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High versus lower quality hospitals: a comparison of environmental characteristics and technical efficiency

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Abstract We seek to determine whether hospitals providing high-quality care are associated with different environmental and organizational factors than hospitals providing lower quality of care. We address this question using congestion analysis, which is an extension of data envelopment analysis (DEA). We employ a rich data set comprised of urban hospitals operating in 34 states in 2004. The data include measures of inputs, outputs, case mix, and indicators of patient safety, which we use to derive separate best-practice frontiers for high-, medium-, and low-quality hospitals. By comparing the frontier of the high-quality hospitals with the lower quality hospital frontiers, we find that higher quality hospitals perform better on the criteria of overall technical efficiency and pure technical efficiency than lower quality institutions. We found that a variety of characteristics, including expenditures, percentage of admissions that are births, Medicaid share of admissions, and government ownership are associated with differences in performance among the medium-quality hospitals. Expenditures and birth rate were associated with differences within low-quality hospital performance, as were variables related to scope and depth of activities, such as capital expenditures per bed and teaching status. We find evidence that hospitals should be able to improve both the quality and efficiency of their operations by adopting, where possible, the characteristics of the highest performing institutions.

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1 Introduction

Two of the most elusive goals confronting healthcare policy makers and practitioners are the efficient production of patient care and the provision of high-quality care. It is often assumed that improvements in one of these dimensions must come at the expense of the other (i.e., trade-offs must be made) (Pauly 2004). However, it can be argued that quality improvement and efficiency enhancement can be achieved simultaneously. It seems plausible, for example, that reducing expensive, potentially preventable complications and adverse events (i.e., patient safety events) could result in care of higher quality and lower cost. Previous research has been mixed on the direct relationship between resource use and quality or at least whether the relationship is statistically significant. See Clement et al. (2008) for a review.

In this article, we seek to contribute to the literature by examining whether high-quality hospitals operate differently than hospitals providing lower quality care. We use an advance in data envelopment analysis (DEA) known as "congestion analysis" as our methodological approach. Congestion analysis relies, in part, on the assumption of weak disposability of outputs (i.e., some hospital outputs, such as patient safety events, are undesirable) in a DEA-based measure of productivity. This analysis extends previous research that found evidence that high-quality hospitals also had higher overall efficiency than lower quality institutions (Valdmanis et al. 2008). We define hospitals experiencing high quality as those who do not experience a crowding out of the production of good outputs because of bad outputs (i.e., adverse patient events). Finding that a hospital does not have congestion does not mean that it does not have patient safety events. Rather, it means that given the production process, other patients are not denied care because of adverse events and the hospital does not incur an additional opportunity cost because of them. Hospitals with congestion experience a crowding out which is analogous to an increase in social costs. This crowding out is larger in hospitals with higher levels of congestion.

This analysis extends previous work by asking a related research question: Do high-quality hospitals have identifiable characteristics that are different from those of lower quality hospitals? An affirmative answer would provide evidence for the contention that some dimensions of quality and efficiency can be improved simultaneously. We believe, therefore, that this type of analysis can yield practical insight regarding approaches for improving the performance of the hospital sector.

2 Background

Many analyses have not been able to account for quality in their examinations of the efficiency of hospital care due, in part, to a lack of data. For example, Ashby et al. (2000) note that a limitation of their research on the effects of productivity and product change on the rate of increase of U.S. hospital costs is the lack of data on hospital quality. Also, in their review of the effects of hospital ownership on medical productivity, Kessler and McClellan (2001) note that, in general, earlier studies have not examined both the quality and the financial effects of ownership structure, thereby making it difficult to draw conclusions about welfare. Jha et al. (2009) note the lack of studies on the relationship between hospital cost and quality and advance the literature by comparing hospital performance as measured by risk-adjusted costs and indicators of quality. They found that hospitals with lower risk-adjusted costs tended to use fewer nurse inputs and had poorer performance on some process measures of quality. Their findings were associative and did not permit a linkage between efficiency and quality. We seek to advance the literature further by using congestion analysis to simultaneously consider economic productivity and quality of hospital care.

DEA-based congestion analysis is a type of frontier-based approach to efficiency measurement. In a comprehensive review of non-parametric and parametric frontier applications measuring efficiency in health care, Hollingsworth (2003) found that only 10 out of 188 studies incorporated quality of care as part of the frontier estimation process. This might have been due to data limitations, which are gradually being overcome, thereby permitting the incorporation of quality in some more recent frontier studies (Clement et al. 2008; Valdmanis et al. 2008; Mutter et al. 2008).

We aim to extend this literature by using measures of hospital quality to compare high-quality hospitals (i.e., those without output congestion, defined below, due to patient safety events) with hospitals producing care at medium- and low-levels of quality. From this analysis, we ascertain whether hospitals incurring different levels of patient safety events offset this deficit through the more efficient use of resources. We also identify the characteristics of high-performing hospitals within the lower quality hospital categories.

3 Model

We use DEA and extensions of this method to compare the production performance of high-, medium- and low-quality hospitals. Overall technical efficiency for hospitals is decomposed as follows:

$$\text{Total efficiency (CRS)} = \text{Pure technical efficiency (VRS)} * \text{Scale efficiency} * \text{Congestion}. \tag{1}$$

In their work examining quality of care and hospital productivity, Valdmanis et al. (2008) examined the congestion component, which measures the impact "bad" outputs have on total productivity. In other words, they discounted total productivity of "good" outputs (defined in terms of patient care services) by the crowding out caused by bad outputs, which were patient safety events in their analysis. The intuition of their approach is similar to the concept of pollution emitted by industrial production.

After determining hospitals' congestion scores, they used those scores to create the following hospital sub-samples: "high-quality hospitals" (i.e., institutions with no congestion), "medium-quality hospitals" (i.e., institutions with a below-median level of congestion), and "low-quality hospitals" (i.e., institutions with an above-median level of congestion). It should be noted that this congestion-based definition of quality is only one component among the many dimensions of hospital quality.

Whereas the focus of Valdmanis et al. (2008) was the over- or under-utilization of specific inputs, this work builds upon their framework by examining whether high-quality hospitals have different production efficiency then institutions of lower quality. By clustering hospitals by quality status (defined above), we can ascertain whether each hospital cluster group operates on a different frontier. Moreover, we can determine if one cluster group's frontier is "superior" to the other group's frontier. In order to accomplish this task, we adopt the method employed by Grosskopf et al. (2001). We describe this method and its applicability to our data below.

The method that we chose to estimate best-practice frontiers for high-, medium-, and low-quality hospitals involves several steps.

Step 1 We assess efficiency using the traditional DEA method under the assumption that some outputs, specifically the adverse events, are weakly disposable, detracting from the overall production of our "good" outputs.

Step 2 We adjust the patient care outputs by the corresponding congestion measure by each hospital to achieve a measure of adjusted output. In other words, we discount total output by output that is attributed to poor quality.

Step 3 We categorize the hospitals in our sample by no congestion, medium congestion, and high congestion based on the median value of the congestion score by hospital.

Step 4 We perform an input-based DEA on the medium and highly congested hospitals in order to derive separate frontiers by congestion type.

Step 5 We adjust the inputs (by dividing the number of actual inputs by the efficiency score) so that all observations are "deemed" efficient within their group. Specifically, we move all observations to the best practice frontier

Step 6 Once this adjustment is made, we can then proceed to the sixth step, where we compare the adjusted frontiers of the medium- and highly congested hospitals to the frontier of the high-quality institutions. This allows us to directly measure two quality-based frontiers where the lower quality frontiers are not confounded by the inefficiency of the medium- or low-quality hospitals.

By analytically eliminating the inefficiency in the lower quality hospitals, we can gauge the role that congestion-based quality may play in differences between the frontiers and technologies employed by the hospitals in each group. A question may arise concerning the problem known in the literature as "the curse of dimensionality," which can occur when the number of inputs and outputs are relatively large compared to the number of firms analyzed, or when different samples each with a different number of firms are compared. We avoid this problem by performing Monte Carlo methods using all the medium- and low-quality hospitals with the same number of randomly selected high-quality hospitals. In this way, we use the average of the score differentials and what we present is, therefore, considered robust since the averages are derived from 10 different sub-samples of high-quality hospitals.

A series of linear programming problems are employed to solve the relative productivity differences between the two hospital frontiers. Since the methods of correcting for congestion are described elsewhere (Valdmanis et al. 2008), we place our presentation of the details of this method in Appendix 1. The focus of our brief discussion below will be on the comparison of the frontiers.

The approach taken here follows Farrell's (1957) measurement of technical efficiency. Recall that in order to compare frontiers, we must first adjust medium- and low-quality hospitals in order to move them to their respective best-practice frontiers. This will permit our comparison to be focused on quality un-confounded by inefficiency.

$$
\begin{aligned}
&\mathrm{Min}\,\theta \\
&\text{s.t.} \ \sum_{i}^{I} z\, y_m \geq y_{im} \quad m = 1, \ldots, M \\
&\sum_{i}^{I} z_{in} \leq x_n \theta x_n \\
&z_i \geq 0
\end{aligned}
\tag{2}
$$

Solving for θ, we adjust all the inputs for the low-quality hospitals by multiplying the resulting efficiency score by all the inputs per hospital.

We accomplish this by using the reciprocal of the Farrell distance function so that we can compare the ratio of, for example, high-quality (*h*) and medium-quality (*m*) hospitals defined as:

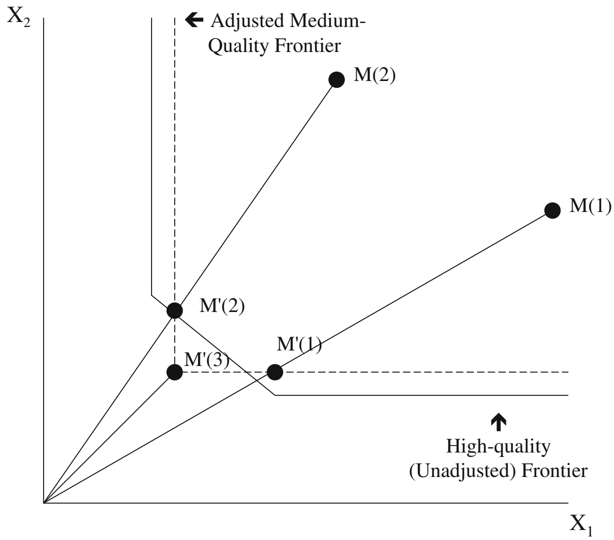
$$F(x^h, y^h, x^m, y^m) = \left(\frac{D^h(x^h, y^h)\ D^m(x^h, y^h}{D^h(x^m, y^m) D^h(x^m, y^m)}\right)^{-1} \tag{3}$$

There are two different frontiers given above: one is formed using the adjusted, medium-quality hospitals, and the other is formed using the unadjusted, high-quality hospitals.

Ratios >1.00 indicate that high-quality hospitals have performance that is superior to the comparison hospital group (either medium- or low-quality hospitals, which we assess separately). Ratios <1.00 indicate that the comparison, lower quality hospitals outperform the high-quality hospitals once inefficiency is eliminated. By analyzing the comparison of frontiers in this way, we are able to compare technologies that are not biased by internal inefficiencies. In other words, once inefficiency is eliminated, the only variable factor that may cause differences in the frontiers is quality (i.e., congestion). This analysis allows us to suggest whether it is possible for hospitals to increase quality and efficiency simultaneously. As an illustration, see Fig. 1 below.

In this figure, X_1 is input one, and X_2 is input two. We display the high-quality hospital frontier as the solid line. The corrected, medium-quality hospital frontier is denoted by the dashed line. Unadjusted, medium-quality hospitals M(1) and M(2) operate interior to the high-quality hospital frontier as well as to their own frontier and are, therefore, inefficient. Once inefficiency is eliminated for the medium-quality hospitals, the new frontier, based on the adjusted outputs and inputs described above and denoted by the dashed line, results in M′(1) and M′(2). Thus, those hospitals have moved closer to the high-quality hospital frontier. Indeed, M′(2) is now on the high-quality hospital frontier; however, M′(1) is still dominated by the high-quality hospitals. Note that hospital M′(3) operates even more efficiently than the high-quality hospitals. Therefore, it is said to dominate the high-quality hospitals.

Fig. 1 Comparing adjusted and unadjusted frontiers



If the adjusted hospital's ratio is <1, then it is producing below the high-quality hospital frontier (e.g., $M'(3)$), and we consider the high-quality hospitals to have performance that is inferior to it. If the ratio is >1, then it is producing above the high-quality hospitals' frontier (i.e., it is producing its output with a higher level of inputs and is, therefore, less efficient), and we regard it as having performance that is inferior to the high-quality hospital, best-practice frontier (e.g., $M'(1)$).

4 Data

Data were obtained from the American Hospital Association (AHA) Annual Survey of Hospitals, augmented by variables from the Medicare Hospital Cost Reports (for number of patient days in non-acute care units), the Agency for Healthcare Research and Quality (AHRQ) (for measures of patient safety and hospital competition), and Solucient, Inc. [for data on county level health maintenance organization (HMO) enrollment and number of residents without health insurance]. Hospitals included in this study are those defined by the AHA as short term, community hospitals that report complete data. Since quality variables from the application of the Patient Safety Indicator (PSI) module of the AHRQ Quality Indicator (QI) software[1] to the Healthcare Cost and Utilization Project (HCUP)[2] State Inpatient Databases (SID)[3] were important in this analysis, this study was restricted to 34 states[4] supplying HCUP data. This yielded an analytical file of 1,371 urban hospitals in 2004.[5]

As in the case of any model, the selection of inputs and outputs may affect the final results and/or ranking of hospitals in terms of quality. Being mindful of this concern, we follow the previous literature in determining inputs and outputs. Our inputs include bassinets, acute beds (i.e., the number of licensed and staffed beds), licensed and staffed "other" beds (i.e., the number of beds in non-acute units, such as long-term care), full-time equivalent (FTE) registered nurses (RNs), licensed practical nurses (LPNs), interns and residents, and other personnel. Outputs include Medicare Case Mix Index (MCMI) adjusted admissions (MCMI * admissions), total surgeries (inpatient + outpatient surgeries), total outpatient visits [emergency room (ER) visits + outpatient visits], total births, and total other patient days (i.e., patient days in non-acute care units). This specification is consistent with previous hospital DEA studies that typically use a mix of inpatient and outpatient care variables and specify surgery separately from total admissions. (See Hollingsworth 2003 for a complete review.) We also note that even though we

[1] AHRQ makes this software available for free on its website, http://www.qualityindicators.ahrq.gov.

[2] HCUP is a family of health care databases and related software tools developed through a Federal-State-Industry partnership to build a multi-State health data resource for health care research and decisionmaking. For more information, go to http://www.hcup-us.ahrq.gov/home.jsp.

[3] For each participating state, the SID contains the discharge record for every inpatient hospitalization that occurred. For more information see http://www.hcup-us.ahrq.gov/sidoverview.jsp.

[4] The 34 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.

[5] The sample sizes may vary depending on whether there was not convergence in the linear programming problem for the comparison of the frontiers. In order to be consistent with the frontier comparisons provided in the text of the paper, we provide the descriptive statistics for only the hospitals which were assessed there.

use the MCMI, it has been shown elsewhere that the MCMI and total hospital case mix are highly correlated ($r = 0.86$) (Jensen and Morrisey 1985).

We used PSIs that were sensitive to the employment of nurses by the hospital. Measures of undesirable events include the following risk-adjusted PSIs that Savitz et al. (2005) indicate are sensitive to nurse staffing: failure to rescue, infection due to medical care, postoperative respiratory failure, and postoperative sepsis. Decubitus ulcer and postoperative pulmonary embolism (PE) or deep vein thrombosis (DVT) are also nurse-sensitive measures of quality; however, Houchens et al. (2008) found that a high percentage of these events are present on admission (POA). Therefore, they are not valid measures of hospital quality, except in data systems that include POA information., and we exclude them from our study. Some endogeneity issues may arise especially if we have not accounted for all the risks patient may incur leading to PSI's. Therefore, what we demonstrate may be an upper bound or conservative estimate of "true" hospital quality of care vis-à-vis these four adverse outcomes.

In a secondary analysis, we examine the relationship between DEA-based inefficiency estimates and various correlates of inefficiency. We include an array of internal factors including ownership [for-profit (FP), not-for-profit (NFP) or government], reflecting the role of property rights. Teaching status is regularly included as an organizational feature that may affect a hospital's productive performance. We included two binary variables: COTH is a binary variable that identified major teaching hospitals [i.e., members of the Council of Teaching Hospitals (COTH)], and MNTEACH is a binary variable that controls for minor teaching hospital status (i.e., non-COTH hospitals that have at least one FTE medical resident). System membership is also included in our study since systems generally have better control of resource use and are better able to exploit bulk purchasing (and other types of discounts) than independent institutions (Rosko et al. 2007).

We can also directly compare our results with more traditional definitions of hospital inputs and productivity. Therefore, we include the number of high-technology services offered,[6] the amount of capital expended (depreciation + interest expense) per bed, and the ratio of FTE personnel to both adjusted admissions and beds.

We also analyze a variety of variables related to patient and payer mix, including the following percentages: births to total admissions, ER visits to total outpatient visits, outpatient surgeries to total outpatient visits, and Medicaid and Medicare admissions to total admissions, as well as average length of stay (ALOS).

A number of stochastic frontier studies have used a Hirschman–Herfindahl Index (HHI) to measure hospital competition. It measures concentration of output among producers and it equals one in a monopoly and approaches zero in highly competitive markets. Several frontier studies found that more competition is associated with lower hospital cost-inefficiency (Rosko 2001b; McKay et al. 2002). Four studies found evidence to support service-based competition (Rosko et al. 2007; Rosko 2001a; Zuckerman et al. 1994; Brown 2003). We include the county-level HHI to reflect the amount of competition faced by the hospitals in our sample.[7] We also use variables compiled by Solucient, Inc. to reflect HMO

[6] Zuckerman et al. (1994) developed an index based on eight advanced technology services. In 2004, the AHA Annual Survey of Hospitals changed the classification system for hospital services. Several services were split into two or more related services (e.g., transplant services were split into seven distinct types of transplants). Counting each separately listed service that was related to the index originally developed by Zuckerman et al. (1994), we included 17 services.

[7] The Hospital Market Structure File contains various measures of hospital market competition based off the algorithms developed by Wong et al. (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

penetration and the percentage of the population without health insurance in the county where the hospital is located as measures of financial pressure. (We used 2002 data for the Solucient variables, as it was the most recent data available to us.) Therefore, we also add to the DEA literature by assessing quality, efficiency and competition directly.

Descriptive statistics for the environmental and organization factors are presented Table 8 in Appendix 2.

5 Results

In Tables 1, 2, and 3, we present the descriptive statistics of inputs, outputs, and PSIs by hospital-quality group.

In Table 4, we present the output-based measures we used to derive the congestion scores in order to discount outputs for the comparison of the frontiers.[8]

Based on the results presented in Table 4, we note that overall technical and pure technical inefficiency progressively increases from the high-quality hospital group to the medium- and low-quality hospital groups. (Congestion increases as well, which is expected since quality status is defined by the congestion score.) However, results on scale inefficiency are somewhat mixed.

In Table 5, we present the input-based efficiency measures we used to construct the adjusted frontiers for the medium- and low-quality hospitals. (The input-based overall technical efficiency measure for the entire sample is the reciprocal of the output-based overall technical efficiency measure because we are assessing this technology under the assumption of constant returns to scale.)

The results from the tables above were used in deriving the relative frontiers for the hospital groups in order to assess if, once inefficiency were disaggregated, the medium- and low-quality hospitals had production technologies similar to the production practices of the high-quality hospitals.

We next present comparative performance results for medium-quality hospitals. In Table 6, we provide descriptive statistics for two categories of medium-quality hospital—those medium-quality hospitals that outperform high-quality hospitals after correction for input inefficiency and those medium-quality hospitals that are still dominated by high-quality hospitals after the correction is made. We make this comparison to identify which environmental and organizational characteristics are associated with the provision of higher quality within the medium-quality hospital group.

We found that medium-quality hospitals that outperform high-quality hospitals have statistically significantly ($p < 0.05$) higher total expenditures, a higher birth rate percentage, a lower percent of total patients covered by Medicaid, are less likely to be government owned, and are more likely to be NFP institutions. We wish to note that we do not observe statistically significant differences based on other key environmental variables. This indicates that once we remove the input inefficiencies, these hospitals are quite similar in other important respects.

Footnote 7 continued
area. They are available to the public for free online at http://www.hcup-us.ahrq.gov/toolssoftware/hms/hms.jsp.

[8] It should be noted that the medium-quality hospitals were re-tested with the high-quality hospitals via Monte Carlo methods. What is reported here is an average of 10 iterations of the comparison. The same procedure was conducted with the comparison of the low-quality hospitals to the high-quality hospitals.

Table 1 Descriptive statistics, high-quality hospitals ($N = 824$)

Variable	Mean	SD
Inputs		
Bassinets	19.16	17.03
Full-time equivalent registered nurses	329.63	231.24
Full-time equivalent licensed practical nurses	30.59	34.38
Full-time equivalent other personnel	872.67	655.00
Full-time equivalent interns and residents	17.18	60.89
Other beds	42.25	55.44
Acute care beds	204.18	130.82
Outputs		
Total outpatient visits	174,487.49	175,089.38
Total surgeries	9,319.96	6,940.64
Total births	1,490.01	1,467.79
Adjusted admissions	18,265.17	13,263.58
Total other days	14,980.99	16,495.03
Patient safety indicators		
Failure to rescue	0.34	0.07
Infection due to medical care	0.04	0.01
Postoperative respiratory failure	0.09	0.03
Postoperative sepsis	0.10	0.06

Table 2 Descriptive statistics, medium-quality hospitals ($N = 233$)

Variable	Mean	SD
Inputs		
Bassinets	21.17	12.89
Full-time equivalent registered nurses	345.99	204.13
Full-time equivalent licensed practical nurses	38.60	35.36
Full-time equivalent other personnel	945.77	584.26
Full-time equivalent interns and residents	19.91	73.25
Other beds	39.88	55.53
Acute care beds	213.36	107.39
Outputs		
Total outpatient visits	164,456.64	124,807.88
Total surgeries	9,431.44	4,764.79
Total births	1,582.23	1,061.08
Adjusted admissions	18,957.66	11,216.14
Total other days	12,389.97	10,772.82
Patient safety indicators		
Failure to rescue	0.34	0.05
Infection due to medical care	0.04	0.01
Postoperative respiratory failure	0.08	0.03
Postoperative sepsis	0.09	0.04

Table 3 Descriptive statistics, low-quality hospitals ($N = 234$)

Variable	Mean	SD
Inputs		
Bassinets	15.61	11.93
Full-time equivalent registered nurses	224.99	179.91
Full-time equivalent licensed practical nurses	29.28	30.44
Full-time equivalent other personnel	622.49	504.19
Full-time equivalent interns and residents	11.63	61.22
Other beds	31.03	43.19
Acute care beds	148.44	103.68
Outputs		
Total outpatient visits	126,495.71	102,529.34
Total surgeries	6,756.98	5,474.79
Total births	1,077.64	986.29
Adjusted admissions	11,851.95	10,235.43
Total other days	8,788.00	9,456.74
Patient safety indicators		
Failure to rescue	0.32	0.07
Infection due to medical care	0.03	0.02
Postoperative respiratory failure	0.06	0.04
Postoperative sepsis	0.03	0.05

Table 4 Descriptive statistics, output-based efficiency scores for high-quality and lower quality hospitals

Efficiency score	Mean	SD
High-quality hospitals		
Overall technical efficiency	1.28	0.28
Technical efficiency	1.05	0.09
Scale	1.21	0.21
Congestion	1.00	0.00
Medium-quality hospitals		
Overall technical efficiency	1.41	0.23
Technical efficiency	1.11	0.09
Scale	1.28	0.17
Congestion	1.02	0.01
Low-quality hospitals		
Overall technical efficiency	1.44	0.26
Technical efficiency	1.20	0.17
Scale	1.20	0.17
Congestion	1.16	0.16

Recall that higher output based efficiency scores mean higher inefficiencies by the percent: efficiency score − 1/efficiency score

Turning next to a comparison of high-quality and low-quality hospitals, the results are much different. None of the low-quality hospitals dominated the high-quality hospitals even after inefficiencies were removed. Therefore, we first divided the number of

Table 5 Descriptive statistics, input-based efficiency scores for high-quality and lower quality hospitals

Efficiency score	Mean	SD
High-quality hospitals		
Overall technical efficiency	0.93	0.09
Technical efficiency	0.96	0.07
Scale	0.97	0.05
Medium-quality hospitals		
Overall technical efficiency	0.86	0.15
Technical efficiency	0.90	0.14
Scale	0.95	0.07
Low-quality hospitals		
Overall technical efficiency	0.90	0.14
Technical efficiency	0.95	0.09
Scale	0.95	0.09

For input-based efficiency, a lower number indicates more inefficiency

low-quality hospitals into equal halves separated by the median value of all low-quality hospitals. Those hospitals that were less inefficient vis-à-vis the other low-quality hospitals were deemed to operate closer to the high-quality hospital frontier. Conversely, those low-quality hospitals that were in the half of the sample that were relatively more inefficient were considered as those operating further away. These findings are given in Table 7.

We found that hospitals closer to the high-quality frontier had lower total expenditures, a lower proportion of total admissions that were births, a higher share of Medicare patients, a lower occupancy rate, spent less capital per bed, and were less likely to be COTH hospitals than hospitals farther from the high-quality frontier. These findings suggest that low-quality hospitals may be trying to operate beyond their abilities.

Similarities between these two hospital groups are also worth mentioning. For example, in neither case, was the difference in the FTE personnel/bed ratio or the cost per admission statistically significant, indicating that these are two variables may be affecting both efficiency and quality of care together and cannot be effectively teased out. Further, market variables, such as HMO penetration and the percent uninsured, did not explain differences among the hospital groups.

6 Discussion

Before discussing the implications of our results it is important to note the limitations of this study. While we advance the literature by considering a dimension of quality [i.e., what Valdmanis et al. (2008) termed congestion-quality], we were not able to include other dimensions of quality, such as structure or process, into the DEA model. Thus, our results are relevant only to a limited dimension of quality.

By comparing hospital frontiers, rather than comparing all hospitals to one frontier, we find that what we deem to be high-quality hospitals are associated with higher measures of technical efficiency. The latter is at least a necessary condition for lowering costs. However, once medium-quality hospitals eliminated their inefficiencies, some of them dominated the high-quality hospitals, especially those medium-quality hospitals that had higher expenditures, higher birth rates as a percentage of total admissions, a lower share of

Table 6 Factors associated with medium-quality hospital performance (1 = high-quality hospitals dominate, 2 = medium-quality hospitals dominate)

Variable	Mean	Wilcoxon test	*P*
Total expenditures			
1	145,127.866	−2.25	<0.02
2	171,771,879		
High-tech services			
1	6.76		
2	6.60	0.23	NS
Birth (%)			
1	11.87	−2.05	<0.03
2	13.34		
Emergency room (%)			
1	32.06	0.77	NS
2	28.93		
Outpatient surgery (%)			
1	4.72	−0.77	NS
2	5.10		
Medicaid (%)			
1	17.56	2.26	<0.02
2	14.89		
Medicare (%)			
1	43.23	1.30	NS
2	41.96		
Occupancy rate			
1	64.58		
2	66.31	−1.18	NS
Cost/admission			
1	12,727.69	0.19	NS
2	12,457.51		
Average length of stay			
1	4.88	0.78	NS
2	4.82		
Capital/bed			
1	48,542.43	−0.70	NS
2	49,580.65		
Full-time equivalent personnel/admission			
1	0.11	0.46	NS
2	0.11		
Full-time equivalent personnel/bed			
1	5.42	−0.79	NS
2	5.48		
Uninsured (%)			
1	13.62	0.25	NS
2	13.81		

Table 6 continued

Variable	Mean	Wilcoxon test	*P*
Health maintenance organization (%)			
1	20.62	−1.54	NS
2	23.37		
Hirschman–Herfindahl Index			
1	0.38	0.63	NS
2	0.36		
Council of Teaching Hospitals (%)			
1	9.0	0.01	NS
2	9.0		
Minor teaching (%)			
1	19.0	−1.03	NS
2	25.0		
For-profit (%)			
1	13.0	0.64	NS
2	10.0		
Government (%)			
1	18.0	3.03	<0.007
2	6.0		
Not-for-profit (%)			
1	68.0	−2.77	<0.01
2	84.0		
System membership (%)			
1	62.0	0.41	NS
2	59.0		

Medicaid patients, and were NFPs. The fact that these medium-quality hospitals could outperform the high-quality hospitals is evidence that they can improve both their efficiency and their quality.

Since no low-quality hospitals dominated high-quality hospitals even after all inefficiencies were eliminated, we took the second-best approach of comparing those low-quality hospitals that were “closer” to the high-quality frontier to those low-quality hospitals that were further away. What was particularly interesting is that the highest performing low-quality hospitals were associated with lower expenditures. It also appears that the low-quality hospitals closest to the high-quality frontier have a higher share of Medicare patients. These findings may be worthy of future research because they suggest that within a range, lower quality hospitals can improve both their efficiency and their quality.

We found that high-quality hospitals perform at higher efficiency levels when measuring hospital output in terms of quality and technical efficiency. However, medium-quality hospitals can improve by eliminating their technical inefficiency by making the “correct” tradeoff between quality and resource use (as measured by eliminating technical inefficiency and moving to a medium-quality, best practice frontier). We make this assertion since we found some medium-quality hospitals were able to dominate high-quality hospitals.

Table 7 Factors associated with low-quality hospital performance (1 = low-quality hospitals further from the high-quality frontier, 2 = low-quality hospitals closer to the high-quality hospital frontier)

Variable	Mean	Wilcoxon test	*P*
Total expenditures			
1	121,784,754	9.06	<0.003
2	74,686,427		
High-tech services			
1	5.81		
2	5.12	1.03	NS
Birth (%)			
1	13.63	4.29	<0.04
2	11.32		
Emergency room (%)			
1	32.87	1.92	NS
2	29.31		
Outpatient surgery (%)			
1	5.08	1.96	NS
2	4.57		
Medicaid (%)			
1	17.1	0.00	NS
2	16.7		
Medicare (%)			
1	41.75	6.11	<0.01
2	46.81		
Occupancy rate (%)			
1	64.89	16.43	<0.0001
2	54.39		
Cost/admission			
1	11,520.35	0.598	NS
2	11.805.88		
Average length of stay			
1	4.83	0.598	NS
2	4.71		
Capital/bed			
1	44,661.27	5.13	<0.02
2	37,880.97		
Full-time equivalent personnel/admission			
1	0.06	0.0.659	NS
2	0.06		
Full-time equivalent personnel/bed			
1	1.08	1.39	NS
2	1.08		
Uninsured (%)			
1	14.8	1.98	NS
2	13.8		

Table 7 continued

Variable	Mean	Wilcoxon test	*P*
Health maintenance organization (%)			
1	25.89	2.00	NS
2	27.13		
Hirschman–Herfindahl Index			
1	12.26	0.57	NS
2	11.44		
Council of Teaching Hospitals (%)			
1	10.00	6.47	<0.01
2	0.00		
Minor teaching (%)			
1	19.2	0.09	NS
2	21.5		
For-profit (%)			
1	23,1	0.37	NS
2	18.5		
Government (%)			
1	17.3	0.58	NS
2	12.3		
Not-for-profit (%)			
1	60.0	1.16	NS
2	69.0		
System membership (%)			
1	29.89	2.00	NS
2	27.06		

For policy-makers and hospital decision-makers, our methodological approach can provide them with empirical information that can lead to different choices. For example, some hospitals can improve quality by reducing overall technical inefficiency. For other hospitals, reducing their range of services may mitigate poor quality/inefficiency outcomes. We base these policy options on the evidence we present that the lowest quality hospitals can outperform their peers when their total expenditures are lowered.

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Appendix 1

DEA model

We first begin by defining the production framework under the assumption of VRS and strong disposability for all outputs:

$$P(x|V,S) = \left\{ y : y \leq z \cdot M, z \cdot K \leq x,\ z \in \Re, \sum_{j=1}^{N} z_j = 1 \right\},$$

where x inputs are used to produce y outputs. M denotes the output matrix, and K represents the input matrix. The z variables represent the intensity variables that are required to map out the best-practice frontier. However, by relaxing the assumption of strong disposability on a vector of outputs, we define this new frontier as:

$$P(x|V,W/S) = \left\{ \left(y^W,\ y^S\right) : y^W \leq \mu \cdot z \cdot M^W,\ y^S \leq z \cdot M^S,\ z \cdot K \leq x,\ 0 \leq \mu \leq 1,\ z \in \Re, \sum_{j=1}^{N} z_j = 1 \right\},$$

where the superscript "S" represents strong disposability and "W" denotes weak disposability. The "μ" is imposed to allow the weakly disposable outputs to move along the backward bend of the production possibility frontier. In other words, it permits the non-linear scaling of these outputs whereas the other outputs can only be radially increased in a linear fashion. The "μ" parameter provides the measure of the bad output, in our case nurse-sensitive patient safety events. The specific linear programs are shown below.

Finally, by taking the ratio of the results from these two models:

$$C_O(x,y|V) = \frac{F_O(x,y|V,S)}{F_O(x,y|V,W/S)} = \frac{\theta^{S^*}}{\theta^{W/S^*}} \geq 1$$

we can derive a measure of congestion reflecting how much of total productivity is reduced by the presence of these bad hospital outcomes. If hospitals do not have any congestion in their production process of patient care, there are no opportunity costs of poor outcomes occupying resources that could be used for the treatment of additional patients. In this way, efficiency and quality can be optimized simultaneously. Since we are directly measuring the impact patient safety events have on efficiency, we do not have to make inferences as if, say, we used two stage least squares or instrumental variables.

Computationally, we solve two linear programming models:

$$
\begin{aligned}
F_O(x, y|V, S) = \max_{z,\theta^S} \theta^S \\
\text{s.t. } \theta^S \cdot y \leq z \cdot M \\
z \cdot K \leq x \\
z \in \Re_N \\
\sum_{j=1}^{N} z_j = 1.
\end{aligned}
$$

and

$$
\begin{aligned}
F_O(x, y|V, W/S) = \max_{z,\theta^{W/S}} \theta^{W/S} \\
\text{s.t. } \theta^{W/S} \cdot y^W \leq \mu \cdot z \cdot M^W \\
\theta^{W/S} \cdot y^S \leq z \cdot M^S \\
z \cdot K \leq x \\
0 \leq \mu \leq 1 \\
z \in \Re_N \\
\sum_{j=1}^{N} z_j = 1
\end{aligned}
$$

The first model measures output efficiency where all outputs are considered positively (i.e., strongly disposable). The second model measures the technology in which some of the outputs are considered as weakly disposable. We adjust our outputs for the presence of congestion by multiplying $C_O(x, y|V) = \frac{F_O(x,y|V,S)}{F_O(x,y|V,W/S)} = \frac{\theta^{S*}}{\theta^{W/S*}} \geq 1$ with the individual outputs to discount outputs to account for the bad outcomes produced.

Appendix 2

Descriptive statistics for all three hospital groups

See Tables 8, 9, 10.

Table 8 Descriptive environmental and organizational variables, high-quality hospitals ($N = 834$)

Variable	Mean	SD
Total expenditures	198,944,690	201,666,465
High-tech services	7.05	4.20
Birth (%)	12.02	8.43
Emergency room (%)	29.67	18.01
Outpatient surgery (%)	4.74	4.88
Medicaid (%)	16.59	10.76
Medicare (%)	42.05	12.47
Occupancy rate	66.68	14.82

Table 8 continued

Variable	Mean	SD
Cost/admission	13,442.27	5,999.63
Average length of stay	5.30	2.76
Capital/bed	50,511.49	27,376.90
Full-time equivalent personnel/admission	0.11	0.04
Full-time equivalent personnel/bed	5.33	2.03
Uninsured (%)[a]	14.24	6.76
Health maintenance organization (%)[a]	25.46	13.25
Hirschman–Herfindahl Index[a]	0.30	0.27
Frequency distribution hospital characteristics		
Council of Teaching Hospitals	14.31%	
Minor teaching	21.64%	
For-profit	17.76%	
Government	10.87%	
Not-for-profit	71.37%	
System member	67.59%	

[a] County-level variables

Table 9 Descriptive environmental and organizational variables, medium-quality hospitals ($N = 217$)

Variable	Mean	SD
Total expenditures	160,598,583	103,054,353
High-tech services	6.67	3.53
Birth (%)	12.72	6.47
Emergency room (%)	30.24	16.32
Outpatient surgery (%)	4.94	6.39
Medicaid (%)	16.01	10.36
Medicare (%)	42.49	10.36
Occupancy rate	65.59	12.70
Cost/admission	12,570.81	3,798.90
Average length of stay	4.85	1.23
Capital/bed	49,107.57	23,551.37
Full-time equivalent personnel/admission	0.11	0.03
Full-time equivalent personnel/bed	5.46	1.81
Uninsured (%)[a]	13.73	7.37
Health maintenance organization (%)[a]	22.21	13.81
Hirschman–Herfindahl Index[a]	0.37	0.29
Frequency distribution hospital characteristics		
Council of Teaching Hospitals	8.75%	
Minor teaching	22.11%	
For-profit	11.52%	
Government	11.05%	
Not-for-profit	77.42%	
System member	59.91%	

[a] County-level variables

Table 10 Descriptive environmental and organizational variables, low-quality hospitals ($N = 234$)

Variable	Mean	SD
Total expenditures	201,756,187.00	203,430,966.00
High-tech services	6.92	4.47
Birth (%)	11.40	8.32
Emergency room (%)	30.34	18.04
Outpatient surgery (%)	5.17	6.72
Medicaid (%)	16.49	10.82
Medicare (%)	42.29	12.23
Occupancy rate	66.98	15.21
Cost/admission	13,216.32	4,868.39
Average length of stay	5.37	3.01
Capital/bed	50,715.31	28,807.27
Full-time equivalent personnel/admission	0.11	0.04
Full-time equivalent personnel/bed	5.27	0.04
Uninsured (%)[a]	14.17	7.29
Health maintenance organization (%)[a]	23.97	13.11
Hirschman–Herfindahl Index[a]	0.32	0.27
Frequency distribution hospital characteristics		
Council of Teaching Hospitals	16.24%	
Minor teaching	22.22%	
For-profit	21.37%	
Government	7.26%	
Not-for-profit	71.36%	
System member	70.01%	

[a] County-level variables

References

Ashby, J., Guterman, S., Greene, T.: An analysis of hospital productivity and product change. Health Aff. **19**, 197–205 (2000)

Brown, H.: Managed care and technical efficiency. Health Econ. **12**, 149–158 (2003)

Clement, J., Valdmanis, V., Bazzoli, G., et al.: Is more better? An analysis of hospital outcomes and efficiency with a DEA model of output congestion. Health Care Manag. Sci. **11**, 67–77 (2008)

Farrell, M.: The measurement of productive efficiency. J R Stat Soc A **120**, 253–278 (1957)

Grosskopf, S., Margaritis, D., Valdmanis, V.: Comparing teaching and non-teaching hospitals: a frontier approach (teaching vs non-teaching hospitals). Health Care Manag. Sci. **4**, 83–90 (2001)

Hollingsworth, B.: Non-parametric and parametric applications measuring efficiency in health. Health Care Manag. Sci. **6**, 203–218 (2003)

Houchens, R., Elixhauser, A., Romano, P.: How often are potential patient safety events present on admission? Jt. Comm. J. Qual. Patient Saf. **34**, 154–163 (2008)

Jensen, G., Morrisey, M.: Role of physicians in hospital production. In: Hospital Research and Educational Trust. American Hospital Association, Chicago (1985)

Jha, A., Orav, E.J., Dobson, A., Book, R., Epstein, A.: Measuring efficiency: the association of hospital costs and quality of care. Health Aff. **28**(1), 897–906 (2009)

Kessler, D., McClellan, M.: The effects of hospital ownership on medical productivity. NBER (2001). http://www.nber.org/papers/w8537. Accessed 6 Oct 2008

McKay, N., Deily, M., Dorner, F.: Ownership and changes in hospital inefficiency, 1986–1991. Inquiry **39**, 388–399 (2002/2003)

Mutter, R., Rosko, M., Wong, H.: Measuring hospital inefficiency: the effects of controlling for quality and patient burden of illness. Health Serv. Res. **43**, 1992–2013 (2008)
Pauly, M.: Competition in medical services and the quality of care: concepts and history. Int. J. Health Care Financ. Econ. **4**, 113–130 (2004)
Rosko, M.: Impact of HMO penetration and other environmental factors on hospital X-inefficiency. Med. Care Res. Rev. **58**, 430–454 (2001a)
Rosko, M.: Cost efficiency of U.S. hospitals: a stochastic frontier approach. Health Econ. **10**, 539–551 (2001b)
Rosko, M., Proenca, J., Zinn, J., et al.: the impact of membership in different types of systems on hospital cost-inefficiency. Inquiry **44**, 335–349 (2007)
Savitz, L., Jones, C., Shulamit, B.: Quality Indicators sensitive to nurse staffing in acute care settings. Advances in Patient Safety: From Research to Implementation, vol 4. AHRQ Publication No. 050021 (4), February 2005. Agency for Healthcare Research and Quality, Rockville, MD (2005)
Valdmanis, V., Rosko, M., Mutter, R.: Hospital quality, efficiency, and input slack differentials. Health Serv. Res. **43**, 1830–1848 (2008)
Wong, H., Zhan, C., Mutter, R.: Do different measures of hospital competition matter in empirical investigations of hospital behavior? Rev. Ind. Organ. **26**, 61–87 (2005)
Zuckerman, S., Hadley, J., Iezzoni, L.: Measuring hospital efficiency with frontier cost functions. J. Health Econ. **13**, 255–280 (1994)