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Characteristics of High- and Low-Efficiency Hospitals

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Abstract

We compared performance, operating characteristics, and market environments of low- and high-efficiency hospitals in the 37 states that supplied inpatient data to the Healthcare Cost and Utilization Project from 2006 to 2010. Hospital cost-inefficiency estimates using stochastic frontier analysis were generated. Hospitals were then grouped into the 100 most- and 100 least-efficient hospitals for subsequent analysis. Compared with the least efficient hospitals, high-efficiency hospitals tended to have lower average costs, higher labor productivity, and higher profit margins. The most efficient hospitals tended to be nonteaching, investor-owned, and members of multihospital systems. Hospitals in the high-efficiency group were located in areas with lower health maintenance organization penetration and less competition, and they had a higher share of Medicaid and Medicare admissions. Results of the analysis suggest there are opportunities for public policies to support improved efficiency in the hospital sector.

Keywords

hospital efficiency, stochastic frontier analysis, hospital quality, patient safety

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Introduction

The United States health care system is the most expensive in the world, spending more than 17.5% of gross domestic product on health care in 2014 (Martin, Hartman, Benson, Catlin, & The National Health Expenditure Accounts Team, 2016). Despite spending so much, the U.S. appears to underperform relative to other developed countries on most dimensions of performance. Among the 11 nations studied in a 2014 report by The Commonwealth Fund, the United States ranked last or near last on dimensions of costs, outcomes, access, and efficiency (Davis, Stremikis, Squires, & Schoen, 2014). After five consecutive years of historically low growth, U.S. health care spending increased 5.3% to $3.0 trillion in 2014.

The faster growth was related to Medicaid and private insurance expansions under the Affordable Care Act (Martin et al., 2016).

A recent study projects that expenditures will increase in the future as the economy improves and the impact of the Affordable Care Act is felt more strongly (Sisko et al., 2014). Separate analysis supports the position that the economic slowdown had a major impact on the decline in health care spending (Dranove, Garthwaite, & Ody, 2014).

While it might be relatively easy to address one of the three critical issues (i.e., cost, access, and quality) confronting the U.S. health care system, dealing with one problem without exacerbating the other two is a daunting challenge. A promising avenue is to increase efficiency (i.e., the maximization of outputs, quality of care, and outcomes given the resources committed), while ensuring that additional investments yield net value over time (Davis et al., 2014). This would stretch existing resources and allow the production of more or better services without incurring new costs. With this in mind, U.S. policy officials have expanded payment schemes to include incentives for increased efficiency. However, there is a concern that the incentives may be too modest to trigger substantial changes in efficiency (Frandsen & Rebitzer, 2015).

In 2014, hospital care comprised approximately 32% of U.S. national health expenditures (Centers for Medicare & Medicaid Services [CMS], 2016). Improving efficiency in the hospital sector, therefore, may be a promising approach to addressing the critical issues confronting the U.S. health care system.

New Contributions

This is the first study based on stochastic frontier analysis (SFA) to contrast the characteristics of high-efficiency and low-efficiency hospitals across most of the nation. In 2015, the Medicare Hospital Value-Based Purchasing Program added efficiency as an important domain (i.e., 25% weight) in this incentive scheme. Our results may give insights about potential winners and losers under this new program. While it is common for SFA-based hospital studies to examine the correlates of efficiency, this study included a wider variety of variables than any previous study and found a relationship between efficiency and hospital profit margin. Our analysis of variables associated with hospital efficiency level found a number of factors, such as hospital competition, system membership, and public payer share, which are associated with high-efficiency hospitals and which can be influenced by public policy.

Data and Method

Stochastic Frontier Analysis

There are two broad ways in which hospital efficiency has been measured. One is a reliance on relatively simple metrics that have been used frequently in the health care industry. These consist of ratios, such as cost per case-mix-adjusted hospital admission, employees per patient day, or risk-adjusted length of stay. These measures suffer from a number of drawbacks, including (1) failure to reflect the multi-input/multi-output nature of hospitals and (2) use of an arbitrary definition of efficiency (i.e., typically the median or some percentile has been used as the efficiency standard, but the choice of benchmark has been strictly arbitrary; Mortimer & Peacock, 2002; Rosko, 1990).

Frontier analytical techniques were developed as methods to overcome the shortcomings of ratio-based measures. The leading frontier techniques are data envelopment analysis (DEA) and SFA (Coelli, Rao, O'Donnell, & Battese, 2005). Both use methodologies that can accommodate multiple inputs and outputs to arrive at a global measure of efficiency. SFA is a regression-based method, and DEA relies on linear programming. Essentially, given a hospital's mix of inputs and outputs, a best practice frontier (BPF) is estimated by the application of DEA or SFA. Inefficiency is calculated by a distance function (from the BPF), obviating the need for arbitrary efficiency assignments.

A preference for SFA or DEA has not been established in the hospital efficiency estimation literature, and it is unlikely that such a consensus will occur. SFA was developed in response to concerns that in DEA all departures from the BPF are assumed to represent inefficiency. Therefore, random events and measurement errors may be confused with inefficiency. In contrast, SFA accounts for statistical noise and random events. On the other hand, SFA has been criticized for its strong assumptions about the form of the cost function and the distribution of the error term (Newhouse, 1994). However, these concerns are assuaged by findings not only in the general literature (Coelli et al., 2005; Greene, 2008) but also in the health care literature (Jacobs, Smith, & Street, 2006; Rosko & Mutter, 2008; Zuckerman, Hadley, & Iezzoni, 1994) that SFA results are stable across assumptions about the distribution of the error term. Furthermore, health care researchers have found that cost-inefficiency estimates are not very sensitive to assumptions about the structure of the cost function (Folland & Hofler, 2001; Rosko & Mutter, 2008; Zuckerman et al., 1994).

Frontier experts suggest that the choice of technique should be context specific (i.e., based on the goals of the analysis and the availability of data; Coelli et al., 2005). In the general literature, comparisons of efficiency results generated by SFA and DEA range from highly similar to very divergent (Greene, 2008). The concordance of results from SFA and DEA increases with the use of higher quality data (Fried, Lovell, &

Schmidt, 2008). Given the availability of a rich data set that allows us to control output heterogeneity (both patient burden of illness and quality), we chose to use SFA for this analysis.[1]

Zuckerman et al. (1994) published the first analysis of the cost-efficiency of U.S. hospitals using SFA. Rosko and Mutter (2011) reviewed the results from 27 U.S. hospital SFA studies. Consistent with most hospital applications, we use a cost-orientation (Rosko & Mutter, 2008). The alternative to this is a production orientation, which would measure technical inefficiency. This is difficult to use for multiproduct organizations like hospitals. It would require a composite output measure as the dependent variable. This would be difficult if not impossible to validly construct. In contrast, cost-inefficiency SFA models can include multiple outputs and multiple product descriptors as independent variables.

SFA decomposes variations from the BPF into a random or classical error and a deterministic error, which is assumed to represent cost-inefficiency. SFA studies of hospitals typically use a model that includes cost function variables and inefficiency-effects variables. The cost function variables are used to estimate a BPF (i.e., where a completely efficient hospital would operate given its input prices and outputs). The inefficiency-effects variables locate a hospital with respect to the cost frontier on the basis of correlates of cost-inefficiency.

Our departure point for the estimation of the BPF is the neoclassical cost function which assumes that total expenses depend upon input prices and output volumes. Recognizing that outputs, such as admissions, are heterogeneous, it is important to control variations in input requirements for different types of admissions by including product descriptor variables that reflect differences in services, patient case mix, and hospital quality. Following theory (Kumbhakar & Lovell, 2000) and the hospital literature (Grannemann, Brown, & Pauly, 1986; Rosko & Mutter, 2014), we use the following hybrid cost function:

$$TC_{it} = f\left(Y_{it},\ W_{it}, PD_{it}\right)\ +\ e_{it} \tag{1}$$

where TC represents total costs; Y is a vector of outputs; W is a vector of input prices; PD is a vector of product descriptors; i and t are the respective indexes for the hospital being observed and the year when the observation was made, and e is the error term, which can be decomposed as follows:

$$e_{it} =\ v_{it} +\ u_{it} \tag{2}$$

where v is statistical noise (i.e., assumed to be distributed as $N(0, \sigma^2)$), and u consists of positive departures from the cost-frontier and represents cost-inefficiency (i.e., the percentage by which observed costs exceed minimum costs predicted for the best practice cost frontier) (Lovell, 1993).

It is important to control for heterogeneity in conducting hospital SFA studies because variations in the amount or type of inputs required to care for patients could otherwise be confused with inefficiency (Greene, 2004; Rosko & Mutter, 2008). For example, without adjustment for case-mix intensity, the cost-inefficiency of academic medical centers would be systematically overstated. Mutter, Rosko, and Wong (2008) demonstrated the importance of controlling for quality and patient burden of illness in studies of hospitals using SFA. In their review of hospital SFA studies, Rosko and Mutter (2008) found that output heterogeneity is usually controlled by including product descriptor variables for quality and for case-mix. The former include structural measures, such as teaching activities, and risk-adjusted outcomes, while the latter include a variety of inpatient and outpatient case-mix measures.

Research Design and Methods

Data Sources

The cost-efficiency estimation in this study is based on panel data of 1,586 U.S. short-term, urban acute care hospitals for the period 2006 to 2010 (t = 5). Since it was critical to control for heterogeneity by including patient burden of illness variables and in-hospital outcome measures of quality in the model, the study was restricted to the 37 states[2] for which the State Inpatient Databases (SIDs)[3] were available through the Healthcare Cost and Utilization Project (HCUP)[4] for the entire study period. A balanced panel was used. We restricted the study to urban areas because rural areas might face different market conditions and because previous work (Folland & Hofler, 2001; Zuckerman et al., 1994) found that it would be inappropriate to pool urban and rural hospitals because their cost structures differ.

The primary source for hospital-level data were the American Hospital Association (AHA) Annual Survey of Hospitals. Medicare Hospital Cost Reports were used to calculate the price of capital and the percentage of acute care beds. The Medicare Case-Mix Index came from the CMS. Health maintenance organization (HMO) penetration at the county level came from Thomson Reuters. AHA data were used to calculate a Herfindahl-Hirschman Index (HHI) to reflect hospital competition at the county level.

Model Specification

Following the methods of Rosko and Mutter (2014), a hybrid translog cost function was employed in the analysis. The general form of the translog cost model was used to estimate the stochastic frontier for U.S. hospitals. It can be expressed as follows:

$$\begin{aligned}\ln TC_{it} = a_0 + \sum_{j=1}^{J} a_j \ln Y_{jit} + \sum_{k=1}^{K} \beta_k \ln W_{kit} + .5 \sum_{j=1}^{J}\sum_{l=1}^{J} \delta_{jl} \ln Y_{jit} \ln Y_{lit} \\ + .5 \sum_{k=1}^{K}\sum_{m=1}^{K} \gamma_{km} \ln W_{kit} \ln W_{mit} + \sum_{j=1}^{J}\sum_{k=1}^{K} \rho_{jk} \ln Y_{jit} \ln W_{kit} + \sum_{r=1}^{R} \eta_r PD_{rit} + v_{it} + u_{it}\end{aligned} \qquad (3)$$

where *TC, Y, W, PD, v*, and *u* are the variables described above; *J* is the number of output variables; *K* is the number of price variables; *R* is the number of product descriptor variables; and α, β, δ, γ, η, and ρ are parameters to be estimated.

To estimate hospital-specific inefficiency, we used a time-varying model proposed by Battese and Coelli (1995). In this model the inefficiency effects are defined by

$$u_{it} = \sum_{n=1}^{N} \kappa_n Z_{it} + w_{it}, u_{it} \geq 0 \tag{4}$$

where Z_{it} is a vector of explanatory variables associated with the inefficiency-effects; κ is a vector of unknown parameters to be estimated; and w_{it} are unobservable random variables assumed to be independently distributed with mean zero and unknown variance, σ^2.

The parameters of the cost frontier and the inefficiency effects variables were simultaneously estimated by a maximum likelihood method using the FRONTIER 4.1c program (Coelli, 1996). The cost efficiency of the *i*th hospital in the *t*th year is defined as the ratio of the estimated stochastic frontier total costs to observed total costs. The stochastic total cost frontier is defined by the value total costs would be if the hospital was fully efficiency. Battese, Heshmati, and Hjalmarsson (2000) show that

$$CE_{it} = \exp\left(-u_{it}\right) \tag{5}$$

where CE_{it} = cost efficiency, and u_{it} was defined previously. The amount by which $\exp(u_{it})$ exceeds 1 is a measure of cost-inefficiency.

Cost Function Variables

The standard assumption of linear homogeneity in input prices was imposed by normalizing the equation by the wage rate. The dependent variable is the logarithm of total expenses divided by the wage rate. The continuous output and input price variables are log-transformed. Inpatient admissions (a proxy for discharges), postadmission days (i.e., total inpatient days minus total admissions), and outpatient visits are included as outputs in the cost function. Hospital outputs were treated as exogenous, an assumption common to hospital cost studies (Grannemann et al., 1986, Rosko & Mutter, 2014).

Two inputs, labor and capital, are included in the cost function. The price of labor was approximated by the area average annual salary per full-time-equivalent employee, and the price of capital was approximated by depreciation and interest expenses per bed. For both inputs, the average price was computed for all short-term general hospitals in the Core Based Statistical Area in which the study hospital was located. A more complete specification of input prices would be desirable. However, given the relatively poor quality of input price information, we followed past practices (Grannemann et al., 1986; Rosko & Mutter, 2014; Zuckerman et al., 1994) and used this limited set of price variables.

To control variations in output, a variety of product descriptor variables were employed. These variables included the following: the Medicare Case-Mix Index, the ratio of outpatient surgeries to total outpatient visits, the ratio of emergency department visits to total outpatient visits, the ratio of births to total admissions, and the ratio of beds classified as acute care to total hospital beds. These variables are consistent with the model employed by Rosko and Mutter (2014). All these reflect severity case-mix and the first four are expected to have positive coefficients. The absence of publicly available case-mix indices for outpatient care necessitated the use of proxies for this measure. While the Medicare Case-Mix Index has been shown to be highly correlated with the overall case-mix index of hospitals, we included the ratio of births to total admissions to reflect one dimension of case-mix among the non-Medicare population. Since some hospitals serve a mixture of acute care and nonacute care patients, we included the proportion of total hospital beds classified as acute care to reflect patients who would not be included in the DRG-based Medicare Case-Mix Index. Teaching status was incorporated by the use of binary variables for academic medical centers (i.e., member of the Council of Teaching Hospitals) and other teaching hospitals. Nonteaching hospital is the omitted reference category. In addition to these variables, 29 log-transformed comorbidity variables measuring the rates of those comorbidities per discharge at the hospital level were also included (Elixhauser, Steiner, Harris, & Coffey, 1998). The comorbidity variables were identified by the application of the Comorbidity Software to HCUP data and control for patient burden of illness.[5] Mutter, Rosko, and Wong (2008) found that without these controls, differences in patient burden of illness can masquerade as hospital inefficiency.

To control for patient safety and inpatient quality, we included four risk-adjusted, hospital-level measures of patient safety from the application of Version 3.2a of the Agency for Healthcare Research and Quality Patient Safety Indicator (PSI) software to the SID: rates of failure to rescue, iatrogenic pneumothorax, infection due to medical care, and accidental puncture/laceration. We included five risk-adjusted, hospital-level measures of inpatient quality from Version 3.2a of the Agency for Healthcare Research and Quality Inpatient Quality Indicator (IQI) software applied to the SID: rates of in-hospital mortality for acute myocardial infarction, congestive heart failure, stroke, gastrointestinal hemorrhage, and pneumonia. To maintain an adequate sample size, we selected IQIs and PSIs that had nonzero denominators for at least 1,500 hospitals per year and which were not among the PSIs found to have a high percentage of events that were present on admission (Houchens, Elixhauser, & Romano, 2008). The IQIs and PSIs were transformed by taking their square root since some hospitals had a value of zero for those variables (Mutter, Wong, & Goldfarb, 2008).

We included a measure of reservation quality in the cost function. The use of reservation quality is consistent with the premise that all empty beds are not waste (Folland & Hofler, 2001). Rather, they provide a safety margin for surges in demand. The use of this variable may reduce a potential bias against small hospitals that typically experience greater variability in inpatient utilization (Folland & Hofler, 2001). We followed Joskow's (1980) method of calculating reservation quality by dividing the difference between total beds and average daily census by the square root of average daily census. We also included a time trend in the cost function.

Inefficiency Effects Variables

Consistent with Rosko and Mutter (2014), we included a vector of inefficiency effects variables drawn from X-inefficiency theory (Leibenstein, 1987) and a review of hospital SFA studies (Rosko & Mutter, 2011). To control for the effect of ownership form on inefficiency, binary variables (1/0) for investor-owned hospitals and public hospitals were used. Not-for-profit hospitals served as the omitted reference category. Variables for Medicare share of admissions and Medicaid share of admissions were used to reflect fiscal pressures associated with public payers. Since a number of SFA studies have shown that hospitals belonging to multihospital systems are more efficient than freestanding hospitals (Rosko & Mutter, 2011), system membership was entered as a binary variable (1/0). HHI was used to reflect competitive pressures. It was calculated by summing the squares of the market shares of admissions for all of the general acute care hospitals in the county. In this calculation, hospitals in the same health care system in the same county were treated as the same producer. This index takes on a value of 1 in monopolistic markets and approaches 0 as output is dispersed among more firms. Thus, higher values reflect less competitive pressure. If service-based competition is being practiced, then cost-inefficiency should be greater in more competitive markets.

While there is some debate about the appropriate way to measure hospital competition, Wong, Zhan, and Mutter (2005) found that inferences about the effect of competition on hospital cost remain the same when alternative hospital competition measures are employed. As a simple robustness check, we reestimated our model using an HHI based on a Health Referral Region (HRR) definition of the market. We found that when the HRR was used the mean value of the HHI decreased from 0.419 to 0.268. This was expected as the geographic area of the HRR is much larger than the county and typically includes more hospitals. The two HHIs were moderately correlated (r = .404). However, the substitution of the HRR-based HHI had virtually no impact on results—that is, the mean cost-inefficiency score decreased from 89.5% to 89.3% and the hospital-level cost-efficiency scores were very highly correlated—that is, r = .992.

HMO penetration, defined as the percentage of the population in the county that is enrolled in HMOs, reflects the financial pressures exerted by managed care organizations. Rosko and Mutter's (2011) review of SFA studies found that HMO penetration rate is usually positively associated with hospital cost-efficiency. However, other results were found in a few studies. The final control variable is time trend (equal to 1 in 2006, equal to 2 in 2007, etc.). This variable allows time-varying efficiency. In contrast, the trend variable in the cost function permits a neutral shift in the cost frontier. Descriptive statistics are provided in Table 1.

Our final cost-inefficiency estimation model was based on the results (all significant at $p < .01$) of a number of likelihood ratio tests (Greene, 2011). As result of the tests, we used SFA (instead of ordinary least square), a translog cost function (instead

Table 1. Variable Names and Descriptive Statistics.

Variable name	Mean	SD
Cost function variables		
Total expenses (normalized by wage rate)	$2,400,885	$2,430,527
Inpatient admissions	14,818	10,816
Outpatient visits	230,729	260,457
Post-admission days	61,302	52,913
Price of capital (normalized by wage rate)	$565.4703	139.5620
Acute care beds as a percentage of total beds in hospital	88.9384	13.2374
Births as a percentage of total admissions in hospital	11.8449	7.8905
Emergency department visits as a percentage of total outpatient visits in hospital	29.2925	16.6631
Medicare Case-Mix Index	1.4866	0.2245
Member of the Council of Teaching Hospitals (COTH) (binary variable 1,0)	0.1415	0.3485
Other teaching hospital (binary variable equals 1 if hospital has medical residents but is not a member of COTH)	0.4047	0.39502
Outpatient surgical operations as a percentage of total outpatient visits in hospital	4.1816	3.5525
Reservation Quality	6.8434	3.3381
Inefficiency-effects variables		
Government, nonfederal hospital (binary variable 1,0)	0.1086	0.3111
Herfindahl-Hirschman Index	0.4199	0.2768
HMO penetration rate in county	24.5042	13.3577
Investor-owned hospital (binary variable 1,0)	0.1653	0.3715
Medicaid admissions as a percentage of total admissions in hospital	18.2206	9.7866
Medicare admissions as a percentage of total admissions in hospital	43.2106	10.1435
Member of multihospital healthcare system (binary variable 1,0)	0.6900	0.4625
Control variables for outcomes		
Risk-adjusted inpatient mortality rate for acute myocardial infarction	0.0569	0.0280
Risk-adjusted in-hospital mortality rate for congestive heart failure	0.0309	0.01510.0493
Risk-adjusted inpatient mortality rate for stroke	0.08190	0.0362
Risk-adjusted inpatient mortality rate for gastrointestinal hemorrhage	0.0215	0.0132
Risk-adjusted in-hospital mortality rate for pneumonia	0.0348	0.0155
Risk-adjusted failure to rescue rate	0.1221	0.0696
Risk-adjusted iatrogenic pneumothorax rate	0.0006	0.0005
Risk-adjusted infection due to medical care rate	0.0012	0.0014
Risk-adjusted accidental puncture/laceration rate	0.0023	0.0012

of Cobb-Douglas), and assumed the composed error followed a truncated-normal distribution (instead of half-normal). The results also suggest that the inefficiency-effects variables as a group have significant explanatory power. The hospitals in the sample were placed in top and bottom 100 most and least efficient groups based on estimated cost-efficiency in 2010.[6] The mean estimated cost-efficiency (with ranges in parentheses) for the two groups of hospitals was as follows: (1) high efficiency: 96.79% (98.22% to 96.29%) and (2) low efficiency: 69.18% (78.12% to 26.66%).

Results

Parameter estimates for the SFA cost frontier model are presented in Table 2. Some of the output variables have negative coefficients and some have insignificant coefficients. This is due to the multi-collinearity caused by the inclusion of the squared and cross-product terms. When a Cobb-Douglas cost function was estimated by removing the higher-order output variables, all of the coefficients of the output variables had the expected positive sign and were significant ($p < .01$). The reader should note that multi-collinearity can cause the estimated parameters to become less reliable but it does not introduce a bias. All the product descriptor variables had positive and significant coefficients. Seventeen of the 29 comorbidity variables had significant coefficients ($p < .05$). Ten of these had positive coefficients. To control for patient outcomes, we used nine risk-adjusted mortality and patient safety events variables. Three of these had positive and significant ($p < .05$) parameter estimates and one (risk-adjusted infection) had a negative and significant coefficient. Finally, we found that reservation quality and the time trend had significant coefficients—the former positive and the latter negative. These results indicate that reservation quality (i.e., standby capacity that protects against surges in demand) is expensive and that the growth in total expense, while holding all the other regression variables constant, has been declining since 2006.

Parameter estimates for the SFA inefficiency-effects variables are presented in Table 3. As a simple robustness test we also estimated an SFA model in which the HHI based on the county as the market area was replaced by an HHI based on the Health Referral Region. These results are provided in Table 3. An inspection of these results indicates that the signs and levels of significance of the inefficiency-effects variables were unaffected (except that the p value for Medicare share of admissions changed from $p < .01$ to $p < .02$) by the change in the HHI variable. The changes in the values of the coefficients of all the inefficiency-effects variables were modest. This is not surprising, however, as mentioned earlier, the hospital level cost-efficiency scores obtained by the two versions of the HHI were very highly correlated. Additional assessments of robustness, presented in Appendix A, involving (a) choice of cost function, (b) assumptions about the distribution of the composed error, (c) inclusion and exclusion of variables suggest that, in general, results are stable across models except for conclusions about Medicaid share of admissions and other teaching status.

All the estimates, except for Medicaid share of admissions in both models and Medicare share of admissions ($p < .02$) in the alternate model were significant at $p <$

Table 2. Parameter Estimates for the Stochastic Frontier Analysis Cost Frontier Model (Translog With Truncated-Normal Residual, *n* = 7,930; 2006-2010 Panel).

Variable name	Coefficient	*t* ratio
Constant	12.7447	12.8993*
Ln(Inpatient admissions)	0.1498	0.5684
Ln(Outpatient visits)	0.2068	2.1090**
Ln(Post-admission days)	−0.2570	−1.1338
Ln(Price of capital)	−1.5676	−5.7439*
Ln(Price of capital-Squared)	0.3002	6.5262*
Ln(Inpatient admissions-squared)	−0.2098	−7.2597*
Ln(Outpatient visits-squared)	−0.0164	−2.2430**
Ln(Postadmission days—squared)	−0.0782	−3.4172*
Ln(Inpatient admissions * Outpatient visits)	0.0920	3.7251*
Ln(Inpatient admissions * Postadmission days)	0.3641	8.1707*
Ln(Outpatient visits * Postadmission days)	−0.0630	−3.0692*
Ln(Price of capital * Inpatient admissions)	−0.0399	−1.0579
Ln(Price of capital * Outpatient visits)	0.0170	1.2337
Ln(Price of capital * Postadmission days)	0.0071	0.2211
Acute care beds as a percentage of total beds in hospital	0.0008	3.3103*
Births as a percentage of total admissions in hospital	0.0008	2.1170**
Emergency department visits as a percentage of total outpatient visits in hospital	0.0008	3.9189*
Medicare case-mix index	0.4527	29.6052*
Member of the Council of Teaching Hospitals	0.1375	15.0186*
Other teaching hospital	0.0581	11.0044*
Outpatient surgical operations as a percentage of total outpatient visits in hospital	0.0119	13.9410*
AIDS/HIV	−0.0053	−2.7116*
Alcohol abuse	−0.0023	−0.2574
Blood loss anemia	0.0078	1.6602
Chronic pulmonary disease	−0.0280	−1.8543
Coagulopathy	0.0497	5.7741*
Congestive heart failure	−0.1074	−10.2622*
Deficiency anemias	−0.0529	−4.9750*
Depression	0.0790	9.1630*
Diabetes, uncomplicated	0.2590	15.5050*
Diabetes, complicated	−0.0503	−5.8024*
Drug abuse	0.0040	0.6145
Fluid and electrolyte disorders	−0.0166	−1.2663
Hypertension	−0.0446	−1.6166
Hypothyroidism	−0.0625	−4.9367*
Liver disease	−0.0151	−2.1296**
Lymphoma	0.0195	2.6683*
Metastatic cancer	0.0530	5.7695*

(continued)

Table 2. (continued)

Variable name	Coefficient	*t* ratio
Obesity	−0.0147	−1.9382
Other neurological disorders	−0.0268	−1.7785
Paralysis	0.0126	1.8258
Peptic ulcer disease, excluding bleeding	0.0025	1.0279
Peripheral vascular disease	−0.0605	−6.8046*
Psychoses	0.0028	0.3848
Pulmonary circulation disorders	0.0112	2.0982*
Renal failure	0.0059	0.5378
Rheumatoid arthritis	0.0593	5.6004*
Solid tumor without metastasis	0.0222	2.2722**
Valvular disease	0.0195	2.9491*
Weight loss	0.0114	2.4145**
Square root (Risk-adjusted inpatient mortality rate for acute myocardial infarction)	0.0012	0.0346
Square root (Risk-adjusted in-hospital mortality rate for congestive heart failure)	0.0159	0.2997
Square root (Risk-adjusted inpatient mortality rate for stroke)	0.1030	3.1922*
Square root(Risk-adjusted inpatient mortality rate for gastrointestinal hemorrhage)	−0.0436	−1.0890
Square-root (Risk-adjusted in-hospital mortality rate for pneumonia)	−0.0320	−0.5788
Square-root (Risk-adjusted failure to rescue rate)	−0.0253	−1.2121
Square-root (Risk-adjusted iatrogenic pneumothorax rate)	0.4288	2.2575*
Square-root (Risk-adjusted infection due to medical care rate)	−0.1840	−2.1955**
Square-root (Risk-adjusted accidental puncture/laceration rate)	0.6398	3.7349*
Reservation Quality	0.0073	11.0943*
Time-Trend	−0.0124	−4.9582*

*$p < .01$. **$p < .05$.

.01. Consistent with expectations, the coefficients of the variables for investor-owned hospitals, Medicaid share of admissions and system membership were negative, suggesting that these factors are associated with less cost-inefficiency. Furthermore, the coefficient on the HHI was also negative; suggesting that concentration of output (i.e., less competition) is associated with less cost-inefficiency. This result is consistent with service-based competition (Rosko, 2001). The coefficient of the government hospital variable was positive and suggests public hospitals are more inefficient than their private counterparts. Contrary to expectations, HMO penetration rate had a positive coefficient. Dugan (2015) suggests that the ability of HMOs to control costs has waned in the past decade. The significant coefficient of MU[7] supports the assumption of a truncated-normal distribution for the inefficiency term. Similarly, the significant coefficient on gamma supports the use of SFA over ordinary least square and indicates that

Table 3. Parameter Estimates for the Stochastic Frontier Analysis Inefficiency-Effects Variables.

Variable	Coefficient	*t* ratio	Coefficient	*t* ratio
MU	−0.7928	−6.1594*	−0.5901	−7.6428*
Government Hospital	0.1351	5.6460*	0.1012	4.4769*
Herfindahl-Hirschman Index (County as market definition)	−0.2639	−6.9016*	—	—
Herfindahl-Hirschman Index (HRR as market definition)	—	—	−0.2832	3.6886*
HMO Penetration Rate	0.0118	9.0588*	0.0098	10.3109*
Investor-owned Hospital	−0.9611	−20.7196*	−0.9143	−17.4620*
Medicaid Share of Patients	0.0008	0.8760	−0.0002	−0.2075
Medicare Share of Patients	−0.0040	−3.9558*	−0.0052	−2.4816**
System-Member	−0.0477	−3.6347*	−0.0375	−2.8193*
Time-Trend	0.0730	7.6560*	0.0724	4.4144*
γ	0.7142	32.9951*	0.6759	15.5732*

Note. HRR = Health Referral Region. While the parameters of the cost function and inefficiency-effects variables were estimated simultaneously, we place the results in separate tables for ease of exposition.
*$p < .01$. **$p < .05$.

in this sample over 71% of the total error term was due to the deterministic error that represents cost inefficiency. Finally, the positive coefficient of the time-trend inefficiency effects variable suggests that hospitals have been moving away from the best practice cost frontier during the study period.

High- and Low-Performing Hospitals Comparisons

Productivity and Expenses

High-efficiency hospitals differ from low-efficiency hospitals in many dimensions including: costs and productivity, operating characteristics, market characteristics and profitability. Mean values for these are summarized in Table 4. The group means were significantly different at $p < .01$ for every variable except for other teaching hospital ($p < .03$) and Medicaid share of admissions ($p < .08$).

High-efficiency hospitals had greater labor productivity (i.e., admissions adjusted for outpatient activity and case-mix divided by FTE employees) than low-efficiency hospitals (31.07 vs. 18.86). The productivity differential partially explains the large difference in average expenses per admission in the two groups ($11,023 vs. $30,231). A more telling comparison would adjust expenses for case-mix and differences in outpatient activity.[8] Expense per admission adjusted for Medicare case-mix and relative outpatient activity was $4,500 and $10,706 in the high- and low-efficiency hospitals, respectively. While the adjustments reduced the absolute differences between the group mean substantially, the relative difference between the groups remained high

Table 4. Mean Characteristics of 1,586 Short-Term General Hospitals, by Efficiency Group, 2010.

	High-efficiency hospitals	Low-efficiency hospitals
Variables	Top 100	Bottom 100
Performance		
Cost efficiency	96.79%	68.98%
Average cost per admission	$11,023	$30,231
Adjusted average cost per admission	$4,500	$10,706
Labor productivity	31.071	18.864
General characteristics		
Total beds	236	371
COTH member (academic medical center)	2.04%	29.12%
Other teaching	21.23%	35.00%
Nonteaching	77.07%	36.34%
System-member	95.09%	61.21%
Ownership		
For-profit	94.09%	0.00%
Not-for-profit	4.02%	72.12%
Government	2.03%	28.06%
Patient population		
Share of admissions (%)		
Medicare	45.76%	37.08%
Medicaid	20.59%	23.58%
Market characteristics		
HMO penetration in county	18.14%	39.03%
Herfindahl-Hirschman Index	.456059	.23420
Financial status		
Operating margin	0.0886	−0.1938
Total margin	0.0997	0.0282

Note. All differences in mean values between top and bottom 100 hospitals, except for Medicaid share of admissions and other teaching hospital, are significant at $p < .01$.

(albeit somewhat smaller)—36.40% using the former measure versus 42.03% with the adjusted measure.

Operating Characteristics

The operating characteristics of the high- and low-efficiency hospitals were very different. Compared to the low-efficiency hospitals, facilities in the most efficient group tended to have fewer beds (236 vs. 371), were more likely to be members of a multihospital system (95% vs. 61%), were more likely to be investor-owned (94% vs. 0%), and were less likely to be not-for-profit (4% vs. 72%) or publicly owned (2% vs. 28%).

The high-efficiency hospitals tended to have fewer teaching activities than their less efficient counterparts. In the high-performing group, 77% were nonteaching, 2% were academic medical centers, and 21% had other teaching programs. In contrast, for the low-efficiency group, the means were 36% nonteaching, 29% academic medical centers, and 35% other teaching.

These results have several implications. First, hospitals in the low-efficiency group might be too large and suffer from dis-economies of scale. Second, in contrast to the concern that hospitals merge primarily to secure market power, hospitals in multihospital systems tend to be more efficient than their freestanding counterparts and may benefit from firm-level economies of scale. Alternatively, they may learn best practices from other system members, which may allow them to develop more efficient processes (Rosko et al., 2007). Third, the benefits of the profit motive described by proponents of Property Rights Theory may include more efficient operations (Mutter & Rosko, 2008; Folland, Goodman, & Stano, 2013). The evidence on the relationship between investor-ownership and costs or efficiency is mixed (Rosko & Mutter, 2011). Some have argued that the lower measured costs in for-profit hospitals are illusionary and are due to cream-skimming or to lower quality. However, we took great care to control for variations in the patient burden of illness and quality. While there is the possibility that some variables were omitted that could cause a systematic bias, we feel it is unlikely.

Fourth, while academic medical centers can be very efficient (e.g., 2 of the 226 academic medical centers in this study were in the most efficient group) teaching activities tend to be associated with inefficiencies. It might be argued that output heterogeneity is masquerading as inefficiency. However, as mentioned previously, we went to great lengths to control output heterogeneity. So a more plausible explanation is that many teaching hospitals (especially academic medical centers [AMCs]) have a difficult time implementing or executing processes associated with high efficiency. This may be due to a conflict between the efficiency objectives and the teaching and research missions (e.g., a bias toward acquiring expensive high-technology equipment to support education and the fact that graduate medical educational activities can be a drag on productivity and efficiency) and incentives for efficiency. It should be noted that the analysis of inefficiency in ACMs is complicated by many factors. For example, the ACMs in this sample are much larger (mean beds equals 584) than nonteaching hospitals (mean beds equals 227) and much less likely to be investor-owned (2.7% vs. 22.7%). Thus, decision makers in ACMs might be more predisposed to take actions which favor their teaching and research missions rather than actions that might favor efficiency. This bias might be re-enforced by the relatively generous Medicare inpatient payments for teaching activities that led to ACMs having a mean Medicare inpatient margin of 7.5% in 2010. In contrast, the Medicare margin for nonteaching hospitals in 2010 was −6.4% (Medicare Payment Advisory Commission, 2013).

Environmental Factors

The environments in which the high- and low- efficiency hospitals are located were very different. For example, the high-efficiency hospitals were located in counties with less competition (0.461 vs. 0.234 using an HHI[9]) and lower HMO penetration rates (18% vs. 39%). The former result is consistent with the practice of service-based competition. There is evidence that a new medical arms race is emerging. In the contemporary landscape providers are practicing a "retail strategy" in which services in the most profitable product-lines are expanded (Berenson, Bodenheimer, & Pham, 2006). The latter result may be due to waning of HMO ability to incent cost savings). Dugan (2015) found that increased HMO penetration in 2005 to 2008 was associated with increases in inpatient hospital costs. He suggests that HMOs now face quality and coverage mandates that restrict them from using their most aggressive strategies for managing costs.

Financial Status

The profit margin[10] of the two groups differed substantially; the high-efficiency group had an average operating margin of 0.0886 while the low-efficiency hospitals on average operated in the red with an operating margin of −0.1938. This suggests the market may "punish" inefficient providers with lower margin. Recall that none of the for-profit hospitals are found in the bottom 100 performers. Since for-profit hospitals are in the business to make profits, it is quite possible that they react more strongly to poor financial results than their not-for-profit counterparts. However, when all sources of income were considered by analyzing the total margin, the group means narrowed substantially (0.0997 vs. 0.0282[11]). Even the less efficient hospitals, on average, were in the black when total margin was analyzed. We also found that the more efficient hospitals depended more on Medicare payments with a Medicare share of admissions of 46% than the low-efficiency hospitals whose Medicare share of admissions was 37%. The results of the SFA analysis suggested that Medicare share of admissions was associated with increased efficiency. This is consistent with the financial incentives of the Medicare prospective payment system. In contrast, the top 100 hospitals had a lower Medicaid share of admissions than those in the bottom 100 (21% vs. 24%).

Quality of Care and Patient Safety

To assess the relationship between efficiency and quality, we analyzed a number of patient outcome measures. Specifically, we used five risk-adjusted, hospital-level measures of inpatient quality: rates of in-hospital mortality for acute myocardial infarction, congestive heart failure, stroke, gastrointestinal hemorrhage, and pneumonia. We also analyzed four risk-adjusted, hospital-level measures of patient safety: rates of failure to rescue, iatrogenic pneumothorax, infection due to medical care, and accidental puncture/laceration. Unlike their counterparts in the multivariate analysis, these variables were not transformed.

As Table 5 shows, the differences in mean values of the clinical quality variables between hospitals in the high- and low-efficiency groups were not substantial. However, when compared to the low efficiency hospitals, the high-efficiency hospitals

Table 5. Mean Inpatient Quality Indicators and Patient Safety Events of 1,586 Short-Term General Hospitals, By Efficiency Group (Top and Bottom 100), 2010.

Variable name	High-efficiency hospitals	Low-efficiency hospitals
Risk-adjusted inpatient mortality rate for acute myocardial infarction	0.0591	0.0580
Risk-adjusted in-hospital mortality rate for congestive heart failure	0.0301	0.0302
Risk-adjusted inpatient mortality rate for stroke	0.0759*	0.0893
Risk-adjusted inpatient mortality rate for gastrointestinal hemorrhage	0.0201	0.0220
Risk-adjusted in-hospital mortality rate for pneumonia	0.0348	0.0368
Risk-adjusted failure to rescue rate	0.1288	0.1406
Risk-adjusted iatrogenic pneumothorax rate	0.0005	0.0006
Risk-adjusted infection due to medical care rate	0.0016	0.0013
Risk-adjusted accidental puncture/ laceration rate	0.0021**	0.0025

*t- value for difference in group means is significant ($p < .01$). **t- value for difference in group means is significant ($p < .05$).

have significant ($p < .01$) favorable differences in one risk-adjusted mortality category (stroke) and in one patient safety event (accidental puncture or laceration, $p < .02$). These results suggest that hospitals do not have to compromise quality or safety for efficiency.

Conclusion

Interest in hospital performance measurement has grown significantly over the last several years. The popularity of websites that make performance information available, such as the Centers for Medicare & Medicaid Services' "Hospital Compare," illustrates the greater attention given to hospital resource use and quality metrics by consumers, payers, and other decision makers.

Increased efficiency is one way to bend the cost curve without compromising quality of care. For example, a hospital that implemented a better care process enjoyed the outcomes of fewer hospital acquired infections and lower costs. The reduction in operating costs holding other factors constant (the solution was very low cost, i.e., changing the site of the catheter insertion and using transparent wound dressings, Spear, 2005) would yield a higher cost-efficiency score for the hospital while giving it a higher quality rating. We found results similar to this in our analysis. Another example, would be to improve labor productivity by either process improvement or by better human resources practices (i.e., recruitment, selection, training, or motivation). This would result in a higher efficiency score (i.e., same output with fewer inputs), and it is consistent with our finding that hospitals in the most efficient group had a higher mean labor productivity score. As these examples illustrate, efficiency is an important dimension of hospital performance and efficiency metrics are an important component of hospital management system. The National Quality Forum, a nationally recognized not-for-profit, nonpartisan, membership-based organization that works to catalyze improvements in healthcare through measurement endorsement and other activities, has several on-going efficiency measurement projects. The addition of rewards for efficiency in the Hospital Value-Based Purchasing Program in 2015 may create stronger incentives for increased efficiency.

Our study provides a useful source of information for these audiences and corresponding policy discussions. We find that variations in efficiency are strongly related to expenses and other dimensions of performance. However, there does not appear to be a trade-off between efficiency and quality or patient safety. Proponents of total quality management and other quality improvement methodologies argue that process improvement could result in increases in quality with reduced costs (Deming, 1982). A DEA study of U.S. hospitals arrived at the same conclusion (Mutter, Valdmanis, & Rosko, 2010).

Understanding the correlates of efficiency might provide insights for policies to improve efficiency. For example, increased efficiency is associated with dependence upon Medicare payments. This suggests that financial incentives can drive improvements in efficiency.

One of the striking differences from a previous hospital cost study and our study is our finding that system membership is associated with higher efficiency. Burns et al. (2015) concluded that system membership in general is not associated with lower costs. This is consistent with the findings in their literature review. However, we would expect that more efficient hospitals would be less costly. The explanation to these apparently different findings lies with the composition of hospitals in the high and low performing groups. Burns et al. (2015) concluded that while systems in general may not be the solution to lower costs, some types of systems are. We found that although hospitals in decentralized systems represented 22% of our sample in 2010, 68% of the top 100 hospitals in our study were members of decentralized systems. Rosko, Proenca, Zinn, and Bazzoli (2007) found that hospitals in decentralized systems tended to be more efficient than those that were members of systems classified as centralized, moderately centralized, or independent. They reported that better performance in these systems might be due to the following: (1) greater autonomy of member hospitals allowing them to respond more flexibly to local contingencies and (2) member hospitals might be exploiting the benefits of information sharing.

Increased competition is also associated with less efficiency, a result that is unexpected under cost-based competition but more likely under service-based competition. The results for system membership and concentration of output, considered jointly, suggest that less competition can be efficiency enhancing. Regulatory agencies may wish to consider this benefit of consolidation (i.e., increased efficiency) against the potential harm of increased market power (i.e., price increases).

It appears from the analysis of the operating margin that the market can punish inefficiency with a poorer bottom line. However, we found that hospitals can escape some of the rigors of the marketplace by finding other sources of revenue. This suggests that it is important to have the correct incentives (i.e., for competition based on value not just service) while bearing in mind other sources of revenue to avoid the consequences of the incentive payment systems.

Finally, our study provides a quantitative range between the most efficient and least efficient hospitals. Such estimates may provide a concrete basis by which rewards could be constructed to incentivize providers in Federal demonstration efforts.

Appendix A

Analysis of Robustness

Coelli et al. (2005) and Kumbhakar and Lovell (2000) describe five major ways in which an SFA empirical model may vary: (a) choice of cost function, (b) assumptions about the distribution of the composed error, (c) inclusion and exclusion of variables, (d) use of one-stage or two-stage estimation approach, and (e) use of cross-section or panel estimation technique. Rosko and Mutter (2008) structured a review the hospital SFA literature around these five areas. They also assessed robustness of varying SFA models along these five dimensions. However, since robustness may vary from sample to sample we repeat this exercise here. Since the advantages of the one-stage approach and use of panels are well established (Rosko & Mutter, 2008; Shen, Eggleston, Lau, & Schmid, 2007), we restrict or analysis to the first three dimensions. Table A1 provides descriptive statistics and correlations for the mean efficiency scores based on the preferred model and four competing models. As discussed in the main section the preferred model uses (1) a translog cost function and (2) the assumption that the inefficiency error term follows a truncated normal probability distribution. These follow the methods of Rosko and Mutter (2014) and are based on the results of log-likelihood tests that could not accept the hypotheses that the high-order output variables have coefficients that were equal to zero (thereby eliminating the Cobb-Douglas cost function) and that the mode of the deterministic error term, which represents cost-inefficiency, was equal to zero, thereby eliminating the assumption of a half-normal distribution for the error term). In our analysis of robustness, we compare the preferred model against models in which the preferred model is altered by (1) using a Cobb-Douglas cost function, (2) assumes a half-normal distribution for the inefficiency error term, (3) uses the preferred model but omits postadmission days, and (4) uses the preferred model but omits reservation quality.[12]

As Table A1 shows varying the models has little impact on the efficiency scores that ranged from 90.71% when the Cobb-Douglas cost function is used to 90.96% when reservation quality is omitted. The Pearson correlations of the hospital-level cost-inefficiency estimates are very strong and range from 0.928 to 0.989. In a final robustness check, we asked the question, "would the conclusions about the values of

Table A1. Descriptive Statistics of Cost-Efficiency Estimates.

			Correlations			
Variable	Mean	*SD*	PM	HN	CD	NO POST
Preferred Model (PM)	0.9091	0.0605				
Half-Normal (HN)	0.9086	0.0566	.970			
Cobb-Douglas (CD)	0.9071	0.0582	.958	.965		
No postadmission days (NOPOST)	0.9080	0.0585	.973	.960	.959	
No reservation quality	0.9096	0.0596	.989	.945	.928	.960

Table A2. Means by Model Type and Performance Status for Medicaid Share and Other Teaching Hospital.

Model	Variable	Mean of high-performing hospitals	Mean of low-performing hospitals	*p* value for significance of differences between group means
Preferred model	Medicaid Share%	20.59	23.58	.076
Half normal		20.78	23.53	.095
Cobb-Douglas		19.92	25.72	.001
Postadmission days omitted		20.72	24.42	.026
Reservation quality omitted		20.13	23.36	.046
Preferred model	Other Teaching Hospital (0/1)	.2100	.3500	.027
Half normal		.2100	.3200	.000
Cobb-Douglas		.2400	.3300	.160
Postadmission days omitted		.2400	.3100	.270
Reservation quality omitted		.2000	.3700	.008

the correlates of efficiency change with the use of different empirical models?" We found that there were only minor changes in the mean values for the low- and high-performing hospitals that were reported in Tables 2 and 3. Specifically, the differences in costs and productivity, operating characteristics, market characteristics and profitability between low and high-performing hospital that were significant ($p < .01$) when the preferred model was used were also significant ($p < .01$) when each of the competing models were used. Similar findings hold for the analysis of the differences in quality indicators and patient safety between the two groups of hospitals.

There were only two variables, Medicaid share of admissions and other teaching hospital, for which the difference in group means between high- and low-performing hospitals was significant at the $p < .10$ level in the preferred model but not in the alternative models or vice-a-versa. Table A2 presents the groups means and p-values of the differences in group means for the five models. Medicaid share of admissions was not significant at $p < .10$ in either the preferred model or in the model in which the composed error was assumed to follow a half-normal distribution. Significant differences in the group means were found when the other three models were used. However, the magnitude of these differences was relatively small.

We also found that the differences in group means for other teaching hospital were significant in the preferred model, the half-normal model and the model in which reservation quality was omitted. They were not significant when the Cobb-Douglas cost function was used or when post-admission days were omitted. Once again, the group means did not vary much when different models were used. In summary, when five alternative models were analyzed and $p < .01$ was used as the threshold of significance there were no differences the sign or level of significance of any of the variables. Furthermore, the magnitude of the differences was relatively small. However, we did find that if $p < .10$ level of significance was used as the threshold for significance, different conclusions would be made about the association of performance with Medicaid share of admissions or other teaching status. Both of these are potentially important policy variables. Accordingly, it is important to examine these results with a finer level of granularity (i.e., consider magnitude of the differences in addition to level of significance). Furthermore, it is important to use a model that is based on both theory and empirical testing. For this reason we chose to base the SFA estimates on an empirical model that comes from theory and uses a rich set of variables to control output heterogeneity and we chose the preferred model on the basis of log-likelihood restriction tests. While perfection is seldom possible, it is important to use the most rigorous methods available.

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Notes

1. A linear programming-based technique like DEA cannot incorporate a large number (we used 46) of product descriptor variables which are required to control for output heterogeneity.
2. The 37 states are Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, New Hampshire, New Jersey, New York, Nevada, North Carolina, Ohio, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Washington, West Virginia, and Wisconsin.
3. The SID contains the universe of the inpatient discharge abstracts in participating states, translated into a uniform format to facilitate multistate comparisons and analyses. See https://www.hcup-us.ahrq.gov/sidoverview.jsp for more information. For some states, permission was obtained from the data organization that provided their data to the AHRQ HCUP project to link the SID to the AHA Annual Survey of Hospitals.

4. HCUP is a family of health care databases and related software tools and products developed through a Federal–state–industry partnership and sponsored by the Agency for Healthcare Research and Quality. See http://www.hcup-us.ahrq.gov/ for more information.
5. The Comorbidity Software assigns variables that identify comorbidities in hospital discharge records using the diagnosis coding of International Classification of Diseases, Ninth Edition, Clinical Modifications. The comorbidities are described in Elixhauser et al. (1998). The software is available for free download at http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp.
6. SFA estimates cost-inefficiency. To simplify the discussion we use cost-efficiency (calculated as 1 − cost-inefficiency) in the analysis of high- and low-performing hospitals. Using the top and bottom 100 hospitals to form the most and least efficient groups of hospitals was a convenient, but somewhat arbitrary, decision. As a simple robustness test we also used tritiles and quartiles and found that all the mean differences between the groups narrowed somewhat; however, there was little impact on the conclusions.
7. The truncated normal distribution is a generalization of the half-normal distribution. It is operationalized by including MU, which is the mode of the deterministic error term that represents inefficiency. If MU equals 0, the truncated normal distribution collapses into the half-normal distribution (Kumbhakar & Lovell, 2000).
8. The numerator includes both inpatient and outpatient expenses, while the denominator only includes inpatient admissions. Expenses per admission would be biased against hospitals with greater outpatient activity. Accordingly, we used AHA-adjusted admissions (this is a commonly used aggregate measure of workload reflecting the sum of admissions and equivalent admissions attributed to outpatient services; the number of equivalent admissions attributed to outpatient services is derived by multiplying admissions by the ratio of outpatient revenue to inpatient revenue) in the denominator of average costs. Furthermore, hospitals that treat patients who require more services or more expensive services will incur more expenses irrespective of how efficient they are. Therefore, we performed a case-mix adjustment by multiplying AHA-adjusted admissions times the hospital's Medicare Case-Mix Index, which has been shown to be very highly correlated with the all-payer case-mix index (Rosko & Carpenter, 1994).
9. The Herfindahl-Hirschman Index is a measure of the concentration of output among producers. It is a commonly used measure of competition. The Herfindahl–Hirschman Index is calculated as the sum of the squares of the market shares of the producers in the market. Its value is 1.0 for monopoly markets and approaches 0.0 in highly competitive markets.
10. We analyzed two measures of financial performance. The operating margin is based on revenues and expenses related to providing inpatient and outpatient medical services to patients. The total margin is a broader measure and is based on revenues from all sources, including patient services, investment income, government grants, donations, and parking fees, and all expenses.
11. Profit margins are notoriously volatile; accordingly, we also examined medians for the operating margin (0.0908 vs -0.0203) and total margin (0.0915 vs 0.0425) for the top and bottom 100 hospitals. The results were similar to the analysis of means.
12. We thank one of the anonymous reviewers for suggesting this analysis. While the robustness of models using different cost functions and error terms has been frequently analyzed (see a review by Rosko & Mutter, 2008), the sensitivity of results to output variables has not been analyzed as much. While Rosko and Mutter (2008) and Mutter, Rosko & Wong (2008) examined the sensitivity of results to inclusion/exclusion of product descriptors and risk-adjusted outcomes, they did not examine sensitivity to exclusion of output variables

or reservation quality. These two variables are of particular interest because the argument could be made that extra capacity and extra patient days could reflect inefficiency and including these in the cost function could mask inefficient practices. We take a different position a suggest that reservation quality represents an important dimension of quality (i.e., standby capacity to assure service availability when there are surges in demand) and that extra patient days (essentially a longer length of stay) represents unmeasured patient factors associated with patient burden of illness (note: we think that after decades of facing incentives from PPS and managed care that most hospitals have reduced length of stay to close to minimal levels). The results indicate that this issue is a moot point in this SFA study as the exclusion of these variables had a very small impact on results.

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