# Inefficiency Differences between Critical Access Hospitals and Prospectively Paid Rural Hospitals

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**Abstract** The Medicare prospective payment system (PPS) contains incentives for hospitals to improve efficiency by placing them at financial risk to earn a positive margin on services rendered to Medicare patients. Concerns about the financial viability of small rural hospitals led to the implementation of the Medicare Rural Hospital Flexibility Program (Flex Program) of 1997, which allows facilities designated as critical access hospitals (CAHs) to be paid on a reasonable cost basis for inpatient and outpatient services. This article compares the cost inefficiency of CAHs with that of nonconverting rural hospitals to contrast the performance of hospitals operating under the different payment systems. Stochastic frontier analysis (SFA) was used to estimate cost inefficiency. Analysis was performed on pooled time-series, cross-sectional data from thirty-four states for the period 1997–2004. Average estimated cost inefficiency was greater in CAHs (15.9 percent) than in nonconverting rural hospitals (10.3 percent). Further, there was a positive association between length of time in the CAH program and estimated cost inefficiency. CAHs exhibited poorer values for a number of proxy measures for efficiency, including expenses per admission and labor productivity (full-time-equivalent employees per outpatient-adjusted admission). Non-CAH rural hospitals had a stronger correlation between cost inefficiency and operating margin than CAH facilities did.

The Social Security Amendments of 1983 (Pub. L. No. 98-21) authorized the implementation of the Medicare prospective payment system (PPS) for

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acute care inpatient hospitals. However, the program also permitted isolated hospitals, defined as sole community hospitals (SCHs), to be reimbursed on a cost basis (Guterman 1986). This exception was intended to provide support to isolated hospitals so they would not close. Under the provision, a hospital could be designated as an SCH if it was the only institution that residents in a geographic region could reasonably access for inpatient services. Medicare policy analysts continue to believe that, given the low population density of rural areas and the concomitant long distances between many rural hospitals, the closure of rural hospitals could create access problems for beneficiaries residing in rural communities (Medicare Payment Advisory Commission [MedPAC] 2001).

The enactment of the Balanced Budget Act (BBA) of 1997 created the critical access hospital (CAH) program. This program, which has been subsequently modified by additional legislation, such as the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, is intended to enhance the financial viability of small, isolated rural and "necessary-provider" hospitals by paying them on a cost basis instead of prospectively. By paying on a cost basis, the Medicare Rural Hospital Flexibility Program (Flex Program) of 1997 keeps small hospitals from being penalized if they lack the economies of scale needed to keep their costs below the prospective payment rates paid by Medicare (Stensland, Moscovice, and Christianson 2002).

In exchange for accepting a number of restrictions, such as limits on the number of acute care patients treated at one time (twenty-five) and average patient length of stay (four days), hospitals in the CAH program receive 101 percent of their costs. The CAH program also reimburses expenses

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for on-call physicians and pays for outpatient laboratory services on a cost basis. They do not receive disproportionate share payments, however. To qualify for the CAH program, a hospital must be at least thirty-five miles by primary road from the nearest hospital or be declared a "necessary provider" by the state. Most states opt to avoid the distance requirement and designate most rural hospitals as "necessary providers." Only 20 percent of CAHs are more than thirty-five road miles from an alternative source of hospital-based emergency care (MedPAC 2008). More details on the CAH program are provided by Stensland, Moscovice, and Christianson 2002 and MedPAC 2005.

MedPAC reports that Medicare payments to CAHs rose at an annualized growth rate of 9.5 percent from 1998 to 2003, compared to a 3.3 percent growth rate for similar hospitals that did not convert to CAH status and were paid prospectively. As a result, Medicare paid approximately $850,000 more per CAH in 2003 than it would have if payment had increased at the rate of nonconverting, comparison hospitals. MedPAC estimates that the difference was nearly $1 million per hospital in 2006. This amounts in total to a projected $1.3 billion in Medicare payments above what would have been made under prospective payment (MedPAC 2005).

The CAH program has succeeded in its aim of halting the closure of small rural and necessary provider hospitals by improving their financial condition. Converting hospitals improved their all-payer profit margins from 1.2 percent in 1998 to 2.2 percent in 2003. In contrast, comparison hospitals experienced a decline from 2.2 percent in 1998 to -0.2 percent in 2003 (MedPAC 2005). In addition to profitability, conversion to CAH status was associated with improvements in liquidity (i.e., ability to meet timely cash needs) and capital structure (i.e., ability to meet debt obligations) (Holmes, Pink, and Slifkin 2006). Over twelve hundred hospitals have converted to CAH status, and very few of them have subsequently closed. These hospitals may be essential to the provision of care for underserved populations. However, there is concern that hospitals in the CAH program are not providing care as efficiently as possible. Indeed, MedPAC reports, "Although the CAH program has helped to preserve access to emergency and inpatient care in isolated areas, it may not have accomplished this goal in an efficient manner" (MedPAC 2005: 167).

It is not surprising that efficiency concerns should arise in the cost-based payment CAH program: Medicare replaced cost-based reimbursement with the PPS in the early 1980s as a cost-control and efficiency-enhancing measure. Retrospective cost-based reimbursement, which was the predominant form of hospital payment prior to PPS, may be inflationary because it contains incentives to increase expenditures. Specifically, if costs increase in the current year, reimbursement will increase in the following year. In contrast, PPS is a fixed-price payment system. Profit is the difference between revenue and expenses. If a patient's expenses exceed the diagnosis-related group (DRG) payment rate, the hospital suffers a loss; conversely, hospitals are allowed to retain the differences between DRG payments and their expenses. These surpluses might be used to subsidize uncompensated care or fund capital improvements. Thus, theory suggests that PPS will contain cost increases, an assertion backed by empirical evidence (Feder, Hadley, and Zuckerman 1987). For example, in the eight years prior to the establishment of PPS, expenditures for Medicare Part A (i.e., the hospital insurance program) increased at an annual rate exceeding 15 percent. In contrast, during the eight years immediately following PPS, the rate dropped to 8.75 percent (Santerre and Neun 2007). A review of state PPS programs found similar effects (Rosko and Broyles 1988).

Although CAHs retain incentives to restrain costs (e.g., they have non-Medicare patients), the incentives are not considered to be as strong as those faced by hospitals that are paid prospectively. Since CAHs receive increased payment per unit of service when they add labor and capital, they may acquire and use more resources than necessary in the provision of care (MedPAC 2005). Of course, since quality improvement was one of the main goals of the CAH program, many of these resources have gone into quality improvement and quality assurance activities (Casey and Moscovice 2004). See Li, Schneider, and Ward 2007 for a summary of the effect of conversion to CAH status on hospital involvement in quality-related programs.

There is a growing interest in evaluating the performance of CAHs. Pink and colleagues (2004) call for the development of comparative performance data for evaluating the financial performance and organizational effectiveness of CAHs as well as the quality of care they provide. In addition, Pink and colleagues (2006) suggest a set of measures that would be suitable indicators of the financial performance of CAHs. MedPAC 2005 evaluates the quality of care provided by CAHs, using a subset of the Inpatient Quality Indicator (IQI) and Patient Safety Indicator (PSI) modules of the Agency for Healthcare Research and Quality (AHRQ) Quality Indicator (QI) software. This study contributes to this body of literature by comparing the hospital-level cost inefficiency of CAHs and nonconverting rural hospitals, using stochastic frontier analysis (SFA) with controls for hospital quality of care and patient burden of illness.

## Using Stochastic Frontier Analysis to Measure Hospital Inefficiency

Since the seminal study by Zuckerman, Hadley, and Iezzoni (1994), over twenty SFA studies of U.S. hospitals have been published (Rosko and Mutter 2008). Chirikos (1998) demonstrated the utility of this technique for policy analysis. This is the first SFA-based study to examine the impact of payment incentives. SFA is a parametric technique, developed independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), which can be used to estimate the cost inefficiency of an organization by comparing actual performance with theoretical best practices. Intuitively, SFA creates a theoretical best-practice frontier (BPF) using actual hospital data and measures a hospital's inefficiency as the distance from the hospital to the frontier. The cost inefficiency of a hospital is defined as the ratio of observed total costs to the best-practice, stochastic frontier total costs. The BPF is defined by the value that total costs would be if full efficiency were attained. For example, given the types and quantities of outputs a hospital produces and the input prices it pays, a theoretical best-practice hospital might incur expenses amounting to \$100 million. If a study hospital were in an identical situation and its total expenses were \$120 million, its estimated cost inefficiency would be 20 percent.

SFA is based on the assumption that departures from the cost frontier can be decomposed into random and deterministic factors. The latter represents inefficiency. The estimation of hospital cost inefficiency requires technical assumptions about the structure of costs and about the statistical distribution of the error term representing inefficiency. (These and other related issues are discussed in the analytic strategy section below.)

The hospital-level cost-inefficiency estimates produced by SFA measure technical inefficiency (i.e., whether output is obtained using the fewest inputs), allocative inefficiency (i.e., whether output is produced using the optimal mix of inputs, given prices), scale inefficiency (i.e., the size of a hospital's operations — whether it is too large or too small), and scope inefficiency (i.e., the range of a hospital's operations — whether it is overspecialized or overdiversified). Folland and Hofler (2001) find that SFA is an appropriate technique for comparing the inefficiency of groups of hospitals.

## Methods

### Data

Using data for the period 1997 – 2004, we examined a subset of U.S. community, general, CAH-designated hospitals as well as a comparison group of prospectively paid, nonconverting, general hospitals that were located in rural areas.[1] A total of 543 hospitals were included in our sample. To be eligible for inclusion in our study, a hospital had to have data for each variable for seven of the eight years in the study period.[2] Since CAH facilities are restricted to twenty-five or fewer acute care beds (although CAH facilities have no restrictions on nonacute beds, and in 2004, 48 percent of the CAH subsample had more than 25 beds with a range of up to 181 beds), we restricted the comparison group to nonteaching[3] rural hospitals that had less than seventy-six beds during at least one year of the study period. The criteria allowed us to maximize sample size while having two groups of hospitals that had a similar number of beds (i.e., the mean for CAH facilities was 49.2 beds while the average comparison group hospital had 55.8 beds). Although there were only 12 CAHs and 531 nonconverting, rural comparison hospitals in our sample in 1997, by 2004 there were 286 CAHs and 257 prospectively paid hospitals in our analytical file. Table 1 shows the distribution of hospitals into the two groups over the entire evaluation period.

The primary hospital-level sources of data were the American Hospital Association (AHA) Annual Survey of Hospitals and the Medicare Hospital Cost Report Minimum Data Set. Our hospital-level quality measures came from the application of the IQI and PSI modules of the AHRQ QI software[4] to the State Inpatient Databases[5] (SID) for thirty-four states[6] participating in the Healthcare Cost and Utilization Project (HCUP).[7]

1. Data for hospital quality were not available prior to 1997.

2. Data for some independent variables were interpolated for twenty-one hospitals. A total of forty-five hospitals were excluded from the study because they were not in operation for at least seven of the eight years in our study.

3. None of the CAH facilities had a graduate medical education program.

4. AHRQ makes this software available for free on its Web site: www.qualityindicators.ahrq.gov.

5. For each participating state, the SID contains the discharge abstract for every inpatient hospitalization that occurred. For more information see www.hcup-us.ahrq.gov/sidoverview.jsp.

6. The thirty-four states are Arizona, California, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, New Hampshire, New Jersey, New York, Nevada, North Carolina, Ohio, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, and Wisconsin.

7. HCUP is a family of health care databases and related software tools developed through a federal-state-industry partnership to build a multistate health data system for health care research and decision making. For more information, see www.hcup-us.ahrq.gov/home.jsp.

**Table 1** Distribution of Hospitals into CAH and Nonconverting Rural Hospital, by Year

| Year | CAH | Nonconverting Rural |
|---|---|---|
| 1997 | 12 | 531 |
| 1998 | 15 | 528 |
| 1999 | 16 | 527 |
| 2000 | 46 | 497 |
| 2001 | 107 | 436 |
| 2002 | 186 | 357 |
| 2003 | 242 | 301 |
| 2004 | 286 | 257 |

*Source*: Authors' calculations
*Note*: CAH = critical access hospital

Our controls for patient burden of illness (i.e., factors that predispose patients to require more services) came from the application of the Comorbidity Software[8] to these thirty-four HCUP SIDs. Therefore, our study was limited to hospitals in these thirty-four states. We augmented our hospital-level data with market-level data on Medicare health maintenance organization (HMO) penetration and median personal income from the Area Resource File and a hospital competition measure from HCUP.[9]

## Analytic Strategy

The estimation of the BPF requires the specification of a cost function of the general form

$$TC_i = \mathrm{f}(Y_i, PD_i, W_i) + e_i,$$

where $TC_i$ represents hospital-level total costs, $Y_i$ is a vector of hospital-level outputs, $PD_i$ is a vector of hospital-level product descriptors, $W_i$ is a

8. The Comorbidity Software is one in a family of databases and software tools developed as part of the HCUP project. It assigns variables that identify comorbidities in hospital discharge records, using the diagnosis coding of the International Classification of Diseases, Ninth Edition, Clinical Modifications (ICD-9-CM). For more information, see www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp.

9. The Hospital Market Structure File contains various measures of hospital market competition based on the algorithms developed by Wong, Zhan, and Mutter (2005). These measures are aggregate and are meant to broadly characterize the intensity of competition that hospitals may be facing under various definitions of market area. The measures are available to the public for free online at www.hcup-us.ahrq.gov/toolssoftware/hms/hms.jsp. This article uses a county-level Herfindahl-Hirschman Index (HHI).

vector of hospital input prices, and $e_i$ is the error term of the equation. The error term can be decomposed as

$$e_i = v_i + u_i,$$

where $v_i$ is random error, and $u_i$ consists of positive departures from the BPF. These positive departures from the BPF are inefficiency estimates at the hospital level (Lovell 1993).

The actual cost equation that we estimated uses the translog functional form, which is taken from the literature.[10] The translog cost equation is specified as

$$\ln TC_{it} = \alpha_o + \sum_{j=1}^{J}\alpha_j \ln Y_{jit} + \sum_{k=1}^{K}\beta_k \ln W_{kit} + .5\sum_{j=1}^{J}\sum_{l=1}^{L}\delta_{jl} \ln Y_{jit} \ln Y_{lit}$$

$$+ .5 \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{jl} \ln W_{kit} \ln W_{mit} + \sum_{j=1}^{J}\sum_{k=1}^{K}\rho_{ij} \ln Y_{jit} \ln W_{kit} + v_{it} + u_{it},$$

where $\alpha_0$, $\alpha_j$, $\beta_k$, $\delta_{jl}$, $\gamma_{jl}$, $\rho_{ij}$, and $\phi$ are parameters to be estimated. (The other terms are defined above.)

We used the model originally developed by Battese and Coelli (1995) for panel data, in which the inefficiency effects are defined by

$$u_{it} = \delta Z_{it} + w_{it,}\, u_{it} \geqslant 0,$$

where $Z_{it}$ is a vector of explanatory variables associated with the inefficiency effects; $\delta$ is a vector of unknown parameters to be estimated; and $w_{it}$ are unobservable random variables, assumed to be independently distributed, obtained by truncation of the normal distribution with mean zero and unknown variance, $\sigma^2$. This model can be used to explain the impact of hospital-specific, system-related, and environmental factors on inefficiency (Hjalmarsson, Kumbhakar, and Heshmati 1996).

## Cost Function Variables

The standard assumption of linear homogeneity in input prices is imposed by normalizing the equation by the wage rate. Thus, the dependent variable (EXPWAGE) is the logarithm of total expenses divided by the wage

10. The Cobb-Douglas form, which is a nested version of the translog in which the coefficients of all of the squared and cross-product terms are assumed to be equal, could not be accepted by a log-likelihood restriction test ($p < 0.01$).

rate. We followed the same procedure with the input price variables in the right-hand side of the equation. Two inputs, capital and labor, are recognized by the cost function. The price of labor (Pl) was approximated by the Medicare state wage index, and the price of capital (Pk) was approximated by depreciation and interest expenses per bed, aggregated at the state level. A more complete specification of input prices would be desirable. However, given the relatively poor quality of input price information, we followed past practices and used this limited set of price variables (Grannemann, Brown, and Pauly 1986; Zuckerman, Hadley, and Iezzoni 1994). The model assumes that excluded input prices are proportional across hospitals.

The outputs in the cost function included outpatient visits (OPV), inpatient admissions (ADMTOT), and postadmission days (POSTDAYS, i.e., total inpatient days minus admissions). The results of a Hausman specification test ($p < 0.05$) suggest that hospital outputs can be treated as exogenous, an assumption common to hospital cost studies (Grannemann, Brown, and Pauly 1986). The continuous output and input price variables are in natural log form.

It is well recognized that hospital outputs are heterogeneous; therefore, it is important to include product descriptors that can control for variations in costs. We used OUTSURG% and ER% to control variations in outpatient output. The former is the ratio of outpatient surgeries to total outpatient visits, and the latter is the ratio of emergency department visits to total outpatient visits. Patients who require surgery and patients seen in the emergency department tend to be a more resource-intensive group of outpatients (Zuckerman, Hadley, and Iezzoni 1994; Dor and Farley 1996; Rosko 2001a). The percentage of acute care beds (ABED%) was used to control for long-term care activities, which tend to be less costly than acute care. Thus, hospitals with a greater concentration of output in acute care should be more expensive. We also control for admissions for births as a percentage of total admissions (BIRTH%).

We also include a time trend (TREND). This variable measures whether hospitals have been adopting a more expensive technology over time.

A particular challenge was controlling for heterogeneity in inpatient output. Most SFA studies of U.S. hospitals have used the Medicare Case-Mix Index (MCMI) in the cost function for this purpose (Rosko and Mutter 2008). However, CAH facilities are not subject to prospective payment and do not report DRG information required to compute the MCMI. Therefore, we had to employ an alternative approach.

We added thirty hospital-level rates of comorbidities per admission, which we log transformed. The comorbidities were identified by the application of the Comorbidity Software to HCUP data. They estimate the presence of comorbidities that are unrelated to the principal diagnosis but which have an important impact on the resources used in the treatment of patients and on the outcomes of the care they receive. Indeed, Elixhauser and colleagues (1998) note that these thirty comorbidities are associated with longer length of stay, higher hospital charges, and greater risk of in-hospital mortality. Mutter, Rosko, and Wong (2008) find that controlling for patient burden of illness in SFA models using the Comorbidity Software results in lower mean estimated hospital inefficiency, which suggests that in the absence of these controls, variations in patient mix can masquerade as hospital inefficiency. In cross-sectional analysis repeated for each of the eight years in the study period, the Comorbidity Software variables as a group explained from 44.5 percent to 50.4 percent of the variation in the dependent variable (logged total costs).

Numerous frontier applications have noted that the inclusion of direct measures of quality in the hospital cost function could result in improved analyses (Folland and Hofler 2001; Li and Rosenman 2001; McKay, Deily, and Dorner 2002/3). Therefore, we included risk-adjusted rates of in-hospital mortality for congestive heart failure (CHF), in-hospital mortality for pneumonia, iatrogenic pneumothorax, infection due to medical care, and accidental puncture/laceration. These outcome measures were selected because they were common across the hospitals in our sample (thereby allowing us to maintain an adequate sample size) and because they were not among the measures found to have a high percentage of events that were present on admission (Houchens, Elixhauser, and Romano 2008).

By including these measures of patient burden of illness and hospital quality in our cost function, we control for changes in case mix and outcome quality that may result from participation in the CAH program.

## Inefficiency-Effects Variables

We included a set of what is termed in the SFA literature as "inefficiency effects" variables as controls; the variables are taken from the literature (Rosko 2001a). They included median income of the county (MEDINCOME), Medicare HMO penetration (MHMO%),[11] Medicare share

11. We could not obtain data for general HMO enrollment for all eight years of the study. Accordingly, we followed Zinn, Proenca, and Rosko (1997), who found that Medicare HMO penetration is a useful proxy for general HMO penetration.

(MEDICARE%) and Medicaid share of admissions (MEDICAID%), county-level Herfindahl-Hirschman Index based on the share of discharges (HERFINDAHL), for-profit ownership status (FP), and government ownership (GOVT). Nonprofit ownership is the omitted reference category. These variables control for external environment pressures for efficiency associated with private and public payment policy, ability to pay, and the degree of market competition, as well as internal pressures for efficiency associated with ownership. We also included membership in a multihospital health care system (SYSTEM) and a time trend (TREND2).

To assess the impact of CAH status on hospital inefficiency, we included a binary variable for whether a hospital was a CAH in a particular year (INCAH) and a counter for the number of years a hospital had been a CAH in a particular year (CAHCOUNT).

## Performance Variables

After we derived the cost-inefficiency estimates using SFA, we compared them to three commonly used measures of hospital performance: expense per AHA-adjusted admission,[12] which is a proxy for overall efficiency; full-time equivalent (FTE) personnel per AHA-adjusted admission, which is a proxy for labor efficiency; and operating margin, which is a measure of profitability.

Tables 2a and 2b present definitions and descriptive statistics for the variables used in the CAH and nonconverting rural hospital samples, respectively, for all years.

## Other Analytic Issues

SFA requires the researcher to specify the statistical distribution of the inefficiency estimates. There are a number of feasible distributional assumptions for the residuals, including the half normal, gamma, exponential, and truncated normal distributions (Greene 1993). One of the concerns about SFA is that the choice of the distribution cannot be made on the basis of economic theory. Stevenson (1980) partially addressed this concern by specifying a truncated-normal distribution, which is a generalization of the half-normal distribution. Since the half-normal distribu-

12. The AHA inflates admissions to reflect outpatient volume to create adjusted admissions.

**Table 2a** Variable Names and Descriptive Statistics, Critical Access Hospitals (All Years)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| *Cost Function Variables* | | | |
| ABED% | (Acute care beds / total beds) × 100 | 74.35 | 33.40 |
| ADMTOT | Total facility admissions | 569.02 | 374.76 |
| BIRTH% | (Births / total admissions) × 100 | 4.54 | 7.12 |
| ER% | (Emergency department visits / total outpatient visits) × 100 | 19.88 | 16.46 |
| EXPWAGE | Total expenses / Medicare area wage index | 78,999.04 | 46,599.90 |
| OPV | Outpatient visits | 21,044.77 | 15,943.47 |
| OUTSURG% | (Outpatient surgical operations / total outpatient visits) × 100 | 2.11 | 2.45 |
| Pk | Depreciation and interest expenses per bed | 21,427.18 | 7,823.68 |
| POSTDAYS | Inpatient days – admissions | 7,842.10 | 9,685.88 |
| RPIQ16 | Risk-adjusted in-hospital mortality rate for CHF | 0.0629 | 0.0663 |
| RPIQ20 | Risk-adjusted in-hospital mortality rate for pneumonia | 0.0865 | 0.0446 |
| RPPS06 | Risk-adjusted iatrogenic pneumothorax rate | 0.0004 | 0.0007 |
| RPPS07 | Risk-adjusted infection due to medical care rate | 0.0008 | 0.0014 |
| RPPS15 | Risk-adjusted accidental puncture/ laceration rate | 0.0030 | 0.0013 |
| RSAIDS | Comorbidity rate—AIDS | 0.0003 | 0.0011 |
| RSALCOH | Comorbidity rate—alcohol abuse | 0.0149 | 0.0145 |
| RSANEMD | Comorbidity rate—deficiency anemias | 0.0826 | 0.0514 |
| RSARTH | Comorbidity rate—rheumatoid | 0.0153 | 0.0116 |
| RSARYTH | Comorbidity rate—cardiac arrhythmias | 2.9724 | 0.1364 |
| RSBLDLO | Comorbidity rate—blood loss anemia | 0.0103 | 0.0114 |
| RSCHF | Comorbidity rate—CHF | 0.1006 | 0.0527 |
| RSCHRNL | Comorbidity rate—chronic pulmonary disease | 0.1316 | 0.0621 |
| RSCOAG | Comorbidity rate—coagulopathy | 0.0105 | 0.0099 |
| RSDEPRE | Comorbidity rate—depression | 0.0547 | 0.0374 |
| RSDM | Comorbidity rate—diabetes, uncomplicated | 0.1348 | 0.0558 |

**Table 2a** (*continued*)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| RSDMCX | Comorbidity rate—diabetes, complicated | 0.0150 | 0.01537 |
| RSDRUG | Comorbidity rate—drug abuse | 0.0048 | 0.0072 |
| RSHTN_C | Comorbidity rate—hypertension | 0.2603 | 0.1117 |
| RSHYPOT | Comorbidity rate—hypothyroidism | 0.0672 | 0.0414 |
| RSLIVER | Comorbidity rate—liver disease | 0.0067 | 0.0073 |
| RSLYMPH | Comorbidity rate—lymphoma | 0.0037 | 0.0051 |
| RSLYTES | Comorbidity rate—fluid and electrolyte disorders | 0.1600 | 0.0761 |
| RSMETS | Comorbidity rate—metastatic cancer | 0.0109 | 0.0095 |
| RSNEURO | Comorbidity rate—other neurological disorders | 0.0172 | 0.0119 |
| RSOBESE | Comorbidity rate—obesity | 0.0219 | 0.0215 |
| RSPARA | Comorbidity rate—paralysis | 0.0095 | 0.0088 |
| RSPERIV | Comorbidity rate—peripheral vascular disorders | 0.0262 | 0.0196 |
| RSPSYCH | Comorbidity rate—psychoses | 0.0181 | 0.0134 |
| RSPULMC | Comorbidity rate—pulmonary circulation disorders | 1.0034 | 0.0054 |
| RSRENLF | Comorbidity rate—renal failure | 0.0263 | 0.0232 |
| RSTUMOR | Comorbidity rate—solid tumor without metastasis | 0.0458 | 0.0272 |
| RSULCER | Comorbidity rate—peptic ulcer disease, excluding bleeding | 0.0086 | 0.0137 |
| RSVALVE | Comorbidity rate—valvular disease | 0.0156 | 0.0149 |
| RSWGHTL | Comorbidity rate—weight loss | 0.0142 | 0.0172 |
| TREND | Time trend = 1 in 1997, 2 in 1998, . . . , 8 in 2004 | 6.48 | 1.54 |
| *Inefficiency Effects Variables* | | | |
| CAHCOUNT | Years in CAH program | 2.64 | 1.75 |
| FP | Investor owned (binary variable 1, 0) | 0.03 | 0.17 |
| GOVT | Government, nonfederal (binary variable 1, 0) | 0.55 | 0.50 |
| HERFINDAHL | Herfindahl-Hirschman Index | 0.84 | 0.23 |
| INCAH | Participated in CAH program (binary variable 1, 0) | 1.00 | 0.00 |
| MEDICAID% | (Medicaid admissions / total admissions) × 100 | 10.42 | 7.58 |

(*continued*)

**Table 2a** Variable Names and Descriptive Statistics, Critical Access Hospitals (All Years) (*continued*)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| MEDICARE% | (Medicare admissions / total admissions) × 100 | 60.77 | 13.67 |
| MEDINCOME | Median income | 35,691.64 | 5,390.28 |
| MHMO% | (Medicare HMO enrollment / population) × 100 | 0.21 | 0.45 |
| SYSTEM | Member of multihospital health care system (binary variable 1, 0) | 0.39 | 0.49 |
| TREND2 | Time trend = 1 in 1997, 2 in 1998, . . . , 8 in 2004 | 6.48 | 1.54 |
| *Performance Variables* | | | |
| EXPENSE/ ADJUSTED ADMIT | Total expenses / AHA-adjusted admissions | 6,114.83 | 4,004.52 |
| FTE/ADJUSTED ADMIT | FTE total personnel / AHA-adjusted admissions | 0.10 | 0.10 |
| OPERATING MARGIN | (Net patient revenue − operating expenses) / net patient revenue | -0.06 | 0.125 |

*Source*: Authors' calculations
*Note*: SD = standard deviation

**Table 2b** Variable Names and Descriptive Statistics, Nonconverting Rural Hospitals (All Years)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| *Cost Function Variables* | | | |
| ABED% | (Acute care beds / total beds) × 100 | 82.60 | 25.87 |
| ADMTOT | Total facility admissions | 1,385.18 | 978.91 |
| BIRTH% | (Births / total admissions) × 100 | 9.19 | 8.70 |
| ER% | (Emergency department visits/total outpatient visits) × 100 | 23.90 | 15.45 |
| EXPWAGE | Total expenses / Medicare area wage index | 133,813.55 | 98,986.16 |
| OPV | Outpatient visits | 33,984.44 | 28,952.92 |
| OUTSURG% | (Outpatient surgical operations / total outpatient visits) × 100 | 3.00 | 2.52 |
| Pk | Depreciation and interest expenses per bed | 18,284.04 | 7,036.95 |
| POSTDAYS | Inpatient days − admissions | 8,632.06 | 9,212.95 |
| RPIQ16 | Risk-adjusted in-hospital mortality rate for CHF | 0.0579 | 0.0441 |

**Table 2b** (*continued*)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| RPIQ20 | Risk-adjusted in-hospital mortality rate for pneumonia | 0.0842 | 0.0391 |
| RPPS06 | Risk-adjusted iatrogenic pneumothorax rate | 0.0005 | 0.0010 |
| RPPS07 | Risk-adjusted infection due to medical care rate | 0.0009 | 0.0009 |
| RPPS15 | Risk-adjusted accidental puncture/ laceration rate | 0.0032 | 0.0019 |
| RSAIDS | Comorbidity rate—AIDS | 0.0003 | 0.0010 |
| RSALCOH | Comorbidity rate—alcohol abuse | 0.0178 | 0.016 |
| RSANEMD | Comorbidity rate—deficiency anemias | 0.0680 | 0.036 |
| RSARTH | Comorbidity rate—rheumatoid | 0.0143 | 0.0083 |
| RSARYTH | Comorbidity rate—cardiac arrhythmias | 2.9527 | 0.1162 |
| RSBLDLO | Comorbidity rate—blood loss anemia | 0.0119 | 0.0107 |
| RSCHF | Comorbidity rate—CHF | 0.0885 | 0.0423 |
| RSCHRNL | Comorbidity rate—chronic pulmonary disease | 0.1309 | 0.0607 |
| RSCOAG | Comorbidity rate—coagulopathy | 0.0099 | 0.0074 |
| RSDEPRE | Comorbidity rate—depression | 0.0464 | 0.0283 |
| RSDM | Comorbidity rate—diabetes, uncomplicated | 0.1180 | 0.0458 |
| RSDMCX | Comorbidity rate—diabetes, complicated | 0.0164 | 0.0144 |
| RSDRUG | Comorbidity rate—drug abuse | 0.0067 | 0.0120 |
| RSHTN_C | Comorbidity rate—hypertension | 0.2253 | 0.0951 |
| RSHYPOT | Comorbidity rate—hypothyroidism | 0.0523 | 0.0286 |
| RSLIVER | Comorbidity rate—liver disease | 0.0078 | 0.0066 |
| RSLYMPH | Comorbidity rate—lymphoma | 0.0032 | 0.0030 |
| RSLYTES | Comorbidity rate—fluid and electrolyte disorders | 0.1475 | 0.0664 |
| RSMETS | Comorbidity rate—metastatic cancer | 0.0117 | 0.0073 |
| RSNEURO | Comorbidity rate—other neurological disorders | 0.0172 | 0.0104 |
| RSOBESE | Comorbidity rate—obesity | 0.0240 | 0.0187 |
| RSPARA | Comorbidity rate—paralysis | 0.0117 | 0.0098 |
| RSPERIV | Comorbidity rate—peripheral vascular disorders | 0.0282 | 0.0212 |

(*continued*)

**Table 2b** Variable Names and Descriptive Statistics, Nonconverting Rural Hospitals (All Years) (*continued*)

| Variable Name | Description | Mean | SD |
|---|---|---|---|
| RSPSYCH | Comorbidity rate—psychoses | 0.0174 | 0.0148 |
| RSPULMC | Comorbidity rate—pulmonary circulation disorders | 1.0033 | 0.0040 |
| RSRENLF | Comorbidity rate—renal failure | 0.0220 | 0.0168 |
| RSTUMOR | Comorbidity rate—solid tumor without metastasis | 0.0433 | 0.0231 |
| RSULCER | Comorbidity rate—peptic ulcer disease, excluding bleeding | 0.0109 | 0.0139 |
| RSVALVE | Comorbidity rate—valvular disease | 0.0159 | 0.0126 |
| RSWGHTL | Comorbidity rate—weight loss | 0.0164 | 0.0185 |
| TREND | Time trend = 1 in 1997, 2 in 1998, . . . , 8 in 2004 | 3.97 | 2.17 |
| *Inefficiency Effects Variables* | | | |
| CAHCOUNT | Years in CAH program | 0.00 | 0.00 |
| FP | Investor owned (binary variable 1, 0) | 0.09 | 0.28 |
| GOVT | Government, nonfederal (binary variable 1, 0) | 0.46 | 0.50 |
| HERFINDAHL | Herfindahl-Hirschman Index | 0.81 | 0.25 |
| INCAH | Participated in CAH program (binary variable 1, 0) | 0.00 | 0.00 |
| MEDICAID% | (Medicaid admissions / total admissions) × 100 | 13.22 | 8.45 |
| MEDICARE% | (Medicare admissions / total admissions) × 100 | 54.31 | 12.32 |
| MEDINCOME | Median income | 34,051.14 | 5,326.93 |
| MHMO% | (Medicare HMO enrollment / population) × 100 | 28.33 | 0.59 |
| SYSTEM | Member of multihospital health care system (binary variable 1, 0) | 0.43 | 0.50 |
| TREND2 | Time trend = 1 in 1997, 2 in 1998, . . . , 8 in 2004 | 3.97 | 2.17 |
| *Performance Variables* | | | |
| EXPENSE/ ADJUSTED ADMIT | Total expenses / AHA-adjusted admissions | 4,602.26 | 2,123.60 |
| FTE/ADJUSTED ADMIT | FTE total personnel / AHA-adjusted admissions | 0.07 | 0.05 |
| OPERATING MARGIN | (Net patient revenue – operating expenses) / net patient revenue | -0.06 | 0.13 |

*Source*: Authors' calculations
*Note*: SD = standard deviation

tion is a special case of the truncated-normal distribution where $\mu = 0$, the appropriateness of using the half-normal distribution was assessed by testing $H_0$: $\mu = 0$. This hypothesis could not be rejected ($p < 0.05$) on the basis of a log-likelihood restriction test (Greene 2003), and the half-normal distribution was used in the final model. However, two things should be noted. First, the results were very robust over alternate specifications of $\mu$. The simple correlation of the inefficiency scores estimated with the two distributions exceeded 0.98. This is consistent with the cross-sectional hospital findings of Zuckerman, Hadley, and Iezzoni (1994) and Rosko and Mutter (2008) in the United States and Jacobs, Smith, and Street (2006) in the United Kingdom as well as those from a wide variety of other industries (Coelli, Rao, and Batteese 1999). Second, although the use of the half-normal distribution could be tested because it is a special case of the truncated normal distribution, there are other plausible distributions, such as the gamma, that cannot be formally tested.

## Results

The parameters of the cost frontier were estimated using the simultaneous maximum likelihood method in the FRONTIER 4.1 program (Coelli 1996). The estimates from the translog cost function are presented in table 3.

### Cost Function Variables

In table 3, Pk and some of the output variables (or their squared terms) had parameter estimates that were either insignificant or counterintuitive. However, this was not unexpected given the high intercorrelations among these variables. Although multicollinearity has an adverse effect on the reliability of the parameter estimates for the output variables and Pk, it does not introduce a bias in the inefficiency estimates. Given that this study does not focus on the cost function parameter estimates per se, we retained the translog cost function based on the results of the previously discussed log-likelihood restriction test. However, in an estimated Cobb-Douglas model (not reported), in which the squared and cross-product terms are eliminated, thereby reducing intravariable correlations, each of the output variables and Pk had positive and significant coefficients ($p < 0.05$). The inefficiency estimates generated by the translog and Cobb-Douglas cost function models are highly correlated ($r = 0.98$), so cost function choice does not affect the results very much.

**Table 3** Parameter Estimates for Frontier Cost Function and Inefficiency Effects

| Variable Name | Coefficient | *t*-ratio |
|---|---|---|
| *Cost Function Variables* | | |
| Intercept | 10.2302** | 10.68 |
| ABED% | 0.0001 | 0.23 |
| ADMTOT | -0.5628** | -4.43 |
| ADMTOT SQUARED | 0.0787** | 4.95 |
| ADMTOT × OPV | 0.1468** | 6.03 |
| ADMTOT × POSTDAYS | -0.0156 | -1.06 |
| BIRTH% | 0.0022** | 4.18 |
| ER% | 0.0043** | 13.03 |
| OPV | 0.1766 | 1.53 |
| OPV SQUARED | -0.0114 | -0.82 |
| OPV × POSTDAY | -0.0742** | -5.91 |
| OUTSURG% | 0.0328** | 17.28 |
| Pk | -1.2215** | -3.91 |
| Pk SQUARED | 0.3391** | 5.41 |
| Pk × ADMTOT | -0.0388 | -1.76 |
| Pk × OPV | 0.0191 | 0.88 |
| Pk × POSTDAY | -0.0494** | -3.65 |
| POSTDAYS | 0.3782** | 4.62 |
| POSTDAYS SQUARED | 0.0450** | 5.56 |
| RPIQ16 | -0.1537* | -2.06 |
| RPIQ20 | -0.0883 | -0.96 |
| RPPS06 | 8.4019** | 7.93 |
| RPPS07 | 1.9975 | 1.72 |
| RPPS15 | -0.3812 | -0.35 |
| RSAIDS | -0.0025 | -0.95 |
| RSALCOH | -0.0095* | -2.08 |
| RSANEMD | -0.0031 | -0.36 |
| RSARTH | -0.0086 | -1.91 |
| RSARYTH | 0.0396** | 3.20 |
| RSBLDLO | 0.0074** | 3.16 |
| RSCHF | -0.0392** | -3.65 |
| RSCHRNL | 0.0691** | 5.35 |
| RSCOAG | 0.0117* | 2.47 |
| RSDEPRE | -0.0060 | -0.87 |
| RSDM | -0.0168 | -1.39 |
| RSDMCX | -0.0049 | -1.47 |
| RSDRUG | -0.0037 | -1.39 |
| RSHTN_C | 0.0474** | 3.53 |
| RSHYPOT | 0.0100 | 1.28 |
| RSLIVER | 0.0071 | 1.80 |

**Table 3** (*continued*)

| Variable Name | Coefficient | *t*-ratio |
|---|---|---|
| RSLYMPH | 0.0096** | 4.45 |
| RSLYTES | -0.0187 | -1.65 |
| RSMETS | 0.0165** | 3.96 |
| RSNEURO | -0.0029 | -0.53 |
| RSOBESE | 0.0018 | 0.48 |
| RSPARA | 0.0188** | 4.67 |
| RSPERIV | -0.0010 | -0.19 |
| RSPSYCH | -0.0144** | -2.80 |
| RSPULMC | 0.0051* | 2.22 |
| RSRENLF | 0.0142** | 2.97 |
| RSTUMOR | -0.0028 | -0.35 |
| RSULCER | -0.0024 | -0.90 |
| RSVALVE | -0.0007 | -0.16 |
| RSWGHTL | 0.0057 | 1.71 |
| TREND | 0.0314** | 12.58 |
| *Inefficiency Effects Variables* | | |
| Mu | -5.0029** | -18.96 |
| CAHCOUNT | 0.1655** | 13.60 |
| FP | -0.4894** | -5.07 |
| GOVT | 0.2606** | 7.86 |
| HERFINDAHL | 0.7303** | 9.66 |
| INCAH | 0.3129** | 8.10 |
| MEDICAID% | 0.0012 | 0.90 |
| MEDICARE% | -0.0046** | -6.96 |
| MEDINCOME | 0.0001** | 21.34 |
| MHMO% | -0.0827** | -5.86 |
| SYSTEM | -0.6902** | -6.93 |
| TREND2 | -0.0297** | -5.48 |

*Source*: Authors' calculations
$^{**}p < 0.01$; $^{*}p < 0.05$

Three of the product mix descriptors (OUTSURG%, ER%, and BIRTH%) had coefficients that were positive and significant ($p < 0.01$), as expected. The coefficient on the risk-adjusted in-hospital mortality rate for CHF (RPIQ16) was negative and significant ($p < 0.05$). This suggests that lower mortality rates are associated with higher costs, which might reflect the resources hospitals need to invest to improve patient outcomes.

Thirteen of the coefficients on the Comorbidity Software variables were statistically significant. Ten were of the expected, positive sign; however, three were of an unexpected, negative sign. We follow Mutter, Rosko, and

Wong (2008) in recognizing the high degree of multicollinearity among these variables; therefore, we do not assign much meaning to the signs of the coefficients. Instead, we include these variables to capture the variations in patient burden of illness that might otherwise be erroneously regarded as inefficiency.

The coefficient on the risk-adjusted iatrogenic pneumothorax rate (RPPS06) was positive and significant ($p < 0.01$), which indicates that the occurrence of this patient safety event is costly to these hospitals. Indeed, Zhan and Miller (2003) estimate that the occurrence of iatrogenic pneumothorax is associated with $17,312 in excess charges.

## Inefficiency Effects Variables

The estimated coefficients of the inefficiency-effects variables suggest that government hospitals tended to be more cost inefficient than nonprofit or investor-owned hospitals ($p < 0.01$). These findings are consistent with a number of recent findings in the literature. See Mutter and Rosko (2008) for a review of the theoretical and empirical literature on hospital ownership and inefficiency.

We find that higher county median income is associated with more cost inefficiency ($p < 0.01$). The coefficients on Medicare share and Medicare HMO penetration were negative and significant ($p < 0.01$). These findings are indicative of the impact that Medicare payment can have on hospital cost inefficiency. The positive coefficient for the Herfindahl-Hirschman Index ($p < 0.01$) suggests that increased competition is associated with less cost inefficiency. This finding is consistent with the literature that finds a persistence of price-based competition (McKay, Deily, and Dorner 2002/3). System membership was associated with reduced cost inefficiency ($p < 0.01$), consistent with results that find that this structural feature has operational benefits (Rosko 2001b).

We found that the cost-inefficiency estimates are negatively associated with a time trend ($p < 0.01$) but positively associated with participation in the CAH program and length of time in the CAH program ($p < 0.01$). The positive coefficient of the time-trend variable in the cost function suggests that rural hospitals (i.e., both CAH and nonconverting hospitals) have been adopting a more expensive technology (i.e., the best-practice cost frontier has shifted out). However, the time trend variable in the inefficiency effects variables (TREND2) has a negative coefficient. This suggests that these hospitals, in general, are moving closer to the BPF. Yet CAH facilities tend to be more inefficient (i.e., the coefficient for INCAH is positive), and they have been moving further away from the BPF the longer they receive cost-based reimbursement (i.e., the coefficient on CAHCOUNT is positive). Finally, the coefficient of CAHCOUNT is more than five times the size of the coefficient of TREND2. This indicates that longer participation in the CAH program is more than offsetting the trend of all rural hospitals moving closer to the BPF.

## Estimated Inefficiency

Table 4 presents the mean estimated cost inefficiency by year for all, CAH, and nonconverting facilities, respectively.

The mean inefficiency score was 11.53 percent for all study hospitals. However, CAH facilities had more cost inefficiency (15.93 percent) than the comparison group (10.34 percent). The mean estimated cost inefficiency of CAH facilities in the study period prior to entry in the CAH program was 10.44 percent, or about the same as the comparison group. These findings reflect the positive coefficient on INCAH.

For the CAH facilities, there was no discernable pattern in cost inefficiency from 1997 to 2000. In 2001, the mean cost inefficiency dipped to a yearly low of 13.41 percent and increased annually thereafter to 17.64 percent in 2004. The annual means for nonconverting hospitals were remarkably stable, ranging from 10.01 percent to 10.62 percent.

Perhaps the most remarkable trend is the positive association between cost inefficiency and the number of years in the CAH program, which reflects the positive coefficient on the CAHCOUNT variable. Table 5 presents mean cost inefficiency by the number of years in the CAH program.

Hospitals with only one year in the CAH program had a mean cost inefficiency of 13.33 percent, but with each extra year (up to seven years) in the program inefficiency increased, reaching a maximum of 21.85 percent. Those with eight or more years in the program had a mean inefficiency of 20.24 percent.

## Insights from Other Performance Measures

We estimated Pearson correlation coefficients between the SFA-derived cost inefficiency estimates and several commonly used hospital performance measures. These results are presented in table 6.

We found positive and significant ($p < 0.01$) coefficients for expense per AHA-adjusted admission and FTE personnel per AHA-adjusted admission in both groups of hospitals. We found a negative and significant cor-

**Table 4** Mean Inefficiency—All, CAH, and Nonconverting Rural Hospitals, by Year

| | All Hospitals | | | CAHs | | | Nonconverting Rural Comparison Hospitals | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | *N* | Mean | SD | *N* | Mean | SD | *N* | Mean | SD |
| 1997 | 543 | 0.1033 | 0.0620 | 12 | 0.1443 | 0.0668 | 531 | 0.1024 | 0.0616 |
| 1998 | 543 | 0.1036 | 0.0596 | 15 | 0.1412 | 0.0617 | 528 | 0.1025 | 0.0593 |
| 1999 | 543 | 0.1034 | 0.0579 | 17 | 0.1562 | 0.0870 | 526 | 0.1017 | 0.0560 |
| 2000 | 543 | 0.1110 | 0.0687 | 48 | 0.1609 | 0.1200 | 495 | 0.1062 | 0.0596 |
| 2001 | 543 | 0.1109 | 0.0961 | 110 | 0.1341 | 0.0729 | 433 | 0.1050 | 0.0904 |
| 2002 | 543 | 0.1168 | 0.0797 | 186 | 0.1489 | 0.1042 | 357 | 0.1001 | 0.0565 |
| 2003 | 543 | 0.1301 | 0.0877 | 242 | 0.1616 | 0.1069 | 301 | 0.1048 | 0.0572 |
| 2004 | 543 | 0.1430 | 0.1016 | 286 | 0.1764 | 0.1184 | 257 | 0.1058 | 0.0602 |
| All years | 4,344 | 0.1153 | 0.0794 | 916 | 0.1593 | 0.1067 | 3,428 | 0.1034 | 0.0654 |

*Source*: Authors' calculations
*Note*: CAH = critical access hospital; SD = standard deviation

**Table 5** Mean Cost Inefficiency by Years in CAH Program

| Year in CAH Program | *N* | Mean | SD |
|---|---|---|---|
| 1 | 278 | 0.1333 | 0.0868 |
| 2 | 238 | 0.1504 | 0.0976 |
| 3 | 185 | 0.1711 | 0.1101 |
| 4 | 110 | 0.1882 | 0.1276 |
| 5 | 48 | 0.1950 | 0.1256 |
| 6 | 16 | 0.1958 | 0.1108 |
| 7 | 15 | 0.2185 | 0.1166 |
| 8+ | 26 | 0.2024 | 0.1180 |
| All years | 916 | 0.1596 | 0.1067 |

*Source*: Authors' calculations
*Note*: SD = standard deviation

**Table 6** Pearson Correlations between SFA Cost-Inefficiency Estimates and Performance Measures

| Variable | All Hospitals | CAHs | Nonconverting Rural Comparison Hospitals |
|---|---|---|---|
| EXPENSE/ADJUSTED ADMIT | 0.473* | 0.407* | 0.480* |
| OPERATING MARGIN | -0.163* | -0.101* | -0.207* |
| FTE/ADJUSTED ADMIT | 0.298* | 0.248* | 0.270* |

*Source*: Authors' calculations
*Note*: SFA = stochastic frontier analysis; CAH = critical access hospital
*$p < 0.01$

relation between cost inefficiency and operating margin in both groups of hospitals. However, the magnitude of the correlation coefficient for cost inefficiency and operating margin was twice as large in the prospectively paid comparison group.

## Discussion and Conclusions

The correlation results for expense per AHA-adjusted admission and FTE personnel per AHA-adjusted admission serve to validate the SFA cost-inefficiency estimates. As expected, SFA-estimated cost inefficiency was positively associated with these two commonly used, albeit simple, measures of hospital inefficiency. We feel that these results, in conjunction with the differences in estimated inefficiency between CAHs and nonconverting, prospectively paid rural hospitals, suggest that CAHs tend to be more cost inefficient than non-CAH rural facilities.

It is possible that these differences could be a reflection of more cost-inefficient hospitals choosing to convert to CAH status. However, our methodology (a multiple time-series, study-group, comparison-group quasi-experimental design) not only compares CAHs to similar, prospectively paid rural hospitals but also compares CAH facilities to their previous, prospectively paid selves. This design was developed to control threats to validity posed by selection bias (Campbell and Stanley 1966). Moreover, we find that CAHs tend to become more cost inefficient over time, which argues against our results being driven entirely by selection bias. Plus, there are theoretical arguments (and historical evidence) for believing that prospective payment results in greater cost efficiency (Feder, Hadley, and Zuckerman 1987; Rosko and Broyles 1988).

Indeed, the negative correlation between SFA-derived cost inefficiency and operating margin in the non-CAH rural hospitals was expected. Medicare uses its DRG-based PPS to establish payment rates for these hospitals. Under PPS, hospitals with expenses less than the DRG payment rates earn a surplus, while hospitals with expenses greater than the DRG payment rates will suffer financial losses. Our results suggest that the more efficient (i.e., less cost-inefficient) nonconverting rural hospitals are rewarded financially.

Although the correlation coefficient between SFA-derived cost inefficiency and operating margin in the non-CAH rural hospitals was highly significant ($p < 0.01$), it was relatively small (-0.207). This suggests that, first, while there is a relationship between efficiency and profitability, a variety of factors, efficiency among them, ultimately determine a hospital's profitability. Second, since a hospital cost equation is, by necessity, an abstraction from reality, there is a limit to the accuracy of our inefficiency estimates. As a result, the true relationship between profitability and inefficiency may be obscured somewhat.

While it was also statistically significant, the correlation between cost inefficiency and operating margin was much smaller in the CAH sample (-0.101). These hospitals have a Medicare share of admissions of about 61 percent. (In comparison, nonconverting rural hospitals have a Medicare share of admissions of approximately 49 percent.) Medicare funds CAHs on a reasonable cost basis. Therefore, it is not surprising that CAHs did not feel strongly the financial repercussions for variations in cost inefficiency. If their costs increased, they would be paid more (within statutory limits).

While this study found that the CAH program was associated with increases in hospital cost inefficiency, an assessment of this program needs to be placed in a proper context. Common concerns about American hospitals are multidimensional and extend beyond inefficiency. Indeed, it is commonly believed that payment mechanisms should (1) increase efficiency, (2) preserve financial viability of efficient providers, (3) support access to high-quality care, and (4) make equitable payments.

The rationale for the development of the CAH program was that PPS did not adequately meet the second and third criteria for isolated hospitals. The mean Medicare PPS margin for rural hospitals was consistently negative for rural hospitals since 1985, with the exception of a few years in the mid-1990s prior to the Medicare cutbacks associated with the passage of the Balanced Budget Act of 1997 (Prospective Payment Advisory Commission [ProPAC] 1996; Medicare Payment Advisory Commission [MedPAC] 2000). Even when Medicare PPS payments to rural hospitals were relatively generous, many small rural facilities still faced severe financial pressures. For example, although the mean Medicare inpatient PPS margin was 5.2 percent for rural hospitals in 1998, 46.3 percent of rural hospitals with less than fifty beds had a negative margin. In contrast, in the same year only 28.9 percent of hospitals in all locations had a negative margin. Sixty-two percent of the converting hospitals were paid less than allowable inpatient costs in 1998, compared to just over one-third of other rural hospitals (Dalton et al. 2003).

Lack of profitability is a key determinant of hospital closure. In recent years, over twelve hundred facilities have converted to CAH status, where they have received generous payments, and closure rates of isolated hospitals have declined (MedPAC 2005). However, the rate of closure for rural hospitals was less in the 1990s than in the 1980s (Poley and Ricketts 2001). Therefore, it is difficult to determine the impact of the CAH program on closure, even though it improved the financial position (an important closure determinant) of these hospitals. Indeed, it should be noted that a direct link between conversion to CAH status and a reduced likelihood of hospital closure has not been formally established in the literature to our knowledge. However, the simulations performed by Stensland, Moscovice, and Christianson (2002) led them to predict that the greater payment generosity of the CAH program would result in fewer rural hospitals closing.

Regarding the third criterion, the implementation of the Medicare PPS was, in general, not associated with changes in quality (DesHarnais et al.

1987). However, the Medicare PPS may have had a deleterious impact on quality to the extent that it placed financial stress on isolated institutions. Encinosa and Bernard (2005) find that hospital financial distress is associated with increases in the rate of patient safety events. Moreover, hospital closure resulting from financial distress can also lead to access problems in isolated communities.

The terms "efficiency" and "efficient" appear in the first two criteria. Accordingly, it is important to examine the concept of efficiency in more detail. Conceptually, the most efficient health care provider is the one that increases health the most with the least expenditure of inputs. However, it is not technically feasible to validly estimate this type of efficiency as health status data are not compiled for the entire population. Consequently, when estimating efficiency, health services researchers examine the relationship between provider inputs and intermediate outputs, such as discharges and outpatient visits. Preferred estimation approaches control for the heterogeneity in the quality, type, and volume of outputs (Mutter, Rosko, and Wong 2008). While SFA is well suited to the estimation of this type of efficiency, it is not well designed to measure efficiency in the production of health. Thus, a comprehensive evaluation of the CAH program needs to go beyond our cost-inefficiency estimates and consider other factors as well.

It is important to consider nonprovider inputs to the process of producing health as well as externalities of the CAH program, such as its impact on providers in the local economy. Certainly, important inputs include those used to transport the patient to the provider. Since these are external to the provider, they are not included in the SFA calculations. In a densely populated urban setting, these may be relatively trivial, as many hospitals are nearby. In rural settings, closures may have a more pronounced impact on the health of individuals through increased opportunity costs that reduce access to care. For example, closure in a rural area has increased mean travel time by as much as thirty minutes. This can have a disproportionate impact on the most vulnerable population groups such as the elderly, poor, disabled, pregnant women, and small children (Bindman, Keane, and Lurie 1990; Hart, Pirani, and Rosenblatt 1991; Muus, Ludtke, and Gibbens 1995).

Research has associated closure with a perception of a loss of quality of life and health status (Hart, Pirani, and Rosenblatt 1991), increases in the waiting time for routine medical care, decreases in medication compliance (Bindman, Keane, and Lurie 1990), and decreases in hospital admission rates by community residents without any potentially compensating increases in physician visits (Rosenbach and Dayhoff 1995). Over 75 percent of the residents of a North Dakota community in which a hospital closed reported that diminished access to emergency care was a problem for them and 17 percent indicated that they or a family member had decided not to seek needed medical attention on one or more occasions because of inconvenience (Muus, Ludtke, and Gibbens 1995).

Closure can also adversely impact the economic health of a community through effects both direct (i.e., loss of jobs in the hospital) and indirect (i.e., loss of jobs among hospital suppliers and others through an economic multiplier effect). Indeed, G. M. Holmes and colleagues (2006) find that rural hospital closure can lead to increases in local community unemployment and decreases in income per capita. They estimate that the closure of the only hospital in a rural community is associated with a 4 percent reduction in per capita income and a 1.6 percent increase in the unemployment rate. Earlier studies also estimated large economic impacts for rural hospital closures (Christianson and Faulkner 1981; McDermott, Cornia, and Parsons 1991).

McNamara (1999) used a discrete-choice, travel-cost model of hospital choice (i.e., the value of avoiding having to travel the extra distance to the second nearest hospital) to estimate the value of hospital services delivered in a given community. The analysis calculated a compensating variation (CV), which is the amount of income that would make an individual indifferent between the set of alternatives and prices before the policy change and after the policy change were estimated. The simulation based on closing the nearest rural hospital (mean distance traveled was nine miles), with the second nearest hospital being on average twenty-five miles away, resulted in an estimated CV of $19,500 per sample hospitalization. McNamara argues that retaining a very limited hospital facility in a rural community appears to have the effect of greatly reducing welfare losses. However, all rural hospitals were not in danger of closure. Thus, a complete assessment of the value of preventing closures should consider the reduction in the probability of closure. This analysis has not been performed but would inform the debate on the efficacy of special financing provisions for rural hospitals.

To put the impact of CAH cost-based reimbursement on increased hospital costs in perspective, we multiply mean expenditures of CAH facilities ($8,145,584) times 5.6 percent (i.e., the difference in efficiency estimates between CAH and nonconverting hospitals) to arrive at an amount less than $600,000. Given the potential impact of hospital closure on the health of individuals and the local economies, this might be a worthwhile expenditure. In addition to this, CAH conversion has been associated with better health outcomes (Li, Schneider, and Ward 2007), a result probably due to the ability of CAH facilities to use their increased cash flow to engage in quality improvement and quality assurance activities. However, the impact of closure is mitigated by the proximity of alternative hospitals and other providers. It is not clear that the closure of the 151 CAHs (17 percent) that are located fifteen road miles or less from another hospital (MedPAC 2005) would have a substantial impact on access to high-quality care.

The fourth criterion requires that payments be similar for services that cost the same. Single-payer programs, like Medicare, allow cost shifting and do not fare well with respect to this criterion (Rosko 1989). Further, MedPAC (2005) expressed the concern that Medicare will have over twelve hundred CAHs that receive higher payment rates than PPS hospitals that compete with them. The problem of the nonlevel playing field exists primarily because CAHs are allowed to be in close proximity to other hospitals.

While it would be desirable to develop a payment mechanism that leads to improvements in efficiency, access, and quality, experience throughout the world shows that trade-offs are probably necessary. In the short term, we believe that, given the potentially devastating effects of hospital closure in isolated communities, the CAH program has achieved a reasonable balance among these three overarching objectives. However, our results, which suggest that inefficiency is increasing with length of participation in the CAH program, raise concern that in the future too much inefficiency may be spawned by cost-based reimbursement of rural hospitals. Accordingly, we urge that their cost and efficiency trends be monitored. Further, we call for more research on (1) the impact of the CAH program on quality and financial viability (especially a more precise estimate of the program's impact on the reduction of the probability of hospital closure) of participating hospitals, (2) the external opportunity costs of closure, especially of hospitals located within fifteen miles of another facility, and (3) the feasibility and potential impact of alternative payment mechanisms (i.e., modified PPS or modified cost-based payments) to increase efficiency without harming financial viability, access, and quality.

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