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Incorporating health outcomes in Pennsylvania hospital efficiency: an additive super-efficiency DEA approach

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Abstract The health care sector is one of the fastest growing sectors in the United States. Researchers are interested in conducting studies in the area of health economics in order to propose solutions to curb the rapid increase in health care spending and to improve the efficiency of the health care system in the United States. Specifically, hospital efficiency is one important research area in health economics. In this paper, data envelopment analysis (DEA) is used to assess hospital efficiency. An additive super-efficiency model is presented and applied to a sample of general acute care hospitals in Pennsylvania. In addition to the conventional choice of input and output variables, we include the survival rate as a quality measure of health outcome in the set of output variables. Thus our model takes both the quantity and the quality of the output into account. With the results obtained from our proposed DEA model, inefficiencies can be identified for hospitals to address without sacrificing the quality of care.

Keywords Data envelopment analysis (DEA) · Health care · Hospital efficiency · Slacks · Super-efficiency

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1 Introduction

The health care sector is one of the fastest growing sectors in the United States. According to the recent update from Centers for Medicare & Medicaid Services (CMS), in 2008 the national health expenditures grew 4.4% to $2.3 trillion, which accounted for 16.2% of U.S. gross domestic product (GDP).[1] The increase in the health care expenditure is much faster than the growth rate of other components of GDP and the overall economy. In fact, health care spending is expected to reach $4.4 trillion or about 20.3% of GDP by 2018 (Sisko et al. 2009). The rapid growth in health care expenditures poses a threat to the fiscal imbalance of our nation. Many economists attribute the reasons of such a rapid increase to the development and adoption of new technology, aging of the population, and perhaps the prevalence of a third party payer system. More resources spent on health care means fewer resources available for spending on other programs, such as funding education, building infrastructure, and enhancing homeland security. Moreover, the rapid growth of health care spending cannot be sustainable for the national budget in the long run. Thus, improving efficiency of the health care system is imperative to slow down the rapid increase in health care spending.

Studying hospital efficiency is important because a variety of stakeholders are interested in ameliorating the current situation. Firstly, policy makers are the voice of the citizens and have a fiduciary duty to make sure our national health care expenditure is on a sustainable path. They need to know where the current inefficiencies are in order to formulate effective policy or provide incentives to help the hospital sector. Secondly, hospital managers need to know whether the resources are utilized efficiently, what dimensions can be improved, and what areas are already at their limit. They are also interested in improving the quality of the output while utilizing the same amount of resources. Hospital managers are often responsible for reducing the operation expenses without sacrificing the quality of care provided by the hospital. Thirdly, the doctors and employees in a hospital hold many responsibilities to preserve the safety of their patients and the quality of their work. Studying hospital efficiency will give the employees indicators as to how their hospital is performing compared to their peers and could highlight processes that need to be streamlined. Finally, patients are the customers of the hospital and want to be provided with the best quality of care. Also, clinical professionals can be regarded as the internal customers of the hospital, thus better health-care quality will benefit them as well. In our model, our output measures incorporate both the financial and health outcomes. Finding ways to improve survival rates not only creates value for the hospital and the clinical providers, but also builds up confidence of the patients.

In this paper, data envelopment analysis (DEA) is used to analyze hospital efficiency. Developed by Charnes et al. (1978), DEA is an effective and widely used method for evaluating the relative efficiency of peer decision-making units (DMUs) with multiple inputs and outputs. Up to now, DEA method has been applied to various settings (Cooper et al. 2004), one of which is the health care area discussed in this paper. First used by Sherman (1984) in evaluating overall hospital efficiency, DEA models have been widely applied to hospital efficiency assessments. Hollingsworth et al. (1999) made a comprehensive review on efficiency studies in health care and found out systematic differences among the average

[1] In 2008, Medicare spending grew 8.6%, Medicaid spending grew 4.7%, private spending grew 3.1%,hospital expenditures grew 4.5%, physician and clinical services expenditures grew 5%, and prescription-drug spending grew 3.2%. Data Accessed on February 24, 2010. Available at http://www.cms.hhs.gov/NationalHealthExpendData/downloads/highlights.pdf.

efficiency and range of DEA scores by ownership type and U.S. hospital systems. Earlier DEA studies mainly study efficiency by different hospital characteristics, such as teaching and non-teaching hospitals studied by O'Neill (1998) and Grosskopf et al. (2001, 2004), U.S. federal hospitals studied by Harrison et al. (2004), and religious not-for-profit hospitals studied by Harrison and Sexton (2006). In addition, much research has been conducted to explore the resulting hospital efficiency changes caused by policy impact, technology and environmental issues. For example, Harris et al. (2000), Ferrier and Valdmanis (2004) used DEA to assess performance after hospital mergers. Lee and Wan (2004) studied the relationship between information system integration and urban hospital efficiency under the framework of DEA.

Furthermore, we employ a slacks-based additive super-efficiency model, which is the VRS (variable returns to scale) version of the super-efficiency model developed by Du et al. (2010). We then apply it to a sample of general acute care hospitals in Pennsylvania to study hospital efficiency. Each hospital in our sample is viewed as a DMU, which utilizes inputs (both physical and financial) to produce outputs (health services and health outcomes). In addition to the conventional choice of input and output variables, health outcomes, a quality measure, are also included as an output variable. Our model not only takes into account the quantity of output produced but also the quality of output. With the results from the proposed DEA model, areas can be identified where hospitals can improve without sacrificing the quality of care.

The rest of this paper is organized as follows. Section 2 presents the additive DEA model and its related super efficiency model. Unlike the existing super-efficiency models based upon the standard DEA, the proposed additive or slacks-based super-efficiency model is always feasible and provides an optimal solution. Section 3 applies the super-efficiency model to a sample of general acute care hospitals in Pennsylvania. Managerial implications are discussed. Section 4 concludes.

2 Additive super-efficiency model

In this section, we present our additive super-efficiency model. This super-efficiency model is based upon the following additive DEA model (Charnes et al. 1982):

$$\begin{aligned}
&\rho_0^* = \max \rho_0 = \sum_{i=1}^{m} s_{i0}^- + \sum_{r=1}^{s} s_{r0}^+ \\
&\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_{i0}^- = x_{i0}, \quad i = 1, 2, \dots, m \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_{r0}^+ = y_{r0}, \quad r = 1, 2, \dots, s \\
&\qquad \sum_{j=1}^{n} \lambda_j = 1 \\
&\qquad \lambda_j, s_{i0}^-, s_{r0}^+ \geq 0, \quad j = 1, 2, \dots, n,\ i = 1, 2, \dots, m,\ r = 1, 2, \dots, s
\end{aligned} \tag{1}$$

where s_{i0}^- and s_{r0}^+ represent input and output slacks for DMU_0 under evaluation. In model (1), it is assumed that there are a set of n DMUs producing the same set of outputs by consuming the same set of inputs. Unit j is denoted by DMU_j $(j = 1, \dots, n)$, and the ith input and rth output of DMU_j $(j = 1, \dots, n)$ are denoted by x_{ij} $(i = 1, \dots, m)$ and y_{rj} $(r = 1, \dots, s)$, respectively.

The additive model (1) is used, because unlike the standard radial DEA model, model (1) enables us to examine inefficiency in each input and each output in order to have a clearer view on which variable(s) causes a specific DMU to be inefficient compared to others. In its related super-efficiency model, we are able to detect super-efficiency in each input and each output. Specifically, the greatest allowable increase in each input and the greatest allowable decrease in each output for DMU_0 can be obtained so that an efficient DMU remains efficient under the production possibility set spanned by all the other DMUs. Based upon model (1), we can develop an efficiency index whose value lies between zero and one.

Let $\{\rho_0^*;\ \lambda_j^*,\ j = 1, 2, \dots, n;\ s_{i0}^{-*},\ i = 1, 2, \dots, m;\ s_{r0}^{+*},\ r = 1, 2, \dots, s\}$ be an optimal solution to model (1). Then we can define

$$\sigma_0^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_{i0}^{-*}/x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_{r0}^{+*}/y_{r0}}$$

as the additive efficiency score for DMU_0. It can be verified that σ_0^* falls between zero and one, and is unit-invariant and monotone decreasing in input/output slacks. DMU_0 is called additive efficient if and only if $\sigma_0^* = 1$, which indicates that all optimal slacks are zero.

For the current application, we use the VRS (variable returns to scale) additive DEA model (1), rather than the CRS (constant returns to scale) one. This is because the CRS additive model can yield survival rate (the variable capturing the quality of output in our DEA model) exceeding 100% based upon efficient target on the DEA frontier. We will demonstrate this in our application section.

Suppose DMU_0 is additive efficient. To obtain the super-efficiency of DMU_0 under model (1), we cannot simply modify additive model (1) by removing DMU_0 from the reference set. If we do that, the resulting model may not have a feasible solution.

For an additive efficient DMU_0, we have the following additive super-efficiency model which is always feasible (Du et al. 2010).

$$\begin{aligned}
\beta_0^* =\ & \min \beta_0 = \frac{1}{m+s}\left(\sum_{i=1}^{m}\frac{t_{i0}^-}{x_{i0}} + \sum_{r=1}^{s}\frac{t_{r0}^+}{y_{r0}}\right) \\
\text{s.t.}\quad & x_{i0} + t_{i0}^- \geq \sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j x_{ij}, \quad i = 1, 2, \dots, m \\
& y_{r0} - t_{r0}^+ \leq \sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j y_{rj}, \quad r = 1, 2, \dots, s \\
& \sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j = 1 \\
& \lambda_j, t_{i0}^-, t_{r0}^+ \geq 0, \quad j = 1, 2, \dots, n,\ j \neq o,\ i = 1, 2, \dots, m,\ r = 1, 2, \dots, s
\end{aligned} \tag{2}$$

It can be seen that after DMU_0 is removed from the reference set of model (1), we need to modify the constraints and objective of model (1) to derive the super-efficiency model. The constraints should be modified because we need to increase the inputs and decrease the outputs for DMU_0 to reach the frontier constructed by the remaining DMUs. We change the objective from maximization to minimization so that the resulting model is bounded. We divide each slack by its corresponding input/output in the objective to make the resulting model unit invariant. In Du et al. (2010), there are actually two types of additive super-efficiency models: one is unit-invariant, and the other is not. Here we choose the unit-invariant model because it is more suitable for the following hospital efficiency application. Hospitals from the same sample may have quite different input and output scales. In that case, unit-invariant super-efficiency model is a better choice to offset the influence on results caused by different scales.

Let $\{\beta_0^*;\ \lambda_j^*,\ j=1,2,\ldots,n,\ j\neq o;\ t_{i0}^{-*},\ i=1,2,\ldots,m;\ t_{r0}^{+*},\ r=1,2,\ldots,s\}$ be an optimal solution to model (2). Then we can define

$$\delta_0^* = \frac{\frac{1}{m}\sum_{i=1}^{m}(x_{i0}+t_{i0}^{-*})/x_{i0}}{\frac{1}{s}\sum_{r=1}^{s}(y_{r0}-t_{r0}^{+*})/y_{r0}} \geq 1$$

as the additive super-efficiency score for DMU_0. As shown in Du et al. (2010), this additive super-efficiency model (2) is always feasible. Therefore, unlike the standard radial super-efficiency DEA model, model (2) enables us to study super-efficiency performance under VRS.

3 Application to Pennsylvania hospitals

We next apply our additive super-efficiency model to a sample consisting of 119 general acute care hospitals located in Pennsylvania. Data for the study were obtained from the American Hospital Association's (AHA) Annual Surveys for 2006 and two hospital reports issued by Pennsylvania Health Care Cost Containment Council (PHC4) for fiscal year 2006. The two reports are Hospital Financial Analysis, which reports the financial health of Pennsylvania's hospitals, and Hospital Performance Report, which discloses the risk-adjusted mortality rates for 31 common medical procedures and treatments identified by ICD-9-CM (International Classification of Diseases, Ninth Revision, Clinical Modification) codes for hospitals in Pennsylvania. We combine these data sources to select our four input variables and three output variables. Three of the input variables, including the number of total hospital beds, the number of full-time physicians and dentists, and the number of full-time registered or licensed nurses, are taken from the 2006 AHA Annual Survey of Hospitals. The remaining input variable, total operating expenses (TOE), and one of the output variables, total operating revenue (TOR), are taken from the PHC4's 2006 Hospital Financial Analysis.[2] The other two output variables, namely, number of total cases and the weighted average of the in-hospital survival rates of 16 common conditions, are computed based upon PHC4's 2006 Hospital Performance Report.[3] The basic features on the data set are summarized in Table 1, which displays the average level, variance, standard variance, maximum/minimum level, and range for each input/output variable. Note that the ranges for almost all input and output variables (except for the output survival rate) are quite large. For example, for the second input variable (the number of full-time physicians and dentists), among the 119 sampling hospitals, the maximum number of full-time doctors in one hospital is 2171, while the range on this input among all 119 hospitals is 2170. This observation indicates that our sample hospitals indeed have huge differences in operating scales. This also justifies our use of the unit-invariant super-efficiency model.

[2] Data Accessed on October 5, 2009. Available at http://www.phc4.org/reports/fin/06/default.htm.

[3] Data Accessed on October 5, 2009. Available at http://www.phc4.org/reports/hpr/06/default.htm.

Table 1 Data summary for hospitals

Summary features	Inputs				Outputs		
	Beds	Doctors	Nurses	TOE ($millions)	TOR ($millions)	Cases	Survival rate (%)
Mean	245.252	93.874	416.891	185.807	194.412	2742.37	97.082
Variance	42073.43	65109.52	202013.9	55027.598	65370.990	3392530	0.780
Standard Variance	205.118	255.166	449.460	234.580	255.678	1841.882	0.883
Maximum	1492	2171	3245	1611	1788	10293	98.686
Minimum	25	1	20	16	16	447	93.819
Range	1467	2170	3225	1595	1772	9846	4.867

To justify our use of a VRS rather than a CRS model, we here illustrate by evaluating DMU1 via the CRS version of model (1) (with the constraint $\sum_{j=1}^{n}\lambda_j = 1$ dropped), and we obtain a set of optimal slacks as follows:

$$s_{11}^{-*} = 0, \qquad s_{21}^{-*} = 230.273, \qquad s_{31}^{-*} = 0, \qquad s_{41}^{-*} = 0,$$
$$s_{11}^{+*} = 37.850, \qquad s_{21}^{+*} = 6602.986, \qquad s_{31}^{+*} = 1166.097.$$

The above results indicate that in order for DMU1 to reach 100% efficiency compared with all 119 DMUs in the observation set, its survival rate has to be increased by 1166.097%, which definitely cannot be achieved in real settings. By using the VRS assumption, the convexity constraint of $\sum_{j=1}^{n}\lambda_j = 1$ ensures that the optimal survival rate cannot exceed 100%. This is because that $\sum_{j=1}^{n}\lambda_j = 1$ ensures $\sum_{j=1}^{n}\lambda_j y_{rj} \le \max_j\{y_{rj}\}$, which further leads to $s_{r0}^{+} = \sum_{j=1}^{n}\lambda_j y_{rj} - y_{r0} \le \max_j\{y_{rj}\} - y_{r0} \le 100\%$. Therefore, VRS assumption has to be imposed in our DEA models with output (or input) index measured by percentage (survival rate).

Our additive DEA model (1) shows that among the 119 hospitals, 31 are additive efficient. The second column in Table 2 shows the additive efficiency scores for all hospitals along with slack values. According to the additive efficiency scores defined by σ_0^*, those (additive) inefficient DMUs are ranked in the third column of Table 2. The higher the score is, the more efficient the DMU is. The non-zero slack values imply wastes for the corresponding inputs and insufficiencies for the corresponding outputs.

The input slacks represent resource excesses. For example, DMU1 could reduce its number of beds, physicians &dentists, and nurses by 32.495, 119.881, 323.861, respectively, and also reduce its TOE by 31.529 million dollars. The output slacks represent output shortfalls. In addition to the possible input reductions, in order for DMU1 to reach 100% efficiency, it should also increase its total medical cases by 1479.568 along with a very small increase of survival rate.

The current study focuses on the performance of additive efficient hospitals using the newly developed additive super-efficiency model (2). Model (2) enables us to analyze the performance of the efficient hospitals, whereas the standard DEA model and its related super-efficiency model cannot. This is because under the condition of VRS, the standard super-efficiency model can be infeasible. As a result, no information can be obtained for efficient DMUs that are infeasible.

Table 3 lists the 31 additive efficient hospitals (identified from Table 2) in our sample. It reports the additive super-efficiency scores δ_0^*, and the corresponding optimal slacks obtained through model (2), along with the resulting rankings for all additive efficient hospitals.

Table 2 Results for additive DEA model (1)[a]

Hospital	Additive efficiency σ^*	Rank[b] by σ^*	Slacks						
			Beds s_1^{-*}	Doctors s_2^{-*}	Nurses s_3^{-*}	TOE s_4^{-*}	TOR s_1^{+*}	Cases s_2^{+*}	Survival rate (%) s_3^{+*}
1	0.7477	67	32.495	119.881	323.861	31.529	0	1479.568	0.058
2	0.5975	103	0	11.975	19.557	0	1.308	1596.799	1.764
3	0.6938	84	168.146	85.293	9.975	28.576	0	3442.211	0.902
4	1	–	0	0	0	0	0	0	0
5	0.6377	97	0	75.875	397.170	28.119	0	3955.799	0.888
6	1	–	0	0	0	0	0	0	0
7	0.6423	95	39.891	0	355.819	0	16.802	3011.375	2.299
8	1	–	0	0	0	0	0	0	0
9	0.5078	113	22.773	9.723	0	0	5.052	1857.346	1.526
10	0.76219	62	0	0.251	81.932	0	0	1303.916	0.119
11	0.9359	33	0.464	0	0	0	1.971	206.237	0.733
12	1	–	0	0	0	0	0	0	0
13	0.8186	45	0	2.214	0	0	6.036	580.067	0.528
14	0.5268	110	17.189	10.643	0	0	5.665	1266.424	0.413
15	0.7738	56	0	2.564	143.888	0	3.111	1328.986	0.355
16	0.7310	74	0	12.850	0.503	0	1.694	1137.752	1.860
17	0.7403	69	0	1.670	6.097	0	4.981	610.398	3.247
18	0.6642	91	0	6.358	29.807	0	3.715	729.538	0.597
19	0.6879	86	26.339	25.977	42.529	0	8.624	1636.536	0
20	0.6091	101	280.995	0	240.626	24.172	0	3893.548	0.437
21	0.7588	64	0	2.599	55.438	0	3.948	1781.525	1.685
22	0.6179	100	137.044	0	291.808	0	4.414	1709.659	0.962
23	0.4850	114	0	17.851	104.174	0	0	2805.425	1.347
24	1	–	0	0	0	0	0	0	0
25	0.6217	99	9.607	3.692	0	0	2.263	942.768	0.104
26	0.6543	94	0	35.576	58.607	0	0	1270.732	0
27	0.5670	107	0	16.717	89.724	0	4.538	1228.445	2.041
28	1	–	0	0	0	0	0	0	0
29	0.5232	111	0	126.112	148.114	0	4.368	1522.305	0.296
30	0.4817	116	0	549.709	418.409	0	0	3732.651	2.323
31	0.6412	96	0	6.295	21.551	0	0	1004.502	0
32	0.8116	46	0	0.756	74.606	0	6.163	608.710	2.997
33	0.7944	52	0	0.478	35.225	0	10.603	1115.629	1.825
34	0.7286	75	0	1.774	37.114	0	0	1888.185	0.108
35	0.8023	48	18.314	0	10.929	0	0.029	378.643	1.916
36	0.4540	118	0	588.562	52.188	36.062	29.562	5963.313	0.442
37	0.6969	82	44.557	0	226.733	0	0	2775.570	1.170
38	0.7357	71	0	0	117.906	0	2.076	1006.514	2.033
39	0.6691	90	0	27.764	100.176	0	0.749	302.918	2.334
40	0.5784	106	0	0	31.415	0	1.650	1446.733	1.154
41	1	–	0	0	0	0	0	0	0

[a] All the results listed under TOE and TOR are measured in million dollars

[b] The ranking is only provided for additive inefficient hospitals. Rankings for efficient ones are provided in Table 3

Table 2 (*Continued*)

Hospital	Additive efficiency σ^*	Rank[b] by σ^*	Slacks						
			Beds s_1^{-*}	Doctors s_2^{-*}	Nurses s_3^{-*}	TOE s_4^{-*}	TOR s_1^{+*}	Cases s_2^{+*}	Survival rate (%) s_3^{+*}
42	0.7729	57	21.799	0	146.004	0	15.699	1781.722	1.935
43	1	–	0	0	0	0	0	0	0
44	0.7472	68	0	6.394	26.675	0	0	932.501	0.987
45	0.8102	47	0	0	0	0	0.543	490.207	0.752
46	0.7722	58	0	0	126.389	0	5.581	1350.385	0.211
47	0.8840	39	17.891	6.877	20.733	0	4.853	881.840	0
48	1	–	0	0	0	0	0	0	0
49	1	–	0	0	0	0	0	0	0
50	1	–	0	0	0	0	0	0	0
51	1	–	0	0	0	0	0	0	0
52	0.5889	105	0	10.637	12.805	0	0	2403.632	0.942
53	0.6619	93	0	32.197	72.728	0	3.672	733.628	1.675
54	0.7385	70	11.884	162.996	420.129	7.397	0	2671.131	0.472
55	0.7077	79	0	54.183	112.950	0	0	425.028	0
56	0.9561	32	0	0	0	0	2.203	242.603	0
57	0.90128	37	0	0	31.709	0	0	1108.962	0.241
58	0.7542	65	0	43.089	25.315	0	7.161	2650.898	0.030
59	0.8785	40	37.607	0	0	0	1.581	55.319	1.174
60	0.6984	81	10.665	1.413	0	0	2.171	2047.333	0.743
61	0.7634	61	0	21.328	128.862	0	7.705	1270.473	1.602
62	0.4834	115	1.975	45.980	16.423	0	0	988.613	0
63	0.90131	36	13.389	0	0	0	2.354	379.092	0.071
64	0.6338	98	0.407	69.244	30.049	0	21.855	3931.852	0.455
65	0.6959	83	0	67.408	0	0	0	687.197	2.379
66	0.7818	54	44.053	0	107.620	0	2.479	1044.087	0.720
67	1	–	0	0	0	0	0	0	0
68	0.9170	34	0.763	0	0	0	6.735	607.221	0.021
69	1	–	0	0	0	0	0	0	0
70	0.7087	78	13.674	0	117.804	0	5.631	1798.811	0.996
71	0.7996	50	0	0	17.679	0	4.717	1358.571	1.023
72	1	–	0	0	0	0	0	0	0
73	1	–	0	0	0	0	0	0	0
74	0.3969	119	0	866.376	448.976	0	21.900	6020.284	1.192
75	0.9047	35	0	0	14.545	0	0	600.419	0
76	0.6718	89	134.190	41.332	215.814	25.999	0	3878.036	2.119
77	0.8862	38	0	0	67.795	0	0	715.539	0.253
78	1	–	0	0	0	0	0	0	0
79	0.8219	44	27.761	0	0	0	3.920	824.074	1.338
80	0.8593	41	0	0	34.451	0	1.288	153.488	0.051
81	0.6912	85	32.066	32.665	191.939	10.599	0	4420.051	1.483
82	0.76215	63	9.142	29.642	0	0	0	1074.419	0
83	0.7985	51	0.611	0	0	0	23.229	649.131	0.650
84	0.5204	112	0	20.485	1.657	0	6.754	2744.202	0
85	0.5471	109	95.593	53.506	158.951	0	13.395	3567.148	0.707

Table 2 (*Continued*)

Hospital	Additive efficiency σ^*	Rank[b] by σ^*	Slacks						
			Beds s_1^{-*}	Doctors s_2^{-*}	Nurses s_3^{-*}	TOE s_4^{-*}	TOR s_1^{+*}	Cases s_2^{+*}	Survival rate (%) s_3^{+*}
86	0.5968	104	0	17.760	96.177	0	2.000	1337.625	0.763
87	0.7046	80	9.568	0	127.245	0	2.469	2074.084	1.457
88	1	–	0	0	0	0	0	0	0
89	0.6757	88	0	1.689	0	0	4.697	1252.300	2.068
90	0.7350	72	101.841	0	199.503	0	7.156	1147.633	0.910
91	1	–	0	0	0	0	0	0	0
92	1	–	0	0	0	0	0	0	0
93	1	–	0	0	0	0	0	0	0
94	0.7771	55	0	2.386	0	0	4.727	518.387	0
95	1	–	0	0	0	0	0	0	0
96	0.7172	77	0	0	96.319	0	7.265	1520.531	0.133
97	1	–	0	0	0	0	0	0	0
98	1	–	0	0	0	0	0	0	0
99	1	–	0	0	0	0	0	0	0
100	1	–	0	0	0	0	0	0	0
101	0.8404	43	0	0.041	75.888	0	1.887	934.816	1.310
102	1	–	0	0	0	0	0	0	0
103	1	–	0	0	0	0	0	0	0
104	0.6030	102	0	9.224	94.787	0	5.048	1876.425	0.254
105	0.7343	73	0	11.188	10.892	0	3.021	1146.998	0.657
106	1	–	0	0	0	0	0	0	0
107	0.6781	87	64.683	509.626	42.024	0	0	546.171	0
108	1	–	0	0	0	0	0	0	0
109	0.7640	60	21.735	0	0	0	1.068	1125.194	0
110	1	–	0	0	0	0	0	0	0
111	0.4591	117	0	20.743	28.492	0	4.295	1351.205	0.521
112	0.7480	66	0	12.080	92.396	0	11.338	1743.328	0.993
113	0.7256	76	0	0.637	0	0	4.272	1012.547	1.591
114	0.7665	59	0	1.891	9.158	0	1.960	477.667	2.512
115	0.8535	42	0	6.404	106.167	0	0	340.385	0.780
116	0.5628	108	33.543	195.899	0	0	5.043	4604.682	0.445
117	0.8006	49	55.980	0	141.093	0	3.166	763.660	0.755
118	0.6622	92	0	9.629	0	0	2.781	456.373	3.882
119	0.7827	53	0	20.917	141.658	0	0	3112.126	1.441

The non-zero slack values indicate the maximum allowable increases for the corresponding inputs and the maximum allowable decreases for the corresponding outputs to remain efficient status.

For example, the additive super-efficiency of DMU4 is only reflected by its survival rate (the only non-zero number for DMU4). If DMU4's survival rate is reduced by more than 0.154%, then DMU4 becomes inefficient. This result indicates that DMU4's current efficiency status is not stable. In addition, DMU49, which is ranked 5th in terms of super-efficiency, has super-efficiency in beds, nurses, TOE, and survival rate. In other words,

Table 3 Results for Additive Super-efficiency Model (2)[a]

Hospital	Super-efficiency δ^*	Rank by δ^*	Slacks						
			Beds t_1^{-*}	Doctors t_2^{-*}	Nurses t_3^{-*}	TOE t_4^{-*}	TOR t_1^{+*}	Cases t_2^{+*}	Survival rate (%) t_3^{+*}
4	1.0005	29	0	0	0	0	0	0	0.154
6	1.1237	9	0	0	0	5.769	0	1060.077	0
8	1.0034	23	0	0	0	0	0	0	0.995
12	1.0470	14	0	0	0	0	13.052	0	0
24	1.0046	22	0	0	0	1.703	0	0	0.559
28	1.1111	10	0	0	0	20.592	0	2434.005	0.204
41	1.0018	25	0	0	0	0	0	0	0.536
43	1.1106	11	0	0	0	0	428.219	0	0
48	1.0202	17	0	0	0	2.696	0	0	1.206
49	1.2304	5	2.571	0	22.286	8.714	0	0	0.341
50	1.1013	12	0	0	0	5.549	0	21.698	0
51	1.0351	15	0	0	0	0	66.786	0	0
67	1.0047	21	0	0	0	0.565	0	0	0
69	1.1456	7	0	0	0	32.576	0	347.091	1.683
72	1.1333	8	0	0	0	0.417	0	1210.500	0.632
73	1.0769	13	0	0	0	7.316	0	0	0.188
78	1.0116	18	0	0	0	5.573	0	0	0
88	1.0077	19	0	0	0	0.974	0	0	0.209
91	1.5353	2	0	0	41.736	0	4.153	0	0
92	2.5709	1	1	0	0	0	423	6080	0.969
93	1.0250	16	0	0	0	6.367	0	285.524	0
95	1.0014	26	0	0	0	0	0	0	0.422
97	1.0003	31	0	0	0	0	0	0	0.100
98	1.00127	28	0	0	0	0	0	0	0.374
99	1.0004	30	0	0	0	0	0	0	0.104
100	1.3188	4	0	0.581	26.405	6.676	0	22.649	0.629
102	1.1616	6	14.476	0	0	1.787	0	28.765	0
103	1.0013	27	0	0	0	0	0	0	0.379
106	1.0021	24	0	0	0	0	0	0	0.604
108	1.3763	3	0	0	0	0	1043.783	2433.702	0
110	1.0070	20	0	0	0	0	2.477	0	0.811

[a] All the results listed under TOE and TOR are measured in million dollars

DMU49 can increase some of its resources and slightly decrease its survival rate, and still maintain its efficiency status.

Table 3 shows that among the 31 additive efficient hospitals, twenty hospitals have superior quality of care (with non-zero t_3^{+*}), measured by the weighted average of the survival rate, compared to the super-efficiency projected survival rate given their financial efficiency. Even if their survival rates were slightly lowered, they are still able to maintain the same level of efficiency.

In addition, five of the additive efficient hospitals (DMUs 49, 91, 92, 100 and 102, with any of t_1^{-*}, t_2^{-*}, or t_3^{-*} non-zero) could increase their number of beds, physicians & dentists, or nurses while still remaining efficient. This result means these hospitals have the capacity to expand without hurting the hospital's overall financial performance.

However, the other 26 of the 31 additive efficient hospitals cannot increase the number of beds, physicians and dentists, or nurses while staying at the same level of efficiency. For the remaining 88 inefficient hospitals, one can tell from Table 2 that 86 of them have waste in at least one of the three inputs. These two observations indicate that probably all hospitals have already devoted both sufficient basic facilities such as beds and sufficient human recourses such as staff members.

Furthermore, 22 of the 31 additive efficient hospitals can afford to increase their operating expenses or to lower revenue but still remain efficient. This result could imply that their operating margin is better than their peers. It is an interesting finding in that only two of these 22 hospitals are for-profit hospitals. The other 20 are both non-government and non-profit hospitals, but still manage to operate with relatively lower costs, or to produce relatively higher revenues.

Finally, for the 15 efficient hospitals (with non-zero t_4^{-*}) that can increase their operating expenses without changing efficiency status, all of them except DMU 28 are not teaching hospitals. Teaching hospitals refer to hospitals that belong to the Council of Teaching Hospital of the Association of American Medical College, and devote resources to research and training in addition to providing patient care. This result could be caused by the possibility that teaching activities require extra operating costs, leading the teaching hospitals to larger expenses compared with their non-teaching peers. This conclusion is supported by the findings in Sloan et al. (1983), Sloan and Valvona (1986), which point out that the cost of care is generally higher in teaching hospitals than in non-teaching ones.

4 Conclusions

The rapid growth in health care spending poses a threat to the fiscal imbalance and cannot be sustainable for the national budget in the long run. Thus much research is urgently needed to propose solutions to curb the rapid increase in health care spending and to improve the efficiency of the health care system in the United States.

Studying hospital efficiency is one of the important areas of research in health economics. In this paper, DEA method is used to evaluate hospital efficiency. We develop a slacks-based additive super-efficiency model and apply it into a sample of 119 general acute care hospitals in Pennsylvania. Each hospital in our sample is regarded as a DMU, which utilizes inputs (both physical and financial) to produce outputs (health services and health outcomes). From the results obtained through the proposed model, we find many meaningful results and implications, and identify areas where hospitals can improve without sacrificing the quality of care.

In the choice of output variables, we consider a quality measure (in-hospital survival rate) in addition to the conventional quantity of output. For further extension, one can also consider the quality of input. For example, in our paper, the number of full-time physicians and dentists is used as a quantity measure, and any two physicians/dentists are viewed equivalently. However, in real situation, one physician/dentist can be quite different from another in skill and experience, thus contributing much more to outputs. One method to consider the quality of such an input is to further divide the input variable into a series of sub-inputs. All these sub-inputs together describe the detailed quality of the discussed input variable.

Our findings have implications for policy makers and hospital managers. Our DEA model and empirical analysis should help policy makers formulate relevant policies that take into account the inefficiencies in the current system and continue to encourage and provide incentive for hospital managers to achieve operational efficiency. In addition, hospital managers can better understand whether their resources are being used efficiently or which areas their hospitals can improve without sacrificing the quality of service. Possible areas of future research in this area can focus on modifying/improving the choice of input and output variables, such as adjusting for case mix to control for the overall severity of patients treated by a hospital. Also in this research input variables include both the number of full-time medical providers and the total operating expenses (TOE). However, it looks like that doctors and nurses are taken into account twice both in the numbers of full-time employees and in the TOE. Thus one may consider it might be more accurate to use non-salary operating expenses instead of TOE to offset such double influences from clinical providers. Researchers can also identify and categorize the underlying determinants of hospital inefficiencies.

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