficiency for the specification of environmental variables [10,22]. The primary variable of interest is a CAH dummy (one if the hospital is a CAH and zero, otherwise) which is used to measure the impact of conversion to CAH status on hospital efficiency. Previous literature showed that Medicare and Medicaid exert financial pressure and can create incentives for hospitals to operate more efficiently. Medicare is a federal program that pays for services for the aged while Medicaid is a joint federal and state program for the poor. It has been shown that Medicaid typically underpays hospitals more than Medicare and exerts cost containment pressure irrespective of the payment mechanism [22]. On the other hand, the effect of Medicare on hospital efficiency has been shown to be dependent on the payment mechanism. Specifically, reimbursement under Medicare PPS creates incentives for reducing inefficiency while cost-based reimbursement might give hospitals few incentives to control their costs. We follow previous literature [10,22] and use two variables to reflect the external pressure for efficiency of public payers: Medicare percent of admissions (Medicare) ((Medicare admissions / total admissions) × 100) and Medicaid percent of admissions (Medicaid) ((Medicaid admissions / total admissions) × 100). While Medicaid percent of admissions is expected to be inversely associated with hospital inefficiency given the cost containment pressure from Medicaid, the effect of Medicare percent of admissions on hospital inefficiency is ambiguous given the joint use in estimation of cost-based reimbursed CAHs and PPS-reimbursed rural hospitals.

Table 2.1. Variable definitions and summary statistics.

		CAH		Rural	
Variable		Mean	Std. dev.	Mean	Std. dev.
Outputs					
Total hospital admissions		801.56	596.89	1,839.01	911.01
Post-admission days		8,580.56	10,147.13	5,829.26	3,145.29
Total outpatient visits		24,676.48	23,143.57	40,654.53	32,353.93
Emergency room visits		4,509.50	4,000.33	9,070.30	5,554.56
Outpatient surgeries		501.23	539.00	1,098.10	916.12
Total births		71.72	103.82	207.98	198.88
Inputs					
Staffed and licensed facility beds		46.04	33.39	46.83	14.76
Full time equivalent (FTE) employees		141.48	87.97	221.18	112.32
Input Prices					
Price of capital($)		17,890.96	21,752.43	26,111.02	23,210.37
Price of labor($)		38,759.67	15,108.06	41,073.32	13,803.73
Environmental Variables	Variable Definition				
Government	Government hospital (1 or 0)	0.51	-	0.38	-
For-profit	For-profit hospital (1 or 0)	0.03	-	0.17	-
Medicare	% Medicare admissions	56.86	13.72	51.44	11.86
Medicaid	% Medicaid admissions	12.11	7.96	16.83	9.47
HHI	Herfindahl-Hirschman index	0.57	0.35	0.58	0.34
System	Multihospital system (1 or 0)	0.29	-	0.39	-
MHMO	% Medicare HMO penetration	2.60	5.43	3.14	6.05
Income	Median household income	34,681.38	6,794.81	33,481.79	8,528.68
Emergency	% Emergency room visits	23.10	18.39	28.61	18.30
Surgeries	% Outpatient surgeries	2.41	2.53	3.35	3.41
Births	% Admissions for birth	7.93	9.13	10.40	8.86

The ownership status is introduced by using dummy variables that define government hospitals (Government), non-profit hospitals and for-profit hospitals (For-profit). Non-profit ownership is the reference category. Consistent with Property Rights Theory (PRT), we expect that for-profit hospitals will place a greater emphasis on earning profits and increasing efficiency than non-profit or government hospitals.

A source of external pressure for efficiency is Health Maintenance Organization (HMO) penetration. Following Rosko and Mutter [10], we used Medicare HMO penetration (MHMO) from the Area Resource File as a proxy for general HMO penetration. A Herfindahl-Hirschman index (HHI) (calculated by summing the squares of the market shares of admissions for all of the hospitals in the county) is used to control for competitive pressure in a hospital's market (defined as the county). Median household income of the county (Income) and a dummy variable for membership in a multihospital system (System) are also included in the second stage regression to explain hospital inefficiency. In addition, dummy variables for each year are included to account for the time effects, with year 1997 as the reference category.

A particular challenge was adjusting outputs to control for case-mix variations. Researchers usually employ a case-mix index − which is a measure of the relative complexity of the patient mix treated in a hospital − to adjust outputs. Unfortunately, there is no case-mix index available for CAHs as these hospitals are exempted from the PPS. Although we are unable to adjust outputs for case-mix, we follow Pilyavsky et al. [23] and control for case-mix variations in the second stage regression using proxies such as percent of emergency room visits (Emergency) ((emergency room visits / outpatient visits) × 100), percent of outpatient surgeries (Surgeries) ((outpatient surgeries / outpatient visits) × 100) and percent of births (Births) ((births / admissions) × 100). Furthermore, Ozgen and Ozcan [24] noted that the lack of case-mix variables in DEA efficiency models is in part compensated by the specification of multiple outputs.

A limitation of this research is the lack of any controls for quality of care. While controlling for quality is important in hospital efficiency studies, finding adequate measures of quality has been difficult. In hospital efficiency studies, the difficulty of controlling for quality relates in principal to data availability [25]. Since 2004, Center for Medicare and Medicaid Services (CMS) Hospital Compare database has provided some quality measures but, unfortunately, the proportion of CAHs reporting quality information has been very small. Only 41 percent of CAHs reported at least one quality measure to Hospital Compare in 2004 [26], making it difficult to find a measurable number of hospitals that reported information on the same quality measures. Our examination of the 2005 Hospital Compare database showed that only 186 CAHs reported information for two of the most common quality measures for pneumonia. CAHs voluntarily report quality information to CMS and they do not have the financial incentives of PPS hospitals to consistently report such information. In our study, controlling for quality is even more difficult because of the lack of quality measures collected and reported by rural hospitals in 1997 and 1998 which are required for purposes of the policy analysis.

Variable definitions for DEA as well as for the second stage truncated regressions are presented in Table 2.1. Summary statistics of these variables are presented for both CAHs (joint data for all four years, irrespective of conversion) and the control group of non-converting, PPS rural hospitals.

2.6 Results and Discussion

In the first stage, we estimated a DEA model with the four years of data jointly. Such pooling of the data over time is a frequent practice in DEA estimation and offers the advantage of a substantial increase in the sample size which is important for obtaining reliable estimates of efficiency [27]. As a preliminary analysis, a kernel density estimator is used to obtain estimates of densities of cost, technical, and allocative inefficiencies (the reciprocal of original efficiency scores). The estimated densities were visualized and indicated that some outliers were present in the sample as shown by the long tails of the densities that stretch out up to inefficiency scores of 10 or 12 (see Figure A.2.1 in Appendix 1). Because such outliers can be very problematic for the convergence of the likelihood function in the second stage, we follow Zelenyuk and Zeka [27] and trim the right tails of the distributions resulting in 165 observations being eliminated from the sample. As sensitivity analysis, we performed a Simar-Zelenyuk-adapted-Li test in order to test the null hypothesis of equality of cost inefficiency distributions between the samples before and after the trimming. Based on this test, we failed to reject the null hypothesis (bootstrap p-value was 0.70) indicating that the trimming had an insignificant effect on the estimated inefficiency distributions. Table 2.2 (column 2) presents the distributions of CAHs and non-CAH, PPS rural hospitals in the sample, by year, after the trimming of outliers. All estimations are based on this trimmed sample.

Table 2.2. Summary statistics of DEA estimated efficiency scores.

		Cost Efficiency		Technical Efficiency		Allocative Efficiency	
Group	N	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
CAH2006	750	0.464	0.144	0.673	0.152	0.693	0.138
CAH2005	752	0.462	0.138	0.676	0.150	0.688	0.137
Pre-CAH1997	771	0.458	0.129	0.645	0.153	0.718	0.139
Pre-CAH1998	767	0.455	0.130	0.645	0.149	0.713	0.138
Rural2006	293	0.580	0.178	0.694	0.147	0.826	0.121
Rural2005	295	0.586	0.170	0.703	0.144	0.825	0.119
Rural1997	294	0.516	0.152	0.652	0.141	0.789	0.128
Rural1998	293	0.531	0.147	0.658	0.133	0.804	0.124
CAH	1,502	0.463	0.141	0.674	0.151	0.690	0.138
Non-CAH	2,713	0.498	0.153	0.659	0.149	0.757	0.140
All	4,215	0.486	0.150	0.665	0.149	0.733	0.143

Table 2.2 also shows summary statistics of DEA-estimated cost, technical, and allocative efficiency scores for CAHs and non-CAH, PPS rural hospitals in each year as well as combined. The average level of cost efficiency for CAHs changed only slightly over the study period (from 45.5 percent in 1998, before conversion to CAH status, to 46.4 in 2006), while for the comparison group of non-converting, PPS rural hospitals, cost efficiency increased from 51.6 percent in 1997 to 58 percent in 2006. While mean technical efficiency increased for both groups, mean allocative efficiency decreased for CAHs from 71.8 percent in 1997 (in the pre-conversion period) to 69 percent in 2006 (after conversion to CAH status), while it increased for the non-converting rural hospitals from 79 percent to 82.6 percent over the same period.

2.6.1 Analysis of Inefficiency Distributions

Figure 2.1 shows the distributions of inefficiency scores for CAHs and the comparison group of non-converting, PPS rural hospitals in 2005 and 2006. We observe a large rightward shift from the efficient unity of the distributions of cost and allocative inefficiency scores of CAHs relative to those of non-converting rural hospitals in 2005 and 2006, suggesting that CAHs tend to be less cost and allocatively efficient than non-converting rural hospitals. The results are also supported by the Simar-Zelenyuk-adapted-Li tests (Table 2.3) which strongly rejected the null hypotheses on equalities of inefficiency distributions between CAHs and non-converting, PPS rural hospitals. On the other hand, the differences are not so clear in terms of technical inefficiency distributions between CAHs and non-converting, PPS rural hospitals, and the Simar-Zelenyuk-adapted-Li test rejected the null hypothesis of equality only for 2005.

Figure 2.2 shows the distributions of inefficiency scores of hospitals before (1997 and 1998) and after (2005 and 2006) the conversion to CAH status. Simar-Zelenyuk-adapted-Li tests (Table 2.3) in conjunction with estimated densities show that CAHs in 2005 and 2006 tend to be slightly less allocatively efficient while they are slightly more technically efficient relative to their pre-conversion selves. In terms of cost inefficiency distributions, there seems to be no significant differences over the same period of time.

A comparison of inefficiency distributions between all CAHs and all non-CAH rural hospitals in our sample (Figure 2.3) shows that CAHs are less allocatively and cost efficient, while they tend to be slightly more technically efficient, than non-CAH, PPS rural hospitals. However, the difference in technical inefficiency between CAHs and non-CAH rural hospitals is not statistically significant as indicated by Simar-Zelenyuk-adapted-Li test in Table 2.3.

Table 2.3. Simar-Zelenyuk-adapted-Li test for equality of inefficiency distributions.

	Cost Inefficiency		Allocative Inefficiency		Technical Inefficiency	
Null Hypothesis	Li test	[a]p-val	Li test	[a]p-val	Li test	[a]p-val
f(cah06)=f(rur06)	25.58	0.000	37.07	0.000	0.22	0.809
f(cah05)=f(rur05)	32.59	0.000	40.49	0.000	1.77	0.040
f(cah06)=f(cah97)	1.35	0.068	1.58	0.042	1.97	0.027
f(cah06)=f(cah98)	-0.23	0.800	0.60	0.419	1.30	0.070
f(cah05)=f(cah97)	1.43	0.055	2.31	0.013	2.11	0.024
f(cah05)=f(cah98)	0.00	0.999	0.80	0.248	2.20	0.023
f(cah)=f(non-cah)	12.67	0.000	45.64	0.000	0.70	0.425

[a] Bootstrap p-value. The number of bootstrap iterations is 2000. All estimations are done by authors in Matlab adopting from programs written for [8].

2.6.2 Bootstrapped Truncated Regressions

Table 2.4 summarizes the results of bootstrapped truncated regressions in which cost, technical, and allocative inefficiency scores are regressed against a set of environmental variables (see Tables A.2.5, A.2.6, and A.2.7 in Appendix 1 for percentile bootstrap confidence intervals). As an interpretation rule, a positive (negative) coefficient indicates a positive (negative) effect on hospital inefficiency.

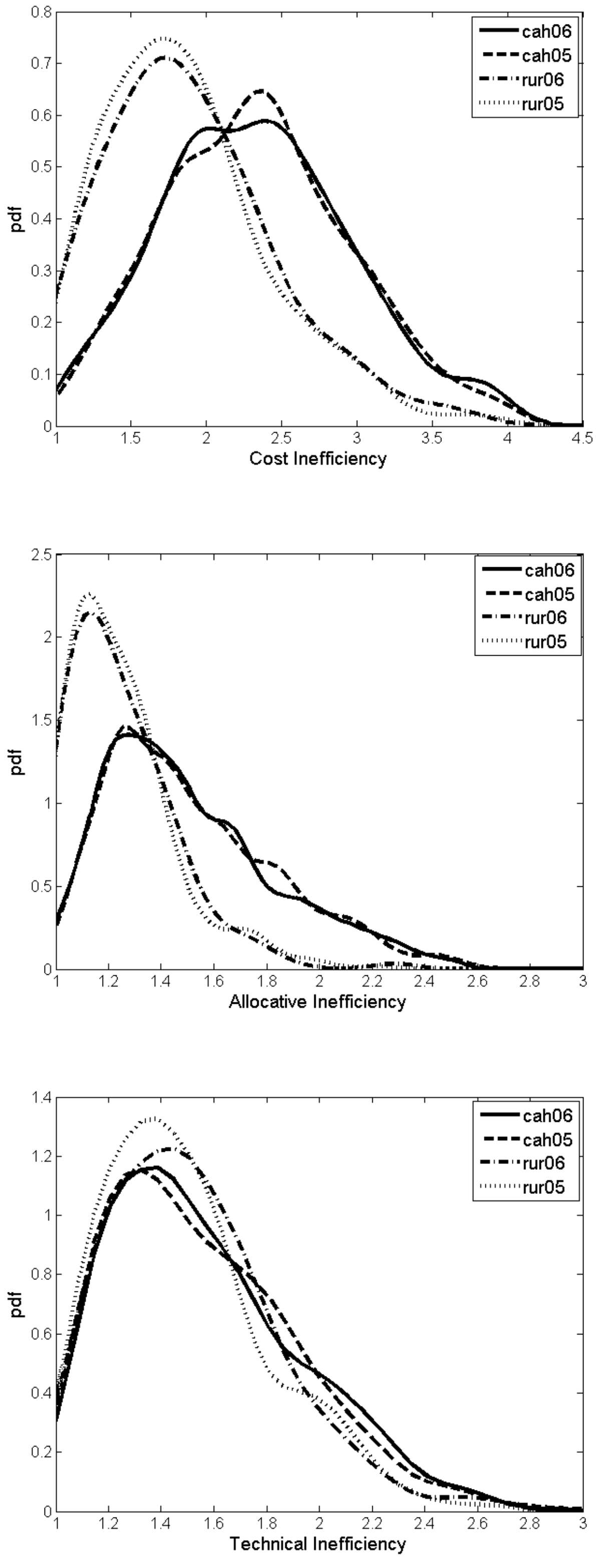

Figure 2.1. Densities of inefficiency scores: CAHs vs. non-converting, PPS rural hospitals in 2005 and 2006.

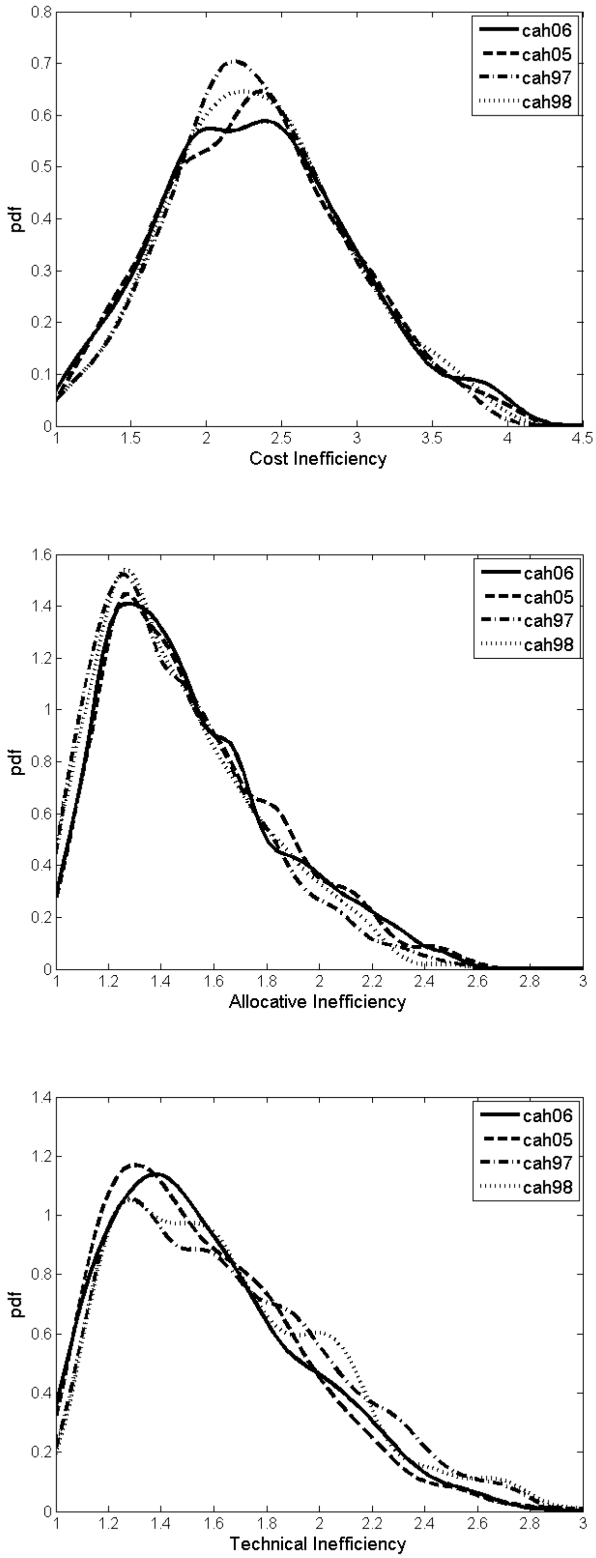

Figure 2.2. Densities of inefficiency scores: CAHs in 2005 and 2006 vs. pre-conversion hospitals in 1997 and 1998.

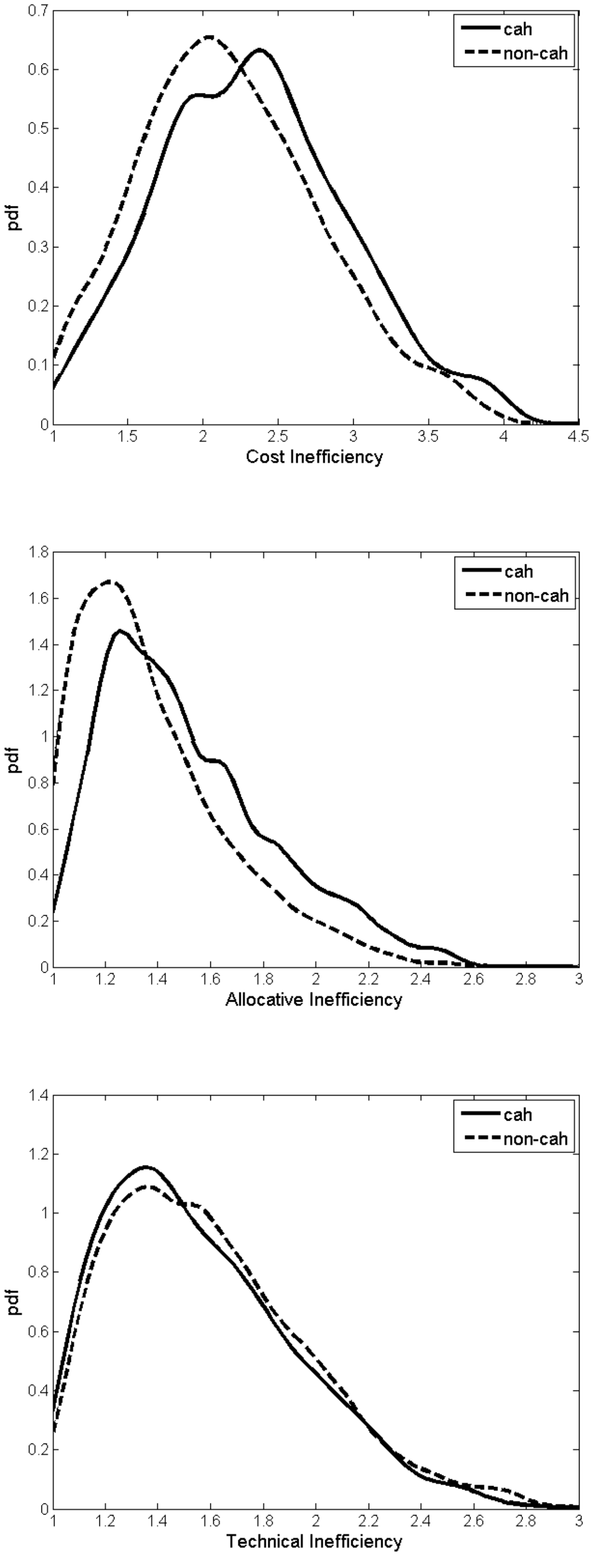

Figure 2.3. Densities of inefficiency scores: CAHs vs. non-CAH, PPS rural hospitals.

The primary variable of interest is the CAH dummy which indicates whether CAHs are more or less inefficient relative to the non-CAH, PPS rural hospitals. The results show that the coefficient of the CAH dummy is positive and significant at the 1 percent level in the cost and allocative inefficiency models and insignificant in the technical inefficiency model, suggesting that CAHs are more cost and allocatively inefficient than non-CAH, PPS rural hospitals, while they are no less technically efficient. These results support, in part, our hypothesis that CAHs are less cost efficient than non-CAH, PPS rural hospitals because of the differences in Medicare reimbursement facing these hospitals.

The results also show that for-profit hospitals are less cost and allocatively inefficient than non-profit hospitals, while government hospitals are more cost, technically, and allocatively inefficient relative to non-profit ones. These results are consistent with PRT which suggests that for-profit hospitals are more efficient than non-profit and government hospitals because a profit maximization objective requires hospitals to reduce their costs and use their resources in an efficient manner.

The estimated results show that Medicare share of admissions has a positive and significant effect on the cost and technical inefficiencies of hospitals. This is in contrast with the negative effect of the same variable on the hospital cost inefficiency found by Rosko and Mutter [10]. An explanation for this discrepancy is that both papers analyze a joint set of cost-based reimbursed CAHs and PPS reimbursed rural hospitals and one can expect an inconclusive effect of Medicare share of admissions on hospital efficiency in this situation. Alternatively, our results show that Medicaid share of admissions has a negative and significant effect (at the 1 percent level) on the cost and technical inefficiencies of hospitals. It is well known that Medicaid payments are low and that Medicaid typically underpays hospitals forcing them to reduce costs in order to maintain their financial viability. Thus, our results are consistent with prior research which has shown that Medicaid exerts cost containment pressure and provides a strong incentive for efficiency [22].

Table 2.4. Results of bootstrapped truncated regressions.

Variable	Cost Inefficiency	Technical Inefficiency	Allocative Inefficiency
CAH	0.3987***	0.0217	0.5482***
Government	0.2028***	0.1374***	0.0746***
For-profit	-0.1453***	0.0501	-0.2948***
Medicare	0.0043***	0.0034***	0.0007
Medicaid	-0.0058***	-0.0053***	-0.00003
HHI	0.0171	0.0806***	-0.0731***
System	-0.1535***	-0.0935***	-0.0524**
Income	-0.000006***	-0.000005***	0.000001
MHMO	-0.0054***	-0.0059***	0.0014
Emergency	-0.0006	0.0005	-0.0010*
Surgeries	-0.0035	-0.0043	-0.0019
Births	-0.0076***	-0.0011	-0.0085***
2006	-0.2987***	-0.0749**	-0.4124***
2005	-0.3417***	-0.1209***	-0.3980***
1998	-0.0165	-0.0184	-0.0136
Constant	2.3273***	1.5242***	1.2826***

***, **, and * denote significance at 1%, 5%, and 10% levels

[a] Estimation based on Algorithm 1 of Simar and Wilson [9], with 2000 bootstrap replications for confidence intervals of the estimated coefficients. All estimations are done by authors in Stata 11.

System membership has a negative and significant effect on hospital inefficiency, suggesting that hospitals belonging to a multihospital system are less cost, technically, and allocatively inefficient than non-system hospitals. These results are consistent with previous literature which suggests that system membership may enhance hospital performance because hospital systems enjoy economies of scale in production, eliminate duplicative administrative functions, and have greater bargaining power in the market [22]. Similarly, the negative effect of Medicare HMO on hospital cost and technical inefficiencies suggests that Medicare HMO penetration creates pressure for hospitals to operate more efficiently. In particular, health maintenance organizations have contributed to health care cost containment by using their market power to extract large discounts from providers and, thus, forcing hospitals to reduce costs in order to remain financially viable [28]. We also found a negative and significant effect (however, small in magnitude) of the county median household income on the cost and technical inefficiencies.

The results show that HHI has an insignificant coefficient in the cost inefficiency model, while the coefficient is negative and significant in the allocative inefficiency model and positive and significant in the technical inefficiency model. Previous literature also reported mixed findings with respect to the effect of HHI on hospital efficiency. For example, an inverse relation between HHI and hospital inefficiency, suggesting that a decrease in HHI (or an increase in hospital competition) leads to an increase in hospital inefficiency, was associated with the theory of service-based competition. That is, hospitals in more competitive markets have higher costs and tend to be more inefficient because they compete for patients based on the services provided. Alternatively, the theory of price-based competition predicts that if competition is increased hospitals will compete for patients by reducing costs and improving efficiency [22].

Our results also indicate that hospitals (both CAHs and non-converting, PPS rural hospitals) in 2005 and 2006 are more cost, technically, and allocatively efficient relative to the same set of hospitals in 1997. This may raise concerns that pooling all data across all time may lead to a trending issue. While the yearly dummies were included to control for time effects, we also performed sensitivity analysis and estimated the models using only data for 2005 and 2006. Specifically, DEA was used, in the first stage, with 2005 and 2006 data jointly to estimate cost, technical, and allocative efficiency scores. The null hypothesis on equality of cost efficiency distributions between 2005 and 2006 was tested and failed to reject (based on Simar-Zelenyuk test with a bootstrap p-value = 0.56). Similarly, the equality of technical efficiency distributions between 2005 and 2006 was not rejected (bootstrap p-value = 0.63). Second stage bootstrapped truncated regressions were estimated with pooled data for the two years. The results were consistent and similar to the estimated models with pooled data for all four years, suggesting that our results were robust (see Table A.2.8 in Appendix 1).

2.6.3 Discussion

The CAH Program appears to have created two separate incentive structures for those rural hospitals that converted to CAH status. The first, a change in mission, appears to have increased the technical efficiency of CAHs in 2005 and 2006 relative to their pre-conversion selves in 1997 and 1998, as shown by the results in Table 2.2 and by the density analysis. At the same time, CAHs appear to be as technically efficient as non-CAH, PPS rural hospitals in our sample, as shown by density analysis and bootstrapped truncated regression results. It is possible that the program's mission change requirements (limitations on the maximum number of acute care beds to 25 and average length of stay to 4 days) may have resulted in the same proportional technical efficiency improvements that PPS cost containment pressures may have had on the non-converting rural hospitals. It might also be the case that all the hospitals in the study experienced general improvements in technical efficiency over the study period.

The second incentive structure associated with CAH conversion is Medicare cost-based reimbursement which has dramatically changed hospitals' financial incentives. Previous research found that hospitals that converted to CAH status significantly increased their Medicare revenue, profitability, employee salaries, and capital expenditures due to Medicare cost-based reimbursement [14]. Furthermore, the average salary per FTE employee increased dramatically for hospitals after CAH conversion while it increased only modestly for non-converting, PPS rural hospitals [16]. Thus, it may be the case that the allocative efficiency declines may be due to the inability of CAH hospitals to substitute away from the higher labor costs identified by previous literature.

Alternatively, anecdotal evidence suggests that after CAH hospitals improved their balance sheets post-conversion, they may have embarked on construction of new hospitals or major infrastructure upgrades at existing CAH hospital locations. These infrastructure improvements add to the average fixed cost of hospitals. Such increased fixed capital expenditure (which cannot be substituted away from) may lead to increased allocative inefficiency in the short term that is mitigated in the longer term as these capital costs are spread over a longer time horizon.[3]

2.7 Conclusions

This study analyzed the impact of conversion to CAH status on hospital efficiency using a two-stage approach and recent methodological advancements in efficiency analysis. In the first stage, DEA was used to estimate hospital cost, allocative, and technical efficiency scores. Using a kernel density estimator and a bootstrap-based test, we estimated and compared the distributions of inefficiency scores of CAH hospitals before and after conversion, as well as with those of a comparison group of non-converting, PPS rural hospitals. In the second stage, bootstrapped truncated regressions were estimated in which cost, technical, and allocative inefficiencies were regressed on explanatory variables.

The results of Simar-Zelenyuk-adapted-Li test and density analysis showed that CAHs were less cost and allocatively efficient than the comparison group of non-converting rural hospitals in 2005 and 2006, while they were no less technically efficient. When compared with their pre-conversion selves in 1997 and 1998, CAHs appeared to be slightly less allocatively efficient, while they were slightly more technically efficient and no less cost

[3] Allocative inefficiency may be driven by the depreciation schedule. Infrastructure improvements (including equipment) may have an accelerated depreciation rate in years just after construction/purchase with reduced depreciation in later years. This would result in CAH hospitals making these improvements to show increased allocative inefficiency in the short term, but allocative efficiency improvements in the long term as the annualized price of capital shifts the isocost curve back toward a lower cost input mix with labor.

efficient. The second stage bootstrapped truncated regression results showed that CAHs were less cost and allocatively efficient than non-CAH, PPS rural hospitals, while they were no less technically efficient.

A shortcoming of this research is the lack of quality controls. While our results would have been strengthened with the inclusion of quality measures, the approach taken here to study the impact of CAH conversion on hospital efficiency made it impossible to find quality measures for the two years before conversion (1997 and 1998). As new data become available, future research on CAH efficiency should incorporate quality controls in the methodological advancements proposed by Simar and Wilson [9].

The Critical Access Hospital program has created incentives to maintain inpatient access in remote rural areas of the U.S. at an increased cost. While the results suggest that overall economic (cost) efficiency declined, the inability to quickly substitute to lower cost inputs as input prices change may be the leading driver of that inefficiency. Federal programs should consider strategies that help CAH hospitals reduce labor inputs as their labor costs increase as well as identify lower cost models for providing up-to-date facilities and equipment.

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CHAPTER 3

COST EFFICIENCY OF RURAL HOSPITALS: DEA, TWO-STAGE APPROACH, AND STOCHASTIC FRONTIER ANALYSIS

3.1 Introduction

In this study, I compare the performance of two groups of rural hospitals in the U.S. operating under different Medicare reimbursement systems. Specifically, I statistically test for cost efficiency differences between cost-based reimbursed Critical Access Hospitals (CAHs) and rural hospitals reimbursed under the Prospective Payment System (PPS) using three methodological approaches. The first method is data envelopment analysis (DEA) which is a nonparametric approach that uses linear programming to estimate cost efficiency scores. A nonparametric kernel density estimator is used to estimate the densities of cost efficiency scores of CAH and PPS rural hospitals, and the null hypothesis on equality between these densities is tested using a bootstrap-based test suggested by Simar and Zelenyuk [1]. The second method is the two-stage, semi-parametric approach in which cost efficiency scores, estimated in the first stage using DEA, are regressed, in the second stage, on explanatory variables expected to influence hospital cost efficiency. In the second stage, both a tobit model (which has been traditionally used in the literature) and a truncated regression with a bootstrap procedure suggested by Simar and Wilson [2] are used to make inferences about the impact of environmental variables (in particular, CAH status) on hospital cost efficiency. Finally, the third method is stochastic frontier analysis (SFA) which is a parametric approach based on a cost function.

The CAH Program was created in 1997 in response to the dramatic deterioration of financial conditions (and the potential threat of closure) of small rural hospitals. Medicare has paid enhanced cost-based reimbursement, representing 101 percent of costs, to rural hospitals participating in the CAH Program, providing they meet several requirements before conversion.[1] In contrast, Medicare PPS pays the remainder hospitals a fixed price per case based on the diagnosis related group (DRG), allowing hospitals to keep the difference between this fixed price and actual cost. The two reimbursement methods provide different incentives for hospitals. In particular, Medicare cost-based reimbursement − which was the reimbursement method for hospitals before 1983 − provided an incentive for hospitals to increase costs in order to receive higher revenues because Medicare paid for the total cost of services [3-4]. The PPS, on the other hand, has been designed to promote efficiency in hospital operations by motivating hospitals to keep their costs below the PPS reimbursement rates [5].

In the efficiency analysis literature, there has been considerable interest in reconciling SFA and DEA [6]. Two of the studies that compared the two methods are Chiricos and Sear [7] for US hospitals and Jacobs [8] for hospitals in the UK. Both studies found significant differences between the results from the two approaches. Using SFA, Rosko and Mutter [9] compared the cost inefficiency of CAHs with that of non-CAH rural hospitals and found that, on average, CAHs were more cost inefficient than non-CAH rural hospitals.

To the best of my knowledge, this is the first study providing empirical applications of methodological approaches of efficiency analysis ranging from fully nonparametric, to semi-parametric, and to fully parametric to analyze cost efficiency differences between two groups of rural hospitals operating under different Medicare reimbursement systems. A nonparametric

[1] To be eligible for CAH conversion, a hospital must be located at least 35 miles by primary road, or 15 miles by secondary road, from another hospital; use no more than 25 acute care beds (however, CAHs have no limitations on non-acute care beds); annual average length of stay cannot be greater than 4 days, and the hospital must provide 24-hour emergency care services.

approach, such as DEA, requires minimal statistical assumptions and, thus, avoids the risk of specification error. However, the deterministic nature of DEA does not account for statistical noise in efficiency estimation. A fully parametric approach, such as SFA, requires restrictive assumptions in terms of a functional form and probability distributions, but it accounts for statistical noise in efficiency estimation. A semi-parametric approach, such as the two-stage approach, is less restrictive than SFA in the sense that some features of the statistical model are left unspecified.

3.2 Methods

3.2.1 DEA Cost Efficiency Estimator

DEA uses linear programming to construct a piecewise linear estimate of the best-practice (efficient) frontier enveloping all the data. The efficiency score of a firm is measured relative to this best-practice frontier. As a nonparametric method, DEA requires no specific assumptions about the functional form of the frontier and, thus, avoids any misspecification problems. However, DEA is deterministic, meaning that deviations from the efficient frontier are entirely assumed to be due to inefficiency and no allowance is made for statistical noise or measurement error. Nevertheless, some good statistical properties have been recently unveiled for the DEA efficiency estimator, the most important of which is consistency [10].

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 (LP). Specifically, let y_{rj} be an output vector ($r = 1,\ldots, m$) and x_{ij} an input vector ($i = 1,\ldots, k$) for hospital j ($j = 1,\ldots, n$). For a given output level y_{ro} and an input price vector w_{io} for hospital o, the minimum cost under the assumption of variable returns to scale is obtained by solving the following LP problem:

$$Min_{\lambda_j, x_{io}^*} \left\{ \sum_{i=1}^{k} w_{io} x_{io}^* \mid \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, (r = 1,...., m), \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}^*, (i = 1,...., k), \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \right\} \quad (1)$$

The optimal solution to this LP problem is the input vector x_{io}^* which minimizes the cost of producing the observed level of outputs given input prices. Cost efficiency δ 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:

$$\delta = \sum_{i=1}^{k} w_{io} x_{io}^* \Big/ \sum_{i=1}^{k} w_{io} x_{io} \ . \quad (2)$$

3.2.2 Density Analysis of DEA Efficiency Scores

Simply comparing only the sample means of DEA cost efficiency scores of CAHs and non-converting rural hospitals may not provide a complete picture. An alternative approach is to estimate and compare the densities of efficiency scores of the two groups of rural hospitals. There are, however, 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 kernel density estimation, and (2) in finite samples, the estimated efficiency scores are biased and not independent (however both these problems vanish asymptotically). To address these problems, Simar and Zelenyuk [1] suggested kernel methods to consistently estimate the densities of DEA estimated efficiency scores and proposed a bootstrapped-based test for testing the null hypothesis on equality of these densities (see Simar and Zelenyuk [1], for details).

3.2.3 Two-Stage, Semi-parametric Approach

In the two-stage approach, cost efficiency scores, estimated in the first stage using DEA, are regressed, in the second stage, on environmental variables to investigate the dependency of hospital efficiency on such explanatory variables. In health care applications of the two-stage approach, the tobit (censored) model has been a popular analytical technique used in the second stage. Simar and Wilson [2], however, criticized previous two-stage studies because of the failure to define a coherent statistical model consistent with the second stage analysis. Additionally, they argue that inference in the previous two-stage studies is invalid because of the failure to account for the serial correlation present among efficiency estimates. Simar and Wilson [2] defined a statistical model consistent with the second stage analysis which requires a truncated regression in the second stage. Further, they suggested a bootstrap procedure to provide valid inference about the effects of explanatory variables on estimated efficiency in the second stage truncated regression.

In the second stage, I specify the following truncated regression model:

$$0 < \hat{\delta}_j = z_j\beta + \varepsilon_j \leq 1, \quad j = 1, 2, \ldots, n \tag{3}$$

where $\hat{\delta}_j$ is DEA estimated cost efficiency score of the j-th hospital, ε_j is assumed to be distributed $N(0, \sigma^2)$ with left truncation at $-z_j\beta$ and right truncation at $1 - z_j\beta$, z_j is a vector of k environmental variables which are thought to affect 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 regression are serially correlated [2]. While this correlation disappears asymptotically, Simar and Wilson [2] 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. Here, I use their Algorithm 1 bootstrap procedure, modified for lower and upper bounds of DEA cost efficiency scores, which has the following steps:

1. Estimate the truncated regression $0 < \hat{\delta}_j = z_j\beta + \varepsilon_j \leq 1$ using the $m < n$ observations where $\hat{\delta}_j < 1$ (j = 1,…., m), to obtain an estimate $\hat{\beta}$ of β.
2. Loop over the next three steps L = 2000 times to obtain a set of bootstrap estimates $B = \{\hat{\beta}^*\}_{b=1}^{L}$:
   i. For each j = 1,…., m, draw ε_j from $N(0, \hat{\sigma}^2)$ with left truncation at $-z_j\hat{\beta}$ and right truncation at $1 - z_j\hat{\beta}$.
   ii. For each j = 1,….., m compute $\delta_j^* = z_j\hat{\beta} + \varepsilon_j$.
   iii. Estimate the truncated regression of δ_j^* on z_j yielding estimates $\hat{\beta}^*$.
3. Use the bootstrap values in B and the original estimates of $\hat{\beta}$ to construct percentile confidence intervals for each element of β.

3.2.4 Stochastic Frontier Analysis

Alternatively, hospital 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 [11]:

$$TC_j = f(y_j, w_j) + \varepsilon_j, \tag{4}$$

and $\varepsilon_j = v_j + u_j$, j = 1, 2, …., n

where TC_j represents the total cost of the j-th hospital, y_j is a vector of outputs, w_j is a vector of input prices, and ε_j is a composite error term. ε_j is decomposed as random statistical noise v_j, assumed normally distributed, plus cost inefficiency u_j for which a distribution must also be assumed.[2] Additionally, one must also specify a functional form for the cost equation. The most

[2] Distributions generally assumed for the inefficiency error term are: half-normal, truncated-normal, exponential and gamma.

popular functional forms used in empirical research have been the translog and Cobb-Douglas cost functions. Given the distributional assumptions for the two error terms, the model is estimated by maximum likelihood [11].

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

$$\hat{u}_j = z_j\beta + \eta_j,\ j = 1, 2, \ldots, n \tag{5}$$

where $\hat{u}_j$ is the SFA estimated cost inefficiency, z_j is the vector of environmental variables, β is a vector of parameters to be estimated and η_j 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 frontier cost function in a one-stage procedure [11].

3.3 Data

In this study, we use data from the 2005 and 2006 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. The analyzed sample consists of CAH rural hospitals and non-converting, PPS rural hospitals. Following Stensland, Davidson, and Moscovice [12], we restrict the PPS rural hospitals to those with no more than fifty beds, allowing us to have two groups of rural hospitals of similar size. While CAHs are restricted to no more than 25 acute care beds, they have no restrictions on long-term care beds such as skilled nursing home beds; the mean for CAHs' total staffed and licensed beds in our sample was 36 while for non-converting rural hospitals was 38 (Table 3.2).

One of the goals of the CAH Program has been to improve the quality of care provided by CAHs. To control for the quality of care, we follow Nayar and Ozcan [13] and use quality measures publicly available from the CMS Hospital Compare database. For this study, only two quality measures reflecting recommended treatments for pneumonia are selected because of a large number of missing observations on the other quality measures. Additionally, only those hospitals for which quality measures were calculated based on at least 25 patients (consistent with CMS recommendations) are used in the analysis, further reducing the sample size. The two 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. Casey et al. [14] found these to be relevant quality measures for CAHs. The data sample consists of 331 rural hospitals in 2005 (of which 178 were rural CAHs), and 429 in 2006 (of which 224 were rural CAHs).[3]

For the specification of the stochastic frontier cost function, we followed previous literature [9,15]. Specifically, we used total hospital expenses (*exptot*) 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, we control for hospital output heterogeneity using product mix descriptors (PMD): 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%*)

[3] For consistency, CAHs located in metropolitan statistical areas were eliminated from the analysis.

((births / admissions) × 100). Additionally, we control for quality of care using percent of patients given pneumococcal vaccination (*pneum_vac%*) and percent of patients given initial antibiotic timing (*initial_antib%*). We also include the number of hospital beds as a proxy for fixed costs in the cost function. Input prices used in the analysis are: the price of labor (*w*) (sum of payroll expenses and employee benefits divided by the full-time equivalent facility personnel) and the price of capital (*pk*) (sum of depreciation expenses and interest expenses divided by the number of facility beds) [15]. 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 [16]. 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 [13]. The physical inputs consist of full time equivalent (FTE) facility personnel and total staffed and licensed hospital beds, and the corresponding input prices are identical to the ones in the SFA (the price of labor and the price of capital) (see Table 3.1 for the specifications of DEA and SFA models).

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 that reports case-mix data. In the stochastic frontier cost function, percent of emergency room visits, percent of outpatient surgeries and percent of births are used to control for heterogeneity in hospital outputs [17].

Table 3.1. Variable definitions and model specifications.

Variable	Variable Definition	DEA	SFA
Outputs			
admtot	Total hospital admissions	Output	Output
postdays	Post-admission days	Output	Output
opv	Total outpatient visits	Output	Output
erv	Emergency room visits	Output	
outsurg	Outpatient surgeries	Output	
births	Total births	Output	
Product Mix Descriptors (PMD)			
erv%	% Emergency room visits		PMD
outsurg%	% Outpatient surgeries		PMD
birth%	% Admissions for birth		PMD
Quality Indicators			
pneum_vac%	%Patients given pneumococcal vaccination	Quality Output	Quality Measure
initial_antib%	%Patients given initial antibiotic timing	Quality Output	Quality Measure
Inputs			
bdtot	Total staffed and licensed hospital beds	Input	Fixed Input
fte	Full time equivalent (FTE) employee	Input	
Input Prices			
pk	$ Price of capital	Input Price	Input Price
w	$ Price of labor	Input Price	Input Price
exptot	$ Total hospital expenditure		Total Cost
Environmental Variables			
Government	Government hospital (1,0)	Env. Variable	Env. Variable
For-profit	For-profit hospital (1,0)	Env. Variable	Env. Variable
Medicare%	% Medicare admissions	Env. Variable	Env. Variable
Medicaid%	% Medicaid admissions	Env. Variable	Env. Variable
HHI	Herfindahl-Hirschman index	Env. Variable	Env. Variable
System	Member of a multihospital system (1,0)	Env. Variable	Env. Variable
MHMO%	% Medicare HMO penetration	Env. Variable	Env. Variable
CAH	CAH hospital (0,1)	Env. Variable	Env. Variable
Income	Median household income	Env. Variable	Env. Variable

Ozgen and Ozcan [18] noted that the lack of case-mix variables in DEA efficiency models is in part compensated by the 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 SFA and the second stage regression in the two-stage approach. For the specification of environmental variables, we follow Rosko and Mutter [9,17]. The primary variable of interest is a CAH dummy (one if the hospital has CAH status and zero otherwise) which is used to test whether CAHs are more or less cost efficient than non-converting, PPS rural hospitals. Dummy variables that define government hospitals (*Government*) and for-profit hospitals (*For-profit*) are included to control for internal pressure for efficiency associated with ownership. Non-profit ownership is the reference category. For-profit hospitals are expected to be more cost efficient than non-profit and government hospitals because their profit-maximization objective provides a strong incentive for cost reduction and efficiency improvement. Membership in a multihospital system (*System*), which is also introduced as a dummy variable, is also expected to be directly associated with hospital efficiency because hospital system membership has been shown to provide significant cost advantages [17].

Two variables are used to control for 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%* on hospital cost efficiency is not clear given the joint use in estimation of the two groups of rural hospitals with different reimbursement systems: cost-based reimbursed CAHs and PPS rural hospitals. Medicaid, on the other hand, typically underpays hospitals and exerts cost containment pressure and, thus, *Medicaid%* is expected to be directly associated with hospital cost efficiency.

Table 3.2. Summary statistics of variables.

	CAH		Rural	
Variable	Mean	SD	Mean	SD
admtot	1,072.12	427.87	1,730.83	737.84
postdays	6,296.83	6,769.26	4,535.68	2,024.08
opv	42,104.53	30,384.28	45,033.72	33,299.60
erv	6,981.46	4,516.93	9,492.27	5,194.94
outsurg	889.98	721.07	1,175.71	885.10
births	97.53	109.61	202.41	213.33
pneum_vac%	62.31	23.66	59.90	24.28
initial_antib%	84.74	8.75	80.87	10.40
bdtot	35.92	22.27	37.93	9.41
fte	191.95	79.35	216.16	98.51
pk	36,824.86	29,993.99	35,780.83	27,633.52
w	50,747.63	13,418.28	49,177.05	12,514.33
exptot	1.80E+07	9.31E+06	2.08E+07	1.20E+07
erv%	20.60	13.52	26.49	16.71
outsurg%	2.60	2.41	3.41	3.59
birth%	7.91	7.90	10.86	10.21
Environmental Variables				
Government	0.32	0.47	0.34	0.47
For-profit	0.03	0.18	0.14	0.35
Medicare%	59.90	12.57	52.47	11.77
Medicaid%	13.05	7.98	17.37	9.65
HHI	0.50	0.35	0.56	0.33
System	0.42	0.49	0.51	0.50
MHMO%	3.26	5.31	2.64	4.76
Income	38,432.78	6,190.83	37,391.59	8,465.68

A Herfindahl-Hirschman index (*HHI*) is used to control for competitive pressure in a hospital's market, which 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 [9]. 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.

Summary statistics of the variables used in the empirical analysis are presented for both CAHs and the PPS rural hospitals in Table 3.2.

3.4 Results

We started the empirical analysis by performing a series of likelihood ratio tests to arrive at an appropriate specification of the SFA model. Based on the results of these tests, we adopted a SFA cost model with a translog functional form and a half-normal distribution for the inefficiency error term. The results of the SFA translog cost function are presented in the Appendix 2 (Table A.3.6), together with the likelihood ratio tests performed for the SFA model.

Table 3.3 shows summary statistics of cost efficiency scores estimated by both DEA and the SFA with the two years of data jointly. We present the reciprocal of SFA cost inefficiency scores. The mean cost efficiency of all rural hospitals estimated using DEA without quality measures was 63.3%, increasing to 70% when quality measures were included. Similarly, the mean cost efficiency estimated using SFA increased from 70.2% to 78.3% after inclusion of the quality measures. Mutter et al. [6] indicate that if quality is not controlled for in hospital efficiency estimation, it will show up as inefficiency. Our results confirm their statement.

The DEA estimated mean cost efficiency (Table 3.3) for CAHs is 67.9% while for the comparison group of non-converting, PPS rural hospitals is 72.4%, indicating that CAHs are less cost efficient. The mean cost efficiency estimated using SFA is 75.1% for CAHs and 81.8% for non-converting rural hospitals, also indicating that CAHs are less cost efficient. As expected, there is a significant difference in the magnitude of efficiency scores estimated by DEA and SFA, which is attributed in principal to the differences in how the two methods account for statistical noise.

3.4.1 Density Analysis of DEA Cost Inefficiency Scores

Figure 3.1 shows the densities of DEA estimated cost inefficiency scores of CAHs and non-converting, PPS rural hospitals in each year (a) as well as with the two years jointly used (b). Consistent with the original Simar and Zelenyuk (2006) test, we use the reciprocal of cost efficiency scores (cost inefficiency ≥ 1) for kernel density estimation. In Figure 3.1(a), we observe a rightward shift from the efficient unity of the densities of cost inefficiency scores of CAHs relative to those of non-converting rural hospitals in 2005 and 2006 (a), suggesting that CAHs tend to be more cost inefficient than non-converting rural hospitals in both years. Figure 3.1(b) shows the densities of cost inefficiency scores of CAHs and non-converting rural hospitals with pooled data. Again, we observe a rightward shift of CAHs' density relative to the one for the PPS rural hospitals, suggesting that CAHs are more cost inefficient than the PPS rural hospitals. These findings are also supported by the Simar-Zelenyuk test (Table 3.4) which rejected the null hypotheses on equality of densities between CAHs and PPS rural hospitals.

Table 3.3. Summary statistics of DEA and SFA estimated cost efficiency.

		DEA		SFA	
Year	N	Mean	SD	Mean	SD
CAH2005	178	0.678	0.184	0.792	0.034
CAH2006	224	0.679	0.181	0.719	0.034
Rural2005	153	0.720	0.163	0.864	0.038
Rural2006	205	0.727	0.171	0.784	0.035
CAH	402	0.679	0.182	0.751	0.050
Rural	358	0.724	0.167	0.818	0.054
All	760	0.700	0.177	0.783	0.062

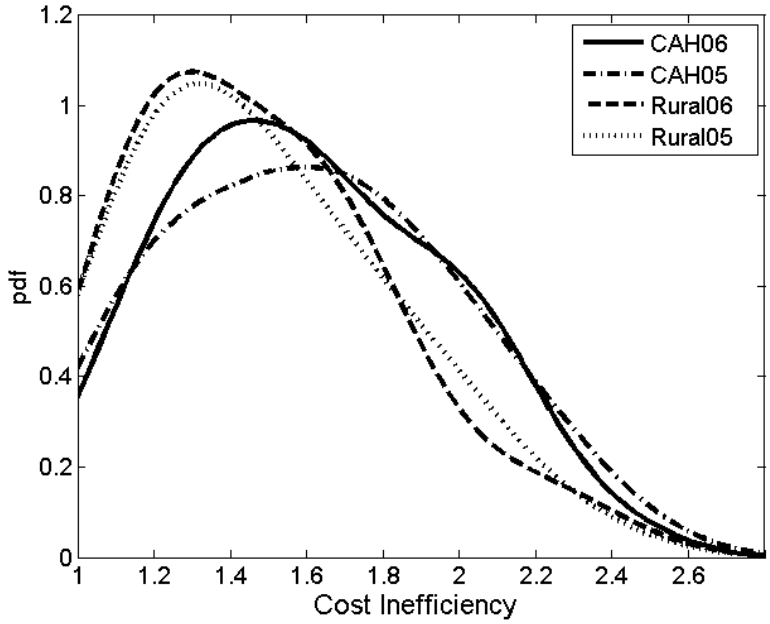
Table 3.4. Simar-Zelenyuk test on equality of densities of DEA cost inefficiency scores.

Null Hypothesis	Test	*p-value
f(CAH06)=f(Rural06)	4.13	0.002
f(CAH05)=f(Rural05)	3.76	0.001
f(CAH)=f(Rural)	6.35	0.000

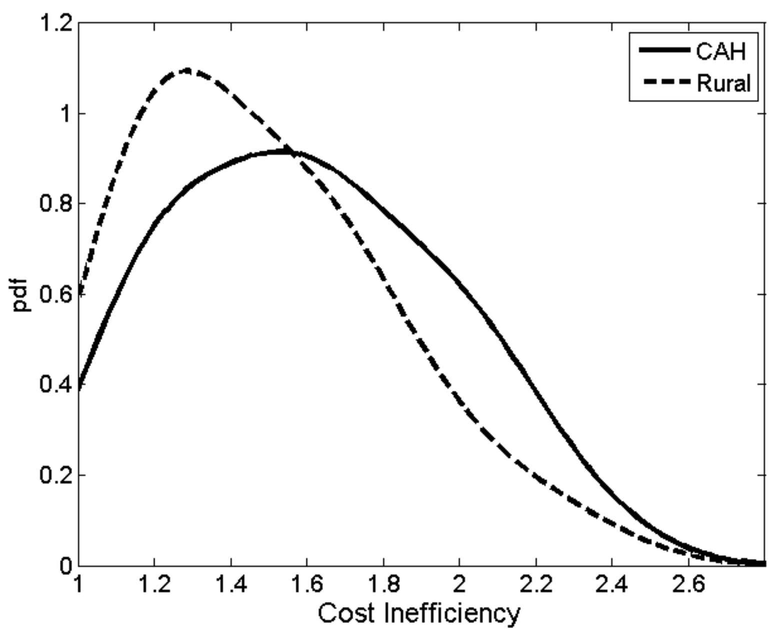
Notes: *Bootstrap p-value. The number of bootstrap iterations is 2000. All calculations are done by authors in Matlab adopting from programs written for Simar and Zelenyuk [1].

3.4.2 Marginal Effects of Environmental Variables

Table 3.5 presents the results of three different approaches to estimate the marginal effects of environmental variables: the DEA two-stage approach with a traditional tobit model, as well as with a bootstrapped truncated regression along the line of Simar and Wilson [2] (for which 99% and 95% bootstrap confidence intervals are shown), and SFA. For tobit and bootstrapped truncated regression models, the dependent variable is DEA cost efficiency; therefore a positive (negative) coefficient suggests a positive (negative) effect on cost efficiency. For SFA, the dependent variable is cost inefficiency, where a positive coefficient implies decreased efficiency. It should be noted that except for the insignificant Medicaid variable, all variables were consistent in sign – all variables that were negative in the DEA bootstrapped truncated regression were positive in the SFA cost inefficiency equation and vice versa.



(a)



(b)

Figure 3.1. Kernel estimated densities of DEA cost inefficiency scores of CAHs and non-converting rural hospitals: (a) 2005 – 2006, and (b) pooled data)

The results show that the coefficient of our key variable, the CAH dummy, is positive and highly statistically significant (p-value < 0.01) in the SFA model. This suggests that CAHs are more cost inefficient than non-converting, PPS rural hospitals. An interpretation of this coefficient is that, after controlling for other factors, CAHs are 7.3% more cost inefficient than non-converting rural hospitals. This is similar to the difference of 6.7% in mean group cost efficiency estimated by SFA (Table 3.3). The marginal effect of the CAH dummy variable on cost efficiency is negative and statistically significant at the 1% level in the bootstrapped truncated regression, suggesting that CAHs are 5.2% less cost efficient than non-converting rural hospitals. This is also similar to the difference of 4.5% in mean group cost efficiency estimated by DEA (Table 3.3). In the tobit model, the same coefficient is negative but statistically insignificant (or significant only at the 10% level) and only half the size of the CAH coefficient in the bootstrapped truncated regression. While these results support our hypothesis that CAHs are less cost efficient than non-converting, PPS rural hospitals because of the differences in Medicare reimbursement facing these two groups of rural hospitals, they also show how results of the tobit model in this case may lead to an alternative interpretation.

The estimated results show a positive and statistically significant coefficient of government ownership in the SFA model, suggesting that government owned rural hospitals are more cost inefficient than nonprofit rural hospitals, a result that is consistent with previous literature [9]. In the two-stage approach, the effect of government ownership on hospital cost efficiency is negative but significant only in the tobit model. For-profit ownership, on the other hand, was not found to impact efficiency in any of the three models.

The share of Medicare admissions has a negative and significant coefficient in both tobit and bootstrapped truncated regression models, suggesting that an increase in Medicare admissions is inversely associated with hospital efficiency. Similar to Rosko and Mutter [9], the coefficient of Herfindahl-Hirschman index is positive and significant only in the SFA model, suggesting that an increase in HHI (or a decrease in market competition) is directly associated with hospital cost inefficiency. This is also consistent with the concept of price-based competition which suggests that if competition is increased, hospitals will compete for patients by reducing costs [17].

The positive and significant coefficient of system membership found in the tobit and bootstrapped truncated regression models suggests that rural hospitals that are members of a multihospital system are more cost efficient than the ones that are not. System membership has been shown to improve hospital performance because hospital systems can take advantage of economies of scale and eliminate duplicative administrative functions [17].

The negative and significant coefficient of Medicare HMO found in the SFA model suggests that HMO penetration creates pressure for rural hospitals to reduce cost inefficiency, a result consistent with previous literature [9]. Finally, the positive and significant coefficient of the county median household income in the SFA model suggests a direct relationship between this variable and hospital cost inefficiency [9].

3.5 Discussion and Conclusions

This study compared efficiencies of two groups of rural hospitals operating under different Medicare reimbursement systems. Cost efficiency scores were estimated using two different frontier methods: DEA and SFA. Comparisons of mean cost efficiencies between cost-based reimbursed CAH rural hospitals and non-converting, PPS rural hospitals revealed that CAHs were less cost efficient than non-converting rural hospitals. I found that CAHs were, on average,

Table 3.5. Estimated effects of environmental variables on cost efficiency/inefficiency.

	Tobit Regression *Cost Efficiency*		Bootstrapped Truncated Regression *Cost Efficiency*					SFA *Cost Inefficiency*	
				99% Bootstrap C.I.		95% Bootstrap C.I.			
Variable	β	t-stat	β	LB	UB	LB	UB	β	t-stat
Constant	0.8522**	11.05	0.8138**	0.6569	0.9712	0.6943	0.9322	0.0058	0.01
CAH	-0.0271	-1.77	-0.0524**	-0.0843	-0.0214	-0.0768	-0.0287	0.0732**	11.90
Government	-0.0384*	-2.38	-0.0152	-0.0474	0.0178	-0.0390	0.0099	0.0285**	22.52
For-profit	0.0180	0.65	0.0249	-0.0385	0.0829	-0.0219	0.0686	-0.0040	-0.17
Medicare%	-0.0017*	-2.38	-0.0015*	-0.0030	0.0000	-0.0026	-0.0003	0.0009	1.83
Medicaid%	-0.0006	-0.56	-0.0005	-0.0026	0.0016	-0.0021	0.0011	-0.0019	-1.93
HHI	-0.0059	-0.28	-0.0157	-0.0573	0.0234	-0.0474	0.0158	0.0541**	2.75
System	0.0481**	3.11	0.0432**	0.0129	0.0730	0.0196	0.0664	-0.0169	-0.95
Income	-8.35E-07	-0.77	-1.34E-06	-3.54E-06	7.95E-07	-3.05E-06	2.80E-07	2.99E-06**	2.85
MHMO%	-0.0008	-0.58	0.0016	-0.0013	0.0045	-0.0006	0.0038	-0.0035*	-2.23
Y2006	0.0123	0.82	0.0011	-0.0286	0.0301	-0.0219	0.0235	0.0856	0.90

Notes: ** and * denote significance at 1% and 5% levels. Estimation of bootstrapped truncated regression is based on Algorithm 1 of Simar and Wilson (2007), modified for left and right truncations, with 2000 bootstrap replications for confidence intervals. The dependent variable in tobit and bootstrapped truncated regression models is cost efficiency while in SFA model is cost inefficiency.

4.5% less cost efficient than non-converting rural hospitals in the DEA model while the results of the SFA model showed that CAHs were, on average, 6.7% less cost efficient than non-converting rural hospitals. Using SFA, Rosko and Mutter [9] found that CAHs were 5.6% less cost efficient than non-converting rural hospitals. Additionally, the densities of DEA cost inefficiency scores were estimated and compared using a nonparametric kernel density estimator and a bootstrap-based test suggested by Simar and Zelenyuk [1]. The results of Simar-Zelenyuk test and density analysis of DEA cost inefficiency scores also showed that CAHs were less cost efficient than non-converting rural hospitals.

An alternative approach employed to analyze the effect of Medicare reimbursement system on rural hospital cost efficiency was incorporated by using a CAH dummy and estimating its marginal effect using SFA as well as the two-stage DEA approach. By now, it is well established in the literature how to use SFA to make valid inferences about the effects of environmental variables on estimated cost inefficiency [11]. The two-stage approach, in which efficiency scores estimated in the first stage by DEA are regressed in the second stage on environmental variables, has been popular in the efficiency analysis literature. Many of the previous studies used a tobit model in the second stage. However, Simar and Wilson [2] criticized previous applications of the two-stage stage approach, mainly because of the failure to account for the correlation present among efficiency estimates and the use of tobit in the second-stage analysis. They defined an alternative statistical model where the truncated regression with bootstrap leads to consistent estimation in the second stage analysis.

In this study, we estimated the marginal effects of environmental variables (CAH status, ownership, Medicare and Medicaid, etc.) on hospital cost efficiency using SFA and the two-stage DEA approach with tobit as well as with the bootstrapped truncated regression suggested by

Simar and Wilson [2]. Our key variable, the CAH dummy, had strongly statistically significant coefficients in the bootstrapped truncated regression and SFA models, suggesting that CAHs were between 5% and 7% less cost efficient than non-converting rural hospitals. These results are consistent with our mean group efficiencies estimated by DEA and SFA where we find similar differences between mean cost efficiencies of CAHs and non-converting rural hospitals. In contrast, the coefficient of the CAH variable was insignificant in the tobit model.

It should be noted that this research has some limitations. In particular, this study cannot be truly considered a policy analysis of the CAH Program because it does not perform a "before" and "after" analysis, nor does it examine the total benefits and the total costs of the CAH Program. An additional concern arises from the fact that CAH conversion is not random because hospitals choose to convert and any comparison group will differ from converting hospitals [19]. It is possible that our conclusion that CAHs are less cost efficient than non-converting rural hospitals could be driven by more inefficient hospitals choosing to convert to CAH status. However, our results are supported by similar findings in the literature and by historical evidence which indicate that the PPS reimbursement results in greater cost containment and improved efficiency [9].

Our research suggests that SFA and the two-stage DEA approach along the line of Simar and Wilson [2] are viable alternatives for analyzing the impact of environmental variables on hospital cost efficiency. We found that both the SFA and 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 [2] 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.

3.6 References

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CHAPTER 4

TECHNICAL EFFICIENCY OF CRITICAL ACCESS HOSPITALS: AN APPLICATION OF THE TWO-STAGE APPROACH WITH DOUBLE BOOTSTRAP[1]

4.1 Introduction

The Critical Access Hospital (CAH) Program, introduced by the Rural Hospital Flexibility (Flex) Program, represents a subset of mostly rural hospitals that receive special cost-based reimbursement for treating Medicare patients. Starting in 1997, the program has allowed for more than 1,300 hospitals to convert to CAH status in exchange for accepting some restrictions. Most importantly, CAH conversion requires hospitals to be at least 35 miles by primary road, or 15 miles by secondary road, from the nearest hospital,[2] have no more than 25 acute care beds, and maintain an annual average length of in-patient stay of 96 hours or less.

Medicare has paid CAHs on a cost basis rather than prospective payment system (PPS)[3] in order to protect these financially vulnerable hospitals that are important for access to care in isolated rural areas [2]. A low patient volume has made it difficult for small rural hospitals to recover their Medicare costs under the PPS [1]. The CAH Program has increased Medicare payments to converting hospitals to improve their financial viability and potentially prevent hospital closure. While it is widely believed that the CAH Program has maintained access to care in remote regions, concerns have been raised about the effect of Medicare reimbursement on the efficiency of CAHs [1]. In particular, cost-based reimbursement − which was used by Medicare to reimburse hospitals before 1983 – provided an incentive for

[1] This chapter has been accepted for publication in *Health Care Management Science*. Authorization from publisher, Springer, for reproduction can be found in Appendix 4. The final publication is available at www.springerlink.com (DOI 10.1007/s10729-012-9209-8).
[2] Before January 2006, states were allowed to waive the distance requirement for hospitals that were declared "necessary providers" and qualify them for CAH conversion. Thus, some CAHs are quite close to other hospitals. For a detailed description of the CAH Program, see [1].
[3] The PPS pays a fixed price per case based on the diagnosis-related group (DRG), constraining hospitals to keep their unit costs bellow the PPS rates in order to remain financially viable.

hospitals to increase costs (i.e., oversupply services and/or overuse resources) in order to receive higher revenues because Medicare paid on a cost basis [3-4].

In a recent article, Rosko and Mutter [5] examined cost inefficiency differences between CAH and non-CAH rural hospitals using stochastic frontier analysis. They found that, on average, CAHs were more cost inefficient than non-CAH rural hospitals and that there was a positive association between the number of years in the CAH Program and cost inefficiency. However, by jointly using CAH and non-CAH rural hospitals in their analysis, they were unable to isolate the marginal effects of Medicare and Medicaid patient mix on CAHs' efficiency. Cost-based reimbursement has been the primary factor driving CAH conversion and the effects of Medicare and Medicaid reimbursement on the efficiency of CAHs may be of interest for policy makers.

In light of the above discussion, the question that arises is: among those hospitals that have already converted to CAH status, does an increased Medicare patient mix have a negative effect on the technical efficiency of CAHs? That is, if cost-based reimbursement creates a disincentive for hospitals to operate efficiently, would we expect to see CAH hospitals with a higher proportion of Medicare cost-based reimbursement patients have greater decreases in technical efficiency?

In this paper, we seek to answer to this question by focusing on the CAH certified rural hospitals and using recent methodological advancements in efficiency analysis. Specifically, we use a two-stage, semi-parametric approach and bootstrap procedures proposed by Simar and Wilson [6] to estimate technical efficiency scores and make valid inferences about the impact of environmental variables (i.e., Medicare and Medicaid reimbursement, hospital ownership, market competition) on CAHs' efficiency.

In the two-stage approach, technical efficiency scores, estimated in the first stage using data envelopment analysis (DEA), are regressed, in the second stage, on environmental variables to investigate their effects on efficiency. A firm (CAH in our case) is technically efficient if it produces its outputs using minimum input quantities [7]. DEA measures efficiency of a firm relative to a nonparametric estimate of the best-practice (efficient) frontier constructed from the most efficient firms. We assess technical efficiency of CAHs in 2005 and 2006, controlling for quality using measures (publicly available) as additional outputs in the DEA model [8-9].

The two-stage approach has been a popular technique for efficiency analysis. In an influential paper, however, Simar and Wilson [6] criticized previous applications of the two-stage approach because of the failure to account for the correlation present among efficiency estimates. They show that the DEA efficiency scores are serially correlated and inference in the second stage regression is invalid based on standard methods. The correlation arises in finite samples because the efficiency score of a firm is estimated relative to the efficiencies of peer firms lying on the frontier. Simar and Wilson [6] defined a statistical model where a truncated regression with a parametric bootstrap procedure (Algorithm #1) allows for valid inference in the second stage analysis.

An additional problem arises from the fact that the DEA efficiency estimator is biased by construction; however, it is a consistent estimator [10]. In order to account for both the bias and serial correlation of efficiency scores, Simar and Wilson [6] developed the so called double bootstrap procedure (Algorithm #2). In the double bootstrap procedure, the DEA efficiency estimator is corrected for bias, in the first stage, using a specific bootstrap procedure. In the second stage, bias-corrected efficiency scores are regressed on environmental variables using a second, parametric bootstrap procedure applied to the truncated regression. Although the methodology proposed by Simar and Wilson [6] has become an important approach for efficiency analysis (see, for example, Zelenyuk and Zheka [11], and Demchuk and Zelenyuk [12] for empirical applications), we are unaware of any study that has applied the double bootstrap procedure to analyze efficiency in the U.S. hospital industry. In this study, we use both bootstrap algorithms of Simar and Wilson [6] to investigate how the technical efficiency of CAHs is influenced by environmental variables, in particular Medicare and Medicaid reimbursement.

4.2 Literature Review

Since its creation, there has been a growing interest in evaluating the performance of the CAH Program. Previous research focused almost exclusively on evaluating financial performance and quality of care of CAHs. Using Medicare Cost Report data, Pink et al. [13] developed comparative financial indicators for CAHs. Based on these financial indicators, Pink et al. [14] found significant differences in financial performance among CAH peer groups. MedPAC [1] reported hospitals that converted to CAH status dramatically increased their Medicare payments and improved their all-payer profit margins between 1998 and 2003. Using an eight-year panel of 89 rural hospitals in Iowa, Li et al. [15] found that hospitals that converted to CAH status significantly increased their operating revenues, expenses, and margins. Li et al. [16] examined the impact of CAH conversion on hospital patient safety and found that CAH conversion was associated with improved performance of certain Patient Safety Indicators. Analyzing quality improvements in CAHs, Casey and Moscovice [17] found that Medicare cost-based reimbursement allowed CAHs to fund additional staff, staff training, and equipment to improve patient care. Rosko and Mutter [5] compared the cost inefficiency of CAHs with that of prospectively paid rural hospitals using stochastic frontier analysis and found that CAHs were, on average, more cost inefficient.

The contribution of our paper to the literature is twofold. First, through focusing solely on the CAH hospital subset, we examine the effect of Medicare cost-based reimbursement on the technical efficiency of CAHs. The second contribution is the application of recent methodological advancements to hospital efficiency analysis, namely the two-stage approach with bootstrap procedures suggested by Simar and Wilson [6].

4.3 Data

Data used in this study come from the American Hospital Association (AHA) Annual Survey of Hospitals, the Centers for Medicare and Medicaid Services (CMS) Hospital Compare public reporting database for hospital quality measures, and from the Area Resource File.[4] We focus on the set of community, general rural hospitals in the U.S. classified as Critical Access Hospitals. For the purpose of this study, we used data on CAH rural hospitals in 2005 and 2006.

4.3.1 DEA Variables

The choice of outputs and inputs used in the DEA model was guided by previous literature [5,9]. Specifically, we used as hospital outputs the number of outpatient visits, the number of admissions, post-admission days (inpatient days – admissions), emergency room visits, outpatient surgeries, and total births (Table 4.1). The inputs used for DEA efficiency estimation consists of labor and capital inputs. The labor inputs are full time equivalent (FTE) registered nurses, FTE licensed practical nurses, and other FTEs, while the capital input is represented by total staffed and licensed hospital beds [9].

To control for the quality of care, we follow Nayar and Ozcan [8] and use quality measures publicly available from the CMS Hospital Compare database. Although the Hospital Compare database provides quality measures reflecting recommended treatments for acute myocardial infarction (AMI), heart failure, and pneumonia, only quality measures for

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[4] AHA data can be obtained from http://www.ahadataviewer.com/book-cd-products/AHA-Survey/, Area Resource File data from http://www.arf.hrsa.gov, and Hospital Compare quality data from http://www.hospitalcompare.hhs.gov.

pneumonia were selected for this study because there were too many missing observations for AMI and heart failure. Unfortunately, the proportion of CAHs reporting quality information in 2005 and 2006 was low. CAHs voluntarily report quality measures to Hospital Compare and they do not have the financial incentives of PPS hospitals to consistently report quality information to CMS. Additionally, only those hospitals for which quality measures were calculated based on at least 25 patients (consistent with CMS recommendations) were used in the analysis, which further reduced the sample size. Two quality measures are used in this study: (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), and (2) percent of patients given initial antibiotic timing (i.e., pneumonia patients given initial antibiotic within four hours after arrival). The data sample consists of 186 rural CAHs in 2005 and 229 rural CAHs in 2006.

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. Ozgen and Ozcan [18] and others noted that the lack of case-mix variables in DEA efficiency models is in part compensated by specification of multiple outputs. In this study, the vector of outputs was expanded beyond the usual inpatient and outpatient outputs used in hospital efficiency studies by including emergency room visits, outpatient surgeries, and births as case-mix controls.

4.3.2 Environmental Variables

The specification of environmental variables used in the second stage regression (Table 4.1) follows recent literature on hospital efficiency. Rosko and Mutter [19] broadly classify these variables as internal factors (ownership status and system membership) and external factors (public payment policy, hospital competition, and health maintenance organization penetration).

Table 4.1. Descriptive statistics of the variables.

DEA Variables		Mean	Std. Dev.
Outputs			
Hospital admissions		1,069.41	428.29
Post-admission days		6,274.87	6,737.47
Outpatient visits		41,773.94	30,092.56
Emergency room visits		6,974.06	4,474.27
Outpatient surgeries		885.82	712.13
Births		96.07	108.97
Quality Measures			
Patients given pneumococcal vaccination (%)		61.90	23.65
Patients given initial antibiotic timing (%)		84.61	8.68
Inputs			
Total staffed and licensed hospital beds		36.08	22.21
Full time equivalent (FTE) registered nurses		40.38	19.63
FTE licensed practical nurses		9.02	6.62
Other FTEs		122.78	56.64
Environmental Variables	Variable Definition		
Government	Government hospital (binary variable 1,0)	0.32	-
For-profit	For-profit hospital (binary variable 1,0)	0.03	-
Medicare	% Medicare admissions	59.93	12.64
Medicaid	% Medicaid admissions	12.98	7.90
HHI	Herfindahl-Hirschman index	0.50	0.35
System	Multihospital system (binary variable 1,0)	0.42	-
MHMO	% Medicare HMO penetration	3.32	5.29
Income	Median household income	38,360.79	6,218.81

Binary variables that define government and for-profit hospitals, with non-profit hospitals as the reference category, are used to control for the internal pressure for efficiency associated with ownership [5,19]. One line of thought in the theoretical literature indicates that the effect of ownership on hospital efficiency should be consistent with property rights theory (PRT) which argues that when property rights are not clearly specified, incentives decline that promote efficient behavior. Based on PRT, we would expect that for-profit hospitals will place a greater emphasis on increasing efficiency than non-profit and government hospitals. However, the empirical literature that examined the impact of ownership on hospital efficiency reported mixed findings. Using DEA, several studies found that non-profit hospitals are more efficient than for-profit hospitals [20] or for-profit hospitals are more efficient than non-profit ones [21]. Another internal factor that has been associated with hospital efficiency is membership in a multihospital system.

Previous studies showed that the external financial pressure from Medicare and Medicaid is a key factor affecting hospital efficiency [19]. While variables representing shares of revenue from Medicare and Medicaid would be desirable to control for external pressure for efficiency of public payers, such measures are not available. Instead, we follow previous literature [5,19] and use proxies such as Medicare percent of admissions ((Medicare admissions / total admissions) × 100) and Medicaid percent of admissions ((Medicaid admissions / total admissions) × 100). The rationale for the Medicare cost-based reimbursement of CAHs has been to improve the financial situation of many of the small rural hospitals that were unable to cover their costs under the PPS. Cost-based reimbursement, however, has been related with inefficiency in hospital operations [3-4]. Since CAHs receive Medicare cost-based reimbursement, we want to test whether Medicare percent of admissions (a proxy for Medicare reimbursement) is inversely associated with CAHs' technical efficiency. It has also been shown that Medicaid typically underpays hospitals and exerts cost containment pressures irrespective of the payment system [19]. Therefore, Medicaid percent of admissions is expected to be directly associated with CAHs' technical efficiency.

We use a Herfindahl-Hirschman index (HHI) to control for competitive pressure in a hospital's market at the county level (consistent with previous studies). HHI is calculated by summing the squares of the market shares of admissions for all of the hospitals in the county [22] and it takes a value between 0 and 1, with values of HHI approaching 1 indicating less competitive pressure. Recent research showed an inverse relationship between HHI and hospital efficiency [5].

Health Maintenance Organization (HMO) penetration constitutes another source of external pressure for efficiency. Previous literature showed that HMO penetration is directly associated with hospital efficiency [22]. Similar to Rosko and Mutter [5], we used percent of

Medicare HMO penetration as a proxy for general HMO penetration. We also included in the second stage model the median household income of the county (from the Area Resource File) and a dummy variable for 2006 to control for time effects.

4.4 Methodology

4.4.1 DEA Efficiency Estimator (First Stage)

For the efficiency analysis of CAHs, we use a two-stage approach along the line of Simar and Wilson [6]. In the first stage, a DEA efficiency estimator is used to obtain technical efficiency scores for individual CAHs. The main advantage of DEA is that it can easily accommodate multiple inputs and outputs and requires no specific assumption about the functional form of the frontier.[5] However, DEA is deterministic, meaning that deviations from the efficient frontier are entirely assumed to be due to inefficiency and no allowance is made for statistical noise.

Consistent with the statistical model defined by Simar and Wilson [6], we specify the following production or technology set:

$$T = \{(x, y) \in R_{+}^{N+M} \mid x \text{ can produce } y\} \tag{1}$$

where $x \in R_{+}^{N}$ is a vector of N inputs used to produce a vector of M outputs, $y \in R_{+}^{M}$. The upper boundary of T, which represents the technology or production frontier, is of interest for efficiency measurement. Inefficient hospitals operate at points in the interior of T, with the distance from each point in T to the frontier representing inefficiency, while those that are efficient operate on the frontier.

In this study, an input-oriented, variable returns to scale (VRS) approach to efficiency measurement is used, based on the assumption that hospitals have more control over their inputs than over the outputs. The Farrell [7] input-oriented measure of technical efficiency is:

$$\theta(x, y) = \inf\{\theta \mid (\theta x, y) \in T\} \tag{2}$$

which gives the radial, proportionate reduction in inputs for a hospital to become technically efficient in the sense that $(\theta x, y)$ is on the efficient frontier. By construction, $0 < \theta(x, y) \leq 1$ and a hospital is efficient if $\theta(x, y) = 1$.

In practice, T and $\theta(x, y)$ are unobserved and their estimates can be consistently obtained from the observed data by employing a DEA efficiency estimator. Let y_{rj} be a vector of outputs (r = 1,…., M) and x_{ij} a vector of inputs (i = 1,….., N) for each hospital j (j = 1,….., n). For a given level of outputs y_{ro} and a given level of inputs x_{io} for hospital o, the input-oriented measure of technical efficiency, assuming VRS, can be estimated by solving the following DEA linear programming problem:

$$Min_{\lambda,\theta} \ \ \theta \ \text{ subject to}:$$

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, (r = 1,....,M) \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, (i = 1,....,N) \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, (j = 1,......,n)
\end{aligned} \tag{3}$$

where λ_j (j = 1, …., n) are the intensity variables over which optimization in (3) is made. The objective of (3) is to find the minimum θ that proportionally reduces the input vector to θx_{io} while guaranteeing at least the output level y_{ro}. The optimal solution is $\hat{\theta} \leq 1$, where $\hat{\theta} = 1$ indicates a point on the efficient frontier and, hence, a technically efficient hospital.

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[5] Alternatively, one can use a stochastic frontier model which, as a parametric approach, requires strong assumptions about the functional form and error distributions. Further, a stochastic frontier model cannot easily accommodate multiple outputs and inputs.

$\hat{\theta} < 1$ indicates that it is possible to produce the observed level of outputs using proportionately less than observed input levels of the hospital.

4.4.2 Truncated Regression (Second Stage)

Our focus in this study is generating valid inferences about the impact of environmental variables on the technical efficiency of CAHs. For this, we follow Simar and Wilson [6] and specify, at the second stage, the truncated regression model:[6]

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

where $\hat{\theta}_i$ is the DEA estimated technical efficiency score of the *i*-th hospital, ε_i is assumed to be normally distributed with left truncation at $-z_i\beta$ and right truncation at $1 - z_i\beta$, z_i is a vector of environmental variables which are thought to have an effect on hospital efficiency, and β is a vector of parameters to be estimated. The implicit assumption is that the environmental variables only affect the efficiency scores and have no effect on the frontier [6]. Unfortunately, $\hat{\theta}_i$ is biased and $\hat{\theta}_i$'s and, implicitly, ε_i's ($i = 1, 2, \ldots, n$) in (4) are serially correlated. While the correlation among ε_i's disappears asymptotically, standard methods for inference are invalid. To provide valid inference in the second stage analysis, Simar and Wilson [6] suggest using a parametric bootstrap of the truncated regression in (4) which they call Algorithm #1. This single bootstrap procedure (Algorithm #1) can improve on inference in the second stage regression, but without correcting the DEA estimator for bias.

Alternatively, Simar and Wilson [6] suggest using a bootstrap procedure to obtain bias-corrected DEA estimates of technical efficiency and use them as the dependent variable in the second stage regression. This approach has been shown to improve the statistical

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[6] Many of the previous two-stage studies used a tobit (censored) regression in the second stage. However, Simar and Wilson showed that tobit is a misspecification under their statistical model.

efficiency of the parameter estimator in the second stage truncated regression [6]. The truncated regression model can be rewritten as

$$0 < \hat{\hat{\theta}}_i = z_i \beta + \varepsilon_i \leq 1 \tag{5}$$

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 $\hat{\theta}_i$. For valid inference about β, a second bootstrap procedure must be applied to the truncated regression in (5). The specific steps of the double bootstrap procedure used in this study follow from Algorithm #2 of Simar and Wilson [6], modified to account for the left and right boundaries of input-oriented technical efficiency scores:

1. Using the original sample of data, estimate the input-oriented DEA technical efficiency scores $\hat{\theta}_i$'s (i = 1,…., n).
2. Obtain estimates $\hat{\beta}$ in the truncated regression $0 < \hat{\theta}_i = z_i \beta + \varepsilon_i \leq 1$ using $m<n$ observations, when $\hat{\theta}_i < 1$.
3. Loop over the next four steps (3.1 - 3.4) L_1 = 100 times to obtain a set of bootstrap estimates $B = \left\{\hat{\theta}^*_{ib}\right\}_{b=1}^{L_1}$, i = 1, ….., n:
   - 3.1. For each i = 1, ….., n draw ε_i from $N(0, \hat{\sigma}^2)$ with left truncation at $-z_i\hat{\beta}$ and right truncation at $1 - z_i\hat{\beta}$.
   - 3.2. Compute $\theta^*_i = z_i\hat{\beta} + \varepsilon_i$, i = 1, ….., n.
   - 3.3. Set $x^*_i = x_i\hat{\theta}_i / \theta^*_i$ and $y^*_i = y_i$, i = 1, ….., n.
   - 3.4. Using x^*_i and y^*_i, estimate $\hat{\theta}^*_i$ (i = 1,…., n) using the DEA estimator.
4. For each i = 1, ….., n, compute the bias-corrected estimates $\hat{\hat{\theta}}_i$ using the bootstrap estimates in B obtained in step 3.4 and the original estimates $\hat{\theta}_i$.

5. Estimate the truncated regression of $\hat{\hat{\theta}}_i$ on z_i to obtain estimates $\hat{\hat{\beta}}$.

6. Loop over the next three steps (6.1 – 6.3) $L_2 = 2000$ times to obtain a set of bootstrap estimates $\Delta = \left\{ \hat{\hat{\beta}}^* \right\}_{b=1}^{L_2}$:

   6.1. For each $i = 1, \ldots, n$, draw ε_i from $N(0, \hat{\hat{\sigma}}^2)$ with left truncation at $-z_i \hat{\hat{\beta}}$ and right truncation at $1 - z_i \hat{\hat{\beta}}$.

   6.2. Compute $\theta_i^{**} = z_i \hat{\hat{\beta}} + \varepsilon_i$, $i = 1, \ldots, n$.

   6.3. Estimate the truncated regression of θ_i^{**} on z_i, yielding estimates $\hat{\hat{\beta}}^*$.

7. Use the bootstrap values in Δ and the original estimates $\hat{\hat{\beta}}$ to construct confidence intervals for each element of β. The (1-α) confidence interval for β_j is constructed by finding values $a_{\alpha/2}$ and $b_{\alpha/2}$ such that $\Pr\left[-b^*_{\alpha/2} \le (\hat{\hat{\beta}}^*_j - \hat{\hat{\beta}}_j) \le -a^*_{\alpha/2} \right] \approx 1 - \alpha$.

4.5 Results

In the first stage, DEA is used with the two years of data (2005 and 2006) jointly to estimate technical efficiency scores of CAHs. This approach offers the advantage of a substantial increase in the sample size which is important for obtaining reliable estimates of efficiency used in the second stage regression [11]. In the second stage, we use a pooled cross-sectional design for the truncated regression model.

4.5.1 Technical Efficiency Scores (First Stage)

Table 4.2 presents original and bias-corrected mean technical efficiency of CAHs. The original (uncorrected) mean technical efficiency of CAHs estimated using DEA without quality outputs was 0.84 and increased to 0.89 when quality outputs were included in the DEA model. These results are consistent with Nayar and Ozcan [8] who found that the average technical efficiency of a sample of hospitals in Virginia increased from 0.81 to 0.86 after the inclusion of three quality measures for pneumonia (from CMS Hospital Compare) in the DEA model. Alternatively, this increase in technical efficiency after controlling for quality could be a consequence of the increased number of outputs in the DEA model.

Table 4.2. Original and bias-corrected efficiency scores.

		DEA without Quality Outputs			DEA with Quality Outputs		
		Original DEA Estimates	Bias-Corrected		Original DEA Estimates	Bias-Corrected	
Year	N		Mean	Std. Dev.		Mean	Std. Dev.
2005	186	0.826	0.707	0.113	0.871	0.750	0.097
2006	229	0.855	0.724	0.099	0.906	0.767	0.084
All	415	0.842	0.716	0.106	0.890	0.759	0.090

Note: Estimation of bias-corrected efficiency scores was based on the first stage of Algorithm #2 of Simar and Wilson, modified for the left and right boundaries of input-oriented efficiency scores. Estimation by authors in Matlab, adopting from code written by V. Zelenyuk and L. Simar.

We further investigated the sensitivity of technical efficiency scores with respect to quality outputs using an approach suggested by Simar and Zelenyuk [23]. Specifically, a nonparametric kernel density estimator was used to estimate the densities of efficiency scores from the two DEA models in which quality outputs were included and excluded. The null hypothesis on equality between these densities was tested using a bootstrap-based test (see Simar and Zelenyuk [23] for details). Simar-Zelenyuk test rejected the null hypothesis of equal densities (Simar-Zelenyuk test = 3.26, bootstrap p-value = 0.003), suggesting that quality has a statistically significant effect on CAHs' technical efficiency.

The results in Table 4.2 also indicate that the bias-corrected efficiency scores are, on average, lower than the uncorrected DEA estimates suggesting that the uncorrected efficiency estimates are upward biased. Specifically, the mean of bias-corrected efficiency scores was 0.76 in the DEA model with quality outputs suggesting that, without correcting for bias, the estimated results would have indicated that CAHs were performing more technically efficient than they actually were.

4.5.2 Truncated Regression Results (Second Stage)

The focus of this study is on using the two-stage approach with bootstrap procedures suggested by Simar and Wilson [6] to make valid inferences about the effects of environmental variables on CAHs' technical efficiency. The dependent variable in the second stage truncated regression is hospital technical efficiency; therefore, a positive (negative) coefficient indicates a positive (negative) marginal effect on efficiency. Table 4.3 summarizes the results of three bootstrapped truncated regression models (see Tables A.4.4, A.4.5, and A.4.6 in Appendix 3 for percentile bootstrap confidence intervals of the truncated regression coefficients).

Model 1 in Table 4.3 was based on Algorithm #2 where bias-corrected efficiency scores, estimated in the first stage DEA model with no quality outputs, were used in the second stage bootstrapped truncated regression. The results of Model 1 show that the coefficients of most environmental variables are insignificant (only system membership has a positive and significant coefficient, as expected). Model 2, in which quality outputs were included in the DEA model, was based on Algorithm #1 where original (uncorrected) technical efficiency scores were regressed on environmental variables in the second stage bootstrapped truncated regression. The results show that Model 2 is also characterized by low statistical significance (only HHI was found significant in Model 2). Model 3 was based on Algorithm #2 in which bias-corrected technical efficiency scores obtained in the first stage DEA model with quality outputs were regressed, in the second stage, on environmental variables. Relative to Model 1, the results of Model 3 show a clear improvement in the statistical significance of the estimated coefficients when quality is accounted for in efficiency estimation. Similarly, Model 3 shows a clear improvement in statistical efficiency relative to Model 2. This is consistent with Simar and Wilson [6] findings that Algorithm #2 improves statistical efficiency in the second stage truncated regression more than Algorithm #1.

Table 4.3. Results of the second stage bootstrapped truncated regressions.

Variable	Model 1	Model 2	Model 3
Constant	0.7232***	0.7885***	0.7124***
Government	-0.0157	-0.0245	-0.0214**
For-profit	0.0148	-0.0132	-0.0166
Medicare	0.0001	0.0012	0.0007
Medicaid	0.0013	0.0029	0.0016**
HHI	0.0031	-0.0691**	-0.0514***
System	0.0388***	0.0364	0.0381***
Income	-1.37E-06	-2.94E-07	-3.34E-07
MHMO	-0.0007	0.0026	0.0017**
Y2006	0.0236**	0.0084	0.0171*
Sigma	0.1033***	0.1400***	0.0851***

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels based on percentile bootstrap confidence intervals. Model 1 is based on Algorithm #2 using no quality outputs in DEA model; Model 2 is based on Algorithm #1 using quality outputs in DEA model; Models 3 is based on Algorithm #2 using quality outputs in DEA model. Estimation by authors in STATA 11 with 2000 bootstrap replications for confidence intervals of the estimated coefficients.

Now, we refer to Model 3 (the benchmark) for the interpretation of the coefficients. The key variables are the two proxies for Medicare and Medicaid reimbursement. It is widely recognized that hospitals respond to the Medicare and Medicaid reimbursement mechanism. For example, previous studies showed that Medicare PPS placed fiscal pressure on hospitals and Medicare percent of admissions was directly related with hospital efficiency [19]. Medicare cost-based reimbursement, on the other hand, was associated with inefficiency in hospital operations. In this study, we test the effect of Medicare percent of admissions (a proxy for Medicare reimbursement) on the technical efficiency of CAHs. The estimated results show that Medicare percent of admissions has a positive but insignificant coefficient, potentially suggesting that Medicare cost-based reimbursement may not have had detrimental effects on CAHs' technical efficiency, after controlling for quality. The results may also suggest that CAHs did not intentionally over-consume hospital inputs in order to maximize reimbursement, but rather increased reimbursement revenues would have been driven primarily by the increased reimbursement rate. Additionally, Medicaid percent of admissions has a positive and significant effect on the technical efficiency of CAHs. This is consistent with prior research which has shown that Medicaid typically underpays hospitals and exerts cost containment pressures irrespective of the payment mechanism [19].

The estimated results show a negative and significant coefficient of government ownership, suggesting that government owned CAHs are less technically efficient relative to non-profit CAHs, a result consistent with previous literature [5]. We found an insignificant effect of for-profit ownership on technical efficiency, suggesting that for-profit CAHs are no more technically efficient than non-profit CAHs.

The results also show that Herfindahl-Hirschman Index (HHI) has a negative and significant coefficient, suggesting that an increase in HHI (or a decrease in hospital market competition) leads to a decrease in CAHs' technical efficiency. This result is consistent with other findings in the literature [5] and with the concept of price-based competition which suggests that if competition is increased, hospitals will compete for patients by reducing costs [19]. This result may also indicate that there may be some hospitals that are not critical for access that have been given the benefits of the CAH status.[7] MedPAC [1] estimated that 16 percent of CAHs are less than 15 miles from another hospital and only 17 percent of CAHs are more than 35 miles from another provider, raising issues of competition between some CAHs and nearby non-converting hospitals.

The positive and significant coefficient of system membership suggests that CAHs that are members of a multi-hospital system are more technically efficient than the ones that are not, a result consistent with previous literature [5]. Similarly, the positive and significant coefficient of Medicare HMO may suggest that Medicare HMO penetration creates pressure for CAHs to operate more efficiently [5]. This is also consistent with other studies that found a direct correlation between managed care penetration and hospital efficiency [22].

4.6 Conclusions

This paper examined technical efficiency of Critical Access Hospitals using recent methodological advancements in efficiency analysis and incorporating measures of quality. Specifically, we used a two-stage DEA approach with Algorithm #1 and Algorithm #2 bootstrap procedures proposed by Simar and Wilson [6] for making valid inferences about the effects of environmental variables on CAHs' technical efficiency. An important finding was that the performance of the double bootstrap procedure (Algorithm #2) in explaining hospital efficiency significantly improved when quality was accounted for in efficiency estimation relative to a similar model without quality. Similarly, we also compared the performance of Algorithm #2 with that of the single bootstrap procedure (Algorithm #1). While both bootstrap algorithms were created to provide valid inference, Algorithm #2 clearly improved statistical efficiency in the second stage truncated regression relative to Algorithm #1.

As a result, our preferred model for estimating the (marginal) effects of environmental variables on the technical efficiency of CAHs was based on the two-stage approach with Algorithm #2 proposed by Simar and Wilson [6]. Specifically, bias-corrected technical efficiency scores, obtained using a bootstrapped DEA model with quality outputs, were regressed on environmental variables using a bootstrapped truncated regression. The key finding was that Medicare percent of admissions variable had an insignificant effect on CAHs' technical efficiency, suggesting that Medicare cost-based reimbursement may not have created a disincentive for these hospitals to operate in a less technically efficient manner. The percent of Medicaid admissions had a positive and significant effect on the

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[7] We thank an anonymous reviewer for pointing out this issue.

technical efficiency of CAHs, consistent with prior studies showing Medicaid's positive effect on hospital efficiency.

A limitation of this research is associated with incomplete information on many of the quality measures reported by CAHs to Hospital Compare. As a result, only quality measures for pneumonia were selected for this study [8], and the two years of data were jointly used in the analysis to increase the sample size. As new data become available, future research on CAH efficiency should incorporate other quality controls in the methodological advancements proposed by Simar and Wilson [6].

Although the two-stage approach has been very popular in the efficiency analysis literature, Simar and Wilson [6] criticized previous applications of this method because of the failure to define a statistical model consistent with the second stage analysis. They show that the DEA efficiency estimates used in the second stage are biased and serially correlated, and, thus, standard methods for inference are invalid. Consequently, the bootstrap methods proposed by Simar and Wilson [6] are the only feasible means for making valid inference in the second stage regression. Our research suggests that, for future hospital efficiency studies, the two-stage DEA approach with double bootstrap can be a viable alternative for analyzing the effects of environmental variables on hospital efficiency.

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CHAPTER 5

CONCLUSIONS

5.1 Summary and Conclusions

With health care costs rising at a rapid rate, cost containment is one of the most important issues in the present health care debate. One approach to address rising health care costs is to improve the efficiency of health care providers. In this dissertation, I examine the efficiency of rural hospitals in the U.S. with a focus on the Critical Access Hospital (CAH) Program. This research is particularly important as Congress weights the tradeoff of increased Medicare costs versus rural health care access.

Rural hospitals have played a critical role for access to health care services in rural communities. Their low-volume of patients, however, makes costs per unit of service disproportionately large and puts rural hospitals (especially small ones) at risk of closure. The CAH Program has been created to maintain access to health care services in isolated communities by improving the financial viability of small hospitals and preventing closure. CAHs receive Medicare cost-based reimbursement, where hospitals' payments must equal hospitals' charges. Cost-based reimbursement, however, has been associated with increased health care costs and inefficiency.

Under the Prospective Payment System (PPS), hospitals are paid fixed prices based on the Diagnosis Related Group (DRG) and are allowed to keep the difference between these fixed prices and their costs. Thus, the PPS provides incentives for hospitals to reduce costs and increase efficiency by motivating hospitals to keep their unit costs below the PPS reimbursement rates in order to make profits. Although there is a large consensus that the CAH Program has improved access to health care services in isolated rural communities, concerns have been raised about the efficiency of CAHs.

The objective of Chapter 2 was to analyze the impact of conversion to CAH status on hospital efficiency. The efficiency scores of a sample of rural hospitals before and after the conversion to CAH status, as well as of a comparison group of non-converting, PPS rural hospitals were estimated and compared. Additionally, overall hospital cost efficiency was decomposed into its allocative and technical components. This allowed me to infer whether the failure to achieve cost efficiency might be due to (a) technical inefficiency in the sense that hospitals do not use minimum quantities of inputs to produce their outputs, or (b) allocative inefficiency in the sense that hospitals do not use the least cost combination of inputs in producing outputs. A two-stage approach was used, where Data Envelopment Analysis (DEA) was used in the first stage to estimate cost, technical, and allocative efficiency scores of each hospital in the sample. The densities of efficiency scores of CAHs and PPS rural hospitals were estimated and compared using a nonparametric kernel density estimator and a bootstrap-based test. In the second stage, a truncated regression with bootstrap was used to investigate the effects of environmental variables on efficiency scores.

The density analysis of efficiency scores showed that CAHs were less cost and allocativelly efficient than the comparison group of non-converting rural hospitals, while they were no less technically efficient. When compared with their pre-conversion selves, CAHs appeared to be slightly less allocativelly efficient, while they were slightly more technically efficient and no less cost efficient. Bootstrapped truncated regression results showed that CAHs tended to be less cost and allocatively efficient than PPS rural hospitals, while they were no less technically efficient.

The objective of Chapter 3 was to analyze the impact of different Medicare reimbursement systems on the cost efficiency of rural hospitals. Specifically, I statistically test whether there are cost efficiency differences between cost-based reimbursed CAHs and rural hospitals paid under the PPS reimbursement system. The analysis controlled for the quality of care as well as compared different models of efficiency analysis. Cost efficiency scores were estimated using two different frontier methods: DEA and stochastic frontier analysis (SFA). The comparison of mean cost efficiencies between cost-based reimbursed CAHs and PPS rural hospitals showed that CAHs were less cost efficient than the PPS rural hospitals. The density analysis of DEA cost efficiency scores also showed that CAHs were less cost efficient than the PPS rural hospitals, and the difference was statistically significant. Additionally, marginal effects of environmental variables were estimated using SFA and the two-stage DEA approach with tobit as well as with the bootstrapped truncated regression. The CAH dummy, the key variable in this study, had a statistically significant coefficient in the bootstrapped truncated regression and SFA models, suggesting that CAHs were less cost efficient than the PPS rural hospitals.

To the best of my knowledge, Chapter 4 provides the first application of the two-stage approach with double bootstrap to analyze efficiency in the U.S. hospital industry. Specifically, bias-corrected efficiency scores obtained in the first stage using a specific bootstrap procedure are regressed on environmental variables, in the second stage, using a bootstrapped truncated regression. An important finding was that the performance of the double bootstrap procedure in explaining hospital efficiency significantly improved when quality was accounted for in efficiency estimation relative to a similar model without quality. Additionally, the double bootstrap procedure clearly improved on statistical efficiency of parameter estimates in the second stage truncated regression relative to the single bootstrap procedure (where original efficiency scores were used in the second stage bootstrapped truncated regression).

The objective of Chapter 4 was also to examine the relationship between Medicare cost-based reimbursement and the technical efficiency of CAHs. Medicare cost-based reimbursement has been the primary factor driving CAH conversion. Cost-based reimbursement, however, has been historically associated with hospital inefficiency. Thus, the question that arises is: does Medicare cost-based reimbursement have a negative effect on CAHs' technical efficiency. Overall, the estimated results suggest that enhanced Medicare reimbursement may not have had detrimental effects on the technical efficiency of CAHs.

5.2 Policy Implications

The results of this dissertation have important implications for policy. First, the results indicate that the technical efficiency of rural hospitals that converted to CAH status improved relative to the pre-conversion period. At the same time, CAHs appear to be as technically efficient as non-converting, PPS rural hospitals. It may be the case that the CAH Program's requirements (limitations on the maximum number of acute care beds to 25 and average length of stay to 4 days) may have resulted in technical efficiency improvements comparable to the PPS. For example, these requirements may have limited the types and complexity of procedures treated by CAHs. The relatively larger proportion of less complex procedures with low resource requirements may have created the increase in CAHs' technical efficiency.

Second, the results also indicate that CAHs are less allocatively efficient not only relative to the pre-conversion period, but also relative to non-converting, PPS rural hospitals. CAH conversion has been primarily associated with Medicare cost-based reimbursement which has dramatically changed hospitals' financial incentives. Stensland, Davidson, and Moscovice [1] found that hospitals that converted to CAH status significantly increased their Medicare revenue, profitability, employee salaries and capital expenditures. Schoenman and Sutton [2] found that, after conversion to CAH status, hospitals increased their profitability due to Medicare cost-based reimbursement. Further, anecdotal evidence suggests that after hospitals improved their finances post-conversion, many CAHs invested in new equipment, new hospitals or major infrastructure upgrades. It may be the case that the allocative inefficiency increase for CAH hospitals may be due to their inability to substitute to lower cost inputs in the production process.

Third, the overall cost efficiency of cost-based reimbursed CAHs was, on average, between 4.5 and 6.7 percent lower (depending on the model choice) than that of non-converting, PPS rural hospitals. To see the impact of Medicare cost-based reimbursement on the costs of CAHs, I multiply mean CAH expenditure ($16,700,000 in 2005 dollars) by the difference in cost efficiency between CAHs and PPS rural hospitals. I found that the cost per CAH was, on average, between $751,500 and $1,119,000 higher than the cost that would have been under the PPS reimbursement. For a total number of 1,055 CAHs in 2005, I estimate the cost of the CAH Program to have been between $793,000,000 and almost $1.2 billion higher than it would have been under the PPS. Given that the CAH Program has been created to increase Medicare payments to low-volume hospitals whose Medicare costs exceed the PPS rates, this increase in spending might be justified if hospital closure and its negative impact have been avoided.

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 policy 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 [3], but also has a positive economic impact on the community as a whole [4]. Holmes et al. [4] estimated that the closure of the sole hospital in the community reduced per-capita income by 4 percent and increased the unemployment rate by 1.6 percent. 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, this research attempts to add to the policy debate by understanding if, and by how much, efficiency declines occurred for hospitals that converted to CAH status.

5.3 Limitations and Future Research

A particular challenge in this research was controlling for the quality of care. While controlling for quality is important in hospital efficiency and cost studies, finding adequate measures of quality has been difficult. The problem is that quality of care has many dimensions, and no single measure will be capable of capturing it. Since 2004, Center for Medicare and Medicaid Services (CMS) Hospital Compare database has provided some quality measures but, unfortunately, the proportion of CAH hospitals reporting quality information has been very small. CAH hospitals voluntarily report quality information to CMS and they do not have the financial incentives of PPS hospitals to consistently report such information. While the approach taken to study the impact of CAH conversion on hospital efficiency in Chapter 2 made it impossible to find quality measures for the two years before conversion (1997 and 1998), I was able to control for quality in the other two essays using quality measures for pneumonia. As new data become available, future research on CAH efficiency should include additional quality controls.

While there is a growing literature on the cost side of the CAH Program, I am unaware of any attempt to estimate the welfare benefits of the CAH Program. These benefits have been mostly associated with improvements in access to health care services in isolated rural areas. Thus, future research should provide an estimate of the value of access to a CAH hospital or the value of preventing closure. Further, future research should evaluate the potential impact of alternative reimbursement mechanisms, such as modified PPS, to increase the efficiency of CAH hospitals without deteriorating financial viability and quality of care of these hospitals.

5.4 References

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4. Holmes GM, Slifkin RT, Randolph RK, Poley S (2006) The effect of rural hospital closures on community economic health. Health Serv Res 41:467–485.

APPENDIX 1

ADDITIONAL RESULTS FOR CHAPTER 2

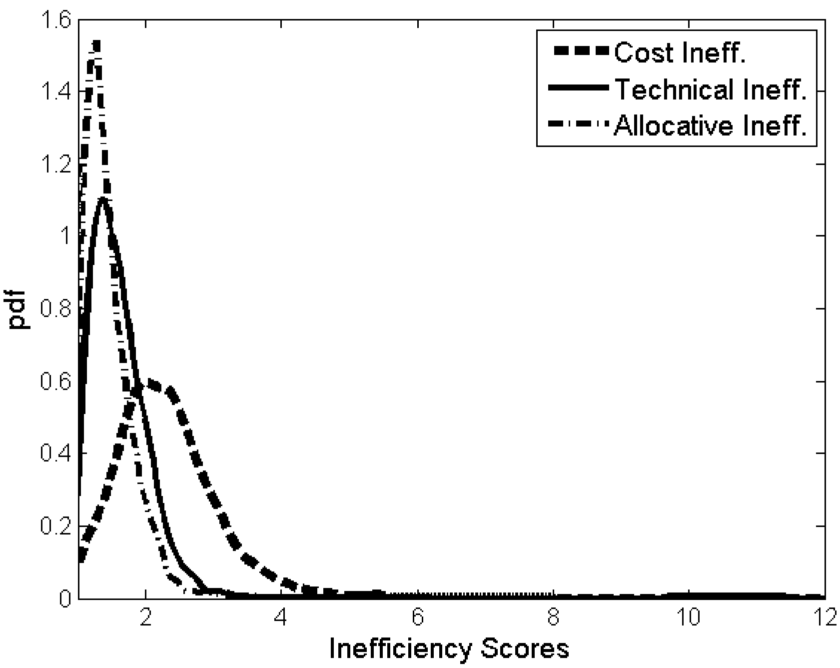

Figure A.2.1. Densities of inefficiency scores for all hospitals in the sample, before trimming of outliers.

Table A.2.5. Bootstrap estimated confidence intervals: cost inefficiency.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
CAH	0.3987	0.3129	0.4875	0.3308	0.4675	0.3419	0.4554
Government	0.2028	0.1489	0.2552	0.1618	0.2440	0.1684	0.2380
For-profit	-0.1453	-0.2574	-0.0282	-0.2346	-0.0541	-0.2176	-0.0656
Medicare	0.0043	0.0018	0.0068	0.0025	0.0062	0.0027	0.0059
Medicaid	-0.0058	-0.0096	-0.0020	-0.0087	-0.0028	-0.0083	-0.0033
HHI	0.0171	-0.0556	0.0855	-0.0397	0.0736	-0.0310	0.0644
System	-0.1535	-0.2150	-0.0910	-0.2019	-0.1055	-0.1938	-0.1138
Income	-0.000006	-0.000011	-0.000001	-0.000010	-0.000003	-0.000009	-0.000003
MHMO	-0.0054	-0.0100	-0.0004	-0.0089	-0.0016	-0.0084	-0.0021
Emergency	-0.0006	-0.0022	0.0008	-0.0017	0.0006	-0.0015	0.0004
Surgeries	-0.0035	-0.0139	0.0064	-0.0113	0.0040	-0.0100	0.0028
Births	-0.0076	-0.0111	-0.0040	-0.0102	-0.0047	-0.0098	-0.0052
2006	-0.2987	-0.4118	-0.1941	-0.3840	-0.2136	-0.3666	-0.2277
2005	-0.3417	-0.4499	-0.2331	-0.4219	-0.2621	-0.4094	-0.2747
1998	-0.0165	-0.0914	0.0572	-0.0701	0.0388	-0.0635	0.0290
Constant	2.3273	2.0709	2.5907	2.1343	2.5148	2.1609	2.4867

Table A.2.6. Bootstrap estimated confidence intervals: technical inefficiency.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
CAH	0.0217	-0.0524	0.0933	-0.0332	0.0737	-0.0253	0.0671
Government	0.1374	0.0916	0.1814	0.1029	0.1720	0.1084	0.1670
For-profit	0.0501	-0.0406	0.1523	-0.0194	0.1206	-0.0073	0.1101
Medicare	0.0034	0.0015	0.0054	0.0020	0.0049	0.0022	0.0046
Medicaid	-0.0053	-0.0085	-0.0021	-0.0077	-0.0029	-0.0073	-0.0034
HHI	0.0806	0.0184	0.1430	0.0345	0.1273	0.0424	0.1193
System	-0.0935	-0.1460	-0.0426	-0.1331	-0.0557	-0.1253	-0.0624
Income	-0.000005	-0.000008	-0.000001	-0.000008	-0.000002	-0.000007	-0.000002
MHMO	-0.0059	-0.0100	-0.0016	-0.0091	-0.0028	-0.0084	-0.0032
Emergency	0.0005	-0.0006	0.0018	-0.0004	0.0014	-0.0002	0.0013
Surgeries	-0.0043	-0.0124	0.0038	-0.0107	0.0016	-0.0096	0.0006
Births	-0.0011	-0.0042	0.0018	-0.0034	0.0011	-0.0030	0.0008
2006	-0.0749	-0.1533	0.0087	-0.1351	-0.0091	-0.1271	-0.0183
2005	-0.1209	-0.1987	-0.0457	-0.1812	-0.0611	-0.1698	-0.0683
1998	-0.0184	-0.0789	0.0418	-0.0645	0.0273	-0.0561	0.0203
Constant	1.5242	1.3031	1.7344	1.3701	1.6828	1.3985	1.6601

Table A.2.7. Bootstrap estimated confidence intervals: allocative inefficiency.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
CAH	0.5482	0.4350	0.6456	0.4642	0.6271	0.4807	0.6156
Government	0.0746	0.0242	0.1252	0.0371	0.1121	0.0432	0.1066
For-profit	-0.2948	-0.4152	-0.1548	-0.3939	-0.1904	-0.3811	-0.2078
Medicare	0.0007	-0.0016	0.0027	-0.0009	0.0022	-0.0006	0.0020
Medicaid	-0.00003	-0.0035	0.0033	-0.0027	0.0026	-0.0023	0.0022
HHI	-0.0731	-0.1427	-0.0069	-0.1207	-0.0225	-0.1136	-0.0335
System	-0.0524	-0.1034	0.0010	-0.0930	-0.0097	-0.0861	-0.0178
Income	0.000001	-0.000003	0.000005	-0.000002	0.000004	-0.000002	0.000004
MHMO	0.0014	-0.0026	0.0059	-0.0017	0.0048	-0.0013	0.0043
Emergency	-0.0010	-0.0023	0.0003	-0.0020	0.00000	-0.0019	-0.0002
Surgeries	-0.0019	-0.0116	0.0076	-0.0092	0.0053	-0.0079	0.0041
Births	-0.0085	-0.0121	-0.0051	-0.0111	-0.0058	-0.0106	-0.0063
2006	-0.4124	-0.5244	-0.2935	-0.5009	-0.3226	-0.4846	-0.3380
2005	-0.3980	-0.5033	-0.2803	-0.4812	-0.3110	-0.4700	-0.3249
1998	-0.0136	-0.0794	0.0529	-0.0612	0.0375	-0.0538	0.0285
Constant	1.2826	1.0652	1.5117	1.1097	1.4447	1.1386	1.4231

Table A.2.8. Results of bootstrapped truncated regressions: pooled data with 2005 and 2006.

Variable	Cost Inefficiency	Technical Inefficiency	Allocative Inefficiency
CAH	0.3183***	-0.0038	0.6619***
Government	0.2105***	0.1673***	0.0672**
For-profit	-0.2013***	-0.0917*	-0.3023**
Medicare	0.0014	0.0021**	-0.0009
Medicaid	-0.0079***	-0.0070***	-0.0004
HHI	-0.0244	0.0399	-0.0861**
System	-0.1661***	-0.0526**	-0.1485***
Income	-2.51E-06	-3.62E-06*	5.03E-06*
MHMO	-0.0097***	-0.0091***	-0.0001
Emergency	-0.0013	0.0008	-0.0030***
Surgeries	-0.0064	-0.0081*	0.0005
Birth	-0.0163***	-0.0025	-0.0226***
2006	0.0381	0.0453**	-0.0273
Constant	2.0298***	1.4975***	0.6573***

***, **, and * denote significance at 1%, 5%, and 10% levels

APPENDIX 2

ADDITIONAL RESULTS FOR CHAPTER 3

For the specification of the SFA cost model, I performed a series of likelihood ratio tests. First, I tested whether SFA is more appropriate than OLS regression as an estimation technique. The null hypothesis that the two approaches were equivalent was rejected at the 5% level of significance and the stochastic frontier cost model was used in empirical analysis. In SFA, an assumption about the distribution of the inefficiency error term, *u*, must be made. One of the concerns about SFA has been that it does not provide a prior justification for the choice of a distribution for *u*. This problem has been partially addressed by using the truncated-normal distribution which is a generalization of the half-normal distribution. The truncated-normal distribution for *u*, defined as $u \sim N^{+}(\mu, \sigma_u^2)$, reduces to the half-normal distribution when $\mu=0$. A likelihood ratio test for H_0: $\mu=0$ failed to reject the null hypothesis and the half-normal distribution was assumed in empirical estimation. I also tested whether a simpler functional form such as Cobb-Douglas could more accurately represent the cost frontier. The null hypothesis was that the parameters of all squared and interaction terms in the translog cost function were equal to zero. Rejection of the null hypothesis indicates that the translog functional form is more appropriate. Finally, Hausman tests for endogeneity suggest that the price of capital and hospital outputs can be treated as being exogenous.

The results of the SFA translog cost function (Table A.3.6) show that the coefficient of the price of capital, *pk*, was found positive and significant, as expected. 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. I also found positive and significant coefficients for the product mix descriptors (*erv%*, *outsurg%*, and *birth%*). Of the two quality control variables, only *pneum_vac%* was found positive and significant, indicating a direct relationship between quality and hospital costs.

Table A.3.6. Results of the SFA translog cost estimation

Variable	Coeff.	t-stat
Constant	2.8369	1.4964
ln(admtot)	-0.5573	-1.4388
ln(postdays)	0.3269	1.4184
ln(opv)	-0.0083	-0.0344
ln(pk)	0.7944	3.9365
ln(admtot)-sq	-0.0428	-0.7137
ln(admtot)*ln(postdays)	-0.0324	-1.4357
ln(admtot)*ln(opv)	0.1381	4.4076
ln(postdays)-sq	0.0472	1.5082
ln(postdays)*ln(opv)	-0.0378	-2.2163
ln(opv)-sq	-0.0402	-1.5293
ln(pk)-sq	0.1044	5.4357
ln(admtot)*ln(pk)	-0.0307	-1.1256
ln(postdays)*ln(pk)	0.0403	2.3325
ln(opv)*ln(pk)	-0.0639	-4.1126
ln(bdtot)	0.1810	4.3104
erv%	0.0027	4.2204
outsurg%	0.0171	5.8217
birth%	0.0048	4.9587
pneum_vac%	0.0007	2.1861
initial_antib%	-0.0002	-0.1976
Y2006	-0.0894	-1.5021
Log-Likelihood		147.0242

APPENDIX 3

ADDITIONAL RESULTS FOR CHAPTER 4

Table A.4.4. Bootstrapped truncated regression: Model 1.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
Constant	0.7232	0.5699	0.8846	0.6055	0.8433	0.6261	0.8244
Government	-0.0157	-0.0459	0.0136	-0.0383	0.0069	-0.0351	0.0039
For-profit	0.0148	-0.0635	0.0918	-0.0446	0.0715	-0.0331	0.0617
Medicare	0.0001	-0.0013	0.0014	-0.0009	0.0011	-0.0008	0.0010
Medicaid	0.0013	-0.0009	0.0033	-0.0004	0.0029	-0.0002	0.0026
HHI	0.0031	-0.0388	0.0413	-0.0277	0.0324	-0.0226	0.0271
System	0.0388	0.0113	0.0690	0.0177	0.0612	0.0213	0.0577
Income	-1.37E-06	-3.78E-06	9.60E-07	-3.21E-06	4.40E-07	-2.89E-06	1.50E-07
MHMO	-0.0007	-0.0032	0.0020	-0.0026	0.0013	-0.0023	0.0009
Y2006	0.0236	-0.0060	0.0518	0.0023	0.0444	0.0050	0.0411
Sigma	0.1033	0.0944	0.1148	0.0970	0.1119	0.0982	0.1108

Table A.4.5. Bootstrapped truncated regression: Model 2.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
Constant	0.7885	0.4078	1.1230	0.4909	1.0721	0.5465	1.0333
Government	-0.0245	-0.0825	0.0349	-0.0709	0.0227	-0.0636	0.0149
For-profit	-0.0132	-0.2256	0.1454	-0.1720	0.1116	-0.1395	0.0864
Medicare	0.0012	-0.0019	0.0043	-0.0012	0.0037	-0.0008	0.0033
Medicaid	0.0029	-0.0027	0.0079	-0.0012	0.0068	-0.0007	0.0062
HHI	-0.0691	-0.1517	0.0243	-0.1332	-0.0035	-0.1258	-0.0155
System	0.0364	-0.0348	0.1018	-0.0171	0.0839	-0.0080	0.0769
Income	-2.94E-07	-5.57E-06	5.25E-06	-4.40E-06	3.77E-06	-3.79E-06	3.22E-06
MHMO	0.0026	-0.0053	0.0088	-0.0029	0.0071	-0.0018	0.0065
Y2006	0.0084	-0.0530	0.0694	-0.0395	0.0566	-0.0312	0.0464
Sigma	0.1400	0.1096	0.1684	0.1219	0.1627	0.1253	0.1600

Table A.4.6. Bootstrapped truncated regression: Model 3.

		99% Bootstrap C.I.		95% Bootstrap C.I.		90% Bootstrap C.I.	
Variable	β	LB	UB	LB	UB	LB	UB
Constant	0.7124	0.5860	0.8449	0.6167	0.8114	0.6322	0.7955
Government	-0.0214	-0.0462	0.0028	-0.0400	-0.0028	-0.0373	-0.0053
For-profit	-0.0166	-0.0804	0.0453	-0.0642	0.0299	-0.0553	0.0221
Medicare	0.0007	-0.0005	0.0017	-0.0002	0.0015	-0.00003	0.0014
Medicaid	0.0016	-0.0001	0.0033	0.0003	0.0030	0.0005	0.0027
HHI	-0.0514	-0.0857	-0.0200	-0.0764	-0.0271	-0.0727	-0.0316
System	0.0381	0.0154	0.0632	0.0208	0.0565	0.0238	0.0538
Income	-3.34E-07	-2.32E-06	1.57E-06	-1.84E-06	1.16E-06	-1.59E-06	9.22E-07
MHMO	0.0017	-0.0004	0.0039	0.00003	0.0033	0.0003	0.0030
Y2006	0.0171	-0.0072	0.0402	-0.0005	0.0342	0.0018	0.0316
Sigma	0.0851	0.0779	0.0945	0.0800	0.0922	0.0811	0.0913

APPENDIX 4

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Iustin Cristian Nedelea was born and raised in a rural area in the southern part of Romania. In 1997, he received a Bachelor of Arts degree in Geography from the University of Bucharest, Romania. He received a Master of Science degree in Agricultural Economics from Louisiana State University in December 2007. Afterward, Cristian enrolled in the doctorate program in the Department of Agricultural Economics and Agribusiness at Louisiana State University. During his graduate program, he authored three peer-reviewed journal articles, presented original research at various conferences, and taught two undergraduate courses in the Department of Agricultural Economics and Agribusiness at Louisiana State University. Cristian will complete his doctorate degree in Agricultural Economics in December 2012.