Chapter 14
Other DEA Applications at Hospital Settings

14.1 Introduction

Chapter 13 introduced various performance models for other health care providers that serve the patient needs including dialysis centers, community mental health centers, community based youth services, organ procurement organizations, aging centers, and dental providers. In addition to those, there are other DEA models designed to evaluate health care provider performance for specific treatments, including stroke, mechanical ventilation, perioperative services, physicians in hospital settings, hospital mergers, hospital closures, hospital labor, hospital services in local markets, etc. (Hollingsworth, 2003).

14.2 Efficiency of Treatment for Stroke Patients

Stroke is the number one cause of adult disability and the third leading cause of death in the US. Stroke killed 150,147 people in 2004. Stroke is also a leading cause of serious, long-term disability in the United States. Although stroke affects people of all ages, genders and races, people over 55, males and African–Americans are at higher risk for stroke (www.americanstroke.org). At the writing of this book, there are around 5.5 million stroke survivors alive and 700,000 people suffer a new or recurrent stroke each year. Thus, it is important to evaluate performance of providers in treatment of stroke.

The study by Ozcan et al. (1998a) used DEA to examine the relationships between provider experience and technical efficiency in treatment of stroke patients. The evaluation further examined the volume–efficiency relationship, and showed that provider experience and high volume practice improve performance.

Ozcan et al. analyze the relative technical efficiency among experience-based peer groups using data envelopment analysis within the input oriented DEA model. The unit of analysis was hospitals that provide stroke treatment. This evaluation used CMS data from 1989. The final sample contained 214 hospitals. Of these 214

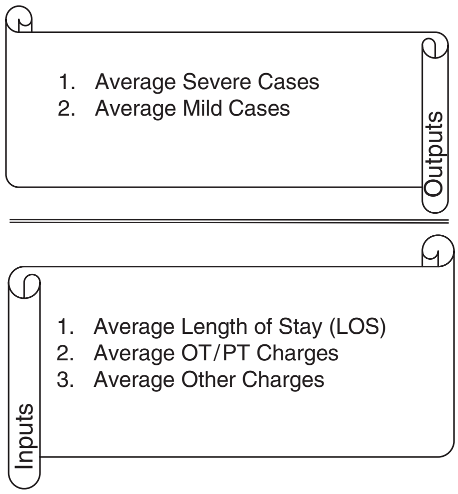

Fig. 14.1 DEA model for stroke treatment

hospitals, 124 are in the low volume category for stroke cases (25–49 cases), 73 are in the medium volume category (50–99 cases), and 17 are in the high volume category (100+cases). Thus, the evaluation uses DEA to test for technical efficiency in stroke treatments based on the average number of cases that the facility treats.

The input variables were an average length of stay (ALOS), average occupational and physical therapy charges, and average all other charges. The output variables are average mild and severe stroke cases per provider. Figure 14.1 displays the DEA model for the stroke treatment.

Results suggest that efficiency scores increase from low to high experience hospitals. The efficiency score for low stroke volume hospitals was 0.59, medium volume hospitals 0.61, and the high volume hospitals 0.81. Upon further analysis, it was determined that the efficient hospitals tend to use lesser inputs to produce a similar number of outputs. The findings of this study also show that high experience providers also have higher charges, which is also associated with higher severity of cases.

14.3 Benchmarking Mechanical Ventilation Services

Mechanical ventilation provides external breathing support to patients who might have ineffective ventilation due to respiratory failure, chest trauma, pneumonia, etc. Mechanical ventilation could be needed in short term (2 days or less), or longer term (3 or more days). Depending upon the patient's condition and severity, the outcomes of mechanical ventilation could be recovery, morbidity or mortality. This technology requires multiple resource use and drives hospitalization costs higher. Thus, it is prudent to identify efficient practices related to mechanical ventilation use.

O'Neal et al. (2002) provided an evaluation of mechanical ventilation services in teaching hospitals. The data was obtained from the University Hospital Consortium (UHC), a national university hospital consortium which keeps a detailed patient level database. The data included 62 UHC hospitals (out of 69) that had non-missing data for 1997. Using DRG 475, for mechanical ventilation, outputs and inputs of the service production was identified. Patient level data was converted to hospital level, thus 62 UHC hospitals were the DMUs. An input-oriented DEA model was employed.

Outputs included adjusted discharges to home, the reciprocal of patients transferred, and the reciprocal of the patients expired. The last two outputs indicate morbidity and mortality, thus, as output, hospitals would want less of them. Hence, using the reciprocal of the measured values, DEA model enforces them to be less. Authors also tested ventilator patient days as an alternative output to adjusted discharges, and conducted sensitivity analysis. Their finding showed that an adjusted discharge variable was more robust.

Inputs included charges occurred from the departments of respiratory, pharmacy, laboratory, and radiology. These are the most common charge centers for the mechanical ventilation patients in addition to other common charges. Figure 14.2 shows the DEA model for mechanical ventilation.

Results showed that practice variation (resource utilization) existed among 62 UHC hospitals in use of mechanical ventilation. Only seven hospitals achieved perfect efficiency. The average efficiency score was 0.49. Inefficient hospitals transferred more patients to other hospitals and more patients expired in them. Examining the efficient targets for 55 inefficient hospitals, it is found that the excessive charges (over utilization of inputs) amounted to \$530,000 for respiratory, \$150,000 for pharmacy, \$570,000 for laboratory, and \$630,000 for radiology services (O'Neal et al., 2002).

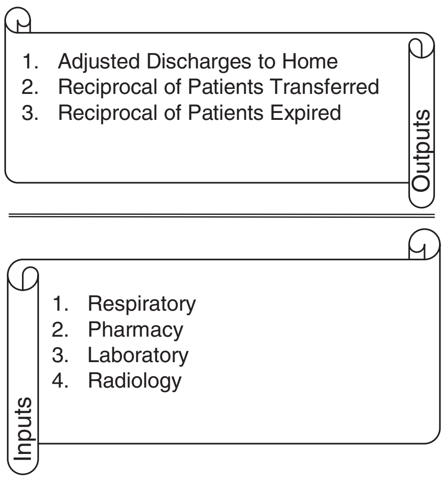

Fig. 14.2 DEA model for mechanical ventilation

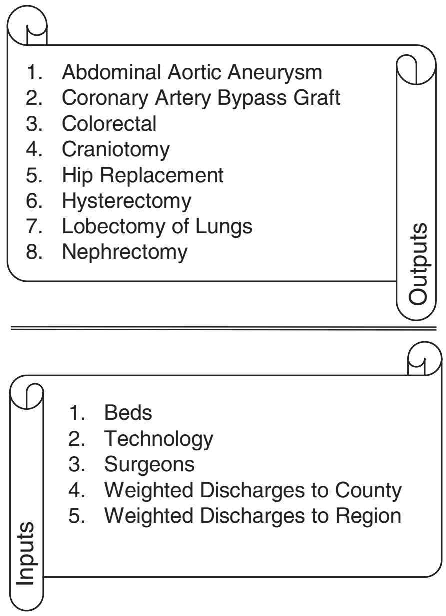

Fig. 14.3 DEA model for perioperative services (Source: O'Neill et al., 2007)

This model provides guidance for administrators and researchers who would like to examine utilization or efficiency of a particular service product in the hospital, and could provide strategies where to look for cost reductions or streamlining the operations.

14.4 Market Capture of Inpatient Perioperative Services

Preoperative care, elective surgery, and post-operative care defines Perioperative Services (POS). According to O'Neill and Dexter (2004), the assessment of efficiency of POS can be used to estimate how many more cases can be accomplished by each specialty hospital.

The O'Neill and Dexter evaluation used an output-oriented DEA CRS, and super efficient model. Output orientation promotes the increase on surgical procedures. Outputs were eight different surgical procedures, most of them with high DRG intensity weights. These outputs included the following surgical procedures: abdominal aortic aneurysm (AAA), coronary artery bypass graft (CABG), colorectal resection, craniotomy not for trauma, hip replacement, hysterectomy, lobectomy or pneumonectomy, nephrectomy. Selection reasons for these particular surgeries were justified by their frequency and availability in many hospitals.

Inputs of the model were beds, technology measured by high tech services offered by the hospital, number of surgeons, weighted hospital discharges for the eight surgical outputs into the county where hospital is located (regardless of where the care is received), and weighted hospital discharges for the eight surgical procedures into surrounding region regardless of where the care received from.

Twenty-nine of the 53 hospitals were identified as efficient performers by DEA. The DEA benchmark targets in inefficient hospitals, specifically for output shortages in various surgery types, provide rich information to their hospital managers for strategic initiatives. This way, hospital mangers can design strategic initiatives to market more surgery time on specific surgical procedures to reach efficiency in perioperative services (O'Neill and Dexter, 2004).

14.5 Physicians at Hospital Setting

Chilingerian (1995) provided an extensive analysis and discussion of a clinical efficiency study involving 36 physicians at a single major teaching hospital. The aim of this evaluation was to determine the various levels of efficiency practiced by physicians. He identified the variance in resources utilized (i.e., diagnostic procedures) between physicians practicing within the same hospital, and identified variance in physician decision making. This evaluation using DEA and the multi-variant Tobit model analyzed physician efficiency and identified key factors associated with the efficient use of clinical resources in the provision of hospital services.

Chilingerian concluded that inefficient physician decision making may be one of the root causes of runaway costs and low hospital productivity. The deficiencies of prior studies are that most of the prior studies did not look at the nature of efficient relationships inside health care organizations. Prior research on physician utilization of hospital services is the reliance on a single-input, single-output analysis, not multiple-input, multiple-output analysis. Also, analytic methods were at the central tendencies rather than identifying the best results.

The physicians included in this study are any physician who treated more than 35 cases during the 3 months as active attending physicians. This sampling rule was generated by a pilot testing result. The data was collected through MedisGroups. To minimize the influence of case mix complexity, the study was conducted using a pair of DEA models. Both a CRS and VRS models were established and partitioned by internist and surgeons, with a 2:1 ratio between them. The second CRS and VRS evaluation models included a relative weight for case mix. The purpose of the two models was to minimize any extraneous variables.

The output variables were the number of high severity discharges and the number of low severity discharge. The input variables were the total length of each patient's stay and the total charges for all ancillary services.

The result indicated that physician practice characteristics are more important factors associated with efficient care than patient illness characteristics. The most of HMO physicians practiced in regions of constant returns to scale, and most of fee-for-services physicians practiced in regions of increasing returns to scale. Physicians affiliated with the group-practice HMO increase their likelihood of being efficient.

The proportion of very high severity cases had a strong negative effect on inefficiency scores while specialization by DRG and the size of a physician's caseload were also found to improve the likelihood of physician efficiency (Chilingerian, 1995). One of the major limitations of this evaluation was that the study was only conducted in one hospital with physicians admitting at least a certain number of patients, so the generalizability of the study result is difficult.

The results indicate a potential savings impact of $1,000,000 if the lesser two-thirds could perform at a level of the more efficient physicians. This value may not be fully rational. A Post-hoc Tobit analysis demonstrated that HMO affiliation was a significant factor (Chilingerian, 1995).

14.6 Hospital Mergers

Harris et al. (2000) conducted a retrospective longitudinal study of hospital mergers and the relationship to enhanced efficiency as a possible result. DEA- CRS and -VRS models were used to investigate the impact of horizontal hospital mergers on technical efficiency. Multi-period analysis was used to study efficiency levels before and after the merger year. Two research questions focus on how mergers enhance efficiency and how soon mergers impact efficiency levels. The unit of analysis was a new hospital created by a merger.

The sample size was 20 hospitals which had been created from mergers in 1992. The sample size was increased to 60 hospitals using the multi-period analysis that considered prior and post merger years (3 years $\times 20$ hospitals). Data included survey data for 1991, 1992 and 1993 from American Hospital Association and the CMS case mix index. Inputs and outputs were the same as shown in robust DEA model in Chap. 8 (see Fig. 8.1). Both CRS and VRS models were used for an input-oriented model.

Of the 20 hospitals under CRS model, 11 hospitals (55%) stayed or improved efficiency in the merger year and 12 (60%) in the post merger year. One hospital (Hospital B) had the greatest improvement and another (Hospital O) had the largest decrease in efficiency. Average efficiency scores were 0.812, 0.803 and 0.852 for years 1991, 1992 and 1993. Total efficiency change from 1991 was 1.51 and 8.46% in years 1992 and 1993, respectively.

Under the VRS model, of the 20 hospitals, 13 (65%) had similar scores or improved in merger year and 13 (65%) in the post merger year. Hospital B had the greatest improvement and Hospital K had the largest decrease in efficiency. Average efficiency scores were 0.862, 0.894 and 0.889 in years 1991, 1992 and 1993, respectively. The total efficiency change was 6.42 and 5.42% in years 1992 and 1993.

For all inefficient hospitals, more post merger work needs to be performed to achieve efficiency levels.

This study used data from 1991 to 1993 to access efficiency changes. Since 1993, the rate of mergers has increased, especially during the mid to late 1990s. The reasons for this change to a market system include but are not limited to government policies. As a result, some mergers were due to offensive efficiency seeking behavior, while others due to defensive strategies. Replication of this study for more recent years and in a larger time span would be prudent.

14.7 Hospital Closures

Hospital closures in rural and inner city locations became epidemic in late 1980s mainly the effect of implementation of prospective payment system (PPS) through DRGs. Ozcan and Lynch (1992) examined hospital closures in rural locations. This study used 1988 AHA survey files and similar inputs and outputs to DEA model presented in Fig. 8.1, although they added a training FTE variable as an additional output. The sample contained 1,535 hospitals of which 726 were located in rural areas and 809 in urban areas. There were 66 hospitals among those that closed and 1,469 remained open. Average efficiency score for closed rural hospitals was 0.75, those remained open was 0.80. In urban locations, the average efficiency for closed hospitals 0.72, those remained open was 0.76. The efficiency differences between closed and open hospitals were not significant, but closed hospitals experienced lower efficiencies.

Later in a separate study with the same data, Lynch and Ozcan (1994) used a combination of DEA and logistic regression to determine if inefficient hospitals are more likely to experience closures. They also investigated the relationship between high Medicaid payer shares and closures. Results showed that hospitals providing larger proportions of Medicaid paid days of care are being driven from the market. They also found that small hospitals that do not experience a demand for their services were found to be at greater risk for closure.

14.8 Labor Efficiency in Hospital Markets

Many hospital cost containment initiatives were introduced in the early 1980s, especially Medicare's prospective payment system and actions by managed care organizations, and a big portion of a hospital budgets are labor costs. Thus, examination of hospital labor markets and labor efficiency became an important issue.

Ozcan et al. (1996a) used AHA Annual Survey for 1989 and 1993 for all nonfederal acute care general hospitals to evaluate hospital labor efficiency in major markets. The hospitals data were aggregated at metropolitan statistical areas (MSAs) – markets and designated as the DMU. A total of 633 MSAs in two time periods (319 in 1989, 314 in 1993) were analyzed. The MSAs were divided into four market groups based on population size to control for the effect of market size on efficiency.

The two outputs were case-mix adjusted discharges and outpatient visits as in the model in Chap. 8. The seven inputs were FTEs in nursing, allied health, administration, salaried physicians and trainees, physician extenders, nonprofessional assistants, and nonprofessional technicians. The study used the input-oriented DEA CRS model.

The descriptive statistics show an increase in outpatient visits, especially dramatic in the small population MSAs (12–160 million), between 1989 and 1993, reflecting the industry trend toward increased outpatient procedures. Clinical labor inputs increased in all categories except large market nursing assistants from 1989 to 1993. Administrative labor inputs increased substantially from 1989 to 1993.

The DEA analysis showed that MSAs in the medium market category significantly decreased in their efficiency score between 1989 and 1993. The percentage of inefficient hospital markets increases over time in every market category. The excessive use of inputs by inefficient labor markets on RN, allied health, and administrative FTEs for medium MSAs also significantly increased. The changes in administrative FTEs were significant for large MSAs.

Why is it that hospital labor markets did not improve their efficiency? Among the potential explanations are (1) hospitals focusing on capital efficiency, not labor efficiency (institutional stronghold delaying significant labor transitions; concerns for quality not allow cutbacks and substitution; uncertainty of job redesign and the effect on efficiency becoming evident later than the study period), (2) hospitals focusing on quality instead of efficiency (TQM adoptions), and (3) the turbulent environment in the early 1990s.

The evaluation also provided recommendations for potential hospital market savings. Inefficient medium MSAs utilized an average of 605 more FTEs than the efficient MSAs, totaling $24 million in excess human resources per inefficient MSA.

14.9 Hospital Service Production in Local Markets

Evaluation of labor efficiency in hospital markets also lead to another study by Ozcan (1995). This evaluation focuses on hospital-generated inefficiencies in local markets as one of three major sources of health care inefficiency. The aim of the study was to provide a preliminary assessment of hospital service delivery performance at the local market level, and to assess the degree of duplication and redundancy in capital resources in health care markets. More specifically, the aim is to assess the variation in efficiency of hospital resources allocation across metropolitan areas in the nation.

The Ozcan (1995) study analyses 319 metropolitan areas (less than 250.00, 250.00–1.000.000, 1.000.000–2.500.000, more than 2.500.000) and the primary source of data is the AHA survey for 1990.

Inputs and outputs of the input-oriented DEA model were similar to the model presented in Fig. 8.1. Outputs were adjusted discharges and outpatient visits; inputs were capital (service complexity and hospital size), labor (non-physician FTEs) and operating expenses.

Findings of this evaluation can be summarized as:

- Average technical efficiency ranges between 0.79 and 0.92 across the different sizes of metropolitan areas
- Increase in average efficiency with size (except medium market size), which may be attributed to economy of scale
- Analysis of efficient targets showed that (except for very large markets), production of adjusted discharges is appropriate. For large markets, there was an average shortage of 427 discharges (0.4%), in very large markets an average of additional 152,940 outpatient visit could have been handled with available resources
- Inefficiency contributes to $\sim$23% of the increase in health care costs, and that
- CON and regulatory environment showed no significant correlation to waste in local markets (Ozcan, 1995).

14.10 Sensitivity Analysis for Hospital Service Production

An Ozcan (1992–1993) article presents a review of hospitals' technical efficiency using DEA and analyzes how sensitive the efficiency to choice of output and inputs as well as peer grouping. In order to analyze sensitivity for the type of variables, 17 models were tested with different output/input variables. A stratified (by size, location and ownership) random sample of 40 acute general hospitals was obtained from AHA 1989 survey data, and another 90-hospitals sample (30 from each category) was obtained for Los Angeles MSA.

The models were tested in the largest bed-size category because of the presence of teaching or training variables (most of teaching hospitals have more than 300 beds). The models included analysis of impact of assets, training, patient days, labor and breaking up labor FTE, DRG weighted category groups and size effect.

The results showed that some variables may be substituted without significant effect on the average efficiency score (assets for case-mix/bed), while others can significantly increase (three DRG weight category discharges for adjusted discharges) or lower (patient days for adjusted discharges) the scores. In terms of size effect, models compare pooled with non-pooled categories and analysis shows that pooling categories creates bias toward higher efficiency scores. In summary:

- Choice of variables for DEA may affect results, and
- Peer-grouping is very important (size effect in DMU), thus the use of VRS model or scaling the data logarithmically would be a prudent action (Ozcan, 1992–1993).

14.11 Summary

This chapter introduced other DEA studies that do not fit into either traditional or non-traditional service provider evaluations discussed in Chaps. 8–13. However, these evaluations provide insight and solutions to many contemporary health care policy and delivery problems.