US hospital performance: A dynamic network analysis

Andrew L. Johnson
Texas A&M University
4033 Emerging Technologies Building, College Station, TX 77843-3131, U.S.A.
ajohnson@tamu.edu

Brandon Pope
Purdue University
315 N. Grant Street, West Lafayette, 47907-2023,U.S.A.
popeb@purdue.edu

Kaoru Tone
National Graduate Institute for Policy Studies
7-22-1 Roppongi, Minato-ku, Tokyo 106-8677, Japan
tone@grips.ac.jp

Abstract: Healthcare is a critical and costly industry. In the U.S. a significant component of healthcare costs are expenses generated in hospitals. This paper reports the results of analyzing 607 U.S. hospitals between 2006-2009 using a dynamic network slack-based Data Envelopment Analysis (DEA) Model. We find accounting for the dynamic and network structure of the hospital lowers efficiency estimates. Further, hospitals are more efficient at providing hospital services compared to hotel services, but the efficiency of hospitals is not correlated with their size. Regarding the dynamic network slack-based DEA Model, we find slack-based approaches combine technical and allocative aspects of inefficiency and thus tend to have significantly lower efficiency levels than just radial technical efficiency measures. Further when applying an envelopment method like DEA, there are some benefits to averaging multiple years of data to remove variation and avoid estimating a frontier based on observations that might have significant noise in their measurement.
Keyword: Slack-base Model, panel data, medical services, hotel services

1. INTRODUCTION

The U.S. spends more on healthcare than any other country, in both absolute terms (~2.5 trillion U.S. dollars) and as a percentage of GDP (17.6%) or on a per capita bases ($8,233), [21]. While the cost of healthcare is growing in most developed countries at rates faster than inflation due to the Baumol Effect [2], the difference between the U.S.'s healthcare expenditures as a percentage of GDP, 15.2%, and the OECD average of 9.7% indicates there are significant improvements that are possible in the U.S. healthcare system, [21]. Estimates of the excess cost in the system consistently exceed $750 billion and range as high as half of all healthcare expenditures [13]. Thirty-one percent of U.S. healthcare expenditures are spent solely on hospital care, totaling 5% of GDP, [12].

The Institute of Medicine [22] finds that improving hospital efficiency is a much-needed approach in order to reduce costs and improve outcomes. The Institute of

Medicine recommendations to improve hospital efficiency include: linking provider payments to outcomes, developing useful pro-competitive regulations, consolidating funding, empowering consumers, and dissemination of successful re-engineering in top hospitals. Currently, consumers, providers, and payers lack clear and reliable information about hospital performance relative to their peers. Therefore they cannot distinguish efficient hospitals, and providers lack an impetus to improve operations. To realize the efficiency gains made possible through these recommended solutions, rigorous analysis methods must be in place to identify which are the best hospitals, which operational strategies contribute to efficiently provided services, which services should be regulated, and how they should be regulated to improve performance.

This paper explores a sample of 607 U.S. hospital between 2006 and 2009 using Dynamic DEA with a internal network structure. The analysis provides insights both to the U.S. hospital industry, but also the methodology. For the industry we find, 1) efficiency levels, when accounting for dynamics and internal structure, are low, 2) no relationship between size and efficiency and 3) hospitals are more efficient at providing medical services than hotel services. Regarding the methodology we find, 1) slack-based approaches combine technical and allocative aspects of inefficiency and thus tend to have significantly lower efficiency levels than just radial technical efficiency measures and 2) averaging the data over two years periods helps to remove variation which leads to better estimates of efficiency by more accurately estimating the frontier.

The paper is organized as follows, Section 2 describes a dynamic hospital model with a internal network structure. Section 3 describes the mathematical formulation. Section 4 introduces the U.S. Hospital data set, the application of the methodology to this data, and the insights gained. Finally, Section 5 concludes.

2. DYNAMIC MODEL WITH INTERNAL NETWORK STURUCTURE

The majority of the efficiency and productivity literature uses the production correspondence approach. This approach begins by specifying a production correspondence indicating a set of resources (referred to as inputs) that are used to generate a set of products or services (referred to as outputs). Then data is gathered for a set of production units using similar resources to produce all or a subset of the outputs. The internal operations of the production unit is typically ignored with a focus on estimating relative efficiency. In a regulation setting relative efficiency is the primary concern, however, when production correspondences are used in other contexts, such as benchmarking, understanding and modeling the internal operations of the production process is critical to identifying operational improvement activities. The managers of the production units under analyzes would like to know more than that they are performing good/poorly, they would like to know, what are the best practices of the industry or how can my operations improve? To do this more detailed models of operations and how those operations perform over time are necessary. We will focus our discussion on the U.S. hospital production process. This section will unfold as first we will introduce a standard model of a production correspondence for a hospital in section 2.1. We will extend this model to characterize the internal network structure in section 2.2. We will then discuss a dynamic model of hospital production in section 2.3. And we will combine the network structure with the dynamic model is section 2.4.

<2>

2.1. Hospital Production Correspondence

The primary purpose of a hospital is to provide medical services. Thus, when characterizing a hospital's production correspondence we can enumerate the resources consumed (i.e. doctor and nurse labor, capital, medicine and consumable materials) and the services provided (i.e. these can be divided in a number of ways including surgical procedures, outpatient procedures, consultation services, etc.). Generally, we define the hospital production correspondence as shown in Figure 1.

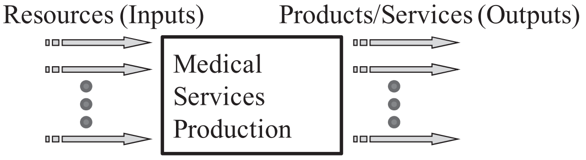

Figure 1: A general production correspondence for medical services production

2.2. Network model of a hospital

Hospitals often provide other services beyond medical services. One of the most significant and costly is hotel services. This involves providing room and board for the patients before and after their medical procedures. This is just one example of an additional service a hospital can provide. In general a hospital might provide a variety of services. If these services can be organized in series network with variables linking the different services, then the model shown in Figure 2 can be used. The assumption of a serial model can be relaxed in some cases with the introduction of additional complexity, see for example [9]. In the hospital setting, a natural link between medical services and hotel services is bed-days. The severity of the procedure will often dictate the number of days (hours) the patient needs to arrive before the procedure and the amount of recovery time the patient will need to stay in the hospital.

2.3. Dynamic model of a hospital

With production, there are various issues that cause resources or finished products to be carried over from one time period to the next. Three examples are production delays, inventories and capital assets. In this setting, static production models that assume all inputs acquired in a particular period are used to generate outputs in that same period are insufficient and dynamic models of production are needed.

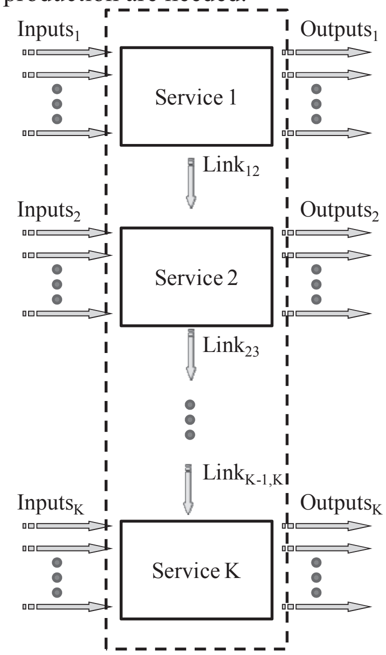

Figure 2: A network model for hospital production

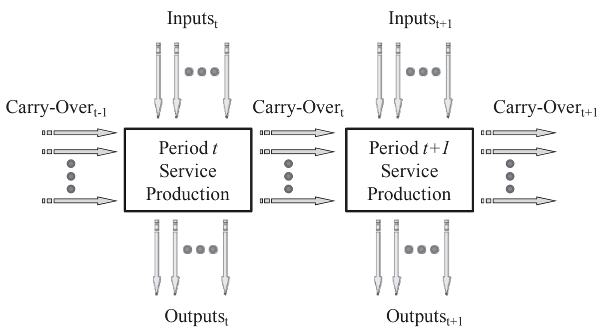

Figure 3: A network model for hospital production

The model in Figure 3 defines a set of carry-over variables. These variables could quantify inputs such as capital or raw materials that are carried over to the next period. Alternatively, these could be finished goods inventories which were produce in earlier periods to meet the demands of later periods.

<3>

2.4. Dynamic model of a hospital with an internal network structure

In some production settings, both network and dynamic aspects of production should be modeled to accurately characterize the production process. The models described in section 2.2. and 2.3 can be combined to characterized a dynamic model of the production system with an internal network structure. A general hospital production system model of this type is shown in Figure 4.

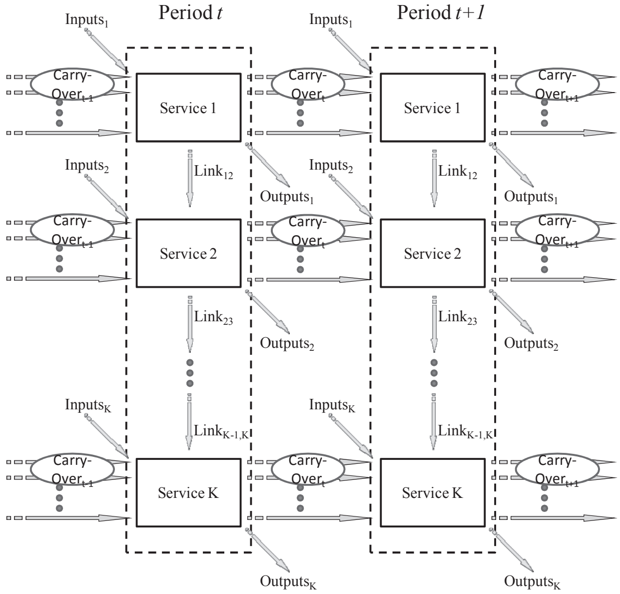

Figure 4: A general network model for hospital production

3. FORMULATION OF DYNAMIC MODEL OF A HOSPITAL WITH AN INTERNAL NETWORK STRUCTURE

To estimate a dynamic model of hospital production with an internal network structure, we will use the axiomatic deterministic approach to estimating production functions pioneered by Sydney Afriat [1] and name Data Envelopment Analysis by Charnes et al. [4]. The relationship of these models to their stochastic counterparts is described in [11]. The measure of efficiency we will use is the slack-based method described in [16]. The network structure of our models builds on the work of Tone and Tsutsui [17]. The dynamic portion of our model builds on the models of Shephard and Färe [15], Färe and Grosskopf [6,7], Tone and Tsutsui [18] and is related to research by Bogetoft, Färe, Grosskopf, Hayes, and Taylor [3]. For consistency purposes, the notation we use in this paper will follow closely with that of Tone and Tsutsui [20] also found in these proceedings. In this section, sub-section 3.1 will define the notation and terminology for the different components of our model. Sub-section 3.2 will specify the math programming formulation to be estimate.

3.1. Notation

Consider n production units ($j = 1,\ldots, n$) consisting of K services ($k = 1,\ldots, K$) over T time periods ($t = 1,\ldots,T$). Let m_k and r_k be the numbers of inputs and outputs to service k, respectively. The analyst should gather and provide data for the inputs, $\left\{x_{ijk}^t \in R_+\right\} (i = 1,\ldots, m_k; j = 1,\ldots, n; k = 1,\ldots, K; t = 1,\ldots, T)$ where x_{ijk}^t is input resource i to production unit j for service k in period t, and outputs, $\left\{y_{ijk}^t \in R_+\right\} (i = 1,\ldots, r_k; j = 1,\ldots, n; k = 1,\ldots, K; t = 1,\ldots, T)$ where y_{ijk}^t is output product i from production unit j, service k, in period t. Data is required for linking resources, $\left\{z_{j(kh)_l}^t \in R_+\right\} (j = 1,\ldots, n; l = 1,\ldots, L_{kh}; t = 1,\ldots, T)$ where $z_{j(kh)_l}^t$ is linking intermediate products of production unit j from service k to service h in period t, where L_{kh} is the number of resources in links from k to h. Further carry-over variables $\left\{z_{jk_l}^{(t,t+1)} \in R_+\right\}$ $(j = 1,\ldots, n; l = 1,\ldots, L_k; k = 1,\ldots, K; t = 1,\ldots, T-1)$ defined as $z_{jk_l}^{(t,t+1)}$ for production unit j, sevice k, from period t to period $t+1$, where L_k is the number of resources in the carry-over from Division k.

3.1.1. Links

Tone and Tsutsui [20] present a variety of options in terms of the types of linking variables. Here we will only present the linking variables used in our analysis of hospital production.

The linking variables we use are "free". This indicates the aggregate value (when weighted by the service specific intensity vector, $\boldsymbol{\lambda}_k^t$) of the free linking variables has to be equal for the two linked services. Thus the production unit under evaluation does not need to keep the level of the linking variable constant and equal to the current operational level.

3.1.2. Carry-over

Tone and Tsutsui [20] present a variety of options in terms of the types of carry-over variables. Here we will only present the linking variables used in our analysis of hospital production.

The carry-over variables in our model are discretionary. This corresponds to carry-over that can be increased or decreased from the observed values. The deviation from the current value is not directly reflected in the efficiency evaluation, but the continuity condition between two periods has an indirect effect on the efficiency score.

3.2. Specification of model estimated

The model we will estimate assumes variable returns-to-scale. This is a natural assumption as we expect maximum productivity levels to be a function of output level. We will use an input oriented slack-based model, [16], to investigate potential resource savings. Hospitals demands are a function of the medical needs of the community. While it is possible to influence these requirements, we prefer to investigate hospital performance from the point of view of the hospital management team and attempt to identifying potential resource savings. Further, a slack-based models imposed that each of the inputs, including linking inputs, contribute to the measure of efficiency. Thus, the model we specify is shown in equation (1).

Recall we have chosen to estimate a deterministic model where all data is assumed to be measured exactly, all observed variables measure the modeling variables exactly, and the dynamic and network relationships are specified correctly. The data used in this analysis is self-reported hospital data. Recognizing that any random variation would bias the frontier upward and efficiency estimates downward, we will employ the strategy suggested in [14] to average the data over multiple years in an attempt to reduce the effects of random fluctuations.

$$\min_{\theta_o,\lambda_{jk}^t,\mathbf{s}_{iok}^t,\mathbf{s}_{o(kh)free}^t} \sum\nolimits_{t=1}^{T}\frac{1}{T}\left[\sum\nolimits_{k=1}^{K}\frac{1}{K}\left[1-\frac{1}{m_k+linkin_k}(R)\right]\right]$$

$s.t.$

$$R=\sum\nolimits_{i=1}^{m_k}\frac{s_{iok}^{t-}}{x_{iok}^t}+\sum\nolimits_{(k,h)_l=1}^{linkin_k}\frac{s_{o(k,h)_l in}^t}{z_{o(k,h)_l in}^t}$$

$$\mathbf{x}_{ok}^t=\sum\nolimits_{j=1}^{n}\mathbf{x}_{jk}^t\lambda_{jk}^t+\mathbf{s}_{iok}^t\ (\forall k,\forall t)$$

$$\mathbf{y}_{ok}^t=\sum\nolimits_{j=1}^{n}\mathbf{y}_{jk}^t\lambda_{jk}^t\ (\forall k,\forall t)$$

$$\mathbf{z}_{(kh)}^t=\sum\nolimits_{j=1}^{n}\mathbf{z}_{j(kh)}^t\lambda_{jk}^t+\mathbf{s}_{o(kh)free}^t\ (\forall (k,h),\forall t)$$

(as inputs to h in period t)

$$\mathbf{z}_{(kh)}^t=\sum\nolimits_{j=1}^{n}\mathbf{z}_{j(kh)}^t\lambda_{jh}^t\ (\forall (k,h),\forall t)$$

(as outputs from k in period t)

$$\mathbf{z}_{l_k}^{(t,t+1)}=\sum\nolimits_{j=1}^{n}\mathbf{z}_{jl_k}^{(t,t+1)}\lambda_{jk}^t\,(\forall l_k,\forall k,t=1,\ldots,T-1)$$

(as carry-over from t)

$$\mathbf{z}_{l_k}^{(t,t+1)}=\sum\nolimits_{j=1}^{n}\mathbf{z}_{jl_k}^{(t,t+1)}\lambda_{jk}^{t+1}\,(\forall l_k,\forall k,t=1,\ldots,T-1)$$

(as carry-over to $t+1$)

$$\sum\nolimits_{j=1}^{n}\lambda_{jk}^t=1\ (\forall k,\forall t),\ \lambda_{jk}^t\geq 0\ (\forall j,\forall k,\forall t),$$

$$\mathbf{s}_{ko}^t\geq\mathbf{0},\quad(\forall k,\forall t)$$

$$\mathbf{s}_{o(kh)free}^t\geq\mathbf{0},\quad(\forall (k,h),\forall t)\qquad(1)$$

Note this formulation needs to be solved once for each observation. Alternatively all observations could be included in one larger optimization problem which would calculate the efficiency of all hospitals in one math program, [10].

The slack-based model, by construction, weights each input and linking input equally. We have chosen equal weighting for each time period and service, but alternative weights are possible, [19]. Poor performance regarding any input variable in any service during any period will reduce the efficiency estimate for the production unit. In this way, slack-based efficiency measure are typically small and can be much smaller than standard radial measures. Making all inputs equally important is similar to assuming equal costs for all inputs and calculating economic efficiency. Production units using extreme mixes of inputs and operating off of the production frontier will have lower efficiency estimates via a slack-based model because SBM mix the measures of technical and allocative efficiency.

4. ANALYSIS OF U.S. HOSPITALS

We will focus our analysis on the hospital performance in the U.S. because of the significant potential for cost savings. In this section, sub-section 4.1 will describe the data used, sub-section 4.2 will describe the specific dynamic network model used given the data available. Sub-section 4.3 will discuss the results of the analysis.

4.1. Data

The data used in this analysis is taken from the Center for Medicare and Medicaid Services' (CMS) Healthcare Cost Reporting Information System (HCRIS) for the years 2006-2009. This data set provides detailed cost and accounting information from U.S. hospitals which provide government supported care. This data set contains approximately 6,000 hospitals in any given year, which may be linked through the National Provider Identifier (NPI). Significant variation exists in the size and production capabilities of these hospitals. Furthermore, hospitals enter and depart from our data set throughout our time horizon due to construction, mergers, closings, etc. In order to construct a balanced, more homogeneous panel, we filtered out all hospitals except those which operated in each of the divisions of our model in each of the time periods considered. Because this data is self-report, which leads to issues of misinterpretation, misunderstanding, and incorrect data entry, we performed the outlier detection method described in [8] to assure we had a set of observations that were similar in terms of input and output vectors. This process leaves us with 607 hospitals for our modeling and analysis.

4.2. Dynamic Network Model

Hospitals can be thought of as an agglomeration of many services and product lines. Many plausible network models could be posed based on the various service distinctions that can be made, e.g., inpatient/outpatient care, routine/ancillary care, medical/hotel services. In this paper, we model hospitals consisting of two divisions, a medical services division and a hotel services division. Particularly, we draw a distinction between medical services provided in an outpatient setting, which do not require hotel services. Each of these divisions is modeled as a single-input, single-output production process. The input for the medical services division is medical services labor, measured by hours of physician labor. We measure the output of the medical services division by revenue from outpatient care. The input of the hotel services division is patient care labor, measured by hours of direct patient care services (nursing, rehab,…) and top-level management services. The output of the hotel services division is routine care revenue. In order to model the link between these two divisions, we use total beds as a free linking variable. We use total capital related costs as a discretionary carry-over variable to model resources within the medical services production process which are carried-over between time periods. See Figure 5 for the graphical representation of the dynamic network model. The summary statistics for 2006-2007 data and for the 2008-2009 data are shown in Tables 1 and 2 respectively.

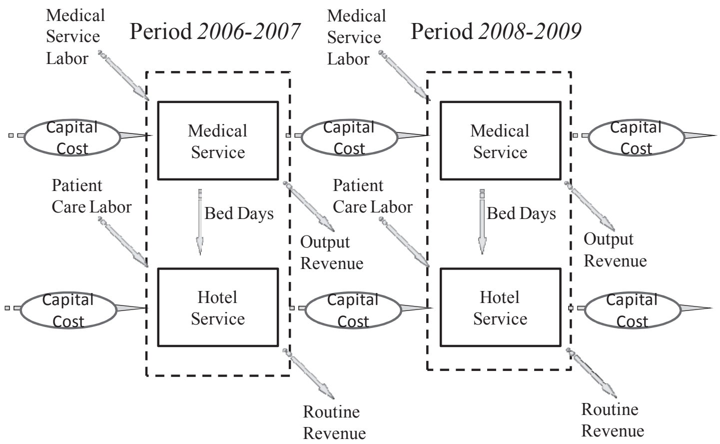

Figure 5: The specific dynamic network model for hospital production estimated

Table 1: 2006-2007 Summary Statistics

		Medical Service				Hotel Services	
		Medical Services Labor	Revenue from Outpatient Care	Bed Days	Capital Costs	Patient Care Labor	Routine Care Revenue
Large	Average	144,820	1,127,033,006	933	63,179,738	238,046	571,016,467
	Max	382,397	2,087,807,241	1,395	156,561,545	775,294	2,136,116,673
	Min	40,153	525,131,861	720	22,239,726	21,525	138,474,822
	St Dev	108,553	443,788,167	209	35,652,036	204,578	464,513,430
Medium	Average	74,730	482,333,660	432	23,116,901	93,236	224,231,690
	Max	199,940	787,624,934	679	71,946,251	280,435	613,410,800
	Min	21,480	214,777,888	302	3,540,891	12,098	72,509,713
	St Dev	45,266	151,815,186	89	11,762,853	62,664	132,413,841
Small	Average	25,091	110,871,468	123	7,642,178	23,979	48,740,117
	Max	133,696	472,634,857	298	36,255,946	138,107	258,341,955
	Min	3,085	11,627,787	17	150,516	1,234	4,314,102
	St Dev	23,213	90,767,149	67	5,836,953	23,010	43,144,684

Table 2: 2008-2009 Summary Statistics

		Medical Service				Hotel Services	
		Medical Services Labor	Revenue from Outpatient Care	Bed Days	Capital Costs	Patient Care Labor	Routine Care Revenue
Large	Average	206,233	1,301,133,883	978	73,547,696	223,122	681,266,011
	Max	580,297	2,657,619,304	1,530	170,843,697	834,096	2,670,772,414
	Min	54,992	603,324,528	704	27,731,242	33,398	168,687,734
	St Dev	168,977	557,132,465	252	41,697,378	210,311	582,418,984
Medium	Average	86,277	555,592,437	429	27,603,067	70,571	248,643,041
	Max	304,779	995,866,907	698	94,317,406	191,385	728,703,346
	Min	21,469	246,087,650	301	5,973,124	11,480	80,779,984
	St Dev	62,459	172,972,928	89	14,773,469	47,680	144,391,223
Small	Average	27,243	126,004,316	128	8,937,102	19,835	54,079,105
	Max	142,533	470,581,454	289	44,742,830	90,022	250,431,676
	Min	1,200	10,863,637	17	425	209	5,037,124
	St Dev	24,322	103,290,330	82	6,960,820	18,929	47,789,194

4.3. Results

In this sections we will first present the results from the dynamic network DEA analysis of the two period hospital data. Then we will discuss how the modeling decisions to use a slack-based model (SBM), a dynamic network model, and to average the data over two year periods effected the results of the analysis.

We divide the data set into small, medium and large hospitals based on the number of bed days. Hospitals with 300 or less bed day are labeled small, 300 to 700 bed days are labeled medium, and more than 700 bed days are large. A 300 bed hospital is already quite big, so this division allows us to focus on the data for hospital with less than 300 beds.

The first observation that is the average efficiency level is low. Tone [16] showed that a constant returns-to-scale SBM gives efficiency estimates that are less than or equal to efficiency estimates from a radial constant returns-to-scale model. Table 3 presents the efficiency results for a slack-based input oriented dynamic network DEA model estimated for each of three categories of hospitals. Note that average inefficiency decreases with size consistent with the hypothesis that in a well functioning economy resources will move towards more efficiency operations. The null hypothesis that the large hospitals have the same distribution of efficiency as the medium or small hospital can be rejected at the 1% level. Further, the hypothesis the small and medium hospitals have the same distribution of efficiency cannot be reject. However, the sample size of each of these groups is different. The large group contains 21 hospitals, the medium 101 hospitals, and the small 485 hospitals. The effects of hospital size and sample size are confounded. To investigate this issue further, we divide each category (small, medium and large) such that the largest hospitals within the category are in a group and the smaller hospitals in a separate group and compare the efficiency. The hypothesis that the large group and the small group have the same distribution of efficiency cannot be rejected for any of the three categories. Thus, we conclude that this is additional evidence indicating that DEA based methods tend to have lower efficiency estimates when the group under analysis is larger. Because DEA is an extreme point method relative efficiency method, the most productive hospitals are fully efficient. Assume there is some random variation in the data and as the sample size increases the spread of the hospital productivity distribution increases causing the average efficiency to decrease.

Investigating the behavior of dynamic network DEA, we observe in Table 3 it is not necessary for at least one hospital to be efficient. For medium size hospitals notice the maximum efficiency level is 0.9886 and for small hospitals 0.7016.

Table 3: Efficiency estimates for hospitals divided by size and service

			Medical Service			Hotel Services		
Large	Hospital Efficiency		2006-2007	2008-2009	Average	2006-2007	2008-2009	Average
	0.5085	Average	0.55	0.58	0.57	0.40	0.50	0.45
	1	Max	1.00	1.00	1.00	1.00	1.00	1.00
	0.1574	Min	0.13	0.12	0.13	0.05	0.06	0.06
	0.2685	St Dev	0.34	0.33	0.33	0.32	0.39	0.34
Medium	0.372	Average	0.45	0.45	0.45	0.25	0.34	0.29
	0.9886	Max	1.00	1.00	1.00	1.00	1.00	1.00
	0.0939	Min	0.11	0.08	0.10	0.04	0.07	0.07
	0.1748	St Dev	0.25	0.27	0.25	0.24	0.26	0.22
Small	0.1608	Average	0.26	0.14	0.20	0.15	0.09	0.12
	0.7016	Max	1.00	1.00	1.00	1.00	1.00	1.00
	0.0183	Min	0.03	0.01	0.02	0.01	0.01	0.01
	0.1179	St Dev	0.23	0.17	0.18	0.19	0.14	0.14

This indicates that, as with network DEA, dynamic network DEA requires the hospital to perform well at all services in all time periods. This coupled with the SBM which requires efficient performance in terms of all inputs (in an input oriented model), leads to lower efficiency estimates than is common in radial static black-box DEA. To determine if the dynamic network structure had a significant impact on the efficiency estimates, we estimated SBM for each service and each year. In these results for some hospitals the efficiency estimates were higher for the dynamic network SBM and for others the standard SBM had higher efficiency estimates. Thus, we conclude that the dynamic network model introduces additional insight into the hospitals operations without systematically biasing the efficiency estimates upwards or downwards.

In our initial analysis we analyzed 2006-2009 data as four separate years. We were concerned that random variation in the data might be shifting the production frontiers outward in each period. Ruggiero [14] observed this same phenomenon and proposed averaging the data over a few years to remove some of the variation in the data. We thus decided to average our data over two year periods, 2006-2007 and 2008-2009. The results were on average a 5 percent increase in efficiency over the three categories. While this change in efficiency is small when compared to the difference in efficiency when changing from a slack-based model to a radial model, we believe that the change is important and supported by the theoretical argument made by Ruggiero [14]. Thus, we report the averaged data results.

From the results in Table 3, we can compare the performance of medical services compared with hotel services. For all sizes of hospitals, medical services are performed more efficiently than hotel services. As stated previously the primary purpose of a hospital is to provide medical services, thus it seems natural that the services which receives more attention have a higher average efficiency.

For large and medium size hospitals, average efficiency improves between 2006-2007 time period and the 2008-2009 time period. However, the average efficiency of small hospital falls for both medical and hotel services. While the majority of small hospitals had similar performance in the 2006-2007 time period as they did in 2008-2009 a few hospitals were able to significantly increase their output levels without commiserate increases in input levels, thus technical progress is observed.

5. CONCLUSIONS

The use of dynamic DEA with internal network structure to investigate U.S. hospital data provides insights both to the U.S. hospital industry, but also the methodology. We find efficiency levels, when accounting for dynamics and internal structure, are low and no clear relationship between size and efficiency was observed after controlling for how hospitals were grouped. Further we observed that hospitals are more efficient at providing medical services than hotel services. Regarding the dynamic DEA with internal network structure model, we find slack-based approaches combine technical and allocative aspects of inefficiency and thus tend to have significantly lower efficiency levels than just radial technical efficiency measures. The use of an averaging strategy helps to remove variation. This can be useful if part of the variation in the data is random.

6. REFERENCES

[1] Afriat, S. N., Efficiency estimation of production functions, International Economic Review 13(3), (1972), pp. 568-598.

[2] Baumol, W.J. and W.G. Bowen, On the Performing

Arts: The Anatomy of their Economic Problems, The American Economic Review, (1965), pp. 495-502.

[3] Bogetoft, P., R. Färe, S. Grosskopf, K. Hayes and L. Taylor, Dynamic Network DEA: An Illustration, Journal of the Operations Research Society of Japan 52(2) (2009) 147-162.

[4] Charnes A, Cooper WW, and Rhodes E, Measuring the efficiency of decision making units, European Journal of Operational Research, 2(6), 429-444 (1978).

[5] Cherchye, L., Moesen, W., Rogge N., and Van Puyenbroeck, T., An introduction to 'benefit of the doubt' composite indicators, Social Indicators Research 82, (2007), 111-145.

[6] Färe, R. and S. Grosskopf, Intertemporal Production Frontiers: with Dynamic DEA, Kluwer, 1996.

[7] Färe, R. and S. Grosskopf , Network DEA, Socio-Economic Planning Sciences 34 (2000) 35–49.

[8] Johnson, A.L. and L. F. McGinnis, 2008. "Outlier Detection in Two-Stage Semiparametric DEA Models " European Journal of Operational Research 187(2): 629-635.

[9] Kao, C., Efficiency measurement for parallel production systems, European Journal of Operational Research, 196 (3) (2009) 1107-1112.

[10] Kuosmanen, T., L. Cherchye, and T. Sipiläinen, The law of one price in data envelopment analysis: Restricting weight flexibility across firms, European Journal of Operational Research 170(3), (2006), pp. 735-757.

[11] Kuosmanen, T. and A.L. Johnson, Data Envelopment Analysis as Nonparametric Least Squares Regression, Operations Research 58(1), (2010), pp. 149-160.

[12] Martin A.B. et al., "Growth In US Health Spending Remained Slow in 2010; Health Share of Gross Domestic Product Was Unchanged from 2009," Health Affairs, (2012).

[13] PricewaterhouseCoopers, The Price of Excess: Identifying Waste in Healthcare Spending". Health Research Institute, (2009). (http://www.pwc.com/us/en/healthcare/publications/the-price-of-excess.jhtml).

[14] Ruggiero, J., Data Envelopment Analysis with Stochastic Data, Journal of the OR Society 55 (2004) 1008-1012.

[15] Shephard, R.W. and R. Färe, *Dynamic Theory of Production Correspondences*. Verlag Anton Hain: Meisenheim, (1980).

[16] Tone, K., A Slacks-based measure of efficiency in data envelopment analysis, European Journal of Operational Research 130(3) (2001) 498-509.

[17] Tone, K.and M. Tsutsui, Network DEA: A slacks-based measure approach, European Journal of Operational Research 197(1) (2009) 243-252.

[18] Tone, K.and M. Tsutsui, Dynamic DEA: A slacks-based measure approach, Omega 38 (2010) 145-156.

[19] Tsutsui, M. and M. Goto, A multi-division efficiency evaluation of U.S. electric power companies using a weighted slacks-based measure, Socio-Economic Planning Sciences 43 (2009) 201-208.

[20] Tone, K.and M. Tsutsui, Dynamic DEA with network structure: A slacks-based measure, Proceedings of Workshop on Dynamic and Network DEA 2013, (2013).

[21] WHO (2011). World health statistics 2011. Geneva: World Health Organization. ISBN 978-92-4-156419-9.

[22] Young, P.L., Saunders, R.S. , and Olsen, L. The Healthcare Imperative: Lowering Costs and Improving Outcomes, Workshop Series Summary. The National Academies Press, Washington D.C., (2010).