**Do High-Quality Hospitals Practice Differently than Lower Quality Hospitals?**

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**Abstract**

We seek to determine whether or not hospitals providing high-quality care have a different production technology than hospitals providing lower quality of care. The methodology we employ is an extension of the data envelopment analysis (DEA) approach. Because of our rich data set – urban hospitals operating in 34 states in 2004 complete with several measures of inputs, outputs, case-mix, and patient safety indicators – we can derive separate production frontiers that account for both efficiency and quality. By comparing the frontier of the high-quality hospitals with the lower quality hospital frontiers, we can ascertain how these frontiers differ, as well as if the cause of the difference is relative measures of inefficiency or quality of care.

We found that medium-quality hospitals can improve performance vis-à-vis high quality hospitals by eliminating their technical inefficiency. This can be accomplished by making the "correct" tradeoff between quality and resource use. We found that low-quality hospitals appear to be in a more difficult predicament but may be able to improve their performance by scaling back their operations.

**Keywords**

Hospitals, quality, data envelopment analysis, congestion

## 1. Introduction

Germane issues explicit in health care policy include the efficient production of patient care and the quality of that care. To this end, much research and many implementation efforts have focused on the relationship between cost and quality. It is often assumed that trade-offs among these objectives have to be made for improvements to occur (Pauly [1]). However, it can be argued that quality improvement and cost containment may be achieved simultaneously, especially when taking the costs associated with in-hospital patient safety events (i.e., potentially preventable complications and iatrogenic events that can be reduced by improving the environment for safety) into account. Previous research has been mixed on the direct relationship between cost and quality or at least whether the relationship is statistically significant. See Clement et al. [2] for a review.

In this article, we contribute to the literature on the trade-off between quality and efficiency by examining whether high-quality hospitals operate differently, or in economic parlance "on a different production frontier," than hospitals providing lower quality, as measured by patient safety events using data envelopment analysis (DEA) as our methodological approach. This analysis is also an extension of previous research that reported that high-quality hospitals also had higher overall efficiency than lower quality institutions (Valdmanis et al. [3]). The authors of that article arrived at their result applying the notion of weak disposability of outputs (i.e., congestion) in data envelopment analysis (DEA). Using that approach, they also identified individual inputs that could be increased to improve quality, as well as which inputs increased inefficiency.

This analysis extends Valdmanis et al. [3] by asking a related research question: Do high quality hospitals practice in a way that is systematically different from lower quality hospitals? An affirmative answer would provide support for the contention that quality and efficiency can be improved simultaneously.

We believe that this type of analysis has practical implications that can be actionable by end users because it is based on the realization that hospitals that wish to maintain a competitive edge have to compete not only on the basis of price, but also on non-price dimensions, including quality (Pauly [1]).

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. [4] 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 limited by the lack of data on hospital quality even though they did find increasing efficiencies over time.. Also, in their review of the effects of hospital ownership on medical productivity, Kessler and McClellan [5] 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. [6] advance this line of research by examining the relationship between risk adjusted costs, nursing levels, quality of care (measured as actual/expected mortality rates) and outcomes. Using difference of means, these authors found that there were differences among hospitals on the cost-quality nexus, but to methodological limitations, these conclusions from these findings were associative without any direct linkage between efficiency and quality. We avoid this problem by simultaneously considering economic productivity and quality of hospital care.

In a comprehensive review of non-parametric and parametric applications measuring efficiency in health care, Hollingsworth [7] reported on the breadth and depth of this literature. In only 10 of the 188 papers cited by Hollingsworth [7] was quality of care incorporated as part of the frontier estimation process. This may be due to data limitations, which are gradually being overcome as measures of quality have been incorporated in some more recent frontier studies (Clement et al. [3]; Mutter et al. [8]; Valdmanis et al. [3]). As we have noted above, a strength of our study is that we measure in-hospital quality of care using indicators of the occurrence of patient safety events. We aim to extend this literature by comparing 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. From a social perspective, we hope to profile high-value hospitals (i.e., those hospitals that operate efficiently without compromising quality of care).

We can accomplish this by following previous research in a multi step approach (Grosskopf et al., [9]). .

## 2. Model

We use DEA and extensions of this method to compare the production performance of high-, medium- and low-quality hospitals. We begin by reviewing the decomposition of the overall technical efficiency measure:

Total Efficiency (CRS) = Pure Technical Efficiency (VRS)*Scale Efficiency*Congestion. (1)

In their work examining quality of care and hospital productivity, Valdmanis et al. (2008) examined the congestion component, which measures the impact patient safety events 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 patient safety events. (The intuition is similar to the concept of pollution emitted by industrial production: the more output a factory produces, the more pollution is released.) 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 our definition of quality is only one part of what should be considered as total hospital quality. To summarize, we consider congestion measuring the crowding out of patient care by patients who remain in the hospital because of the poor quality of care provided.

Whereas the focus of Valdmanis et al. [3] was the over- or under-utilization of specific inputs, this work examines whether high-quality hospitals have a different productive efficiency then institutions of lower quality. By clustering hospitals by quality status (defined above), we can ascertain if 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. [9]. 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. After determining the hospitals' congestion scores, the first step of our analysis is to adjust the level of outputs by dividing them by the congestion measure. This is done in order to discount the total amount of outputs in order to account for adverse outcomes. The result is the hospital's adjusted production, reflecting the value of the good outputs produced.

In the second step, we perform an input-based DEA on the medium- and low-quality hospitals using their actual inputs and congested-adjusted outputs. Once this problem is solved, we adjust all the hospitals so that each will lie on its respective best-practice frontier. This is accomplished by multiplying each hospital's input by its corresponding efficiency score. That is, we create two frontiers – one for medium-quality hospitals and another one for low-quality hospitals. Once this adjustment is made, we can then proceed to the third step, where we compare the adjusted frontiers of the medium- and low-quality hospitals to the frontier of the high-quality institutions, which is, by definition, not adjusted. This allows us to directly measure two frontiers on quality that is not confounded by inefficiency by the medium- or low-quality hospitals. Hence, by eliminating the inefficiency in the lower quality hospitals, we can gauge the role that quality may play in differences between the frontiers and technologies employed by the hospitals in each group.

A series of linear programming (LP) problems are employed to solve the relative productivity differences between these two hospital clusters. Since the methods of correcting for congestion are described elsewhere, 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 [10] 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.

$$
\begin{aligned}
&Min\phi \\
&s.t.\sum_{i}^{I} z \;\; y_m \geq y_{im} m = 1,...,M \\
&\sum_{i}^{I} z_{i\,n} x_n \phi x_n \\
&z_i \;\; \geq 0
\end{aligned}
\qquad (2)
$$

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

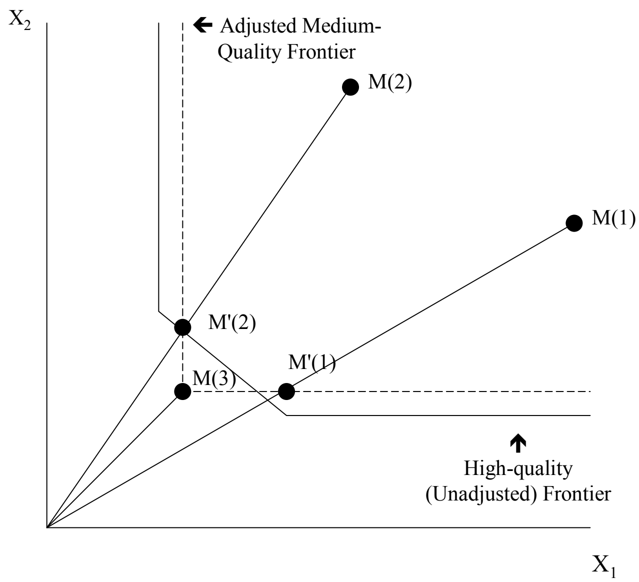
We accomplish this by using the reciprocal of the Farrell distance function so that we can compare the ratio of, for example, high-quality (h) and medium-quality (m) hospitals defined as:

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

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 greater than 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 less than 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 Figure 1 below.

**Figure 1: Comparing Adjusted and Unadjusted Frontiers.**




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 hospitals M(1) and M(2) operate interior to the high-quality hospital frontier. Once inefficiency is eliminated for the medium-quality hospitals, the new frontier (denoted by the dashed line) demonstrates that M'(1) and M'(2) have moved closer to the high-quality hospital frontier. Indeed, M'(2) is now on the high-quality hospital frontier, but 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.

To summarize, if the adjusted hospital's ratio is less than 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 the comparison group. If the ratio is greater than 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 these hospitals as having performance that is inferior to the high-quality hospital, best-practice frontier (e.g., M'(1)).

## 3. Data

Data come 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

[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~~decision-making. 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.

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), medical 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 [7] for a complete review.) We also note that even though we use the MCMI, it has been shown elsewhere (Jensen and Morrisey, [11] that the MCMI and total hospital case mix are highly correlated (0.86).

Measures of undesirable events include the following risk-adjusted PSIs that Savitz et al. (2005) indicate are sensitive to nurse staffing: failure to rescue (RPPS04), infection due to medical care (RPPS07), postoperative respiratory failure (RPPS11), and postoperative sepsis (RPPS13). Decubitus ulcer (RPPS03) and postoperative pulmonary embolism (PE) or deep vein thrombosis (DVT) (RPPS12) are also nurse-sensitive measures of quality; however, Houchens et al. [12] found that a high percentage of these events are present on admission (POA). Therefore, they are not valid measures of hospital quality, 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, we demonstrate may be an upper bound or conservative estimate of "true" hospital quality of care vis-à-vis these four negative 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 (Lindrooth et al. [13]).

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 studies have used a Hirschman-Herfindahl (HHI) to measure hospital competition.  The HHI measures concentration of output.  It equals one in a monopolistic market

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[6] Zuckerman et al. [14] developed an index based on 8 advanced technology services. In 2004, the AHA Annual Survey of Hospitals changed the classification system for hospital services. Several services were split into 2 or more related services (e.g., transplant services were split into 7 distinct types of transplants). Counting each separately listed service that was related to the index originally developed by Zuckerman et al. [14]), we included 17 services.

and approaches zero in highly competitive markets. Several studies (Rosko [15]; McKay et al. [16]) found that more competition is associated with lower hospital cost-efficiency. Four studies (Rosko [17]; Brown [18]; Rosko et al. [19]; and Mutter and Rosko [19]) found evidence to support service-based competition. 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 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.)

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

## 4. 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].

We note that overall technical and 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.

[7] The Hospital Market Structure File contains various measures of hospital market competition based off the algorithms developed by Wong et al. [21]. These measures are aggregate and are meant to broadly characterize the intensity of competition that hospitals may be facing under various definitions of market area. 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.

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.)

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 eliminated, the medium- and low-quality hospitals had production technologies similar to the production practices of the high-quality hospitals.

To reiterate, the process we employed in order to compare the frontiers for high-quality hospitals with those frontiers of medium- and low-quality hospitals involves several steps. We first adjust the outputs for the medium- and low-quality hospitals to reflect the burden of "congestion," which is the reduction in total patient care production associated with the PSIs. We then estimate each of these hospital type's individual production frontier and then adjust inputs by the inefficiency measure to move all these hospitals to their respective best-practice frontier. By moving all the medium- and low-quality hospitals to their own frontier, we are able to compare them to the high-quality, best-practice frontier in order to determine differences in production practice that are not biased by internal inefficiencies.

We next present comparative performance results for medium-quality hospitals. In Table 6, we identify 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, which indicates that once we remove the input inefficiencies, these hospitals are quite similar in some respects.

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 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. These findings suggest that low-quality hospitals may be trying to operate beyond their abilities. This suggestion is corroborated by the result that the most inefficient, poor-quality hospitals in our sample spend relatively more, have a relatively higher percentage of births, have relatively higher occupancy rates while devoting relatively more capital per bed and being relatively more likely to offer teaching services.

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

## 5. Discussion

By comparing hospital frontiers, rather than ~~caomparing~~comparing all hospitals to one frontier~~, we~~, 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 Medicaid patients, and were ~~NFPs~~Naps.

Since no low-quality hospitals dominated high-quality hospitals even after all inefficiencies were eliminated, we take 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. This finding may be worthy of future research.

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. Unfortunately, we found that low-quality hospitals may be in a more difficult predicament.

The methodological approach used here also demonstrates how to compare performance among firms in an industry that differ on one aspect of interest. We show that with specific data, we were able to compare production technologies as they differ with respect to quality without technical inefficiency obfuscating the interpretation of the results.

For policy-makers and hospital decision-makers, our methodological approach can provide them with empirical information that can lead to different choices. For example, for some hospitals can improve quality by reducing overall technical inefficiency. For other hospitals, reducing their range of services may mitigate poor quality outcomes. We base these policy options on the basis that the lowest quality hospitals can outperform their peers when their total expenditures are lowered. This last point is especially salient in the current health care reform debate.

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Table 1: Descriptive Statistics, High-Quality Hospitals (N = 824)

| **Variable** | **Mean** | **Std. Deviation** |
|---|---|---|
| **INPUTS** | | |
| Bassinets | 19.16 | 17.03 |
| FTE RNs | 329.63 | 231.24 |
| FTE LPNs | 30.59. | 34.38 |
| FTE other personnel | 872.67 | 655.00 |
| FTE 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 |
| **PSIs** | | |
| RPPS04 | 0.34 | 0.07 |
| RPPS07 | 0.04 | 0.01 |
| RPPS11 | 0.09 | 0.03 |
| RPPS13 | 0.10 | 0.06 |

Table 2: Descriptive Statistics, Medium-Quality Hospitals (N = 233)

| **Variable** | **Mean** | **Std. Deviation** |
|---|---|---|
| **INPUTS** | | |
| Bassinets | 21.17 | 12.89 |
| FTE RNs | 345.99 | 204.13 |
| FTE LPNs | 38.60 | 35.36 |
| FTE other personnel | 945.77 | 584.26 |
| FTE 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 |
| **PSIs** | | |
| RPPS04 | 0.34 | 0.05 |
| RPPS07 | 0.04 | 0.01 |
| RPPS11 | 0.08 | 0.03 |
| RPPS13 | 0.09 | 0.04 |

Table 3: Descriptive Statistics, Low-Quality Hospitals (N = 234)

| **Variable** | **Mean** | **Std. Deviation** |
|---|---|---|
| **INPUTS** | | |
| Bassinets | 15.61 | 11.93 |
| FTE RNs | 224.99 | 179.91 |
| FTE LPNs | 29.28 | 30.44 |
| FTE other personnel | 622.49 | 504.19 |
| FTE 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 |
| **PSIs** | | |
| RPPS04 | 0.32 | 0.07 |
| RPPS07 | 0.03 | 0.02 |
| RPPS11 | 0.06 | 0.04 |
| RPPS13 | 0.03 | 0.05 |

Table 4:: Descriptive Statistics, Output-Based Efficiency[a] Scores for High-Quality and Lower Quality Hospitals

| **Efficiency Score** | **Mean** | **Std. Deviation** |
|---|---|---|
| **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 |

a. Recall that higher output based efficiency scores mean higher inefficiencies by the percent: Efficiency Score-1/Efficiency score.

Table 5: Descriptive Statistics, Input-Based Efficiency[b] Scores for High-Quality and Lower Quality Hospitals

| Efficiency Score | Mean | Std. Deviation |
|---|---|---|
| **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 |

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

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 | | |
| **ER%** | | | |
| 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 | | |
| **ALOS** | | | |
| 1 | 4.88 | 0.78 | NS |
| 2 | 4.82 | | |
| **Capital/Bed** | | | |
| 1 | 48,542.43 | -0.70 | NS |
| 2 | 49,580.65 | | |
| **FTE Personnel/ Admission** | | | |
| 1 | 0.11 | 0.46 | NS |

| | | | |
|---|---|---|---|
| 2 | 0.11 | | |
| **FTE Personnel/ Bed** | | | |
| 1 | 5.42 | -0.79 | NS |
| 2 | 5.48 | | |
| **Uninsured%** | | | |
| 1 | 13.62 | 0.25 | NS |
| 2 | 13.81 | | |
| **HMO%** | | | |
| 1 | 20.62 | -1.54 | NS |
| 2 | 23.37 | | |
| **HHI** | | | |
| 1 | 0.38 | 0.63 | NS |
| 2 | 0.36 | | |
| **COTH%** | | | |
| 1 | 9.0 | 0.01 | NS |
| 2 | 9.0 | | |
| **MNTEACH%** | | | |
| 1 | 19.0 | -1.03 | NS |
| 2 | 25.0 | | |
| **FP%** | | | |
| 1 | 13.0 | 0.64 | NS |
| 2 | 10.0 | | |
| **Government%** | | | |
| 1 | 18.0 | 3.03 | 0.007 |
| 2 | 6.0 | | |
| **NFP%** | | | |
| 1 | 68.0 | -2.77 | 0.01 |
| 2 | 84.0 | | |
| **System Membership%** | | | |
| 1 | 62.0 | 0.41 | NS |
| 2 | 59.0 | | |

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 | | |
| **ER%** | | | |
| 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 | | |
| **ALOS** | | | |
| 1 | 4.83 | 0.598 | NS |
| 2 | 4.71 | | |
| **Capital/Bed** | | | |
| 1 | 44,661.27 | 5.13 | 0.02 |
| 2 | 37,880.97 | | |
| **FTE Personnel/** | | | |

| | | | |
|---|---|---|---|
| **Admission** | | | |
| 1 | 0.06 | 0.0.659 | NS |
| 2 | 0.06 | | |
| **FTE Personnel/ Bed** | | | |
| 1 | 1.08 | 1.39 | NS |
| 2 | 1.08 | | |
| **Uninsured%** | | | |
| 1 | 14.8 | 1.98 | NS |
| 2 | 13.8 | | |
| **HMO%** | | | |
| 1 | 25.89 | 2.00 | NS |
| 2 | 27.13 | | |
| **HHI** | | | |
| 1 | 12.26 | 0.57 | NS |
| 2 | 11.44 | | |
| **COTH%** | | | |
| 1 | 10.00 | 6.47 | 0.01 |
| 2 | 0.00 | | |
| **MNTEACH%** | | | |
| 1 | 19.2 | 0.09 | NS |
| 2 | 21.5 | | |
| **FP%** | | | |
| 1 | 23,1 | 0.37 | NS |
| 2 | 18.5 | | |
| **Government%** | | | |
| 1 | 17.3 | 0.58 | NS |
| 2 | 12.3 | | |
| **NFP%** | | | |
| 1 | 60.0 | 1.16 | NS |
| 2 | 69.0 | | |
| **System Membership%** | | | |
| 1 | 29.89 | 2.00 | NS |
| 2 | 27.06 | | |

## Appendix 1

### A1.1 DEA Model

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

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

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:

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

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:

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

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:

$$
\begin{aligned}
F_O\left(x, y \mid V, S\right) \;=\; & \max_{z,\theta^S} \; \theta^S \\
s.t. \quad & \theta^S \cdot y \le z \cdot M \\
& z \cdot K \le x \\
& z \in \Re_N \\
& \sum_{j=1}^{N} z_j = 1.
\end{aligned}
$$

and

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

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 $C_O\left(x, y \middle| V\right) \;=\; \dfrac{F_O\left(x, y \middle| V, S\right)}{F_O\left(x, y \middle| V, W/S\right)} \;=\; \dfrac{\theta^{S*}}{\theta^{W/S*}} \;\ge\; 1$ with the individual outputs to discount outputs to account for the bad outcomes produced.

**Appendix 2: Descriptive Statistics for all Three Hospital Groups**

Table A2-1: Descriptive Environmental and Organizational Variables, High-Quality Hospitals (N = 834)

| Variable | Mean | Standard Deviation |
|---|---|---|
| **Total Expenditures** | 198,944,690 | 201,666,465 |
| **High-Tech Services** | 7.05 | 4.20 |
| **Birth%** | 12.02 | 8.43 |
| **ER%** | 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 |
| **Cost/Admission** | 13,442.27 | 5,999.63 |
| **ALOS** | 5.30 | 2.76 |
| **Capital/Bed** | 50,511.49 | 27,376.90 |
| **FTE Personnel/ Admission** | 0.11 | 0.04 |
| **FTE Personnel/ Bed** | 5.33 | 2.03 |
| **Uninsured %**[c] | 14.24 | 6.76 |
| **HMO%**[c] | 25.46 | 13.25 |
| **HHI**[c] | 0.30 | 0.27 |
| **COTH** | 14.31% | |
| **MNTEACH** | 21.64% | |
| **FP** | 17.76% | |
| **Government** | 10.87% | |
| **NFP** | 71.37% | |
| **System Member** | 67.59% | |

c. County-level variables

Table A2-2: Descriptive Environmental and Organizational Variables, Medium-Quality Hospitals (N = 217)

| Variable | Mean | Standard Deviation |
|---|---|---|
| **Total Expenditures** | 160,598,583 | 103,054,353 |
| **High-Tech Services** | 6.67 | 3.53 |
| **Birth%** | 12.72 | 6.47 |
| **ER%** | 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 |
| **ALOS** | 4.85 | 1.23 |
| **Capital/Bed** | 49,107.57 | 23,551.37 |
| **FTE Personnel/ Admission** | 0.11 | 0.03 |
| **FTE Personnel/ Bed** | 5.46 | 1.81 |
| **Uninsured %**[c] | 13.73 | 7.37 |
| **HMO%**[c] | 22.21 | 13.81 |
| **HHI**[c] | 0.37 | 0.29 |
| **COTH** | 8.75% | |
| **MNTEACH** | 22.11% | |
| **FP** | 11.52% | |
| **Government** | 11.05% | |
| **NFP** | 77.42% | |
| **System Member** | 59.91% | |

c. County-level variables

Table A2-3 Descriptive Environmental and Organizational Variables, Low-Quality Hospitals (N = 234)

| Variable | Mean | Standard Deviation |
|---|---|---|
| **Total Expenditures** | 201,756,187.00 | 203,430,966.00 |
| **High-Tech Services** | 6.92 | 4.47 |
| **Birth%** | 11.40 | 8.32 |
| **ER%** | 30.34 | 18.04 |
| **Outpatient Surgeries%** | 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 |
| **ALOS** | 5.37 | 3.01 |
| **Capital/Bed** | 50,715.31 | 28,807.27 |
| **FTE Personnel/ Admission** | 0.11 | 0.04 |
| **FTE Personnel/ Bed** | 5.27 | 0.04 |
| **Uninsured %**[c] | 14.17 | 7.29 |
| **HMO%**[c] | 23.97 | 13.11 |
| **HHI**[c] | 0.32 | 0.27 |
| **COTH%** | 16.24% | |
| **MNTEACH** | 22.22% | |
| **FP** | 21.37% | |
| **Government** | 7.26% | |
| **NFP** | 71.36% | |
| **System Member** | 70.01% | |

c. County-level variables