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COMPARATIVE EFFICIENCY ANALYSIS OF HOSPITALS BASED ON THE REGION, OWNERSHIP, AND SERVICE USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

The health care industry is growing rapidly in the United States. Along with the growth, the way of reducing health care spending and improving the efficiency of the health care system has been discussed among researchers. In particular, hospital efficiency has been one of main topics in the health care industry. This paper employs a nonparametric approach to measure the efficiency of hospitals. Using a Data Envelopment Analysis model and publicly available data, the performance of hospitals in the United States is evaluated. The efficiency levels of the hospitals are compared and analyzed by considering different types of variables describing main characteristics of hospitals. The results of this study gives administrators not only an insight on their current efficiency rate and the ranking among the hospitals participated but also a way of changing their inefficiencies.

Keywords: Hospital efficiency, Data Envelopment Analysis (DEA), Decision Making Unit (DMU), Variable Returns to Scale (VRS)

INTRODUCTION

As our life expectancy is getting longer, living healthy life has become one of the most important discussion topics. Getting good health care services is considered critical to maintain a healthy life. As hospitals have been a central part of the health care services, finding and improving inefficiencies of hospitals can provide patients with better services and can lead to a huge reduction of health care spending.

Data Envelopment Analysis (DEA) was introduced by Charnes, Cooper, and Rhodes (1978) and was extended later by Banker, Charnes, and Cooper (1984). DEA has been used to measure efficiency of a set of peer entities called Decision Making Units (DMUs) such as hospitals, universities, and business firms, based on observational data. While several techniques such as stochastic frontier analysis and fixed effects regression models have been used to estimate an efficiency, DEA has been used as a preferred method for measuring hospital efficiency due to the following reasons. First, DEA is a nonparametric frontier method that uses linear programming to evaluate the relative technical efficiency of a DMU. Second, DEA can handle multiple inputs and outputs easily and is less vulnerable to the misspecification problems that can affect econometric models (Cordero et al, 2015). Third, DEA measures inputs and outputs in their natural units and does not require a functional form to be prescribed explicitly (Charnes, Cooper, Lewin, & Seiford, 1994). Fourth, unlike statistical regressions that evaluates the average performance of multiple DMUs, DEA evaluates the performance of an individual DMU that compares each DMU with every other DMU in the sample (Cooper, Seiford, & Zhu, 2011).

Since the first paper on the topic of DEA many papers have been published in a wide range of areas including the education sector (Abdullah, Tulus, Suwilo, Efendi, & Mawengkang, 2018; Sagarra, Mar-Molinero, Agasisti, 2017; Thanassoulis et al, 2016), banks and mutual funds (Kai, Worthington, & Zelenyuk, 2018; Nasseri, Ebrahimnejad, & Gholami, 2018), public libraries (Guajardo, 2018; Park & Rhee, 2016), regional welfare (Helmig & Lapsley, 2001; Labaj, Luptacik, & NeZinsky, 2014; Habibov & Fan, 2010), environment (Martin-Gamboa, Iribarren, & Dufour, 2018; Wang, Wei, & Huang, 2018; Zhou, X. et al, 2018), local services (Guccio, Mignosa, & Rizzo, 2018; Zhang, Tone, & Lu, 2018), and the water sector (Emrouznejad, Paker, & Tavres, 2008; Guajardo, 2015; Guerrini, Romano, Leardini, & Martini, 2015).

DEA provides a lot of different models, and all DEA models can employ two orientations, input-oriented and output-oriented. Input-oriented models focus on minimizing input resources while trying to produce at least the given level of outputs. Whereas, output-oriented models attempt to produce maximum outputs with a given set of inputs.

Depending on the DEA models, constant returns to scale (CRS) or variable returns to scale (VRS) method can be used. Constant returns to scale means an increase in inputs results in a proportional change in outputs. But in variable returns to scale, an increase in inputs is not reflected as a proportional change in outputs.

This study uses an input-oriented variable returns to scale (VRS) estimation model to assess the efficiency of hospitals in the United State. The efficiency scores are later combined and analyzed by seven geographic locations, ownership, and service types.

LITERATURE REVIEW

According to Emrouznejad and Yang (2018), health care including hospital is one of the most popular application areas in DEA along with energy, banking, and education. Sherman's doctoral dissertation in 1981 is considered as the first application of DEA in health care (Chilingerian & Sherman, 2011). After that, Nunamaker (1983) and Sherman (1984) published the first and second DEA papers respectively in health care. Hollingsworth et al. (1999) was able to count 91 DEA studies in health care by 1997. In the later survey, Emrouznejad, Paker, and Tavres (2008) identified 103 journal papers using a keyword, health care or hospital.

In recent studies, various DEA models and input/output variables have been used to evaluate hospital efficiencies. Khushalani and Ozcan (2017) used dynamic network DEA to examine efficiency of hospitals between 2009 and 2013 using patients' visits, surgeries, and discharges. Omrani, Shafaat, and Emrouznejad (2018) used an integrated fuzzy clustering cooperative game DEA approach with application in hospital efficiency to investigate non homogenous DMUs. Miller, Wang, Zhu, Chen, and Hockenberry (2017) developed an integer-valued non-radial Russell DEA model to calculate and compare the efficiency of hospitals in Massachusetts and Connecticut pre- and post-health care reform. The inputs considered in Johannessen, Kittelsen, and Hagen (2017) were number of full-time equivalent physician, salary of physicians, nurses, secretaries, and other personnel. The outputs selected were number of patients treated by hospitalization, daycare treatment, total number of patient contacts, and outpatient treatment. Bahrami, Rafiei, Askari (2018) conducted a case study to assess economic, allocative, and technical efficiency in intensive care units of hospitals in Iran. They selected four input variables – number of physicians, nurses, active beds and equipment. Bed occupancy rate, the number of discharged patients, economic information such as bed price and physician's fee were selected as output variables. They found that the average scores of allocative, economic, technical, managerial, and scale efficiency were relatively high. Interestingly, Valdmanis, Rosko, Leleu, and Mukamel (2017) evaluated overall, technical, and scale efficiency on home health care agencies, which they believe play a vital role in the production of health. They found that home health care agencies, on average, could reduce inputs by 28% (overall efficiency), 23% (technical efficiency), and 6% (scale efficiency).

RESEARCH METHODOLOGY

This study employs an input-oriented Banker-Charnes-Cooper (BCC) DEA model known as a variable returns to scale (VRS) estimation model to assess an efficiency of hospitals located in the United States. Data were obtained from the annual survey of the American Hospital Association and contained observations for 10 variables on a total of 200 hospitals. These variables include geographic region, control, service, 4 inputs, and 3 outputs. The examples of other studies that have developed DEA frameworks for measuring hospital efficiency are considered when inputs and outputs are selected (Dyson et al, 2001; Tiemann & Schreyögg, 2012). Table 1 shows a list of variables used in this study.

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Table 1. A List of Variables

Type	Description
Geographic region	1. South 2. Southwest 3. Northeast 4. Northwest 5. Midwest 6. Rocky Mountain 7. California
Control	1. Government, Nonfederal 2. Nongovernment, Not-for-profit 3. For-profit 4. Federal government
Service	1. General Medical 2. Psychiatric
Inputs	1. Number of beds 2. Total amount of expenditures 3. Payroll 4. Personnel
Outputs	1. Number of admissions 2. Number of outpatient's visit 3. Number of births

The variable of a geographic region contains 7 areas – South, Southwest, Northeast, Northwest, Midwest, Rocky Mountain, and California. The control variable represents the four types of ownership including 1) government, nonfederal, 2) nongovernment, not-for-profit, 3) for-profit, and 4) federal government. The service variable is the type of hospital, and two types of hospitals were used including 1) general medical and 2) psychiatric.

Four inputs and three outputs are utilized in this study. The first input variable is the number of beds (Beds), which is used as a proxy for material resources. The second and third input variable are the total amount of expenditures and payroll expenditures respectively. Both represent monetary inputs. The fourth input variable that represents a labor input is personnel including staffs, registered nurses, and doctors. The number of admissions, the number of outpatient's visits, and the number of births are used as outputs of hospital services.

As shown in figure 1, this study includes a two-stage process. In the first process, three input and two output variables are fed into a DEA model, and the efficiency measurements generated by DEA is analyzed in the second stage to see if there are any significant efficiency differences by geographic region, control, and service type.

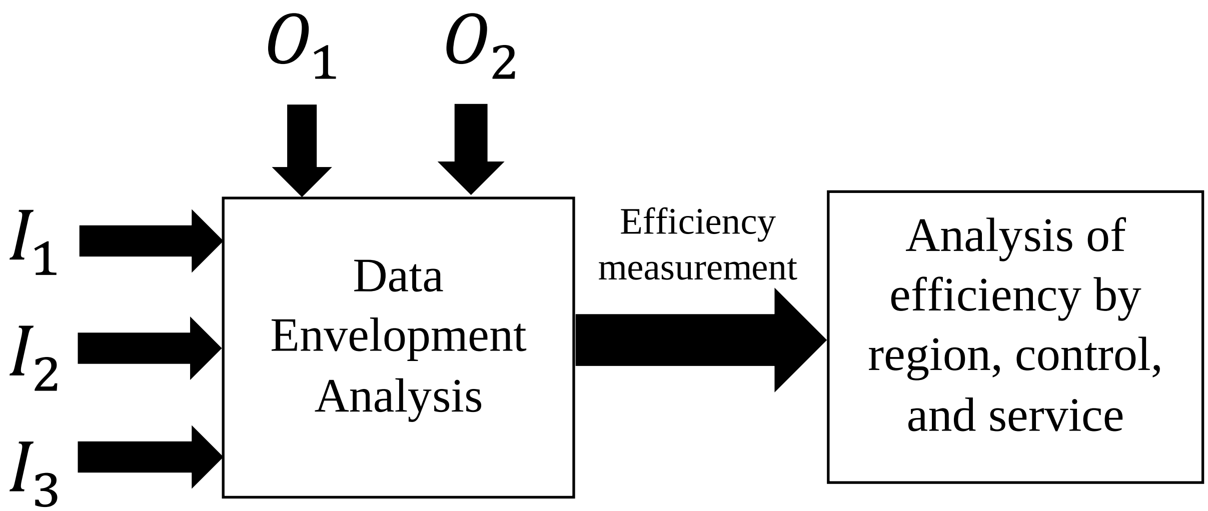


Figure 1. Two Stage Experiment Framework

RESEARCH RESULTS AND DISCUSSIONS

An input-oriented BCC model produces an ample amount of useful information. Table 2 shows a basic statistics on input and output data whereas table 3 gives correlation between data. The total expenditures and payroll expenditures are in units of $1,000. Table 2 depicts that research data contains wide range of hospitals from a small hospital with 7 beds and 50 personnel to a large hospital with 1,297 beds and 4,087 personnel. In output statistics, a small hospital has only 111 admissions whereas a large hospital has 37,375 admissions. According to the table 3, a high correlation is noticed between three input variables including total expenditures, payroll expenditures, and personnel and an output variable, admission. This table also tells that an input variable Beds is not highly correlated with two output variables, Outpatient's Visits and Births. From the correlation between Total Expenditures and Payroll Expenditures, we can have a reasonable guess that payroll expenditures occupies a good portion of total expenditures.

Table 2. Descriptive Statistics on Inputs and Outputs

Decision Making Unit	**Inputs**				**Outputs**		
	Beds	**Total Exp.**	**Payroll**	**Personnel**	**Admission**	**Visit**	**Birth**
Mean	209.9	67139.8	30500.9	861.5	6831.8	98224	874
St. Dev	171.65	70210.30	32633.9	819.54	6629.5	118567	1061
Min	7	2082	1053	50	111	0	0
Max	1297	367706	188865	4087	37375	813369	5699

Table 3. A Correlation between Data

	Beds	**Tot. Exp.**	**Payroll Exp.**	**Personnel**	**Admissions**	**Outpatient's Visits**	**Births**
Beds	1	0.71092	0.73658	0.75273	0.62487	0.34023	0.42888
Tot. Exp.	0.71092	1	0.98254	0.96471	0.90249	0.62942	0.71322
Payroll Exp.	0.73658	0.98254	1	0.95187	0.84821	0.62614	0.65958
Personnel	0.75273	0.96471	0.95187	1	0.87946	0.64402	0.69746
Admissions	0.62487	0.90249	0.84821	0.87946	1	0.60246	0.85562
Outpatient's Visits	0.34023	0.62942	0.62614	0.64402	0.60246	1	0.56709
Births	0.42888	0.71322	0.65958	0.69746	0.85562	0.56709	1

The values of efficiency scores range from 0.0 to 1.0. Any DMU that has a less than 1.0 is considered as inefficient DMU. Out of 200 hospitals, 30 hospitals are marked as efficient DMUs with an efficiency score of 1.0. 13 hospitals are ranked as the second best efficient hospitals with an efficiency score ranged from 0.901 to 0.9886. This means the second group of hospitals are ranked as about 90% to 98% of the best group of hospitals. 23 hospitals are ranked in the third group with an efficiency score between 0.802 and 0.8931. The rest of 123 hospitals are ranked under 80%. The hospitals under 80% of efficiency have a lot of rooms to improve their efficiency compared to their peer hospitals as indicated later in this section. Table 4 shows the first 30 hospitals' efficiency score, rank, lambda value with reference DMUs, and the returns to scale (RTS) of a projected DMU. As an example, DMU #5 has efficiency score of 0.5841 and ranks at 142nd. The efficiency score and rank are calculated using references (lambda) of the best three DMUs including #6, #21, and #30. Along with the reference DMUs, distance numbers of 0.887, 0.047, and 0.024 show how far away DMU #5 is from each reference DMU. The last column reveals the returns to scale. If output increases by less than the proportional change in inputs, there are decreasing returns to scale (DRS), whereas if output increases by more than the proportional changes in inputs, there are increasing returns to scale (IRS). Some of DMUs have constant returns to scale (CRS) meaning there is neither decreasing nor increasing returns to scale.

Table 4. Efficiency Score, Rank, Reference, and RTS

DMU	BCC Efficiency Score	Rank	Reference(Lambda)						RTS of Projected DMU
1	0.7167	93	6	0.059	29	0.122	30	0.663	Decreasing
2	0.7668	76	29	0.599	128	0.285	181	0.116	Decreasing
3	0.9815	35	68	0.402	128	0.55	181	0.049	Decreasing
4	0.8141	60	25	0.23	29	0.365	46	0.057	Constant
5	0.5841	142	16	0.887	21	0.047	30	0.024	Increasing
6	1	1	6	1					Decreasing
7	0.7343	84	29	0.219	68	0.17	159	0.04	Constant
8	0.5736	149	16	0.025	68	0.005	82	0.64	Increasing
9	0.937	39	6	0.275	29	0.467	68	0.033	Decreasing
10	0.8432	54	16	0.465	29	0.185	68	0.05	Increasing
11	0.705	103	16	0.273	21	0.025	29	0.094	Increasing
12	0.9612	38	16	0.489	29	0.133	30	0.16	Increasing
13	0.5817	145	25	0.066	29	0.166	68	0.03	Increasing
14	0.8388	56	29	0.282	30	0.598	48	0.052	Decreasing
15	1	1	15	1					Constant
16	1	1	16	1					Increasing
17	1	1	17	1					Constant
18	0.8199	58	29	0.093	30	0.319	48	0.166	Decreasing
19	0.6	138	29	0.628	30	0.264	48	0.09	Decreasing
20	0.2867	185	16	0.014	30	0.495	176	0.491	Increasing
21	1	1	21	1					Constant
22	0.7767	72	6	0.349	30	0.405	68	0.015	Decreasing
23	0.619	131	6	0.037	30	0.566	68	0.023	Decreasing
24	0.862	49	30	0.179	48	0.521	176	0.282	Decreasing
25	1	1	25	1					Constant
26	0.7164	94	6	0.097	29	0.207	30	0.657	Decreasing
27	0.7976	67	29	0.183	30	0.73	68	0.025	Constant
28	0.6703	115	6	0.14	30	0.645	48	0.193	Decreasing
29	1	1	29	1					Constant
30	1	1	30	1					Constant
31	0.5441	158	6	0.166	29	0.111	30	0.584	Decreasing
32	0.5815	146	15	0.086	16	0.597	30	0.317	Increasing
33	0.9852	33	16	0.537	68	0.019	82	0.014	Increasing
34	0.6246	129	6	0.51	30	0.118	181	0.373	Decreasing
35	0.6378	126	6	0.436	30	0.441	128	0.022	Decreasing
36	0.5692	151	29	0.783	128	0.196	181	0.021	Decreasing
37	0.7197	90	16	0.07	82	0.167	108	0.511	Increasing
38	0.5644	155	16	0.002	30	0.589	68	0.013	Increasing

Figure 2 is another representation of efficiency scores of 200 hospitals as a bar chart to help visualize each DMU's efficiency.

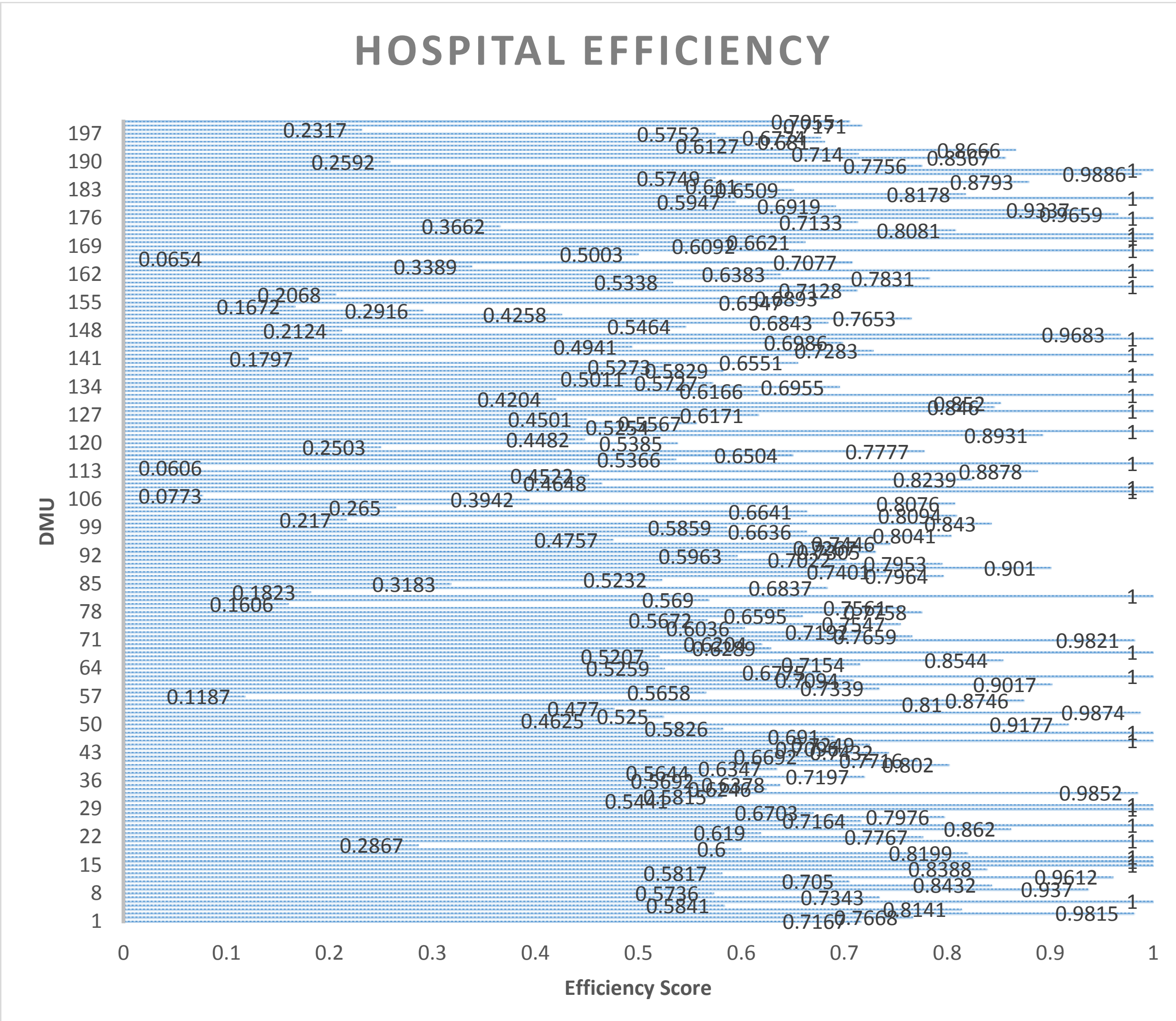


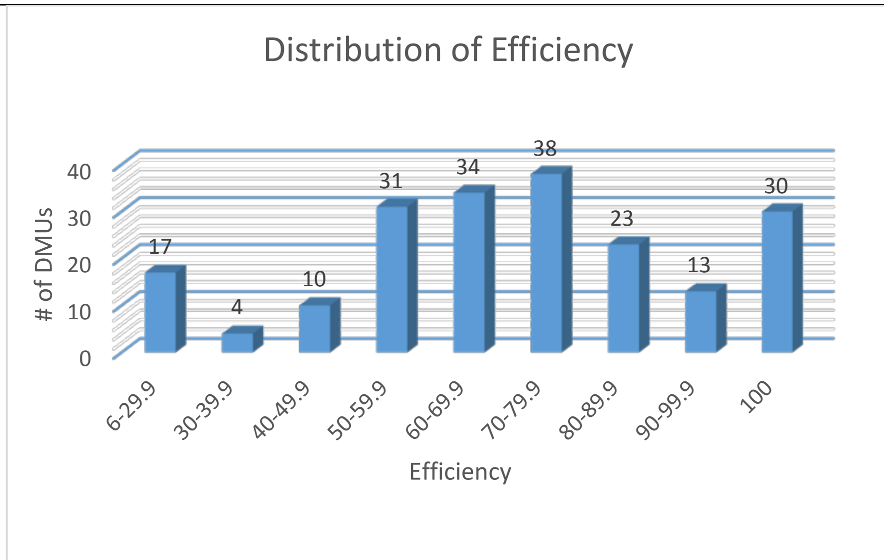
Figure 2. Hospital Efficiency Score Graph

As shown in table 5, 17 hospitals are identified under less than 30% of maximum possible efficiency, and 14 hospitals are between 30 and 49.9% of a maximum efficiency. 103 hospitals (31+34+38 = 103) occupy the middle section which ranges from 50.0% to 79.9% of a maximum efficiency. 36 hospitals (23+13 = 36) are close to the full efficiency ranging between 80 and 99.9% of a maximum efficiency.

The second stage of the study is to analyze efficiency score by the geographical region, control, and service type to see if there is any difference. Figure 3 shows the average efficiency score of hospitals scattered in 7 geographical regions – South, Northeast, Midwest, Southwest, Rocky Mountain, California, and Northwest. Hospitals in California are ranked the top highest with the efficiency score of 0.817, and hospitals in south and southwest area mark the second highest with the efficiency score of 0.769 and 0.75 respectively. Hospitals in Rocky Mountain are ranked right below these two regions with the efficiency of 0.744. Hospitals in Northeast and Midwest are ranked bottom two with the efficiency of 0.628 and 0.611 respectively. The average efficiency between hospitals in California and in Midwest has a large gap of 20.6%. To look at the efficiency of an individual DMU, the scattered plot of DMUs by geographical regions is illustrated in figure 4. In the figure 4, we can see that most hospitals in California are ranked above 80% whereas more than 70% of hospitals in Midwest are ranked below 60% of efficiency though there are 6 hospitals have a 1.0 efficiency score.

Table 5. Distribution of Efficiency Scores

Efficiency (%)	# of Hospitals
6-29.9	17
30-39.9	4
40-49.9	10
50-59.9	31
60-69.9	34
70-79.9	38
80-89.9	23
90-99.9	13
100.0	30



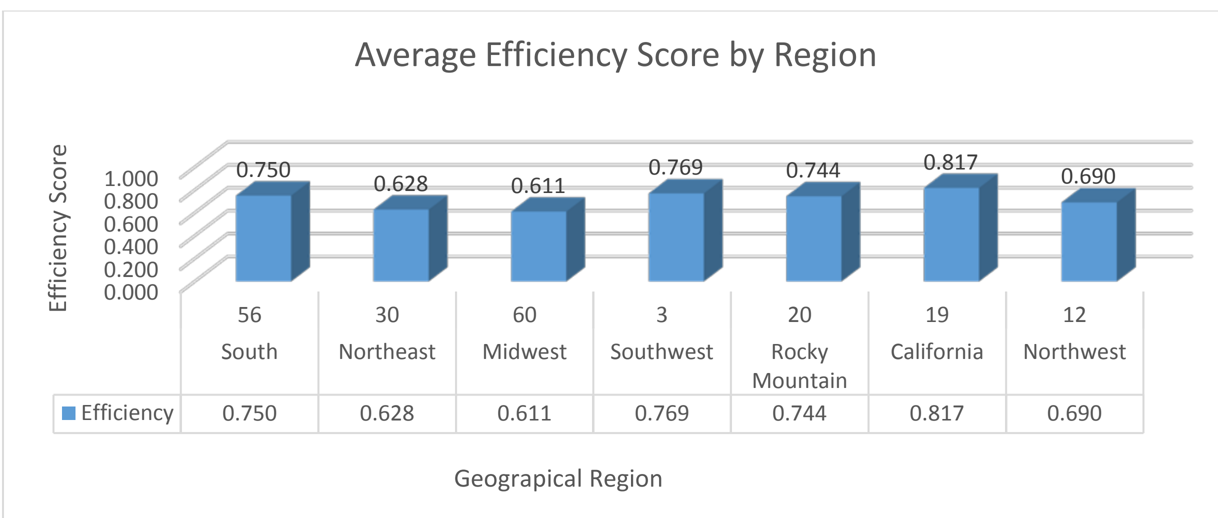
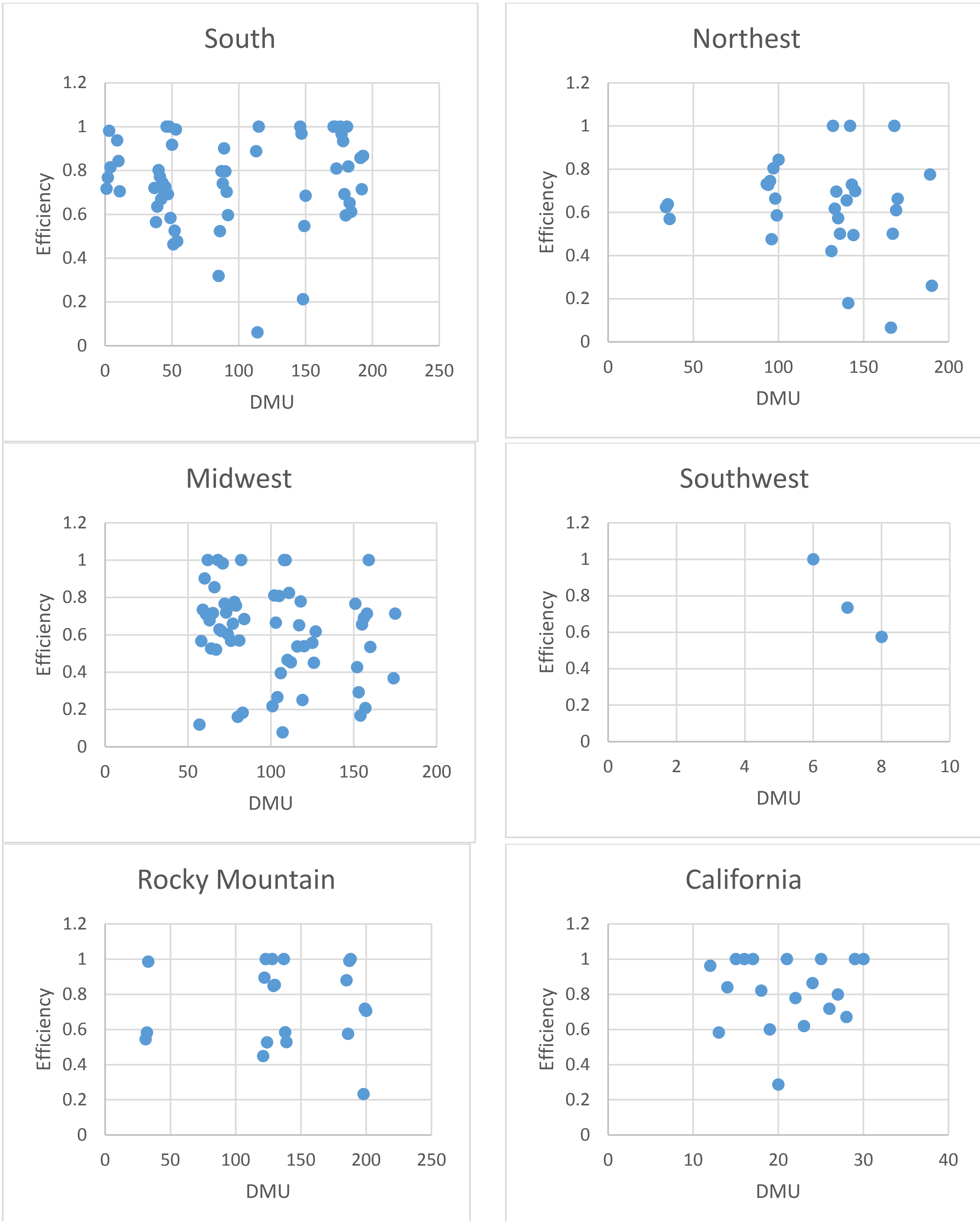


Figure 3. Average Efficiency Score by Region



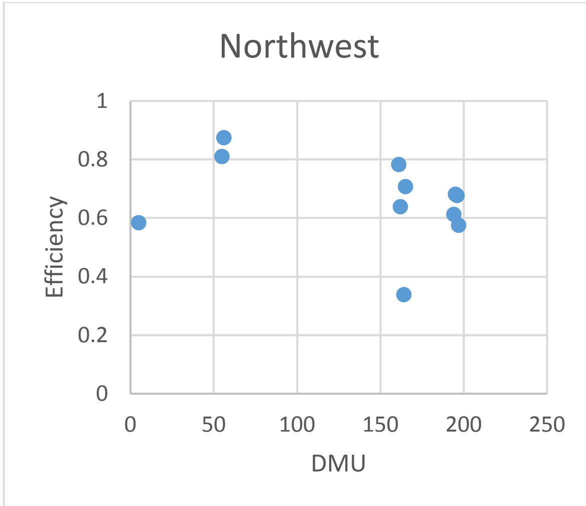


Figure 4. Scatter Plot of DMUs by Geographical Region (Continued)

Mean efficiency scores by ownership is shown in figure 5. This figure clearly shows that for-profit hospitals are operated most efficiently with a mean efficiency score 0.768 compared to other hospitals owned by government (non-federal), nongovernment (not-for-profit), and federal government. Also, not-for-profit, nongovernment hospitals have the second highest mean efficiency score (0.717). Government, non-federal hospitals and federal government hospitals have a lowest mean DEA score of 0.613 and 0.610 respectively. The mean efficiency gap between for-profit hospitals and federal government owned hospitals is more than 15%.

Average efficiency of two different types of hospitals is shown in figure 6. As shown in the figure, the general medical hospitals are more efficient than psychiatric hospitals by more than 21%.

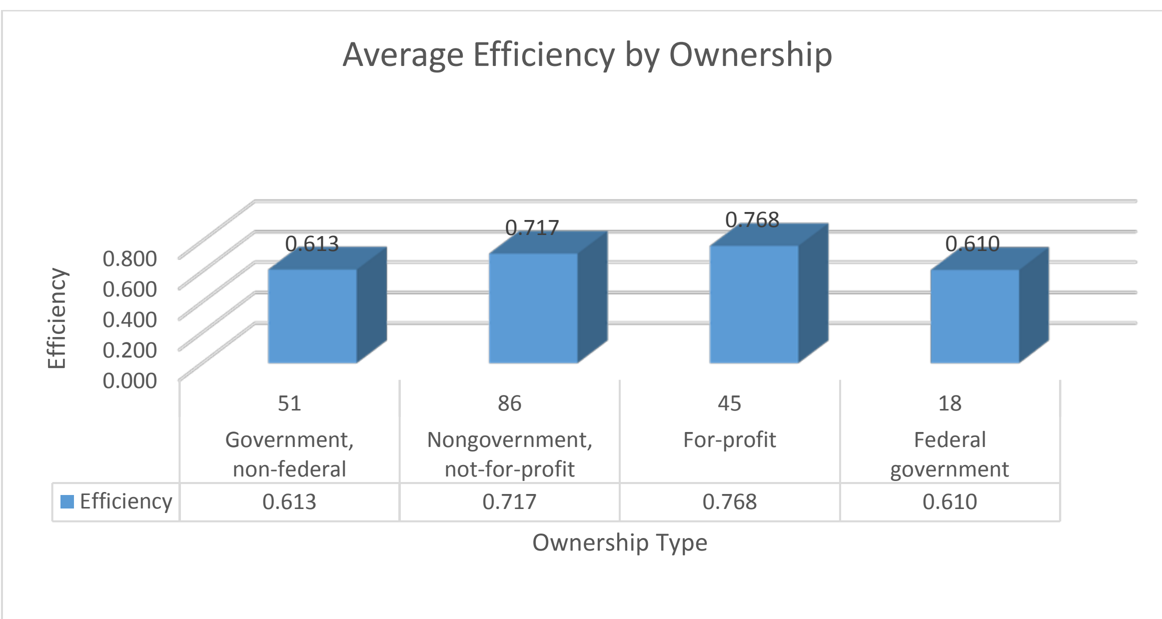


Figure 5. Average Efficiency Score by Ownership

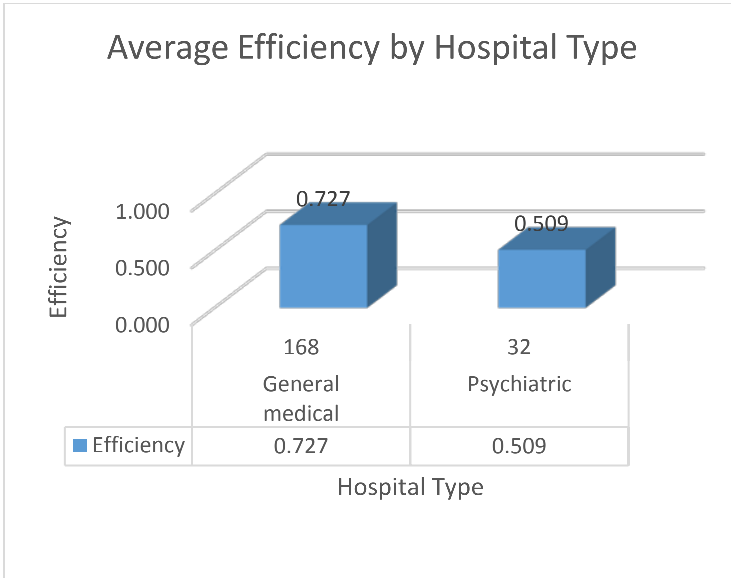


Figure 6. Average Efficiency Score by Control

Table 6 exhibits the projection of input variables. Total expenditures and payroll expenditures are in units of $1,000. This table tells hospital administrators what they need to do to improve their inefficiencies. For example, DMU #1 has an efficiency score of 0.7167 with 210 beds, total expenditures of $56,831, payroll expenditures of $22,061, and 792 employees. To lift the current efficiency to 1.0, or to be the best among the peer hospitals in the experiment, DMU #1 should 1) reduce the number of beds to 84.5, which is 59.8% reduction, 2) reduce the total expenditures to $40,730, which is 28.3% reduction, 3) reduce the payroll expenditures to $15,811, which is 28.3% reduction, and 4) reduce the number of employees to 567.6, which is 28.3%. Which actions administrators can take is depend on their situation, but the table 6 clearly displays where the inefficiency is and how to improve the efficiency for individual DMUs.

As shown in this section, some organizational factors such as geographic locations, the type of ownership of hospitals, and the service type of hospitals are compelling factors of efficiency.

Table 6. Projection of Input Variables

DMU	Score	Beds Data	Projection	Diff.(%)	Tot. Exp. Data	Projection	Diff.(%)	Payroll Exp. Data	Projection	Diff.(%)	Personnel Data	Projection	Diff.(%)
1	0.7167	210	84.5	-59.8	56831	40730.7	-28.3	22061	15811.1	-28.3	792	567.6	-28.3
2	0.7668	347	252.8	-27.2	127223	97559.7	-23.3	55799	42681.5	-23.5	1762	1129.9	-35.9
3	0.9815	511	398.2	-22.1	157093	150627	-4.1	61326	60191.5	-1.9	2310	1991.2	-13.8
4	0.8141	142	75.9	-46.6	24462	19915.5	-18.6	10503	8550.91	-18.6	328	267.0	-18.6
5	0.5841	40	23.4	-41.6	13730	6617.4	-51.8	6368	3237.51	-49.2	181	105.7	-41.6
6	1	220	220.0	0.0	93257	93256.9	0.0	33920	33920	0.0	1077	1077.0	0.0
7	0.7343	137	73.5	-46.4	45458	33378.7	-26.6	26919	14496.1	-46.1	742	544.8	-26.6
8	0.5736	80	45.9	-42.6	6151	3363.54	-45.3	2768	1587.73	-42.6	131	74.3	-43.3
9	0.937	440	250.7	-43.0	98992	92758.7	-6.3	40956	38377.1	-6.3	1594	1089.9	-31.6
10	0.8432	48	40.5	-15.7	11569	9755.18	-15.7	5664	4513.48	-20.3	233	193.2	-17.1
11	0.705	56	39.5	-29.5	11356	8006.37	-29.5	5084	3584.4	-29.5	241	147.8	-38.7
12	0.9612	46	44.2	-3.9	15200	14610.2	-3.9	7085	6810.1	-3.9	203	195.1	-3.9
13	0.5817	109	63.4	-41.8	20848	12126.2	-41.8	9709	5647.24	-41.8	325	189.0	-41.8
14	0.8388	306	131.3	-57.1	62778	52656.6	-16.1	28958	22683.7	-21.7	676	567.0	-16.1
15	1	7	7.0	0.0	20300	20300	0.0	12300	12300	0.0	347	347.0	0.0
16	1	16	16.0	0.0	3836	3835.97	0.0	2015	2014.99	0.0	79	79.0	0.0
17	1	167	167.0	0.0	41417	41417	0.0	20633	20633	0.0	505	505.0	0.0
18	0.8199	444	298.2	-32.8	144966	118858	-18.0	61667	50561	-18.0	1543	1265.1	-18.0
19	0.6	236	110.9	-53.0	67997	40797.6	-40.0	31285	18770.7	-40.0	755	453.0	-40.0
20	0.2867	247	70.8	-71.3	123175	26330	-78.6	41899	11757	-71.9	959	275.0	-71.3
21	1	93	93.0	0.0	28318	28318	0.0	12589	12589	0.0	325	325.0	0.0
22	0.7767	236	171.3	-27.4	88080	68318.3	-22.4	32191	25001.9	-22.3	954	740.9	-22.3

Table 6. Projection of Input Variables

		Beds			Tot. Exp.			Payroll Exp.			Personnel		
DMU	Score	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
23	0.619	220	136.2	-38.1	107313	61878.3	-42.3	38668	23936.1	-38.1	1091	675.3	-38.1
24	0.862	228	196.5	-13.8	116486	70086.5	-39.8	49017	30851.4	-37.1	671	578.4	-13.8
25	1	83	83.0	0.0	20625	20625	0.0	3009	3009	0.0	300	300.0	0.0

CONCLUSION

This study analyzes the efficiency of hospitals in the United States by using a BCC DEA model known as a variable returns to scale estimation. Further, the efficiency scores generated by the DEA model are classified and examined by seven geographical locations, four types of ownership, and finally, two types of service. Hospitals in California are standout among the seven regions and the for-profit hospitals have a better efficiency than the not-for-profit hospitals, government owned hospitals (non-federal), and federal owned hospitals. Comparison between general medical hospitals and psychiatric hospitals shows that the general medical hospitals outperform the other.

The main contribution of this study can be summarized as follows. First, the presented efficiency scores of hospitals give administrators not only an insight on their current hospital's efficiency rate and the ranking among the peer hospitals under consideration but also a way of improving their inefficiencies. Second, research results can help administrators set target hospitals for benchmarking and identify the performance gap between their hospitals and the best hospitals. Third, the analysis of hospital efficiency by region, ownership, and service gives an overview on how main characteristics of hospitals play a role in efficiencies.

Future research efforts might include an artificial neural network (ANN) combining with a DEA model to have a capability of prediction. Also, experiments with a larger data set will definitely enhance our understanding on the subject matter.

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