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Health Care Benchmarking and Performance Evaluation

An Assessment using Data Envelopment Analysis (DEA)

Yasar A. Ozcan

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HEALTH CARE BENCHMARKING AND PERFORMANCE EVALUATION

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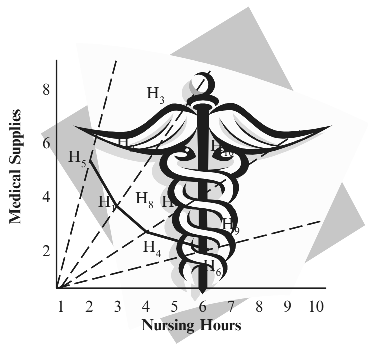

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Yasar A. Ozcan
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To my wife Gulperi Ozcan

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No book can be written without the support and encouragement of loved ones. I am indebted to my wife Gulperi Ozcan, who served as my sounding board for every aspect of this text. Moreover, she extended her support throughout the development of the manuscript even as I deprived her of my time in favor this manuscript. I thank her for the sustained support she has given me throughout my academic career and our personal lives.

Yasar A. Ozcan
Richmond, VA

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Foreword

Improving the efficiency of health care, the primary focus of this book, is one of the most important management challenges of this century. US health care spending exceeded $2 trillion in 2005 and credible estimates suggest this amount will double by 2016. Over one of every seven dollars (16%) of gross domestic product is devoted to health care. In addition to spending more on health care than other countries by some measure, this weakens US based business' global competitiveness. Globally, on average, over 10% of gross domestic product is spent on health care, and the national health systems are feeling the stress of high costs and seeking ways to improve efficiency, contain costs, and maintain quality of care. The value and relevance of this book are significant and can benefit government policy makers, health care managers, and students of management, public health, and medicine; and of course the value and relevance applies around the globe to wherever there are organized health care systems.

Professor Yasar Ozcan is literally one of a handful of academics that has the background, experience, and acumen to develop this book focusing on improving health care productivity using of data envelopment analysis (DEA) and related methods. He has been actively researching and publishing on issues of health care management, use of operations research methods in health care to improve delivery and quality of care, and specifically DEA for over 20 years. A study in *Socio-Economic Planning Sciences* (by Gattoufi, Oral, Kumar and Reisman – vol. 38 – 2004) notes that Prof. Ozcan is one of the 15 most prolific DEA contributors as of 2001, measured in volume of academic journal publications. More importantly, I believe Prof. Ozcan is distinguished as the only one of these major DEA contributors that is a widely recognized expert in health care management. In addition to his significant body of work in health care operations research and DEA, Prof. Ozcan is the founder and editor of *Health Care Management Science*. Professor Ozcan's work on health systems in several countries around the globe makes the perspective of his writing sensitive to and applicable to health system issues throughout the globe.

While Professor Ozcan's volume of work is substantial and impressive, the element that makes this book particularly valuable is that Prof. Ozcan's work focuses on applications to a broad set of health care fields and organizations. The focus on field studies and the quality of that work will allow managers and policy makers to gain new insights into ways to enhance the productivity of their health care services or to understand the way alternative initiatives will impact efficiency and cost of care. After offering a perspective on health care productivity management, a primer on DEA, and alternative models, this book provides field examples that speak directly to every significant facet of health care services that I can think of. Included are major providers: hospitals, managed care (health maintenance – HMO) organizations, nursing homes, home health agencies, dialysis center, mental health centers, dental clinics, aging program, and others specialized activities. The focus also extends both to managing the organization and its method of delivering health services as well as the providers practice patterns (physicians, nurses) in their delivery of general care and in specialized disease treatments.

This book offers a perspective on the unique strengths of DEA in addressing the types of service management issues common to most health care services. Specifically, DEA is particularly powerful in managing services where there are multiple outputs (types of patients, diverse severity of patients, etc.) and multiple inputs used to provide these services. At the same time, Prof. Ozcan identifies the boundaries of DEA and also describes related methods that are used for health care productivity analysis such as regression analysis and total factor productivity. The result is that the reader is encouraged, challenged, and energized to apply these concepts to their research or directly to their organization, as has occurred with many students that have worked with Prof. Ozcan over the years.

Managers, government policy makers, consultants, students, and academics can all gain new insights in the quest to improve productivity of health care services, manage costs of care, and develop methods to tackle related problems from this book. *HealthCare Benchmarking and Performance Evaluation: An Assessment Using Data Envelopment Analysis* is, in my view, a welcome and needed addition to the DEA literature and health care management literature.

Boston, MA H. David Sherman

Preface

This book places emphasis on the application of contemporary performance and efficiency evaluation methods, using data envelopment analysis (DEA), to create optimization-based benchmarks including, but not limited to hospitals, physician group practices, health maintenance organizations, nursing homes, and other health care delivery organizations. Hence, this book will not only be useful for graduate students to learn DEA applications in health care, but will also be an excellent reference and "how to book" for practicing administrators.

There are various evaluation methods to assess performance in health care. Each method comes with its strengths and weaknesses. Key to performance evaluation is how to conceptualize the service production in various health care settings, as well as appropriately measuring the variables that would define this process. The research papers published in various health care and operations research journals provide insight to conceptualization of service production processes in various health care organizations. Also many research papers delineate methods that can be used for this purpose. Depending upon when and where the research was conducted, and the availability of the measures for inputs and outputs or their proxies, researchers can determine what variables they should employ in conceptualization of the health service production process. The nature of data availability further implies that some research findings on performance may produce sensitive results, thus a comparison of the results using different variables, if possible, is prudent.

Section 1 of this book has seven chapters that are designed to introduce performance concepts and DEA models of efficiency most frequently used in health care. An example consisting of ten hospitals is used throughout these seven chapters to illustrate the various DEA models. This example includes only two output and two input variables. The intent for the example is to create understanding of the methodology with a small number of variables and observations. In practice, measurement of efficiency in hospitals or in other health care organizations using DEA goes beyond the presented example and requires appropriate conceptualization of service production in these organizations. The extensive health care provider applications are left to the second section of this book, where DEA models with appropriate output and input variables for various health care providers and the like are presented.

In this first section of the book, Chap. 1 provides a brief survey of performance evaluation methods for health care and discusses their strengths and weaknesses for performance evaluation. These methods include ratio analysis, the least-square regression analysis, total factor productivity (TFP) including Malmquist index, stochastic frontier analysis (SFA), and DEA.

Efficiency measures and efficiency evaluations using DEA is the subject of Chap. 2. This chapter explains the most commonly used concepts of efficiency, such as technical, scale, price, and allocative efficiency. Other sections of the Chap. 2 provide more detail on DEA techniques, including model orientation (input vs. output), and various frontier models such as constant returns to scale (CRS). The hospital example and software illustration on how to run these models provides enhanced understanding to readers.

Chapter 3 further develops the returns to scale concept and introduces variable returns to scale (VRS) model with software illustration. Multiplier or weight restricted models (cone ratio or assurance region models) are presented and illustrated in Chap. 4. Chapter 5 discusses non-oriented or slack-based models and shows how and under what circumstances they can be used.

Longititudunal (panel) evaluations are illustrated in Chap. 6 using Malmquist Index. This chapter illustrates not only an efficiency change between two time periods, but also accounts for technological changes.

The last chapter of this section, Chap. 7, introduces effectiveness in a performance model and shows the potential misuse of quality variables in DEA models. Furthermore, it suggests a procedure to evaluate both efficiency and effectiveness. Finally, other less frequently used DEA-based methods are discussed.

The aim of this book is to reduce the anxiety for complex mathematics, and promote the use of DEA for health care managers and researchers. Thus, the mathematical formulations of various DEA models used in this book purposefully placed in the appendices at the end of appropriate chapter for interested readers.

Section 2 includes the health care applications. In this section, DEA is applied to health care organizational settings to determine which providers are functioning efficiently when compared to a homogenous group of providers in their respective services. The most frequently evaluated health care providers are hospitals, nursing homes, physician practices, and health care maintenance organization (HMOs). The DEA models for these providers are discussed in Chaps. 8–11, respectively.

Many DEA studies defined hospital service production and delineated the variations in hospital production by suggesting models that provide conceptualization of inputs and outputs in this process. Hollingsworth et al. (1999) and Hollingsworth (2003) provided extensive review of non-parametric and parametric performance evaluation applications in the health care arena. In these reviews, the focus was on health care issues conducted in both the US and abroad. Hollingsworth (2003, p. 205) shows that about 50% of the 168 DEA health care applications are for hospitals. Chapter 8 develops a robust hospital DEA model based on these previous studies, where we also provide a synopsis of some of these studies and suggest a model that can serve as standard for future hospital performance evaluations.

The scope of physician studies is varied based on different categorization methods. These different categories are working place, diseases, and type of physician. The working place related studies assess physicians in IPA type HMOs, physicians in hospitals, and physicians in a general group practice. The studies based on the disease encompass heart failure and shock, otitis media, sinusitis, stroke, and so on. Other studies focused on generalists or specialists.

Due to different scopes of these studies, the inputs and outputs selected to assess efficiency via DEA are not consistent. In those studies that focused on diseases and primary care, the variables of PCP visits, specialist visits, emergency visits, test, and description were usually selected to be input variables; and patient episodes with different degrees of severity of disease are usually selected to be output variables. The studies that focused on diseases and hospitals or in HMOs, the length of stay was added to the input group. The output variables are almost the same as the variables in the primary care studies. Chapter 8 provides an in-depth look to DEA based physician evaluations. Few studies focused on dental services, but they are discussed in Chap. 13.

The nursing home studies are more consistent and provide a more focused scope. Common observations for nursing homes are the type of outputs used, and definition of the DMUs as intermediate care and skilled nursing facilities. The second consistency is in the overall theme of the inputs such as staff numbers and financial issues. Chapter 10 specifies the DEA-based nursing home models.

Chapter 11 introduces a few studies on health maintenance organizations and DEA models associated with them. Chapter 12 explores home health, and introduces DEA models for home health agencies.

Other types of health care providers covered include dialysis centers, community mental health centers, community-based youth services, organ procurement organizations, aging agencies, and dental providers. DEA models for these providers are shown in Chap. 13.

Chapter 14 provides an insight to other DEA models designed to evaluate health care provider performance for specific treatments including stroke, mechanical ventilation, and perioperative services. This chapter also includes DEA models for physicians at hospital settings, hospital mergers, hospital closures, hospital labor markets, hospital services in local markets, and sensitivity analysis for hospital service production.

A CD-ROM containing limited version of DEAFrontier software written by Professor Joe Zhu accompanies this text. This limited version of DEAFrontier can solve up to four-input and four-output DEA models for 100 DMUs. For Malmquist evaluations, it can solve approximately 50 DMUs. For full version of the software, reader is advised to check www.deafrontier.com. Reader should examine the section on "Running the DEAFrontier Software," especially data format for the Excel worksheet.

Developing examples for the techniques explained in each chapter has been a consuming task. Any errors and oversights in that process are solely mine. I will appreciate reader comments to improve or correct the mistakes, as well as suggestions for incorporating additional material in future editions. Please email your comments to ozcan@vcu.edu.Yasar A. Ozcan.

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This is a limited version of the software and only allows for up to 100 DMUs with maximum of four inputs and four outputs.

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Part I
Methods

The next seven chapters introduce performance concepts and models of efficiency that can be solved using DEA and incorporate effectiveness into performance model. Chapter 1 provides a brief survey of performance evaluation methods for health care and discusses their strengths and weaknesses for performance evaluation. Efficiency measures and efficiency evaluations using DEA is the subject of Chap. 2. Ensuing sections of the Chap. 2 provide more detail on DEA techniques, including model orientation (input vs. output), and various frontier models such as constant returns to scale (CRS). Chapter 3 introduces variable returns to scale (VRS) model with software illustration. Chapter 4 presents multiplier or weight restricted models (cone ratio or assurance region models). Chapter 5 discusses non-oriented or slack based models and shows how and under what circumstances they can be used. Chapter 6 illustrates panel evaluations (longititudunal) using Malmquist Index. The last chapter of this section, Chap. 7, introduces effectiveness in a performance model and shows the potential misuse of quality variables in DEA models. Finally, other less frequently used DEA-based methods in health care are surveyed at the end.

Chapter 1
Evaluation of Performance in Health Care

1.1 Introduction

The health care industry faces new challenges every day, and comprises one-seventh of the GNP in the United States. There are new regulations, new technologies, and new organizations being created continuously as a result of public policy. Managers of health care need to respond to these challenges with sound performance evaluation and decision making. This book will offer state of the art performance evaluation methods as well as relevant and current examples to aid practicing managers and graduate students studying in this field.

Management in all industries is moving toward more objective performance evaluation and decision making. The health care industry, however, has lagged behind many other industries in this respect. When the prospective payment system first began in 1983, the health care industry had to scramble to meet the needs of their clients due to significant decreases in reimbursements for Medicare patients. The reaction to this was first to cut costs or avoid cases that would likely lose money, but later most administrators realized that the only way to keep their institutions financially viable was to improve their performance. Hence, benchmarking became the new buzz word. Unfortunately, the benchmarks established using old analytical schemes based on various multiple ratios created more dilemmas than solutions. Performance evaluation based on optimization techniques and their normative structure not only creates benchmarks, but also provides information for lacking organizations and illustrates how to improve performance. This is what is needed in the health care industry today.

This book places emphasis on the application of contemporary performance and efficiency evaluation methods, using data envelopment analysis (DEA), to create optimization-based benchmarks including, but not limited to hospitals, physician group practices, health maintenance organizations, nursing homes, and other health care delivery organizations. Hence, this book will not only be useful for graduate students to learn DEA applications in health care, but will also be an excellent reference and "how to book" for practicing administrators.

1.2 Performance Measurement

During the past few decades, parametric and non-parametric methods have been employed increasingly to measure and analyze the performance of health care services. This section reviews the issues in performance measurement for health services.

Health care managers must adapt new methods to use the resources at their disposal in order to achieve high performance, namely effective and high quality medical outcomes. Performance, as in other service industries, can be defined as an appropriate combination of efficiency and effectiveness. However, those frequently used terms, efficiency and effectiveness, are often used with a somewhat vague sense of meaning in the health care context. *Efficiency* generally refers to using the minimum number of inputs for a given number of outputs. Efficient care, therefore, means a health care facility produces a given level of care or quantity that meets an acceptable standard of quality, using the minimum combination of resources. In performance literature, *efficiency* and *productivity* are often used interchangeably. While productivity generally connotes a broader meaning, both terms are considered a component of performance. As conceptualized in Fig. 1.1, research studies suggest that improving efficiency should lead to greater health service performance, while holding constant the quality, staff skill-mix, and case-mix. *Effectiveness*, more specifically, evaluates the outcomes of medical care and can be affected by efficiency or can influence efficiency as well as have an impact on the health service performance. For instance, *effectiveness* encourages us to ask if the necessary inputs are being used in order to produce the best possible outcomes. A hospital can be efficient, but not effective; it can also be effective, but not efficient. The aim is to be both.

Health care organizations will continue to face turbulent times and more intense competition. Health care managers must face up to promoting and improving performance within their institutions if they are to survive. There is not a standard

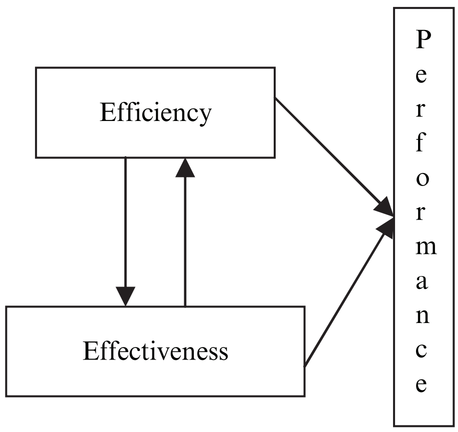


Fig. 1.1 Components of performance

formula for improving performance. Each health care organization, service and/or procedure must be examined individually. In some areas, the organization may have to increase the inputs used to improve quality. In other areas more must be done with fewer resources while holding quality constant. Health care managers will always be challenged with one of the most difficult tasks, determining the proper mix of inputs and outputs.

The relationship between efficiency and quality of care has had mixed results in prior studies. Singaroyan et al. (2006) study concluded that improving quality of health care may not always lead to efficient operations. On the other hand, Helling et al. (2006) found that increasing efficiency will result in quality. Mobley and Magnussen (2002) indicated that poor quality outcome is associated with less efficiency. Ferrando et al. (2005) mentioned that with proper guidelines, hospitals can increase efficiency without affecting the quality of care.

Performance needs to be measured and compared across health care providers for several purposes, including:

- Detecting changes from one period to another
- Determining how organizations are functioning relative to others in a given competitive market (benchmarking or peer comparisons)
- Investigating deviations from plan

Performance in this context should be viewed as a *relative* phenomenon across health care organizations. Thus it can be compared across different providers at one point in time or it can be compared for the same provider across multiple points in time.

Table 1.1 illustrates the measurements of performance where efficiency and effectiveness are measured in time as well as across health care organizations, using efficiency and effectiveness scores (these will be explained later in Chap. 2). Performance scores range from 0.0 to 1.0, where 1.0 is the highest achievable. For the time being, let us assume that 0.90 is an acceptable performance criterion for either high efficiency or effectiveness.

In this example there is no question about the performance of Hospital 3, which held its efficiency and effectiveness score at the top for both periods. *Relative* to other hospitals, this particular hospital would be considered a *benchmark* health care organization. Conversely, the other hospitals relative to Hospital 3 had some performance issues. Hospital 4, although relatively inefficient and ineffective in Time 1,

Table 1.1 Multi-facility and multi-time performance comparison

Health care organization	Efficiency Time 1	Efficiency Time 2	Effectiveness Time 1	Effectiveness Time 2
Hospital 1	0.81	0.88	0.86	0.93
Hospital 2	1.00	0.84	0.84	0.91
Hospital 3	1.00	1.00	1.00	1.00
Hospital 4	0.78	0.94	0.86	0.96
Hospital 5	0.62	0.55	0.71	0.62

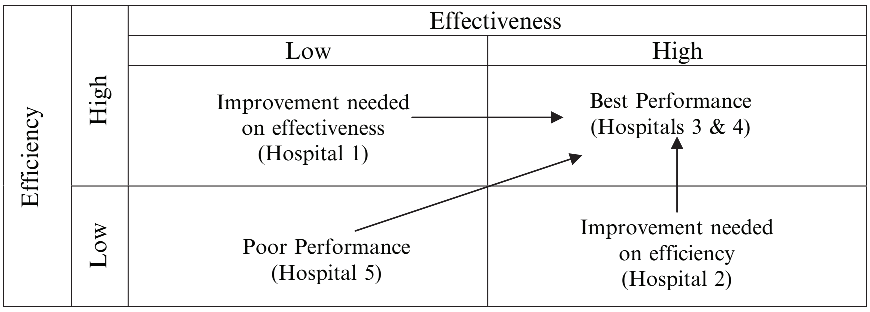


Fig. 1.2 Performance classification schema

closed this gap and became a high performer in Time 2. The situation for Hospital 1 is also promising. Both efficiency and effectiveness improved over time; however, this hospital needs more improvement on its efficiency to become as high a performer as Hospitals 3 and 4. Hospital 2 exhibits a mixed performance from Time 1 to Time 2, since its efficiency went down while effectiveness reached a relatively high standard. In the past, many health care managers argued this point, suggesting that to improve quality (effectiveness) something has to be taken away from efficiency. Of course, performance of Hospital 4 argues against this point, since both efficiency and effectiveness increased over time. Lastly, Hospital 5 was a poor performer in Time 1, and this poor performance was amplified in Time 2. Given these scenarios, one can classify the health care performance by these organizations into four groups based on their efficiency and effectiveness scores using Time 2 scores as shown in Table 1.1. Hospitals exhibiting less than high performance in either measure should aim towards the upper-right quadrant of the performance classification schema (Fig. 1.2).

The challenge of performance improvement planning is determining the values that yield efficiency and effectiveness scores, namely, what should health care managers do to improve the performance situation of the health care organization? This brings us to the methodologies that are used to calculate efficiency and effectiveness measures.

1.3 Performance Evaluation Methods

Comparative performance analysis can be undertaken by various methods, including:

- Ratio analysis,
- Least-squares regression (LSR),
- Total factor productivity (TFP),
- Stochastic frontier analysis (SFA), and
- Data envelopment analysis (DEA).

1.3.1 Ratio Analysis

As well as an effectiveness score, this approach is the simplest of the methods for calculating performance, especially productivity/efficiency. It produces information on the relationship between *one input* and *one output*. That is, efficiency is defined as the number of output units per unit of input:

$$Efficiency\ (Productivity) = \frac{Output}{Input} \tag{1.1}$$

Many ratios often have to be calculated to capture various dimensions of performance among compatible units or a given unit over different time periods. This is especially true for the hospital sector, where organizations such as MECON Inc. provide comparative benchmark and performance statistics via *MECON-Peer Guide* (1995).

The hospital industry reports, through such publications as *MECON-Peer Guide*, many inpatient as well as outpatient statistics displaying crude and adjusted patient volume for a given facility. These reports also characterize hospital operational information from labor, supply and cost points of view across the peer groups of hospitals.

Similarly, physician group practice performance statistics are reported by departmental and group levels for subscribing groups by various organizations such as Medical Group Management Association (MGMA). Either hospital or group practices receive these thick volumes of quarterly reports containing several hundred ratios to be monitored for benchmarking by health care managers.

Using multiple ratios often produces mixed results that confuse health care managers in comparative performance analysis. To illustrate this, let us examine the situation presented in Table 1.2, where we compare ten hospitals.

For simplicity, let us assume there are two inputs, nursing hours and medical supplies; and two outputs, inpatient admissions and outpatient visits. Using this information, one can calculate four possible performance ratios as illustrated in Table 1.3.

These ratios are analogous to what is being reported in hospital performance statistics by MECON Inc. and similar organizations.

In order to identify benchmarks (i.e., best performers) one can standardize each of these performance ratios across the hospitals by identifying the best score in each

Table 1.2 Hospital inputs and outputs

	Inputs		Outputs	
Provider ID	Nursing hours	Medical supplies ($)	Inpatient admissions	Outpatient visits
H1	567	2,678	409	211
H2	350	1,200	90	85
H3	445	1,616	295	186
H4	2,200	1,450	560	71
H5	450	890	195	94
H6	399	1,660	209	100
H7	156	3,102	108	57
H8	2,314	3,456	877	252
H9	560	4,000	189	310
H10	1,669	4,500	530	390

Table 1.3 Hospital performance ratios

Provider ID	Nursing hours/inpatient admissions	Medical supplies/inpatient admissions	Nursing hours/outpatient visit	Medical supplies/outpatient visits
H1	**1.39**	6.55	2.69	12.69
H2	3.89	13.33	4.12	14.12
H3	1.51	5.48	2.39	**8.69**
H4	3.93	**2.59**	30.99	20.42
H5	2.31	4.56	4.79	9.47
H6	1.91	7.94	3.99	16.60
H7	1.44	28.72	2.74	54.42
H8	2.64	3.94	9.18	13.71
H9	2.96	21.16	**1.81**	12.90
H10	3.15	8.49	4.28	11.54

Table 1.4 Standardized efficiency ratios and ranking of the hospitals

Provider ID	Nursing hours/inpatient admissions	Medical supplies/inpatient admissions	Nursing hours/outpatient visit	Medical supplies/outpatient visits
H1	**1.00 [1]**	0.40 [5]	0.67 [3]	0.68 [4]
H2	0.36 [9]	0.19 [8]	0.44 [6]	0.62 [7]
H3	0.92 [3]	0.47 [4]	0.76 [2]	**1.00 [1]**
H4	0.35 [10]	**1.00 [1]**	0.06 [10]	0.43 [9]
H5	0.60 [5]	0.57 [3]	0.38 [8]	0.92 [2]
H6	0.73 [4]	0.33 [6]	0.45 [5]	0.52 [8]
H7	0.96 [2]	0.09 [10]	0.66 [4]	0.16 [10]
H8	0.53 [6]	0.66 [2]	0.20 [9]	0.63 [6]
H9	0.47 [7]	0.12 [9]	**1.00 [1]**	0.67 [5]
H10	0.44 [8]	0.30 [7]	0.42 [7]	0.75 [3]

ratio, then dividing this into the particular ratio of each hospital. For example, Hospital 1 (H1) has the best ratio for the Nursing Hours per Inpatient Admission, which is 1.39. Dividing this into other hospitals' nursing hours per Inpatient Admissions we can obtain a relative value compared to H1, which is considered a benchmark hospital for this particular ratio. We can label this relative benchmarking score as the standardized efficiency ratio. Table 1.4 depicts the standardized efficiency ratios for four categories. Based on the relative scores of each hospital one can rank the hospitals (shown in brackets in Table 1.4). This case further illustrates the dilemma for the health care managers that occurs when benchmark performance shown with rankings varies according to which ratio is under consideration.

For example, while H1 is considered a benchmark hospital for nursing hours per inpatient admissions, it ranks fifth on "medical supplies per inpatient admissions," third on "nursing hours per outpatient visit," and 4th on "medical supplies per outpatient visit." On the other hand, H4 displays more dramatic results: while ranking first on "medical supplies per inpatient admissions," it ranks tenth on "nursing hours per inpatient admissions" as well as "nursing hours per outpatient visits," and nineth on "medical supplies per outpatient visits." Similar mixed results can be interpreted from Table 1.4 for H9, which is a benchmark hospital, on "nursing hours per outpatient visits," and for H3, which ranks highest on "medical supplies per outpatient visits."

This illustrates the weakness of ratio-based analysis, where health care mangers often cannot pinpoint a consistent benchmark incorporating all inputs and outputs of the health care organization.

1.3.2 The Least-Squares Regression

The least-squares regression (LSR) is a very popular parametric technique, and by its formulation, it assumes that all health care organizations are efficient. While it can accommodate multiple inputs and outputs, it can also account for noise, using an error term (see "e" in (1.5)). A general formula for a least squares regression is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots \beta_n x_n + e \tag{1.5}$$

For this model, it is further assumed that

- For any fixed value of x, y is a random variable $(y|x) = \beta_0 + \beta_1 x$,
- The y values are independent of one another,
- The mean value of y is a straight-line function of x, $y = \beta_0 + \beta_1 x_1 + e$,
- The variance of y is the same for any x, and
- y has a normal distribution for any fixed value of x.

The least-square regression has some benefits. It can be used to measure technical change if time-series data are used. In addition, scale economies can be calculated. However, its weaknesses are greater.

Using LSR in performance analysis poses many weaknesses. Firstly, the LSR uses central tendency measures (averaging techniques), which are not necessarily efficient relationships. Furthermore, LSR does not identify the individual inefficient units, and it requires a pre-specified production function due to it is parametric formulation.

Let us illustrate these weaknesses using the example developed in Sect. 1.2. Consider the first two ratios where nursing hours and medical supplies per inpatient admissions were calculated. Using these two ratios one can map the hospitals on a scatter diagram, as shown in Fig. 1.3 to analyze the hospital performance from an inpatient admissions perspective (let us label this "Hospital Performance I").

We established earlier that H1 was the best hospital considering "nursing hours per inpatient admissions," while H4 was the best based on "medical supplies per inpatient admissions." Using regression analysis, an estimate of hospital performance from the inpatient admissions perspective (Hospital Performance I), is described by line $y = 13.83 - 1.42x$, as show in Fig. 1.3. This average line best predicts efficiency relationships when observations in a scatter diagram are closer to the estimated line. Hence, H2, H6 and H10 are the closest hospitals to this line while H1 and H4 show further distance. Thus, according to regression analysis, for better performance H1

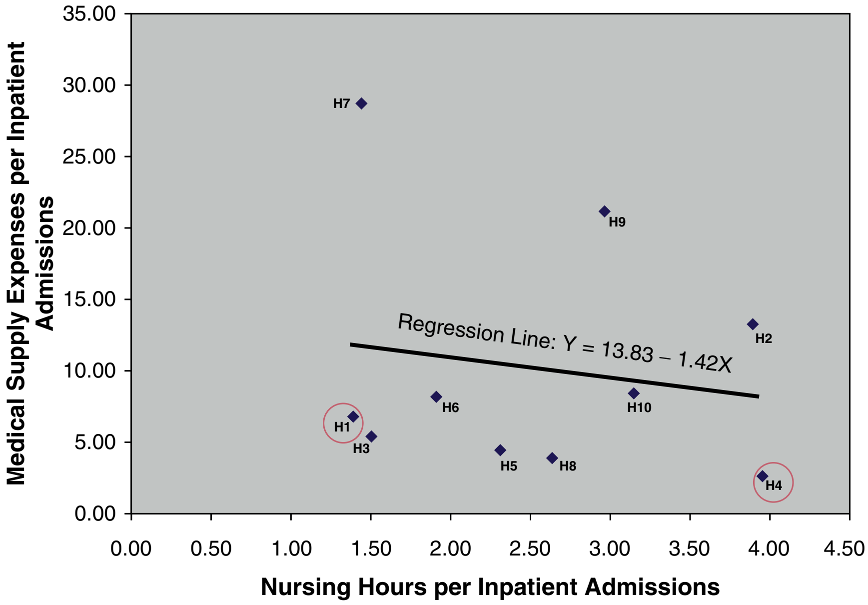


Fig. 1.3 Hospital Performance I

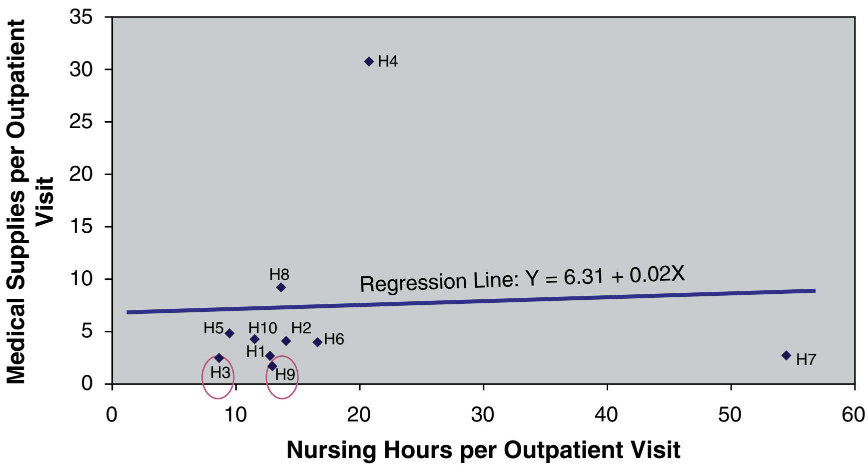


Fig. 1.4 Hospital Performance II

and H4 should further move toward the average, as illustrated by the regression line. In reality, this means H1 and H4 should give up their benchmark status with respect to these ratios and actually become inefficient.

We can replicate the same evaluation for the second dimension of the performance using a regression estimate of hospital performance from the outpatient visits perspective (Hospital Performance II). This case is described by line $y = 6.31 - 0.02x$, as show in Fig. 1.4. As it can be interpreted from this figure, H3 and H9, which were considered benchmark hospitals for this dimension of the hospital performance, are not good examples of performance based on the regression line because they are further away from the average performance with respect to H2, H5, H6, H8, and H10.

As these two examples illustrate, the regression analysis does not necessarily predict the best performance or the most efficient relationships. Hence, we must explore other methodologies that would describe more robust performance measures.

1.3.3 Total Factor Productivity (TFP)

TFP overcomes the weakness of single ratio analysis and incorporates multiple inputs/outputs into a single performance ratio. More specifically, TFP is measured using index numbers. Index numbers can be used to measure price and quantity changes over time, and also measure differences across health care organizations.

$$TFP_{ab} = \frac{\sum_{i=1}^{N} p_{ib} q_{ib}}{\sum_{i=1}^{N} p_{ia} q_{ia}} \tag{1.6}$$

In formula (1.2) $\mathrm{TFP}_{\mathrm{ab}}$ index measures the change in the value of selected quantities of N outputs from period "a" to "b", where p represents the prices of these outputs. The most commonly used indices are: Laspeyres index, Pasche index, Fisher index, Tornqvist index, and Malmquist index. The difference between the Laspeyres and Pasche indices is whether the base period or current period quantities are used as weights. To overcome this difference, the Fisher index uses a geometric mean of the Laspeyres and Pasche indices. Similarly, Tornqvist index uses various geometric averages for price and quantity.

The Laspeyres, Pasche, Fisher and Tornqvist indices are non-parametric techniques that can be used with panel or cross-sectional data to measure the performance of two health care organizations in one time period or performance of one health care organization in two time periods. However, when more than two health care organizations needed to be compared at the same time or over time, these methodologies are not useful. Since TFP is not commonly used by the health care industry, we will not elaborate on these four indices any further. Of the TFP measures, the most frequently used method in health care is the Malmquist index.

The Malmquist index overcomes some of the shortcomings of the other indices discussed above. With the Malmquist index, health care managers can compare many organizations across two time periods. The Malmquist index can be obtained through frontier approaches such as DEA or SFA. The Malmquist index does not assume that all firms are efficient nor require price data.

Malmquist index numbers can be defined using either the output-oriented approach or the input-oriented approach. An important feature of the DEA Malmquist index is that it can decompose the overall efficiency measure into two mutually exclusive components, one measuring change in technical efficiency (catching-up effect) and the other measuring change in technology (innovation). In Chap. 6, we will illustrate the use of Malmquist index for hospital performance in multi-periods.

1.3.4 Stochastic Frontier Analysis (SFA)

SFA is also a parametric technique. SFA assumes that all firms are not efficient (this is improvement over LSR) and accounts for noise.

A general stochastic frontier model can be formulated as:

$$\mathrm{TC} = \mathrm{TC}(\mathrm{Y}, \mathrm{W}) + \mathrm{V} + \mathrm{U} \tag{1.7}$$

where TC=total cost

Y = output
W = input prices
V = random error assumed normally distributed with zero mean and variance
U = the inefficiency residual.

SFA can be used to conduct tests of hypotheses. It can also be used to measure technical efficiency, scale economies, allocative efficiencies, technical change, and TFP change (if panel data are available). However, SFA requires input and output quantities for empirical estimation of production functions. It can also be used to analyze panel or cross-sectional data.

SFA comes with certain shortcomings as well. For example, it requires specification of functional form and specification of a distributional form for the inefficiency term, U in (1.7). With the use of price information as well as quantity information, additional measurement errors may be added to the results (Kooreman, 1994). The resulting inefficiency may be due to technical or allocative inefficiency or combination of both. These two sources of inefficiencies cannot be separated, which is prudent since such knowledge might illustrate the need for different policy actions (Kooreman, 1994).

1.3.5 Data Envelopment Analysis (DEA)

DEA is non-parametric technique. DEA assumes that not all firms are efficient. It allows multiple inputs and outputs to be used in a linear programming model that develops a single score of efficiency for *each* observation used to measure technical efficiency, scale efficiency, allocative efficiency, congestion efficiency, technical change and TFP change (if panel data available and Malmquist indices calculated).

DEA requires input and output quantities if production efficiency is examined and can be used with both cross-sectional and panel data.

DEA does not account for noise due to its deterministic nature (deviation from the frontier is a result of inefficient operations). However, researchers are currently developing stochastic and other variants of DEA models that incorporate a random error component.

Since the DEA is considered as the main performance evaluation methodology considered in this book, the remaining chapters will illustrate the various DEA models and their applications.

1.4 Measurement Difficulties in Health Care

Measurement of the variables that describe the true nature of service production is an important prerequisite for performance measurement. In health care, due to the nature of the services provided, it is often difficult to find the appropriate variables and their measurements. Of course this depends on the level of analysis and whether it is carried out at the hospital level or the departmental level. Often, the departmental level measurements cannot be aggregated to the hospital level. For example, unit measures in a laboratory are different than in radiology or in nursing units. Thus, when hospital level measures are considered, what has been included in service production measures might be considerably different if these evaluations are carried out at the departmental level. For instance, performance of laboratories or radiology services across hospitals can be carried out as long as the measurements are consistent for each department.

Defining and measuring the output at the hospital level varies considerably across providers by the volume and scope of services provided, and also by patients' severity. Thus appropriate adjustments, such as case-mix adjustment, should be undertaken. In addition, outputs such as education, research, and certain community services may not be available in all hospitals. Lack of homogeneity in outputs produced and scale of operations may force one to conduct the performance analysis on those facilities considered peer-group organizations. Similarly, defining and measuring the inputs may pose difficulties as well. For example, differences may arise in pricing of input units, supply and materials or labor costs across facilities depending upon region. Similarly, capital assets valuation, depending upon when these are acquired and what type of depreciation rates are used, may render great variations in inputs. These issues will be further visited as various performance measurement applications are presented in ensuing chapters.

1.5 Summary

This chapter has introduced concepts of performance measurement in health care organizations. These included two dimensions of performance; efficiency and effectiveness (quality). To evaluate the performance, a survey of methods was provided including their strengths and weaknesses. These methods include: ratio analysis, the least squares regression, total productivity indices including Malmquist index, SFA and DEA. In what follows, we describe the various DEA models and their extensive use for performance evaluation in health care.

Chapter 2
Performance Measurement Using Data Envelopment Analysis (DEA)

2.1 DEA in Health Care

The 1980s brought many challenges to hospitals as they attempted to improve the efficiency of health care delivery through the fixed pricing mechanism of diagnostic related groupings (DRGs). In the 1990s, the federal government extended the fixed pricing mechanism to physicians' services through resource based relative value schedule (RBRVS). Although these pricing mechanisms attempted to influence the utilization of services by controlling the amount paid to hospitals and professionals, effective cost control must also be accompanied by a greater understanding of variation in physician practice behavior and development of treatment protocols for various diseases.

Theoretical development of the approach started by Charnes et al. (1978) who worked to measure the efficiency of decision making units (DMU). Data Envelopment Analysis (DEA) is a non-parametric programming technique that develops an efficiency frontier by optimizing the weighted output/input ratio of each provider, subject to the condition that this ratio can equal, but never exceed, unity for any other provider in the data set (Charnes et al. 1978). In health care, the first application of DEA dates to 1983, in the work of Nunamaker and Lewin (1983), who measured routine nursing service efficiency. Since then DEA has been used widely in the assessment of hospital technical efficiency in the United States as well as around the world at different levels of DMUs. For example, Sherman (1984) was first in using DEA to evaluate overall hospital efficiency.

2.2 Efficiency and Effectiveness Models

In order to understand the nature of the models that will be shown throughout the book, expanding on the definitions of the efficiency and effectiveness measures presented in Chap. 1 is in order. This will help not only to understand the models developed here, but will also be useful for the curious reader examining other research in this area.

2.2.1 Efficiency Measures

As shown in (1.1), basic efficiency is a ratio of output over input. To improve efficiency one has to either: (1) increase the outputs, (2) decrease the inputs, (3) if both outputs and inputs increase, the rate of increase for outputs should be greater than the rate of increase for inputs, or (4) if both outputs and inputs are decreasing, the rate of decrease for outputs should be lower than the rate of decrease for inputs. Another way to achieve higher efficiency is to introduce technological changes, or to reengineer service processes – lean management – which in turn may reduce inputs or ability to produce more outputs (Ozcan, 2005; pp 121–123 and 220–222).

DEA models can generate new alternatives to improve performance compared to other techniques. Linear programming is the backbone of DEA methodology that is based on optimization platform. Hence, what differentiates the DEA from other methods is that it identifies the optimal ways of performance rather than the averages. In today's world, no health care institution can afford to be an average performer in a competitive health market.

Identification of optimal performance leads to benchmarking in a normative way. Using DEA health care managers can not only to identify top performers, but also discover the alternative ways to stir their health care organizations into becoming one of the best performers.

Since the seminal work of Charnes et al. (1978), DEA has been subject to countless research publications, conferences, dissertations, and applications within both the non-profit and for-profit sectors. Until now, the use of DEA within health care has been limited to conference sessions and research publications. Thus health care managers have not adopted DEA as a standard tool for benchmarking and decision-making. Part of this is due to its complicated formulation and to the failure of DEA specialists to adequately bridge the theory–practice gap. The aim of this book is to present DEA from a practical perspective, leaving the black box of sophisticated formulations in the background, so that health care managers can use Excel spreadsheet software, which they are familiar with, to analyze the performance of their organizations. The practical approach shown in this book will not only ease the fears of managers towards a new technique, but will also enable them to understand the pitfalls of the performed evaluations so they would feel confident in presenting, validating, and making decisions based on DEA results.

DEA is a comparative approach for identifying performance or its components by considering multiple resources that are used to achieve outputs or outcomes in health care organizations. These evaluations can be conducted not only at the organization level, but also in sub-units, such as departmental comparisons, where many areas of improvement in savings of particular input resources or strategies to augment the outputs can be identified.

In summary, DEA can help health care managers to:

1. Assess their organization's relative performance, and identify top performance in the health care market, and
2. Identify ways to improve their performance, if their organization is not one of the top performing organizations.

2.2.2 Efficiency Evaluations Using DEA

As described in Chap. 1, one of the major components of performance is efficiency. Efficiency is defined as the ratio of output(s) to input(s). Efficiency calculated by DEA is relative to these health organizations analyzed in a particular evaluation. The efficiency score for best performing (benchmark) health organizations in this evaluation would only represent the set of organizations considered in the analysis. Health care organizations identified as top performers in one year may not achieve this status if evaluations are repeated in subsequent years. Additionally, if more health organizations are included in another evaluation, their status may change since the relative performance will consider the newcomers. Although DEA can clearly identify improvement strategies for those non-top-performing health care organizations, further improvement of top performers depends on other factors, such as new technologies and other changes in the health service production process.

Efficiency attainment of health care organizations may also be the result of various factors, such as the price of the inputs or scope of the production process (scale) and other factors. Thus, it is prudent to understand types and components of efficiency in more depth. Major efficiency concepts can be described as technical, scale, price and allocative efficiency.

2.2.2.1 Technical Efficiency

Consider Hospital A treating brain tumors using the Gamma-Knife technology. Hospital A can provide 80 procedures per month with 120 h of neurosurgeon time. Last month, Hospital A produced 60 procedures while neurosurgeons were on the premises for 120 h. As shown in Table 2.1, the best achievable efficiency score for Hospital A is 0.667 (80/120), while due to their output of 60 procedures, their current efficiency score is 0.5 (60/120). We assess that Hospital A is operating at 75% ($0.75 = 0.5/0.667$) efficiency. This is called technical efficiency. In order for Hospital A to become technically efficient, it would have to increase its current output by 20 procedures per month.

2.2.2.2 Scale Efficiency

Also consider Hospital B, which does not have the Gamma-Knife. Hence neurosurgeons oat Hospital B remove tumors using the standard surgical technique (i.e., resection); for 30 procedures a month a neurosurgeon spends 180 h. The efficiency

Table 2.1 Technical efficiency

Hospital	Treatment capacity per month	Neurosurgeon time in hours	Current treatments per month	Best achievable efficiency	Efficiency
A	80	120	60	0.667	0.500

Table 2.2 Technical and scale efficiency

Hospital	Treatment capacity per month	Neurosurgeon time in hours	Current treatments per month	Best achievable efficiency	Efficiency	Scale efficiency
A	80	120	60	0.667	0.500	–
B	30	180	30	0.167	0.167	0.333

score of Hospital B is 0.167 (30/180). Compared to what Hospital A could ideally provide, Hospital B is at 25% efficiency ($0.25 = 0.167/0.667$) in utilizing the neurosurgeon's time. If we consider only what Hospital A was able achieve, Hospital B is operating at 33.3% ($0.33 = .167/0.5$) relative efficiency in this comparison. If Hospital B used similar technology as Hospital A, then it could have produced 90 additional procedures given 180 h of neurosurgeon time; or produce an additional 60 treatments to achieve the same efficiency level as Hospital A. The total difference between Hospital B's efficiency score and Hospital A's best achievable efficiency score is 0.5 (0.667–0.167). The difference between Hospital B's efficiency score from Hospital A's current efficiency score is 0.333 (0.5–0.167). Thus, we make the following observations:

1. Hospital B is technically inefficient, illustrated by the component 0.167,
2. Hospital B is also scale inefficient, illustrated by the difference 0.333.

The scale inefficiency can only be overcome by adapting the new technologies or new service production processes. On the other hand, the technical efficiency is the managerial problem, where more outputs are required for a given level of resources.

We should also add that even Hospital A produced 80 procedures a month, though we cannot say that Hospital A is absolutely efficient unless it is compared to other hospitals with similar technology. However, at this point we know that differences in technology can create economies of scale in the health service production process. Using various DEA methods, health care managers can calculate both technical and scale efficiencies (Table 2.2).

2.2.2.3 Price Efficiency

Efficiency evaluations can be assessed using price or cost information for inputs and/or outputs. For example, if the charge for the Gamma-Knife procedure is $18,000 and for traditional surgery is $35,000, the resulting efficiency for Hospital A and Hospital B would be as follows:

Efficiency(A)= $(60^{*}18,000)/120 = \$9,000.00$
Efficiency(B)= $(30^{*}35,000)/180 = \$5,833.33$

Assuming that a neurosurgeon's time is reimbursed at the same rate for either traditional surgery or Gamma-Knife procedures, Hospital A appears more efficient than Hospital B, however, the difference in this case due to price of the output. If Hospital B used 120 h to produce half as many procedures (30) as Hospital A, their price efficiency score would have been $8,750, which clearly indicates the effect of the output price. If health care managers use the cost information in inputs or charge/revenue values for outputs, DEA can provide useful information for those inefficient health care organizations on potential reductions in input costs and needed revenue/charges for their outputs. In health care, although charges/revenues are generally negotiated with third party payers, these evaluations would provide valuable information to health care managers while providing a basis for their negotiations.

2.2.2.4 Allocative Efficiency

When more than one input (and/or output) is part of health services delivery, health managers are interested in the appropriate mix of the inputs to serve patients so the organization can achieve efficiency. Let us consider three group practices, A, B and C, where two type professionals, physicians (P) and nurse practitioners (NP), provide health services. Furthermore assume that a physician's time costs $100 per hour, whereas a nurse practitioner's time costs $60 per hour. Let us suppose group practice A employs three physicians and one nurse practitioner; and that group practice B employs two physicians and two nurse practitioners, and finally that the group practice C employs three physicians and three nurse practitioners. Further assume that all group practices produced 500 equivalent patient visits during a week. Further assume that the practices are open for 8 h a day for 5 days a week (40 h). Input prices for the group practices are:

Inputs for Group Practice A = $[(3^{*}100) + (1^{*}60)]^{*}40 = \$14,400$
Inputs for Group Practice B = $[(2^{*}100) + (2^{*}60)]^{*}40 = \$12,800$
Inputs for Group Practice C = $[(3^{*}100) + (3^{*}60)]^{*}40 = \$19,200$

Since the output is the same, evaluating the input mix for these two group practices per visit yields the following ratios:

Group Practice A = $14,400/500 = \$28.80$
Group Practice B = $12,800/500 = \$25.60$
Group Practice C = $19200/500 = \$38.40$.

Table 2.3 summarizes these calculations as follows:

We can also illustrate these three group practices graphically on a production possibilities curves [pp] and [p′p′] shown in Fig. 2.1. Group practices A and B lie on production possibilities curve [pp]. Because group practice C operates with a higher number of physicians and nurse practitioners when compared to practices A and B, the production possibilities curve [p′p′] is in a higher position. Furthermore,

Table 2.3 Allocative efficiency

Group practice	Physicians ($100/h)	Nurse practitioners ($60/h)	Input prices	Output: visits	Efficiency	Allocative efficiency
A	3	1	$14,400	500	$28.80	0.889
B	2	2	$12,800	500	$25.60	1.000
C	3	3	$19200	500	$38.40	0.667

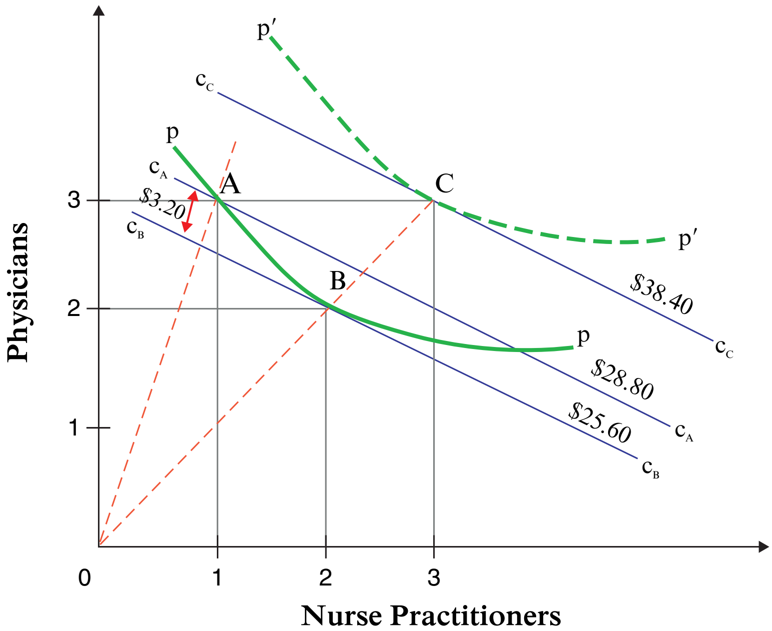


Fig. 2.1 Allocative efficiency

the cost per case is shown using cost lines c_A ($28.80), c_B ($25.60), and c_C ($38.40), where Group Practice B is producing the services for $3.20 less per case compared to Group Practice A, as shown by cost line c_A. Furthermore, group practice B is producing the services for $12.80 less per case when compared to Group Practice C.

Comparing these costs, one can conclude that Group Practice A is 88.9% (25.60/28.80) efficient compared to Group Practice B. Similarly, the group practice C is 66.7% (25.60/38.40) efficient compared to Group Practice B. In addition, the group practice C is not only allocatively inefficient, but it is also technically inefficient, since it operates on a less efficient production possibilities curve [p′p′]. This example illustrates the concept of allocative efficiency, where various combinations (mixes) of inputs and their prices will yield different efficiencies.

We should also note that the contribution to outputs from each input might be different. In this example, while physicians can provide a full spectrum of services to the patients, nurse practitioners may be able to provide only a fraction, say, 70%, due to their limited training and other legal matters. This raises the concern of whether using physicians and nurse practitioners as equal professions in efficiency calculations is appropriate, or if a weighting scheme should be imposed to correctly assess the nurse practitioners contributions to the total output. These weights are not readily available in most instances; however, DEA can estimate these weights in comparative evaluations.

2.2.3 Effectiveness Measures

Effectiveness in health care measured by outcomes or quality is of prime importance to many constituencies including patients, clinicians, administrators, and policy makers. Measuring the outcomes and quality is more problematic than efficiency measures. While inputs and outputs of the processes are relatively known to health care managers, multiple perspectives on outcomes and quality introduce additional practical difficulties in measurement. Although most hospitals report their inputs and outputs, until recently most outcome measures and quality measures, aside from mortality and morbidity statistics, were not reported on a systematic basis. The current quality reports from hospitals will be discussed in Chap. 7, and appropriate models will be developed to evaluate performance using both efficiency and effectiveness components.

2.3 Data Envelopment Analysis (DEA)

DEA essentially forms a frontier using the efficient organizations. To illustrate the conceptualization of the DEA frontier, consider the performance ratios (Table 2.4) of the first five hospitals from the example in Chap. 1. Here we consider two inputs,

Table 2.4 Hospital performance ratios

Provider ID	Nursing hours/inpatient admissions	Medical supplies/inpatient admissions
H1	**1.39**	6.55
H2	3.89	13.33
H3	1.51	5.48
H4	3.93	**2.59**
H5	2.31	4.56
H6	1.91	7.94
H7	1.44	28.72
H8	2.64	3.94
H9	2.96	21.16
H10	3.15	8.49

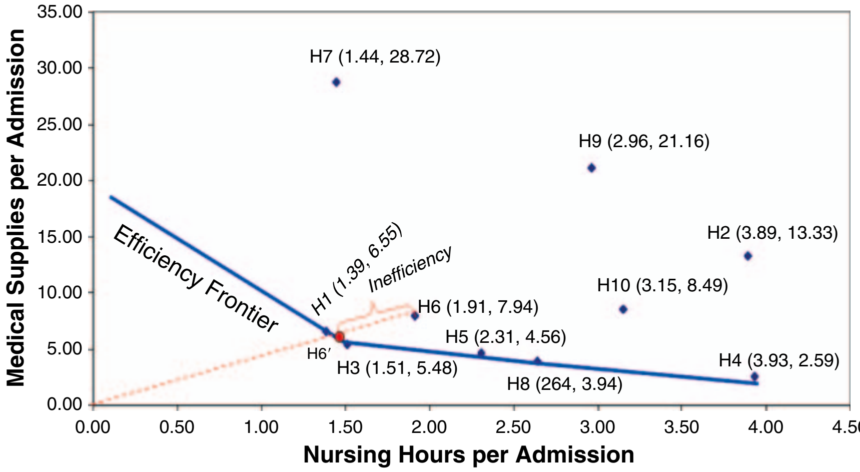


Fig. 2.2 Efficiency frontier

nursing hours and medical supplies, by dividing them by inpatient admissions; thus we obtain standardized usage of each input per inpatient admission.

As we observed before, H1 and H4 are efficient providers with their respective mix of use on these two inputs. We also know that H3 was an efficient provider from other dimensions of the performance. Graphically, as shown in Fig. 2.2, we can draw lines connecting these three efficient providers. As can be observed, there are two more hospitals, H5 and H8, that fall on the boundaries drawn by these lines between H1 and H4. Hence, these lines connecting H1, H3, H5, H8 and H4 represent the efficiency frontier for this example and they are among the benchmark hospitals, because these hospitals have the lowest combinations of the inputs when both ratios taken into account.

If we go back to the logic used to create the Table 2.4, where standardized efficiency ratios were calculated, we can observe that H1 and H4 received a standardized efficiency score of 1, and the other hospitals' standardized efficiency scores were somewhere between 0 but less than 1 from one dimension of the performance. Here also in DEA, the efficient hospitals will receive a score of 1 and those that are not on the efficiency frontier line will be less than 1 but greater than 0. Although we cannot explain why H5 and H8 are on the frontier line based on the graphic (due to its two dimensions), it suffices to say that they also have the lowest combinations of the inputs when both ratios are taken into account. Later when we employ all inputs and outputs into the model, we will demonstrate with DEA why H5 and H8 receive a score of 1 and efficient.

Hospital H6 compared to H1 and H3 is considered inefficient using these input combinations. The amount of inefficiency can be understood by examining the dashed line from the origin to H6. In this dashed line, the amount of inefficiency exists from the point it crosses the efficiency frontier to H6. So, for H6 to become efficient, it must reduce usage of both inputs proportionately to reach point H6′.

This is the normative power of DEA, where it can suggest how much improvement by each inefficient hospital is needed in each dimension of the resources.

2.4 Model Orientation

As in ratio analysis, when we calculate efficiency output over input, and place emphasis on reduction of inputs to improve efficiency, in DEA analysis this is called *input orientation*. Input orientation assumes health care managers have more control over the inputs rather than arriving patients either for outpatient visit or admissions. Figure 2.2 is an example of an input-oriented model, where H6 must reduce its inputs to achieve efficiency.

However, the reverse argument can be made that the health care managers, through marketing, referrals or by other means (such as reputation on quality of services) can attract patients to their facilities. This means they can augment their outputs given their capacity of inputs to increase their organization's efficiency. Output augmentation to achieve efficiency in DEA is called *output orientation*. Output orientation will be further discussed in Sect. 2.11 below.

Various DEA models have been developed to use either the input or output orientation, and these models emphasize proportional reduction of excessive inputs (input slacks) or proportional augmentation of lacking outputs (output slacks). However, there are also models where health care managers can place emphasis on both output augmentation and input reduction at the same time by improving output slacks and decreasing input slacks. These slack based-models are also called the additive model or non-oriented models in DEA literature and software.

2.5 Basic Frontier Models

This book will consider various models that would be needed by health care managers. In this chapter, the basic frontier models will be presented. The following chapters will introduce the extensions to these basic models for those specific management needs in evaluation of health care organizational performance.

There are various types of DEA models which may be used depending on the conditions of the problem on hand. Types of DEA models concerning a situation can be identified based on scale and orientation of the model. If one can assume that scale of economies do not change as size of the service facility increases, then constant returns to scale (CRS) type DEA models is an appropriate choice.

The initial basic frontier model was developed by Charnes et al. (1978), known as the CCR model, using the last initials of the developers, but now widely known as the *constant returns-to-scale* (CRS) model. The other basic frontier model followed CRS as the *variable returns-to-scale* (VRS) model, though in this model one cannot assume that scale of economies do not change as size of the service facility increases. Figure 2.3 shows the basic DEA models based on returns to scale and model orientation. These models will be referred as "Envelopment Models."

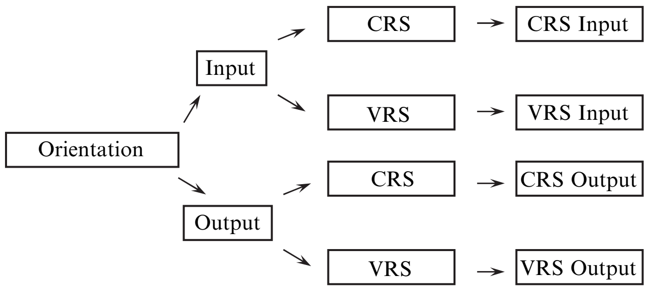


Fig. 2.3 Basic DEA model classifications – envelopment models

2.6 Decision Making Unit (DMU)

Organizations subject to evaluation in the DEA literature are called DMUs. For example, the hospitals, nursing homes, group practices, and other facilities that are evaluated for performance using DEA are considered as DMUs by many popular DEA software.

2.7 Constant Returns to Scale (CRS) Model

The essence of the CRS model is the ratio of maximization of the ratio of weighted multiple outputs to weighted multiple inputs. Any health care organization compared to others should have an efficiency score of 1 or less, with either 0 or positive weights assigned to the inputs and outputs.

Here, the calculation of DEA efficiency scores are briefly explained using mathematical notations (adapted from Cooper Seiford, and Tone, 2007). The efficiency scores (θ_o) for a group of peer DMUs ($j = 1 \ldots n$) are computed for the selected outputs ($y_{rj},\ r = 1, \ldots, s$) and inputs ($x_{ij},\ i = 1, \ldots, m$) using the following fractional programming formula:

$$Maximize\ \theta_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{2.1}$$

$$\text{subject to} \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \tag{2.2}$$

$$u_r,\ v_i \geq 0\ for\ all\ r\ and\ i.$$

In this formulation, the weights for the outputs and inputs, respectively, are u_r and v_i, and "o" denotes a focal DMU (i.e., each hospital, in turn, becomes a focal hospital when its efficiency score is being computed). Note that the input and output values, as well as all weights are assumed by the formulation to be greater than zero. The weights u_r and v_i for each DMU are determined entirely from the output and input data of all DMUs in the peer group of data. Therefore, the weights used for each DMU are those that maximize the focal DMU's efficiency score. In order to solve the fractional program described above, it needs to be converted to a linear programming formulation for easier solution.

Since the focus of this book is not on the mathematical aspects of DEA, an interested reader is referred to the appendix at the end of this chapter for more detail on how the above equations are algebraically converted to a linear programming formulation. Other DEA books listed in the references may also be consulted for an in-depth exposure.

In summary, the DEA identifies a group of optimally performing hospitals that are defined as efficient and assigns them a score of one. These efficient hospitals are then used to create an "efficiency frontier" or "data envelope" against which all other hospitals are compared. In sum, hospitals that require relatively more weighted inputs to produce weighted outputs or, alternatively, produce less weighted output per weighted inputs than do hospitals on the efficiency frontier, are considered technically inefficient. They are given efficiency scores of strictly less than one, but greater than zero.

Although DEA is a powerful optimization technique to assess the performance of each hospital, it has certain limitations which need to be addressed. When one has to deal with a significantly large numbers of inputs and outputs in the service production process and a small number of organizations are under evaluation, discriminatory power of the DEA will be limited. However, the analyst could overcome this limitation by only including those factors (input and output) which provide the essential components of the service production process, thus not distorting the outcome of the DEA results. This is generally done by eliminating one of pair of factors that are strongly positively correlated with each other.

2.8 Example for Input-Oriented CRS DEA Model

Consider again the sample data presented in Chap. 1 with ten hospitals, two inputs and two outputs. Table 2.5 depicts the inputs and outputs according to formulation discussions presented above. As one can observe, peer hospitals ($j = 1, \ldots, 10$) are listed for the selected inputs ($x_{ij},\ i = 1,\ 2$) and outputs ($y_{rj},\ r = 1,\ 2$).

The next step is to enter this information into the DEA Frontier solver, which is Excel add-on software. For information regarding installation of the software and other relevant details, readers are referred to "Running the DEAFrontier" section of the book at the end. The Excel sheet containing the data for DEA analysis required to be named "Data" is shown in Fig. 2.4 below.

Please note that the first column is recognized as the hospital identifier, followed by two columns of inputs. Please also note that there is a blank column between

Table 2.5 Hospital inputs and outputs

Hospitals$_j$	Inputs		Outputs	
	Nursing hours x_{1j}	Medical supplies ($) X_{2j}	Inpatient admissions Y_{1j}	Outpatient visits Y_{2j}
1	567	2678	409	211
2	350	1200	90	85
3	445	1616	295	186
4	2200	1450	560	71
5	450	890	195	94
6	399	1660	209	100
7	156	3102	108	57
8	2314	3456	877	252
9	560	4000	189	310
10	1669	4500	530	390

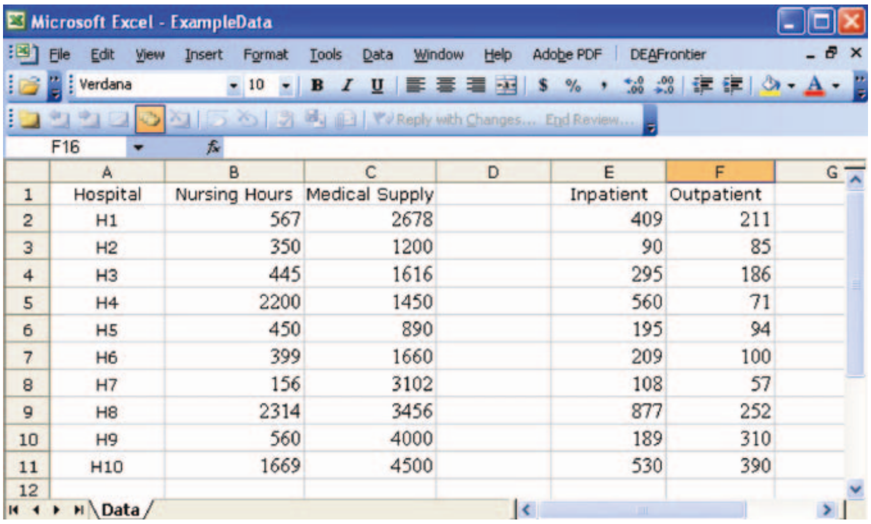


Fig. 2.4 DEAFrontier data setup

last input and first output. To run this model, open the Excel file shown in Fig. 2.4 and when the security warning comes up click on "Enable Macros" to activate the "DEAFrontier" add-on software. To run the model, click on the "DEAFrontier" button on the top banner shown in Fig. 2.4.

Once the "DEAFrontier" is clicked, a pull-down menu appears with a choice of DEA models, as depicted in Fig. 2.5. To run the initial CRS model, choose the "Envelopment Model" option. This will prompt another screen to appear, as shown in Fig. 2.6. For model orientation select "Input-Oriented", and for the returns to scale select "CRS", then click OK to run the model. For certain DEA models another screen (shown in Fig. 2.6) will pop up asking if the second stage input and output slacks should be calculated. Click "OK", and the resulting screen should correspond to Fig. 2.7.

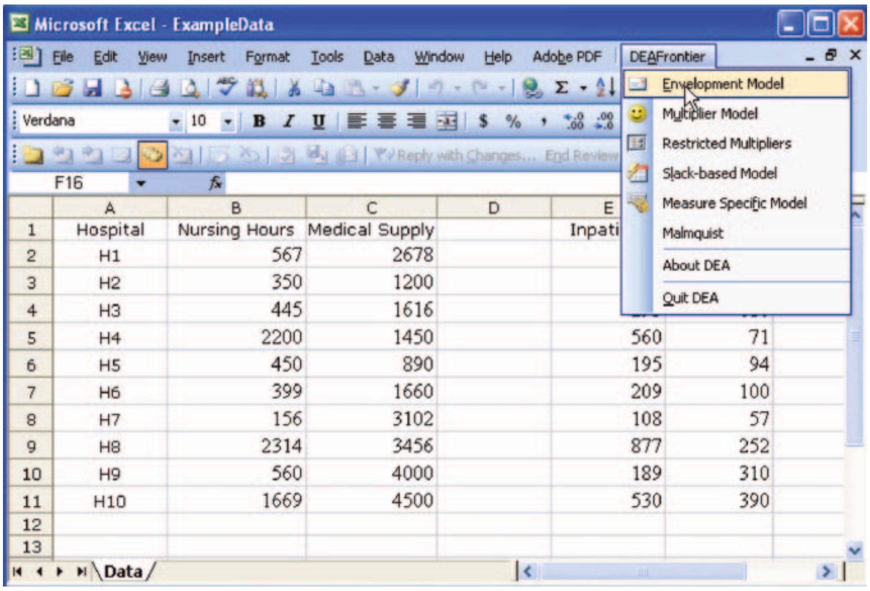


Fig. 2.5 DEAFrontier run

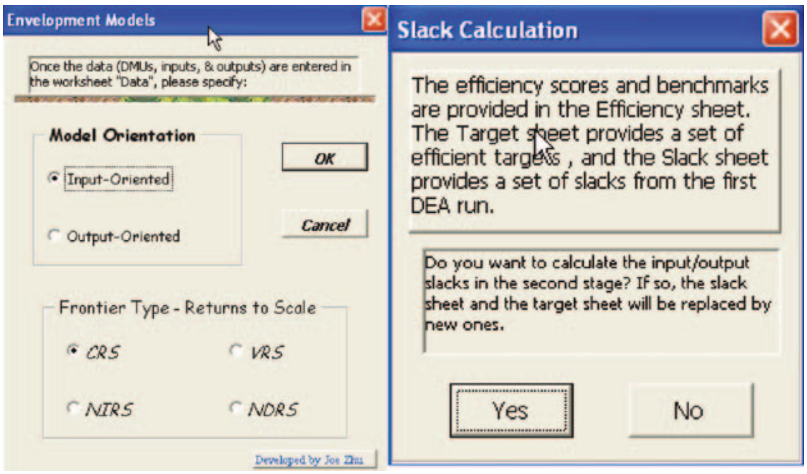
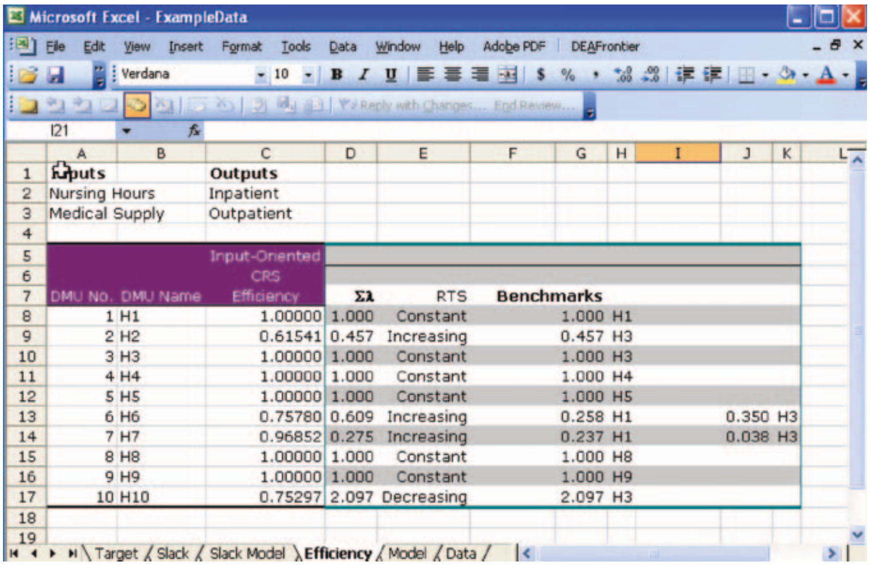


Fig. 2.6 DEAFrontier envelopment model

At this stage the health care manager can observe many results of the model to not only identify benchmark hospitals, but to also identify improvement strategies for those hospitals that are currently inefficient.

The results are organized in various Excel sheets, as shown at the bottom banner in Fig. 2.7. These sheets include results of efficiency analysis in the "Efficiency" sheet, target inputs and outputs in the "Target" sheet, and the amount of



DMU No.	DMU Name	Input-Oriented CRS Efficiency	Σλ	RTS	Benchmarks			
1	H1	1.00000	1.000	Constant	1.000	H1		
2	H2	0.61541	0.457	Increasing	0.457	H3		
3	H3	1.00000	1.000	Constant	1.000	H3		
4	H4	1.00000	1.000	Constant	1.000	H4		
5	H5	1.00000	1.000	Constant	1.000	H5		
6	H6	0.75780	0.609	Increasing	0.258	H1	0.350	H3
7	H7	0.96852	0.275	Increasing	0.237	H1	0.038	H3
8	H8	1.00000	1.000	Constant	1.000	H8		
9	H9	1.00000	1.000	Constant	1.000	H9		
10	H10	0.75297	2.097	Decreasing	2.097	H3		

Fig. 2.7 Results of CRS input-oriented model

inefficiencies (slacks) in the "Slack" template. Next we will discuss the results from each of these templates.

2.9 Interpretation of the Results

Figure 2.8 depicts the abridged version of the efficiency report, where efficiency scores of all ten hospitals are reported. This two-input and two-output model shows that six of the ten hospitals are efficient using these four dimensions. There is no surprise that H1, H3, H4 and H9 all received a score of 1 and are considered efficient. Furthermore, we observe that the efficiency of two additional hospitals, H5 and H8, could not be determined in ratio based analysis. However, with DEA using multiple inputs and outputs at the same time, we are able to discover them.

2.9.1 Efficiency and Inefficiency

Hospitals H2, H6, H7 and H10 have scores of less than 1 but greater than 0, and thus they are identified as inefficient. These hospitals can improve their efficiency, or reduce their inefficiencies proportionately, by reducing their inputs (since we run an input-oriented model). For example, H2 can improve its efficiency by reducing certain inputs up to 38.5% (1.0–0.61541). Similarly, H6 and H10 can do so with

DMU Name	Input-Oriented CRS Efficiency
H1	1.00000
H2	0.61541
H3	1.00000
H4	1.00000
H5	1.00000
H6	0.75780
H7	0.96852
H8	1.00000
H9	1.00000
H10	0.75297

Fig. 2.8 Efficiency report for input-oriented model

approximately 25% input reduction. However, H7 is closer to an efficiency frontier, and needs only a 3.2% reduction in resources.

This raises the question: which inputs are needed to be reduced by calculated proportions? These input reductions (or output augmentations in some cases) are called slacks.

2.9.2 Slacks

Figure 2.9 comes from the "Slack" sheet of the DEA run results. Mathematical derivation of these slacks is presented in Appendix B of this chapter. Here, we observe that none of the efficient hospitals have any slacks. Slacks exist only for those hospitals identified as inefficient. However, slacks represent only the leftover portions of inefficiencies; after proportional reductions in inputs or outputs, if a DMU cannot reach the efficiency frontier (to its efficient target), slacks are needed to push the DMU to the frontier (target).

It is interesting to note that H2 is required to reduce its nursing hours by approximately 12 h. However, despite the reduction in this input, it would not achieve efficiency. No other input can be reduced, thus, H2 should also augment its inpatient admission by 44.8. A similar situation in a different magnitude exists for H10. On the other hand, H6 cannot reduce any inputs, but must augment outpatient visits by 19.7 or 20 visits. Lastly, H7 should spend $2,309.19 less for medical supplies. Please note that these calculations are the results of Models two and four executed in succession or Model five, as explained in the appendices at the end of the chapter.

Input-Oriented
CRS Model Slacks

DMU No.	DMU Name	Input Slacks: Nursing Hours	Input Slacks: Medical Supply	Output Slacks: Inpatient	Output Slacks: Outpatient
1	H1	0.00000	0.00000	0.00000	0.00000
2	H2	12.03405	0.00000	44.81183	0.00000
3	H3	0.00000	0.00000	0.00000	0.00000
4	H4	0.00000	0.00000	0.00000	0.00000
5	H5	0.00000	0.00000	0.00000	0.00000
6	H6	0.00000	0.00000	0.00000	19.66368
7	H7	0.00000	2309.18646	0.00000	0.00000
8	H8	0.00000	0.00000	0.00000	0.00000
9	H9	0.00000	0.00000	0.00000	0.00000
10	H10	323.65061	0.00000	88.54839	0.00000

Fig. 2.9 Input and output slacks for input-oriented model

2.9.3 Efficient Targets for Inputs and Outputs

We can summarize these findings further by examining the "Target" sheet. Here, for each hospital, target input and output levels are prescribed. These targets are the results of respective slack values added to outputs. To calculate the target values for inputs, the input value is multiplied with an optimal efficiency score, and then slack amounts are subtracted from this amount. For detailed formulations of these calculations, the reader is referred to Appendix B, Part 3. Figure 2.10 displays these target values. As the reader can observe, the target values for efficient hospitals are equivalent to their original input and output values.

However, for the inefficient DMUs, in the CRS input-oriented DEA model, the targets for input variables $(\widehat{x}_{io})$ will comprise proportional reduction in the input variables by the efficiency score of the DMU minus the slack value, if any, given by the formula:

$$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i = 1, \ldots, m \tag{2.3}$$

For example, the target calculations for nursing hours (NH) and medical supply (MS) inputs of Hospital H2 are calculated as follows:

$$\widehat{x}_{NH,H2} = \theta^* x_{NH,H2} - s_{NH}^{-*}$$
$$\widehat{x}_{NH,H2} = 0.61541^*350 - 12.03405$$
$$\widehat{x}_{NH,H2} = 203.36022$$

where 0.61541 comes from Fig. 2.8, 350 from Fig. 2.4, and 12.03405 from Fig. 2.9. The reader can confirm the results with Fig. 2.10. Similarly, target calculation of Medical Supply for H2 is:

$$\widehat{x}_{MS,H2} = \theta^* x_{MS,H2} - s_{MS}^{-*}$$
$$\widehat{x}_{MS,H2} = 0.61541^*1200 - 0$$
$$\widehat{x}_{MS,H2} = 738.49462$$

Input-Oriented CRS Model Target

DMU Name	Efficient Input Target: Nursing Hours	Efficient Input Target: Medical Supply	Efficient Output Target: Inpatient	Efficient Output Target: Outpatient
H1	567.00000	2678.00000	409.00000	211.00000
H2	203.36022	738.49462	134.81183	85.00000
H3	445.00000	1616.00000	295.00000	186.00000
H4	2200.00000	1450.00000	560.00000	71.00000
H5	450.00000	890.00000	195.00000	94.00000
H6	302.36067	1257.94164	209.00000	119.66368
H7	151.08945	695.16914	108.00000	57.00000
H8	2314.00000	3456.00000	877.00000	252.00000
H9	560.00000	4000.00000	189.00000	310.00000
H10	933.06452	3388.38710	618.54839	390.00000

Fig. 2.10 Input and output efficient targets for input-oriented model

Again, the reader can confirm the result from Fig. 2.10.

In an input-oriented model, efficient output targets are calculated as:

$$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r = 1, \ldots .s \tag{2.4}$$

In our ongoing example with H2, inpatient admissions (IA) and outpatient visits (OV) can be calculated as:

$$\widehat{y}_{IA,H2} = y_{IA,H2} + s_{IA}^{+*} \; \widehat{y}_{OV,H2} = y_{OV,H2} + s_{OV}^{+*}$$
$$\widehat{y}_{IA,H2} = 90 + 44.81183 \; \widehat{y}_{OV,H2} = 85 + 0$$
$$\widehat{y}_{IA,H2} = 134.81183 \; \widehat{y}_{OV,H2} = 85.00$$

The reader can confirm these results from Fig. 2.10 for Hospital H2. The other inefficient hospitals are calculated in the same manner.

2.10 Input-Oriented Model Benchmarks

The "Efficiency" sheet in Fig. 2.7 provides more results shown in columns such as $\Sigma\lambda$ and RTS. These are subject to Chap. 4 and will be discussed in more detail with more foundation material presented. However, here we will explain the remaining information presented. These are the "Benchmarks" created by the DEA technique.

Figure 2.11 is taken from portions of the results of the initial "Efficiency" sheet. Here, health care managers whose hospital is inefficient can observe the benchmark hospitals that they need to catch up to.

Obviously efficient hospitals may consider themselves to be their own "benchmarks." So, Benchmark for H1 is H1, for H3 is H3, and so on. However, for inefficient hospitals, their benchmarks are one or many of the efficient hospitals. For

DMU Name	Input-Oriented CRS Efficiency	Benchmarks λ_j		λ_j	
H1	1.00000	1.000	H1		
H2	0.61541	0.457	H3		
H3	1.00000	1.000	H3		
H4	1.00000	1.000	H4		
H5	1.00000	1.000	H5		
H6	0.75780	0.258	H1	0.350	H3
H7	0.96852	0.237	H1	0.038	H3
H8	1.00000	1.000	H8		
H9	1.00000	1.000	H9		
H10	0.75297	2.097	H3		

Fig. 2.11 Benchmarks for input-oriented CRS model

example, a benchmark for H2 and H10 is H3 (observe that H3 is efficient). A benchmark for H6 and H7 are two hospitals, H1 and H3. This means, to become efficient, H6 and H7 must use a combination from both H1 and H3 (a virtual hospital) to become efficient. How much of H1 and how much of H3 (what combination) are calculated to achieve efficiency and reported next to each Benchmark hospital. These are λ weights obtained from the dual version of the linear program that is solved to estimate these values. Further formulation details are provided in Appendix A at the end of this chapter. For example, H7 will attempt to become like H1 more than H3 as observed from respective λ weights of H1 and H3 ($\lambda_1 = 0.237$ vs. $\lambda_3 = 0.038$).

2.11 Output-Oriented Models

The essence of output orientation comes from how we look at the efficiency ratios. When we illustrated the input orientation we used the ratios in which inputs were divided by outputs. Hence we can do the opposite by dividing outputs by inputs, and create reciprocal ratios. Using the same inputs and outputs from Table 2.2 from Chap. 1, we can calculate these mirror ratios as shown in Table 2.6 below. The first two columns show two different outputs, inpatient admissions and outpatient visits, being divided by the same input, nursing hours. The higher ratio values here would mean better performance for the hospitals.

H1 has the highest inpatient admissions per nursing hour compared to other providers, as can be observed from the first column. However, H4 has the highest outpatient visits per nursing hour as displayed in the second column.

A graphical view of these measures is shown in Fig. 2.12, where H1, H3 and H9 have the highest combination of these ratios when considered together. Here, no other hospital can generate more outputs using the nursing hours as input. However, when other inputs are included in the model using DEA, we may discover other hospitals joining the efficiency frontier.

Table 2.6 Hospital performance ratios

Provider ID	Inpatient admissions/ nursing hours	Outpatient visit/ nursing hours
H1	0.72	0.37
H2	0.26	0.24
H3	0.66	0.42
H4	0.25	0.03
H5	0.43	0.21
H6	0.52	0.25
H7	0.69	0.37
H8	0.38	0.11
H9	0.34	0.55
H10	0.32	0.23

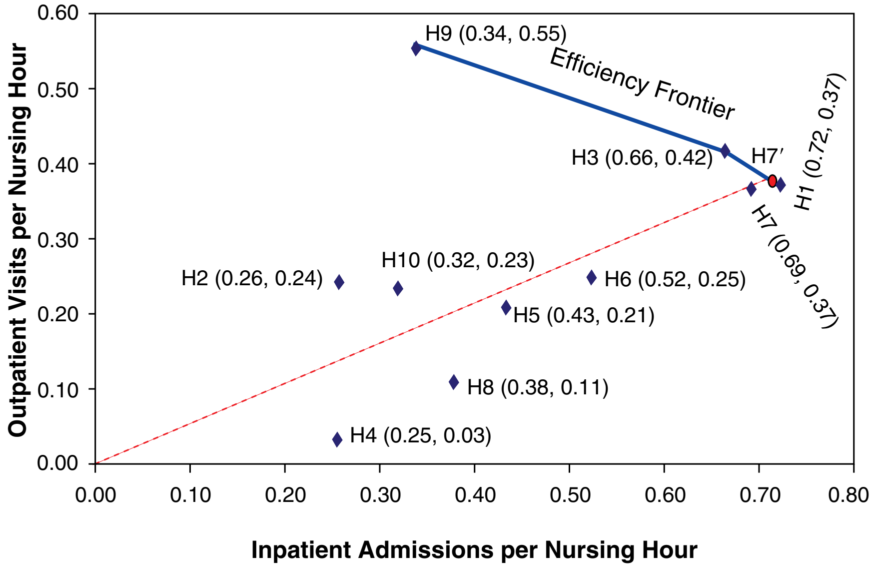


Fig. 2.12 Efficiency frontier for output-oriented model

The reader should also note that H7, an inefficient hospital, can reach this output-oriented frontier by increasing its inpatient admissions and outpatient visits along the direction of the dashed line to H7′. The distance given by H7′—H7 defines the amount of inefficiency for H7.

2.12 Output-Oriented CRS DEA Model

Using the similar steps in Sect. 2.8, this time we will select "Output-Oriented" from the Model Orientation box as shown in Fig. 2.13.

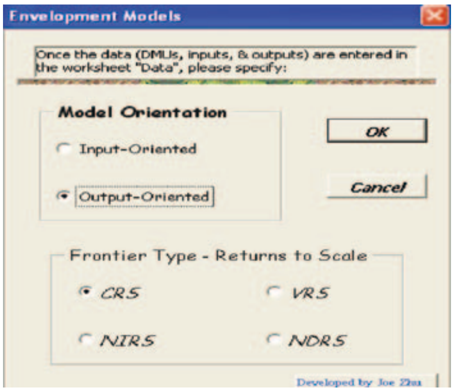
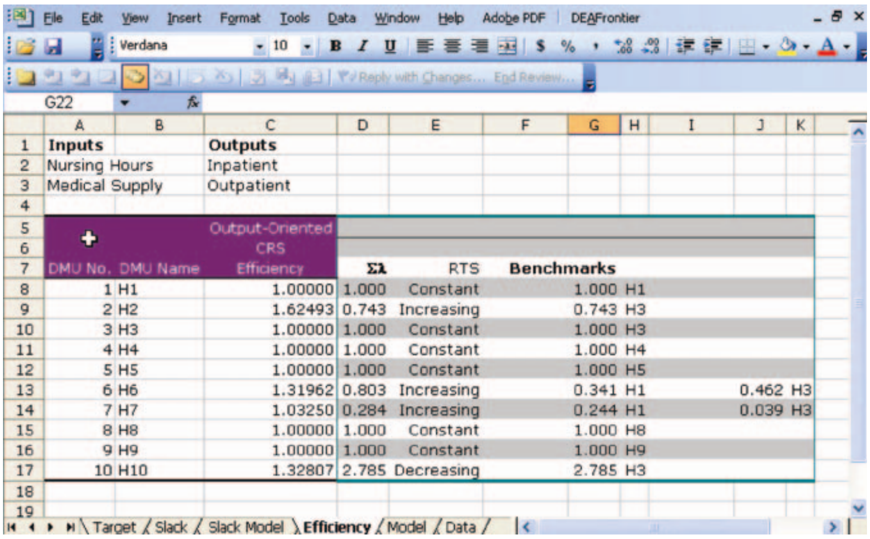


Fig. 2.13 Output-oriented envelopment model



Inputs	Outputs
Nursing Hours	Inpatient
Medical Supply	Outpatient

DMU No.	DMU Name	Output-Oriented CRS Efficiency	Σλ	RTS	Benchmarks			
1	H1	1.00000	1.000	Constant	1.000	H1		
2	H2	1.62493	0.743	Increasing	0.743	H3		
3	H3	1.00000	1.000	Constant	1.000	H3		
4	H4	1.00000	1.000	Constant	1.000	H4		
5	H5	1.00000	1.000	Constant	1.000	H5		
6	H6	1.31962	0.803	Increasing	0.341	H1	0.462	H3
7	H7	1.03250	0.284	Increasing	0.244	H1	0.039	H3
8	H8	1.00000	1.000	Constant	1.000	H8		
9	H9	1.00000	1.000	Constant	1.000	H9		
10	H10	1.32807	2.785	Decreasing	2.785	H3		

Fig. 2.14 Results of output-oriented CRS model

Again answering "Yes" to the second stage slack calculations, we get the results shown in Fig. 2.14, which is similar to Fig. 2.7, however, the results report as output orientation.

2.13 Interpretation of Output-Oriented CRS Results

Figure 2.15 depicts the abridged version of the efficiency report, where efficiency scores of all ten hospitals are reported. This two-input and two-output model shows six of the ten hospitals are efficient using these four dimensions in an output-oriented model.

DMU Name	Output-Oriented CRS Efficiency
H1	1.00000
H2	1.62493
H3	1.00000
H4	1.00000
H5	1.00000
H6	1.31962
H7	1.03250
H8	1.00000
H9	1.00000
H10	1.32807

Fig. 2.15 Efficiency report for output-oriented model

2.13.1 Efficiency and Inefficiency

Hospitals H2, H6, H7 and H10 have scores greater than 1; thus they are identified as inefficient in the output-oriented model. These hospitals can improve their efficiency, or reduce their inefficiencies proportionately, by augmenting their outputs (since we run an output-oriented model). For example, H2 can improve its efficiency by augmenting certain outputs up to 62.5% (1.62493–1.0). Similarly, H6 and H10 can do so with approximately 33% increase. However, H7 is closer to efficiency frontier, and needs only a 3.3% increase in outputs.

2.13.2 Slacks

Figure 2.16 comes from the "Slack" sheet of the DEA run results. Here again we observe that none of the efficient hospitals have any slacks. Slacks exist only for those hospitals identified as inefficient.

It is interesting to note that H2 is required to increase its inpatient admissions by 72.8 patients, after having proportionately increased this output by its efficiency score. However, despite the augmentation in this output, it still would not achieve efficiency. No other output can be increased. Thus, H2 should also reduce its nursing hours by 19.5 hours. A similar situation in a different magnitude exists for H10. On the other hand, H6 can augment its outpatient visits by 26. Lastly, H7 cannot augment its outputs at all, but could decrease its medical supplied cost by $2,384.24.

Output-Oriented
CRS Model Slacks

DMU No.	DMU Name	Input Slacks: Nursing Hours	Input Slacks: Medical Supply	Output Slacks: Inpatient	Output Slacks: Outpatient
1	H1	0.00000	0.00000	0.00000	0.00000
2	H2	19.55446	0.00000	72.81596	0.00000
3	H3	0.00000	0.00000	0.00000	0.00000
4	H4	0.00000	0.00000	0.00000	0.00000
5	H5	0.00000	0.00000	0.00000	0.00000
6	H6	0.00000	0.00000	0.00000	25.94851
7	H7	0.00000	2384.23721	0.00000	0.00000
8	H8	0.00000	0.00000	0.00000	0.00000
9	H9	0.00000	0.00000	0.00000	0.00000
10	H10	429.82921	0.00000	117.59806	0.00000

Fig. 2.16 Slacks of output-oriented CRS model

Output-Oriented
CRS Model Target

DMU No.	DMU Name	Efficient Input Target: Nursing Hours	Efficient Input Target: Medical Supply	Efficient Output Target: Inpatient	Efficient Output Target: Outpatient
1	H1	567.00000	2678.00000	409.00000	211.00000
2	H2	330.44554	1200.00000	219.05941	138.11881
3	H3	445.00000	1616.00000	295.00000	186.00000
4	H4	2200.00000	1450.00000	560.00000	71.00000
5	H5	450.00000	890.00000	195.00000	94.00000
6	H6	399.00000	1660.00000	275.79976	157.91012
7	H7	156.00000	717.76279	111.51010	58.85255
8	H8	2314.00000	3456.00000	877.00000	252.00000
9	H9	560.00000	4000.00000	189.00000	310.00000
10	H10	1239.17079	4500.00000	821.47277	517.94554

Fig. 2.17 Efficient targets for inputs and outputs for output-oriented CRS model

2.13.3 Efficient Targets for Inputs and Outputs

Again, we can summarize these finding further by examining the "Target" sheet. For each hospital, target input and output levels are prescribed. These targets are the results of respective slack values added on to original outputs, and subtracted from original inputs. To calculate the target values for inputs, the input slacks are subtracted from the inputs. Targets for outputs are calculated by multiplying optimal efficiency scores by the outputs and then adding the slack values to that value. For a detailed formulation of these calculations, the reader is referred to Appendix C, Part 2. Figure 2.17 displays these target values. As the reader can observe, the target values for efficient hospitals are equivalent to their original input and output values.

Health care managers should be cautioned that some of these efficiency improvement options (and the target values) may not be practical. Health care managers can opt to implement only some of these potential improvements at the present time due to their contracts with labor and supply chains and insurance companies.

DMU Name	Output-Oriented CRS Efficiency	Benchmarks λ_j		λ_j	
H1	1.00000	1.000	H1		
H2	1.62493	0.743	H3		
H3	1.00000	1.000	H3		
H4	1.00000	1.000	H4		
H5	1.00000	1.000	H5		
H6	1.31962	0.341	H1	0.462	H3
H7	1.03250	0.244	H1	0.039	H3
H8	1.00000	1.000	H8		
H9	1.00000	1.000	H9		
H10	1.32807	2.785	H3		

Fig. 2.18 Benchmarks for output-oriented model

2.14 Output-Oriented Model Benchmarks

Figure 2.14 displays portions of the results from initial "Efficiency" sheet. Here health care managers whose hospital is inefficient can observe the benchmark hospitals.

As in the input-oriented model, the efficient hospitals for output-oriented model (Fig. 2.18) will consider themselves as their own "benchmark." So, Benchmark for H1 is H1, for H3 is H3, and so on. On the other hand, for those inefficient hospitals the benchmarks are one or many of the efficient hospitals. For example, benchmark for H2 and H10 is H3 (observe that H3 is efficient). Benchmark for H6 and H7 are two hospitals, and these are H1 and H3. This means, to become efficient, H6 and H7 must use a combination of H1 and H3 (a virtual hospital) to become efficient. How much of H1 and how much of H3 are calculated and reported next to each benchmark hospital? These are λ weights obtained from the dual version of the linear program that is solved to estimate these values. Further formulation details are provided in the appendix. For example, H7 will attempt to become like H1 more than H3, as observed from respective λ weights of H1 and H3 ($\lambda_1 = 0.244$ vs. $\lambda_3 = 0.039$).

2.15 Summary

This chapter introduced the basic efficiency concepts and DEA technique. The model orientation and returns to scale are basic concepts that help health care managers in identifying what type of DEA model they should use. We discussed only input and output-oriented CRS models in this chapter.

Appendix A

A.1 Mathematical Details

Fractional formulation of CRS model is presented below:

Model 1

$$Maximize\ \theta_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} \upsilon_i x_{io}}$$

$$subject\ to \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} \upsilon_i x_{ij}} \leq 1$$

$$u_r,\ \upsilon_i \geq 0 \quad for\ all\ r\ and\ i.$$

This model can be algebraically rewritten as:

$$Maximize\ \theta_o = \sum_{r=1}^{s} u_r y_{ro}$$

$$subject\ to \sum_{r=1}^{s} u_r y_{rj} \leq \sum_{i=1}^{m} \upsilon_i x_{ij}$$

with further manipulations we obtain the following linear programming formulation:

Model 2

$$Maximize\ \theta_o = \sum_{r=1}^{s} u_r y_{ro}$$

Subject to:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} \leq 0 \quad j = 1, \ldots .n$$

$$\sum_{i=1}^{m} \upsilon_i x_{io} = 1$$

$$u_r, \upsilon_i \geq 0$$

A.2 Assessment of the Weights

To observe the detailed information provided in Fig. 2.7, such as benchmarks and their weights (λ), as well as Σλ leading to returns to scale (RTS) assessments, a dual version of the Model 2 is needed. The dual model can be formulated as:

Model 3

$Minimize\ \theta_o$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \quad i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad r = 1, \ldots, s$$
$$\lambda_j \geq 0 \quad j = 1, \ldots, n.$$

In this dual formulation, Model 3, the linear program, seeks efficiency by minimizing (dual) efficiency of a focal DMU ("o") subject to two sets of inequality. The first inequality emphasizes that the weighted sum of inputs of the DMUs should be less than or equal to the inputs of focal DMU being evaluated. The second inequality similarly asserts that the weighted sum of the outputs of the non-focal DMUs should be greater than or equal to the focal DMU. The weights are the λ values. When a DMU is efficient, the λ values would be equal to 1. For those DMUs that are inefficient, the λ values will be expressed in their efficiency reference set (ERS). For example, observing Fig. 2.7, H7 has two hospitals in its ERS, namely H1 and H3. Their respective λ weights are reported as $\lambda_1 = 0.237$ and $\lambda_3 = 0.038$.

Appendix B

B.1 Mathematical Details for Slacks

In order to obtain the slacks in DEA analysis, a second stage linear programming model is required to be solved after the dual linear programming model, presented in Appendix A, is solved. The second stage of the linear program is formulated for slack values as follows as:

Model 4

$$Maximize \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io} \quad i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots, s$$
$$\lambda_j \geq 0 \quad j = 1, \ldots, n$$

Here, θ^* is the DEA efficiency score resulted from the initial run, Model Two, of the DEA model. Here, s_i^- and s_r^+ represent input and output slacks, respectively. Please note that the superscripted minus sign on input slack indicates reduction, while the superscripted positive sign on output slacks require augmentation of outputs.

In fact, Model Two and Model Four can be combined and rewritten as:
Model 5: Input-Oriented CRS Model

$$Minimize\, \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots, s$$
$$\lambda_j \geq 0 \quad j = 1, \ldots, n$$

The ε in the objective function is called the non-Archimedean, which is defined as infinitely small, or less than any real positive number. The presence of ε allows a minimization over efficiency score (θ) to preempt the optimization of slacks, s_i^- and s_r^+. Model Five first obtains optimal efficiency scores (θ^*) from Model Two and calculates them, and then obtains slack values and optimizes them to achieve the efficiency frontier.

B.2 Determination of Fully Efficient and Weakly Efficient DMUs

According to the DEA literature, the performance of DMUs can be assessed either as fully efficient or weakly efficient. The following conditions on efficiency scores and slack values determine the full and weak efficiency status of DMU:

Condition	**Θ**	θ^*	**All s_i^-**	**all s_r^+**
Fully efficient	1.0	1.0	0	0
Weakly efficient	1.0	1.0	At least one $s_i^- \neq 0$	At least one $s_r^+ \neq 0$

When Models Two and Four run sequentially (Model Five), weakly efficient DMUs cannot be in the efficient reference set (ERS) of other inefficient DMUs. However, if only Model Two is executed, then weakly efficient DMUs can appear in the ERS of inefficient DMUs. The removal of weakly inefficient DMUs from the analysis would not affect the frontier or the analytical results.

B.3 Efficient Target Calculations for Input-Oriented CRS Model

In input-oriented CRS models, levels of efficient targets for inputs and outputs can be calculated as follows:

Inputs: $\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i = 1, \ldots, m$
Outputs: $\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r = 1, \ldots, s$

Appendix C

C.1 CRS Output-Oriented Model Formulation

Since Model Five, as defined in Appendix B, combines the needed calculations for input-oriented CRS model, we can adapt the output-oriented CRS model formulation using this fully developed version of the model.

Model 6: Output-Oriented CRS Model

$$Maximize\ \phi - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{ro} \quad i = 1, \ldots, s$$
$$\lambda_j \geq 0 \quad j = 1, \ldots, n$$

The output efficiency is defined by ϕ. Another change in the formula is that the efficiency emphasis is removed from input (first constraint) and placed into output (second) constraint.

C.2 Efficient Target Calculations for Output-Oriented CRS Model

In output-oriented CRS models, levels of efficient targets for inputs and outputs can be calculated as follows:

Inputs: $\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i = 1, \ldots, m$

Outputs: $\widehat{y}_{ro} = \phi^* y_{ro} + s_i^{+*} \quad r = 1, \ldots, s.$

Chapter 3
Returns to Scale Models

3.1 Constant Returns Frontier

Health care managers can seek alternative evaluations to assess which components of their organization are contributing to the inefficiency of their organization, such as the size of their operation, poor organizational factors, flow processes, or other related factors. For example, a small hospital, in certain instances, may appear less efficient compared to larger ones, and this may be due to its scale size. On the other hand, the reverse can be seen as well, due to diseconomies of scale, which occurs when larger hospitals may be operating inefficiently due to other reasons, such as poor management or a lack of strategic focus.

The CSR models assume a constant rate of substitution between inputs and outputs. Figure 3.1 depicts the CRS efficiency frontier for the sample hospital data we have been familiar with. Considering one output and one input, hospital H1 defines the CRS frontier. To reach this frontier all the hospitals must move their positions proportionately either to the left or towards the top wherever they can reach to this target line, which is constant.

On the other hand, when scale economies exist, and for various other reasons, the frontier may be defined differently. For instance, if a proportional increase in one or more inputs can cause greater than proportion increase in outputs, then constant returns are not present. Similarly, a proportional increase in inputs may yield less than a proportional increase in outputs. These situations raise the notion of varying returns, and in DEA literature this is identified as variable returns to scale (VRS).

3.2 Variable Returns Frontier

Let us consider the health care managers in our sample facilities, and assume that they are planning to increase nursing hours by 25% to satisfy the 25% increase in inpatient admissions. Some of these facilities may reach this goal and exceed it, while others may not realize the expected levels of inpatient admissions. Those

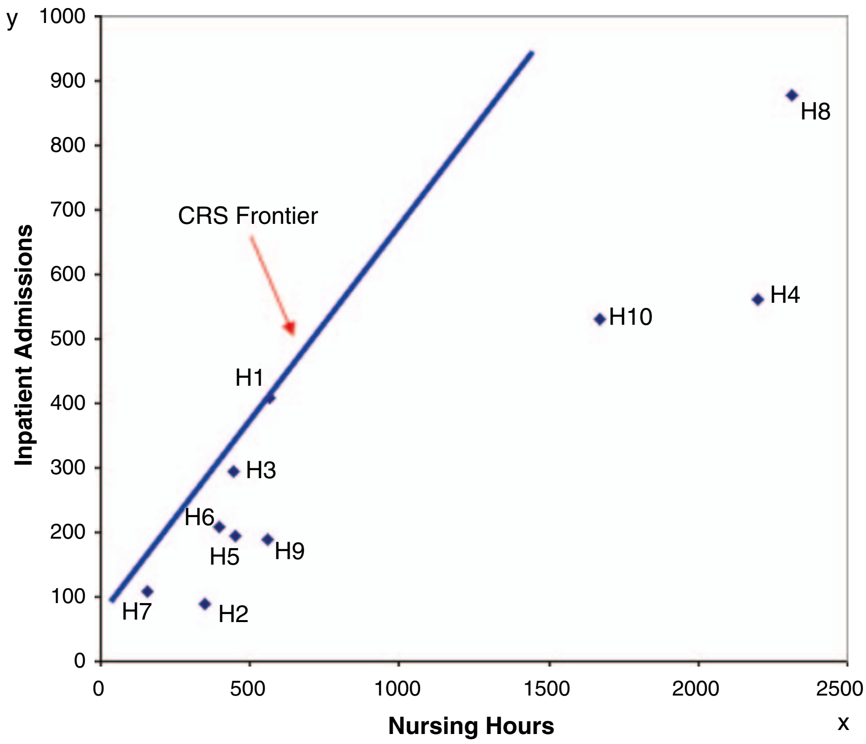


Fig. 3.1 Conceptualization of CRS frontier

hospitals that realize more than 25% inpatient admissions achieved an increasing rate of return, while others that have an increase in inpatient admission of less than 25% rate have achieved a decreasing rate of return.

Figure 3.2 shows conceptualization of variable returns and the associated frontier. Here, H7, H1 and H8 define the different parts of the frontier. Close examination of the line segment between H7 and H1 shows a sharp increase (the slope of the line is steep in this segment), and the segment between H1 and H8 also displays an increase, but in a decreasing pattern (slope of the line segment is less steep compared to H7 vs. H1). While the hospitals on the frontier exhibit these varying returns, the cluster of the hospitals in the region between H7 and H1, namely H2, H3, H5, H6 and H9, would expect increasing returns as well, since they are closer to the frontier defined by H7 and H1. The remaining hospitals H4 and H10 may exhibit decreasing returns.

Although returns to scale (RTS) discussions may be more meaningful for those hospitals that comprise the VRS frontier, the efficient targets are less obvious for non-frontier hospitals. The orientation of the model, input vs. output, further plays a role in how inefficient hospitals would move toward to VRS frontier.

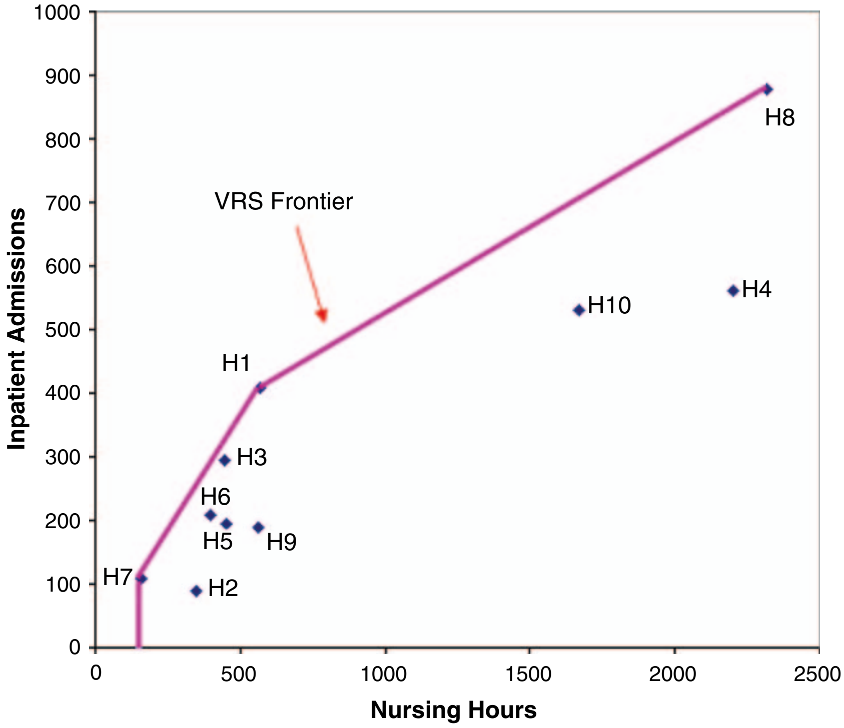


Fig. 3.2 Conceptualization of VRS production frontier

To illustrate, consider Fig. 3.3, in which both CRS and VRS frontiers are displayed. In addition, we know which segments of the VRS frontier are either increasing or decreasing. H1 is at a point where CRS and VRS are tangent to each other, indicating that H1 is both CRS- and VRS-efficient, and that thus H1's returns are constant. Hence, H1 would be considered the "optimal" scale size, as described below.

Let us investigate the position of H9 ($x = 560,\ y = 189$), a non-frontier hospital. If an input-oriented VRS model is used, to reach efficiency H9 must reduce its nursing hours by moving horizontally to $H9^{iv}$ ($x = 250,\ y = 189$), where it becomes VRS efficient. Since $H9^{iv}$ is located at the increasing scale to returns (IRS), H9 can reduce its nursing hours further to the point $H9^{ic}$ ($x = 175,\ y = 189$), where it becomes CRS efficient.

If H9 wishes to reach the efficiency frontier via output augmentation, the nearest point it can reach vertically is $H9^{ov}$ ($x = 560,\ y = 420$). It should be noted that point $H9^{ov}$ is at a decreasing returns to scale (DRS) section of the VRS frontier. Similarly, H9 can further augment its outputs to $H9^{oc}$ ($x = 560,\ y = 460$), where it can reach output-oriented CRS efficiency. A summary of these potential efficiency points and their coordinates for H9 are summarized in Table 3.1.

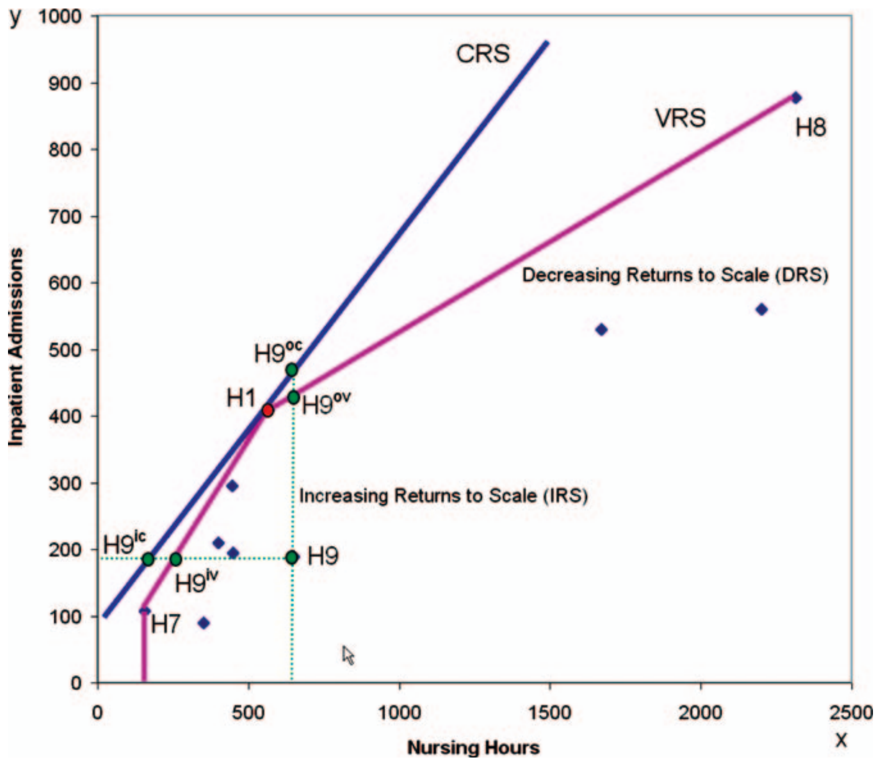


Fig. 3.3 CRS and VRS models and RTS

Table 3.1 Potential efficiency coordinates for H9

	Original	Input VRS	CRS	Output VRS	CRS
Coordinates	H9	$H9^{iv}$	$H9^{ic}$	$H9^{ov}$	$H9^{oc}$
Nursing hours (x)	560	250	175	560	560
Inpatient admissions (y)	189	189	189	420	460

Using the values from these coordinates, the efficiency scores of H9 based on different orientations and returns to scale assumptions can be calculated. Using the input orientation we get:

VRS efficiency through input reduction (x): $H9^{v}/H9$ or $250/560 = 0.4464$.
CRS efficiency through input reduction (x): $H9^{c}/H9$ or $175/560 = 0.3125$.
Here CRS efficiency score generally does not exceed VRS efficiency score.

Similarly, for output orientation we get:

VRS efficiency through output augmentation (y): $H9^{o}/H9$ or $420/189 = 2.2222$.
CRS efficiency through output augmentation (y): $H9^{o}/H9$ or $460/189 = 2.4339$.

Here, conversely the CRS output efficiency score will generally be greater than the VRS output efficiency score, as shown in Fig. 3.3.

3.3 Assessment of RTS

In order to calculate and assess the RTS whether it is increasing, constant or decreasing, we need to sum the lambda (λ_j) weight values. If the summation of lambda weights $\Sigma\lambda < 1.0$, then such DMU exhibits increasing rates to return. If $\Sigma\lambda > 1.0$, then the DMU exhibits decreasing rates of return. The efficient DMUs are considered as having constant returns to scale and they will have $\Sigma\lambda = 1.0$. The reader can verify these from Fig. 3.4, which displays $\Sigma\lambda$ and RTS for the sample hospitals. For those "maverick" hospitals that have only one benchmark in their reference set, $\Sigma\lambda$ is equal to λ weight of that reference hospital. However, for those with more than one hospital in their benchmark set (i.e., H6 and H7), $\Sigma\lambda$ is an addition of their respective λ weights. For example, $\Sigma\lambda$ value of H7, 0.275, is calculated by adding λ weight of H1 and λ weight of H3 ($0.237 + 0.0.038 = 0.275$).

3.4 Input-Oriented VRS Model Example

As before, we will leave the mathematical details for the curious reader to the end of this chapter. Mathematical formulation of VRS DEA model is presented in Appendix D for input orientation and Appendix E for output orientation. Consider again the sample data presented in Chap. 1 with ten hospitals, two inputs and two outputs. Now, we can employ the FrontierDEA software add-on to calculate VRS input and output-oriented models (Fig. 3.5) using the same data presented in Table 2.5, which depicts the input and outputs according to required formulations.

DMU Name	Input-Oriented CRS Efficiency	Benchmarks					
		Σλ	RTS	λ_j		λ_j	
H1	1.00000	1.000	Constant	1.000	H1		
H2	0.61541	0.457	Increasing	0.457	H3		
H3	1.00000	1.000	Constant	1.000	H3		
H4	1.00000	1.000	Constant	1.000	H4		
H5	1.00000	1.000	Constant	1.000	H5		
H6	0.75780	0.609	Increasing	0.258	H1	0.350	H3
H7	0.96852	0.275	Increasing	0.237	H1	0.038	H3
H8	1.00000	1.000	Constant	1.000	H8		
H9	1.00000	1.000	Constant	1.000	H9		
H10	0.75297	2.097	Decreasing	2.097	H3		

Fig. 3.4 Increasing, constant and decreasing returns

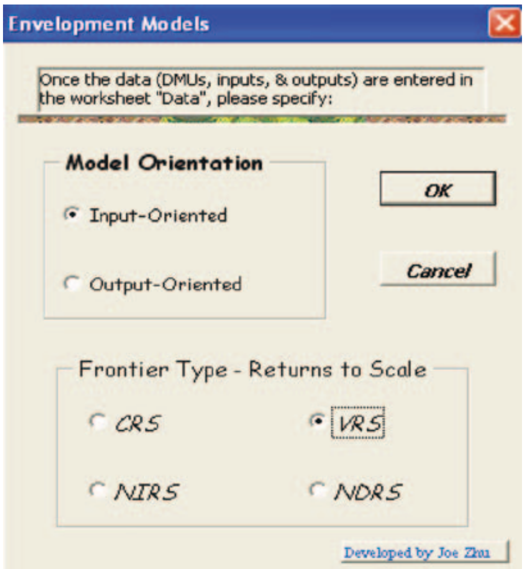


Fig. 3.5 Envelopment model selections for VRS input orientation

DMU Name	Input-Oriented VRS Efficiency
H1	1.00000
H2	1.00000
H3	1.00000
H4	1.00000
H5	1.00000
H6	0.96541
H7	1.00000
H8	1.00000
H9	1.00000
H10	1.00000

Fig. 3.6 Efficiency scores for VRS input-oriented model

3.5 Input-Oriented VRS DEA Model Results

In order to run an input-oriented VRS model, we will select input-oriented and VRS radio buttons, and then click OK, as shown in Fig. 3.4.

The resulting efficiency scores are displayed in Fig. 3.6. Now, all but one hospital are efficient. As demonstrated in an earlier section of this chapter, this is not surprising.

In VRS models, more DMUs can find their way to the frontier. Additionally, VRS efficiency scores are generally higher than CRS efficiency scores (for input-oriented models). Thus, more hospitals are considered to be efficient using this approach.

3.6 Slacks and Efficient Targets for Input-Oriented VRS Model

Figures 3.7 and 3.8 display the slacks and targets for the input-oriented VRS model. The calculation of targets is the same as for the CRS model and they can be found in Sect. 2 of Appendix D.

Only one hospital, H6, is inefficient, and this hospital cannot reach VRS frontier only through input reduction, but output augmentation of approximately 16 outpatient visits is needed. The reader should recall the inputs and outputs of H6.

Input-Oriented VRS Model Slacks

DMU Name	Input Slacks		Output Slacks	
	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	0.00000	0.00000	0.00000	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	0.00000	0.00000	0.00000	16.12707
H7	0.00000	0.00000	0.00000	0.00000
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	0.00000	0.00000	0.00000	0.00000

Fig. 3.7 Slack report for input-oriented VRS model

Input-Oriented VRS Model Target

DMU Name	Efficient Input Target		Efficient Output Target	
	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	567.00000	2678.00000	409.00000	211.00000
H2	350.00000	1200.00000	90.00000	85.00000
H3	445.00000	1616.00000	295.00000	186.00000
H4	2200.00000	1450.00000	560.00000	71.00000
H5	450.00000	890.00000	195.00000	94.00000
H6	385.20004	1602.58663	209.00000	116.12707
H7	156.00000	3102.00000	108.00000	57.00000
H8	2314.00000	3456.00000	877.00000	252.00000
H9	560.00000	4000.00000	189.00000	310.00000
H10	1669.00000	4500.00000	530.00000	390.00000

Fig. 3.8 Target report for input-oriented VRS model

Table 3.2 Inputs and outputs for H6

Hospitals j	Inputs		Outputs	
	Nursing hours x_{1j}	Medical supplies($) X_{2j}	Inpatient admissions y_{1j}	Outpatient visits Y_{2j}
6	399	1,660	209	100

Using these values and the target formulations from Appendix D, for inputs we get

$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i = 1, \ldots .m$, more specifically for this case
$\widehat{x}_{16} = \theta^* x_{16} - s_1^{-*}$ and
$\widehat{x}_{26} = \theta^* x_{26} - s_2^{-*}$

By substituting efficiency score (see Fig. 3.6), actual inputs (Table 3.2) and optimal slack values (Fig. 3.7) in these formulas we get:

$\widehat{x}_{16} = 0.96541 * 399 - 0 = 385.200$ and
$\widehat{x}_{26} = 0.96541 * 1660 - 0 = 1602.587$

Similarly for outputs we get

$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r = 1, \ldots .s$, more specifically for H6:
$\widehat{y}_{16} = y_{16} + s_1^{+*}$ and
$\widehat{y}_{26} = y_{26} + s_2^{+*}$

By substituting actual output values and optimal slack scores in these formulas we get:

$\widehat{y}_{16} = 209 + 0 = 209$ and
$\widehat{y}_{26} = 100 + 16.127 = 116.127$

The reader can verify the results of these calculations by comparing the target values of H6 from Fig. 3.8.

3.7 Benchmarks for Input-Oriented VRS Model

Since the VRS model forms a different frontier, the benchmarks for a two-input and two-output model is certainly different than the CRS frontier. Here, the only inefficient hospital, H6, has three benchmark hospitals. That is, H6 can reach VRS frontier by any combination of H3, H5 and H7, a virtual hospital. The λ weights corresponding to these reference hospitals are shown in Fig. 3.9.

3.8 Output-Oriented VRS Model Example

In order to run the output-oriented VRS model, this time we will select "Output-Oriented" and VRS radio buttons, and then click OK as shown in Fig. 3.10.

DMU Name	Input-Oriented VRS Efficiency	Benchmarks					
H1	1.00000	1.000	H1				
H2	1.00000	1.000	H2				
H3	1.00000	1.000	H3				
H4	1.00000	1.000	H4				
H5	1.00000	1.000	H5				
H6	0.96541	0.327	H3	0.458	H5	0.215	H7
H7	1.00000	1.000	H7				
H8	1.00000	1.000	H8				
H9	1.00000	1.000	H9				
H10	1.00000	1.000	H10				

Fig. 3.9 Benchmarks for input-oriented VRS model

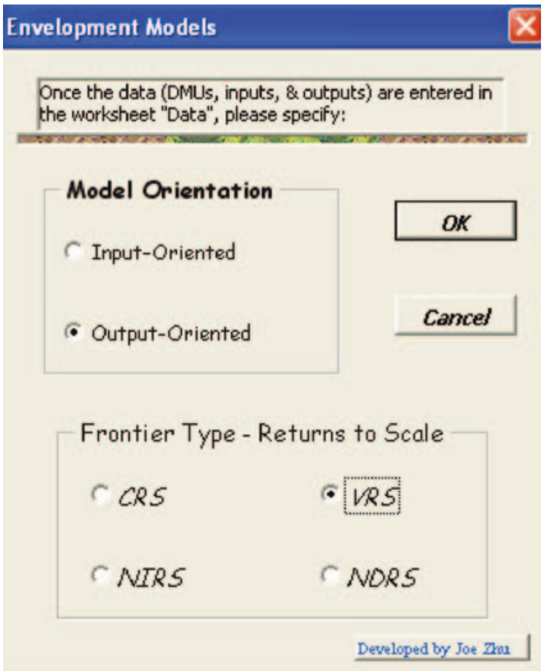


Fig. 3.10 Envelopment model selections VRS output orientation

3.9 Output-Oriented VRS Model Results

At this point readers are familiar with the presentation of the results, thus we will only show the calculation of targets using Figs. 3.11–3.13.

Using the values from Table 3.2 and the target formulations from Appendix E, for inputs we get:

DMU Name	Output-Oriented VRS Efficiency
H1	1.00000
H2	1.00000
H3	1.00000
H4	1.00000
H5	1.00000
H6	1.13327
H7	1.00000
H8	1.00000
H9	1.00000
H10	1.00000

Fig. 3.11 Efficiency results for output-oriented VRS model

Output-Oriented VRS Model Slacks

DMU Name	Input Slacks		Output Slacks	
	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	0.00000	0.00000	0.00000	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	0.00000	0.00000	0.00000	26.23358
H7	0.00000	0.00000	0.00000	0.00000
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	0.00000	0.00000	0.00000	0.00000

Fig. 3.12 Slack report for output-oriented VRS model

Output-Oriented VRS Model Target

DMU Name	Efficient Input Target		Efficient Output Target	
	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	567	2678	409.00000	211.00000
H2	350	1200	90.00000	85.00000
H3	445	1616	295.00000	186.00000
H4	2200	1450	560.00000	71.00000
H5	450	890	195.00000	94.00000
H6	399	1660	236.85355	139.56064
H7	156	3102	108.00000	57.00000
H8	2314	3456	877.00000	252.00000
H9	560	4000	189.00000	310.00000
H10	1669	4500	530.00000	390.00000

Fig. 3.13 Target report for the input-oriented VRS model

$\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i = 1, \ldots .m$, more specifically for this case
$\widehat{x}_{16} = x_{16} - s_1^{-*}$ and
$\widehat{x}_{26} = x_{26} - s_2^{-*}$

and by substituting actual output values (Table 3.2) and optimal slack scores (Fig. 3.11) in these we get:

$\widehat{x}_{16} = 399 - 0 = 399$ and
$\widehat{x}_{26} = 1660 - 0 = 1660$

Similarly for outputs we get

$\widehat{y}_{ro} = \phi^* y_{ro} + s_i^{+*} \quad r = 1, \ldots .s$, more specifically for H6:
$\widehat{y}_{16} = \phi^* y_{16} + s_1^{+*}$ and
$\widehat{y}_{26} = \phi^* y_{26} + s_2^{+*}$

By substituting efficiency score (see Fig. 3.11), actual outputs (Table 3.2) and optimal slack values (Fig. 3.12) to these formulas we get:

$\widehat{y}_{16} = 1.13327 * 209 + 0 = 236.854$ and
$\widehat{y}_{26} = 1.13327 * 100 + 26.233 = 139.561$

The reader can verify the results of these calculations by comparing the target values of H6 from Fig. 3.13.

Benchmarks are the same reference set hospitals as for the input orientation. However, the λ weights corresponding to these reference hospitals are different in output orientation, as shown in Fig. 3.14, in which inefficient H6 has three benchmark hospitals (H3, H5, and H7) in its reference set.

DMU Name	Output-Oriented VRS Efficiency	Benchmarks					
H1	1.00000	1.000	H1				
H2	1.00000	1.000	H2				
H3	1.00000	1.000	H3				
H4	1.00000	1.000	H4				
H5	1.00000	1.000	H5				
H6	1.13327	0.561	H3	0.275	H5	0.164	H7
H7	1.00000	1.000	H7				
H8	1.00000	1.000	H8				
H9	1.00000	1.000	H9				
H10	1.00000	1.000	H10				

Fig. 3.14 Benchmarks for output-oriented VRS model

3.10 Comparison of CRS and VRS Models, and Scale Efficiency

In this section we will provide a brief overview of basic envelopment models and compare efficiency results. Figure 3.15 summarizes the results that were generated using input and output orientation on CRS and VRS models. As the reader can verify, input- and output-oriented models identify the same exact DMUs as efficient. Furthermore, the reciprocals of the efficiency scores for the output-oriented models are equal to the efficiency scores of the input-oriented models. Average efficiency scores for input-oriented VRS models will generally be greater than those for an input-oriented CRS model. The reverse can be shown for the output-oriented models.

Comparing CRS and VRS models, health care managers can depict another important aspect of efficiency briefly discussed in Chap. 2. Cooper, Seiford and Tone (2007) show that the scale efficiency can be calculated by dividing the optimal CRS efficiency score by the optimal VRS efficiency score. Hence, it can be written as:

$$ScaleEfficiency\ (SE) = \frac{\theta^*_{CRS}}{\theta^*_{VRS}}.$$

The VRS efficiency scores, θ^*_{VRS}, are considered pure technical efficiency, while CRS efficiency scores, θ^*_{CRS}, are considered technical efficiency. Thus, the formula above can be used to decompose the technical efficiency into pure technical efficiency and scale efficiency, as in: $\theta^*_{CRS} = SE^*\theta^*_{VRS}$. Applying this formula to our results, we obtain the SE scores as shown in Fig. 3.16.

This also relates to the concepts introduced earlier in Sect. 3.2. The conceptual distances from CRS and VRS fronts to an inefficient hospital were shown in Fig. 3.3. Once the distances are calculated, one would have the respective CRS and VRS efficiency scores. Substituting these values into the above ratio, scale efficiency can be obtained.

DMU Name	Input-Oriented CRS Efficiency	Output-Oriented CRS Efficiency	*Input-Oriented VRS Efficiency*	*Output-Oriented VRS Efficiency*
H1	1.00000	1.00000	1.00000	1.00000
H2	0.61541	1.62493	1.00000	1.00000
H3	1.00000	1.00000	1.00000	1.00000
H4	1.00000	1.00000	1.00000	1.00000
H5	1.00000	1.00000	1.00000	1.00000
H6	0.75780	1.31962	0.96541	1.13327
H7	0.96852	1.03250	1.00000	1.00000
H8	1.00000	1.00000	1.00000	1.00000
H9	1.00000	1.00000	1.00000	1.00000
H10	0.75297	1.32807	1.00000	1.00000
Average	0.90947	1.13051	0.99654	1.01333

Fig. 3.15 Comparison of efficiency scores in basic envelopment models

DMU Name	Input-Oriented CRS Efficiency	Input-Oriented VRS Efficiency	SE=CRS/VRS	θ^*_{VRS} PURE TE	θ^*_{CRS} TE
H1	1.00000	1.00000	1	1.00000	1.0000
H2	0.61541	1.00000	0.615412186	1.00000	0.6154
H3	1.00000	1.00000	1	1.00000	1.0000
H4	1.00000	1.00000	1	1.00000	1.0000
H5	1.00000	1.00000	1	1.00000	1.0000
H6	0.75780	0.96541	0.784944545	0.96541	0.7578
H7	0.96852	1.00000	0.968522114	1.00000	0.9685
H8	1.00000	1.00000	1	1.00000	1.0000
H9	1.00000	1.00000	1	1.00000	1.0000
H10	0.75297	1.00000	0.75297491	1.00000	0.7530
Average	0.90947	0.99654			

Fig. 3.16 Scale efficiency

3.11 Summary

In this chapter, we examined the concept of RTS and demonstrated the increasing, constant and decreasing RTS. In addition, VRS models were introduced. Finally, we showed how to obtain the scale efficiency scores from the results of CRS and VRS models.

Appendix D

D.1 VRS Input-Oriented Model Formulation

Adopting from the input-oriented Model Five defined in Chap. 2, Appendix B, the VRS input model formulation requires an additional set of constraint, in which summation of λ values are set equal to 1.

Model 7: Input-oriented VRS model

$$Minimize\ \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad i = 1, \ldots .m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots .s$$

$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots .n$$

$$\lambda_j \geq 0 \quad j = 1, \ldots .n$$

D.2 Efficient Target Calculations for Input-Oriented VRS Model

The efficiency targets in the input-oriented VRS model are calculated in the same way as in CRS model, and the levels of efficient targets for inputs and outputs can be obtained as follows:

Inputs: $\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i = 1, \ldots .m$
Outputs: $\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r = 1, \ldots .s$

Appendix E

E.1 VRS Output-Oriented Model Formulation

Adopting from output-oriented Model Six defined in Chap. 2, Appendix C, the VRS output orientation model formulation requires an additional set of constraints, in which summation of λ values are set equal to 1.

Model 8: Output-oriented VRS model

$$Maximize\ \phi - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots .m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{ro} \quad i = 1, \ldots .s$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots .n$$
$$\lambda_j \geq 0 \quad j = 1, \ldots .n$$

The output efficiency is defined by ϕ. Another change in the formula is that the efficiency emphasis is removed from input (first constraint) and placed into output (second) constraint.

E.2 Efficient Target Calculations for Output-Oriented VRS Model

Efficient targets in the output-oriented VRS model are calculated in the same way as in the CRS model, and the levels of efficient targets for inputs and outputs can be obtained as follows:

Inputs: $\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i = 1, \ldots .m$
Outputs: $\widehat{y}_{ro} = \phi^* y_{ro} + s_i^{+*} \quad r = 1, \ldots .s.$

Chapter 4
Multiplier Models

4.1 Introduction

When considering various inputs and outputs in the envelopment models discussed in earlier chapters, we made no judgment about the importance of one input vs. another, and we assumed that the all outputs had same importance. In fact, in our example data, we assumed outpatient visits would consume the resources at the same level as inpatient admissions. Similarly, in producing the patient outputs, we valued the contribution of nursing hours the same as the contribution of medical supplies. Beside these assumptions, DMUs in a DEA can become efficient by simply taking advantage of a particular input or output variable. Simply, a hospital can become efficient by emphasizing on favorable input or output. For instance, observing from the example data, Hospital 9 has relatively low nursing hours but a high amount of medical supplies. The low nursing hours may be the reason this hospital is at the efficiency frontier (see Fig. 2.7). In the DEA literature, these DMUs are sometimes called maverick DMUs that take advantage of these weak assumptions.

To address this issue, health care managers can alter their models using prior information regarding inputs and outputs. For example, if one average inpatient admission is equivalent to four outpatient visits, then inpatient admissions can be weighted accordingly. On the other hand, if health care mangers do not have a priori information on such weights, the relative weights can be estimated from the data using the multiplier models. In any case, imposing restrictions based on weights should be done based on known and reliable substitution among either inputs or outputs. Furthermore, health care researchers can test the impact of substitution among inputs (and/or outputs) to answer various policy or managerial questions. For example, practice patterns for physicians vs. nurse practitioners as shown in Fig. 2.1 can be evaluated so that efficient practices using extreme values on either of these inputs can be constrained to a balanced or acceptable practice patterns. Ozcan (1998) showed how various substitutions among inputs or outputs can impact on physician practice patterns from the managed care perspective. The study demonstrated how using reasonable weight restrictions can result in more balanced models of physician practice, and the economic impact of these models can be estimated.

4.2 Multiplier Models

Optimal input and output weights, v_i and u_r, shown in formulation in Sect. 2.7, are derived by solving the DEA based on relative evaluation of all DMUs in the data. To observe these weights, health care managers and researchers can run the multiplier model as shown in Figs. 4.1 and 4.2. The set-up of the data, as shown in Fig. 4.1, is not different from the original CRS model setup: however, this time "Multiplier Model" option is selected.

Furthermore, Fig. 4.2 shows the specification as CRS input-orientation for this selection.

The results of the multiplier model are shown in Fig. 4.3. Here, one can observe the optimal multipliers (weights) for each input, v_1 (nursing hours) and v_2 (medical supplies), and each output, u_1 (inpatient admissions) and u_2 (outpatient visits).

These weights also yield information on how efficiency improvements can be achieved for the inefficient hospitals. For example, Hospital 7 has an efficiency ratio of 0.969. This means that this hospital must increase its rating by 3.15% (1.00-0.969 $=$ 0.031) to become relatively efficient among the other nine hospitals. Using the weights reported in Fig. 4.3, the hospital can decrease its nursing hours by $(0.031)/0.00641 = 4.92$ h, to an efficient target of 151.08, as reported in Fig. 2.10. Our aim in this chapter is to use this weight information to assure a better practice pattern for the group of hospitals in the data set.

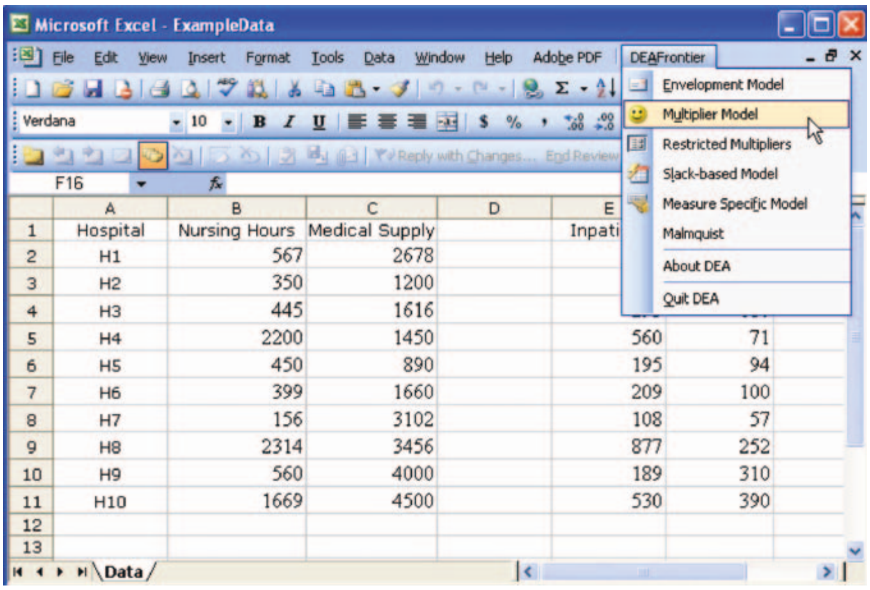


Fig. 4.1 Multiplier model setup

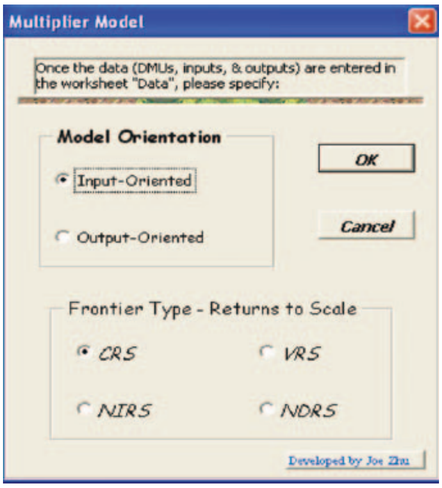


Fig. 4.2 Multiplier model specification

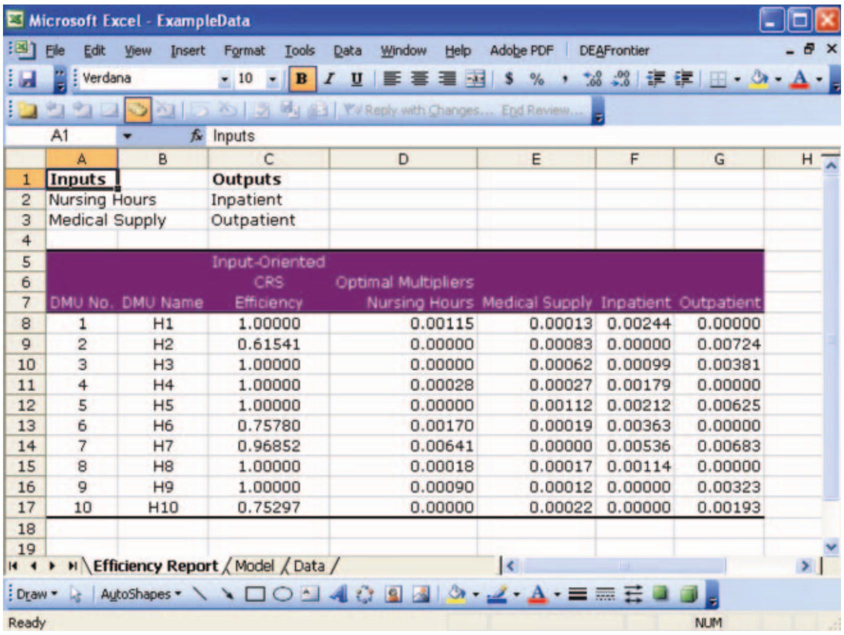


Fig. 4.3 Results of multiplier model

4.3 Assurance Regions or Cone Ratio Models

Also called assurance region (AR) models as developed by Thompson et al. (1990) or cone ratio models, a more generalized version developed by Charnes et al. (1990) can impose restrictions (constraints) on weights to control how much a DMU can

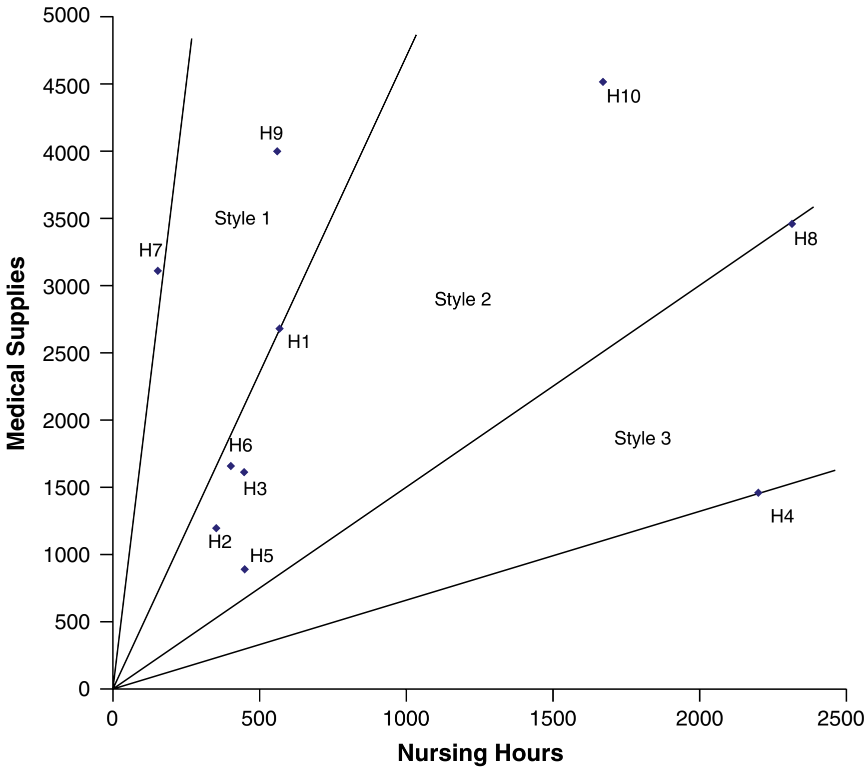


Fig. 4.4 Conceptualization of assurance region for inputs

freely use the weights to become efficient. This means that lower and an upper bounds can be established on a weight ratio of a given pair of inputs or outputs to assure that no DMU can freely choose to become efficient through using excessive outputs or insufficient inputs. Thus, the DMUs will reassess their input usage and output production within given limits (constraints) that are equivalent to policy or managerial restrictions.

Figure 4.4 illustrates the conceptualization of assurance region for the ongoing example data, where three styles of input usage are identified. These styles are identified by drawing lines from the origin to the extreme use of either input. For example, the line from the origin passing through H7 represents a practice that proportionately uses more medical supplies and very little nursing hours. On the other extreme, the line passing through H4 represents a high usage of nursing hours while a proportionately lower usage of medical supplies. The other two lines going through H1 and H8 show more balanced usages of either input. This way, three styles of input usage patterns can be identified. Each style can be shown in a cone, in which the tip of the cone is in the origin, and thus the name of *cone-ratio* originates. Once the health care manager/researcher decides that style one and style three are not acceptable practice, then he or she can impose restrictions on weights so that any efficient hospital in style one or style three would become inefficient and advised to practice input usage represented in style two. We can also call style two, for practical purposes, an assurance region.

In order to impose the restrictions on input or output weights, we can define the following ratios with upper and lower bound restrictions for inputs:

$$L_{i,k} \leq \frac{v_i}{v_k} \leq U_{i,k} \quad i = 1, \ldots, m \tag{4.1}$$

V_i and v_k represent the weights for two different inputs, and $L_{i,k}$ and $U_{i,k}$ denote the lower and upper bounds on this ratio, respectively. This implies that many such ratios can be calculated and their lower and upper bounds can be determined. For example, if there are three inputs, one can calculate six such ratios $(v_1/v_2,\ v_2/v_1,\ v_1/v_3,\ v_3/v_1,\ v_2/v_3,\ v_3/v_2)$. The number of ratios that can be calculated is n! Of course, it does not make sense to calculate a complete set of these ratios to impose the restrictions on input weights. This can also be complicated by the presence of zeroes in the input data. Health care managers/researchers should therefore use prudent judgment and practical vision in proper selection of these ratios so that managerial and policy implications can be tested appropriately.

We can imagine similar restrictions to output production as well. This means that a hospital cannot become efficient by only producing high level inpatient admissions or outpatient visits. Figure 4.5 illustrates the conceptualization of assurance region for outputs, in which three styles of output usage are identified.

Restrictions to outputs via weights can be imposed using the following formula:

$$L_{r,z} \leq \frac{\mu_r}{\mu_z} \leq U_{r,z} \quad r = 1, \ldots, s \tag{4.2}$$

where, μ_i and μ_k represent the weights for two different outputs, and $L_{r,z}$ and $U_{r,z}$ denote the lower and upper bounds on this ratio, respectively.

4.4 Assessment of Upper and Lower Bound Weights

Although health care managers and researchers can impose their own estimates for lower and upper bounds on input and output weight ratios, we suggest a practical statistical approach to obtain the limits placed on these ratios. Once the multiplier model has run and optimal multipliers are obtained, as shown in Fig. 4.3, various distributional values of each weight can be calculated. For example, first, second (median), and third quartiles of the distribution for each weight can be easily obtained using Excel function "Quartile" to obtain these values. For example "=QUARTILE(D9:D18, 1)" would yield the first quartile of the data identified in an array (cells in a column D9–D18). Although quartiles are suggested in this example, one can easily examine various percentiles of the distributions on each weight as well.

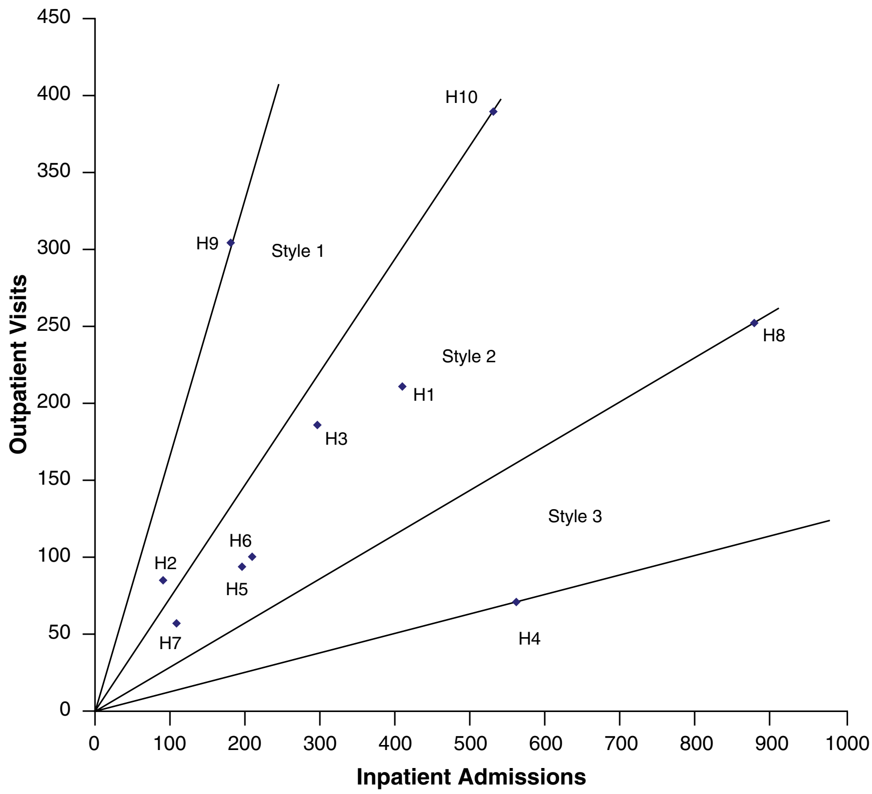


Fig. 4.5 Conceptualization of assurance regions for outputs

Table 4.1 Median and third quartile values

	Nursing hours	Medical supply	Inpatient	Outpatient
Median	0.000228583	0.000208129	0.001462983	0.002578256
Quartile-3	0.001083252	0.000530692	0.002363101	0.005636614

Imposing upper bound restrictions, for example, at the third quartile, and the lower bound restrictions at the median, would provide a tightening of the assurance region closer to style two. However, for further tightening, one can choose the first quartile as a lower bound and the median as an upper bound. These decisions should be assessed case by case, depending upon the distributional values of the weights.

Let us demonstrate this with our example data set. Using the values from Fig. 4.3, median and third quartile values of input and output weights are shown in Table 4.1.

The next step would be to assess substitutability of inputs to each other, as well as the outputs. In terms of policy, we can test the outpatient substitution to inpatient care. This is in line for the developments that occurred within the past two decades.

For example, due to advances in technology, such as interventional radiology for hysterectomies, many surgical procedures can now be done on an outpatient basis.

This means that we prefer the outpatient treatment to inpatient, or that, second output variable is preferred to the first output variable, μ_2/μ_1. Thus, we need to divide outpatient weights by inpatient weights to impose restrictions; however, these restrictions should have lower and upper bound values. Having calculated median and third quartile values on weights of each output variable (Table 4.1), we can use median values for lower bounds, as follows:

$$L_{2,1} \leq \frac{\mu_2}{\mu_1} \leq U_{2,1}$$

or

$$L_{2,1} \leq \frac{Outpatient}{Inpatient} \leq U_{2,1}$$

Outpatient/Inpatient= $0.002578256/0.001462983 = 1.762328(L_{2,1})$.

Similarly we can use the third quartile for the upper bound, as:

$$\text{Outpatient/Inpatient} = 0.005636614/0.002363101 = 2.385262(U_{2,1}).$$

Hence we have the restriction ratio for output weights, as:

$$1.762328 \leq \frac{Outpatient}{Inpatient} \leq 2.385262$$

Again, in this formula, health care managers and researchers are implying their preference of outpatient treatment to inpatient.

Using a similar analogy, we can write a preference ratio stating that nursing hours are a preferred input to medical supplies (the first input is preferred to the second input)

$$L_{1,2} \leq \frac{v_1}{v_2} \leq U_{1,2}$$

or

$$L_{1,2} \leq \frac{Nursing\ Hours}{Medical\ Supplies} \leq U_{1,2}$$

Since median and third quartile values on weights of each input variable are available from Table 4.1, we can use median values for lower bound, as:

$$\text{Nursing Hours/MedicalSupplies} = 0.000228583/0.000208129 = 1.098276(L1, 2).$$

Similarly we can use the third quartile for an upper bound, as:

$$\text{Nursing Hours/Medical Supplies} = 0.001083252/0.000530692 = 2.041207(U_{1,2}).$$

Hence we have the restriction ratio for input weights, as:

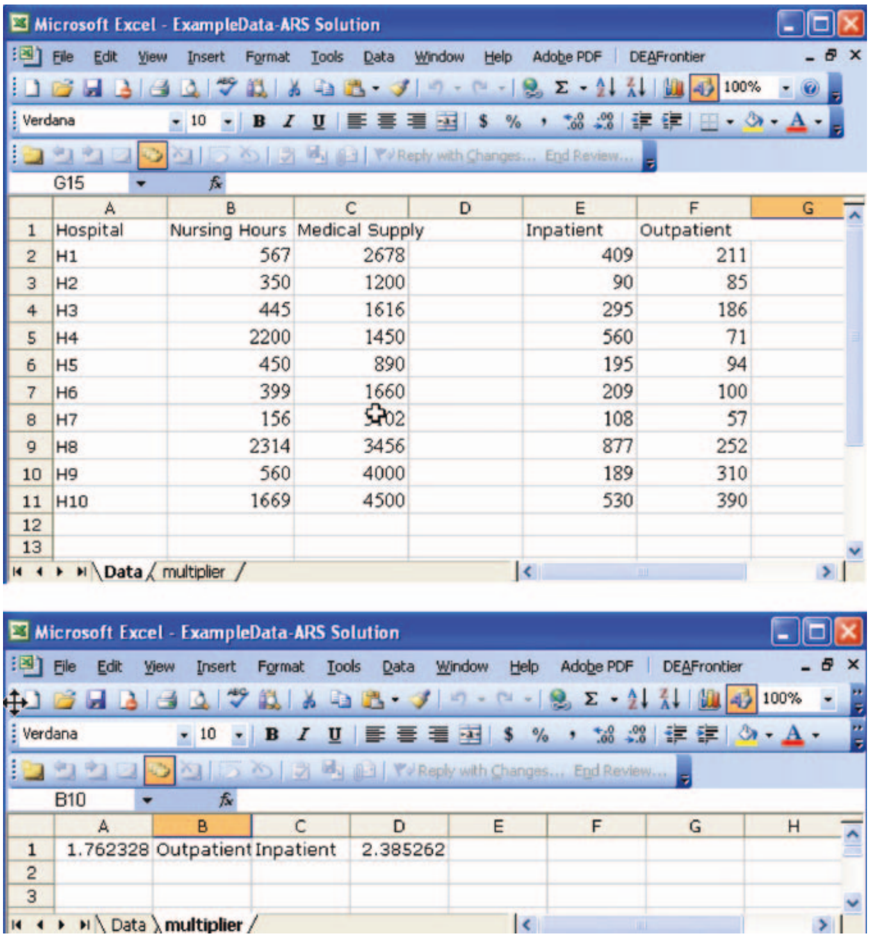
$$1.098276 \leq \frac{Nursing\ Hours}{Medical\ Supplies} \leq 2.041207$$

Once these lower and upper bounds on input and output weights are determined, we can impose these as constraints in a subsequent run in a multiplier restricted model.

4.5 Multiplier (Weight Restricted) Model Example

Multiplier restrictions can be imposed in stages or all at once. However, to see the impact of different policies or managerial preferences [outpatient preferred to inpatient or more nursing hours (human contact) preferred to medical supplies], one may want to test each policy independently or in succession.

In order to implement the first preference, outpatient to inpatient, we need to include the constraint into the model. In DEA-frontier software, this is done by creating another worksheet that is named "multiplier." The top part of the Fig. 4.6 shows the original data and the bottom part shows the new multiplier sheet. In the multiplier sheet, outpatient and inpatient variables shown in columns B and C indicate the ratio of weights for these two variables, whereas column A shows the lower



	A	B	C	D	E	F	G
1	Hospital	Nursing Hours	Medical Supply		Inpatient	Outpatient	
2	H1	567	2678		409	211	
3	H2	350	1200		90	85	
4	H3	445	1616		295	186	
5	H4	2200	1450		560	71	
6	H5	450	890		195	94	
7	H6	399	1660		209	100	
8	H7	156	502		108	57	
9	H8	2314	3456		877	252	
10	H9	560	4000		189	310	
11	H10	1669	4500		530	390	

	A	B	C	D	E	F	G	H
1	1.762328	Outpatient	Inpatient	2.385262				

Fig. 4.6 Data setup for multiplier restricted model

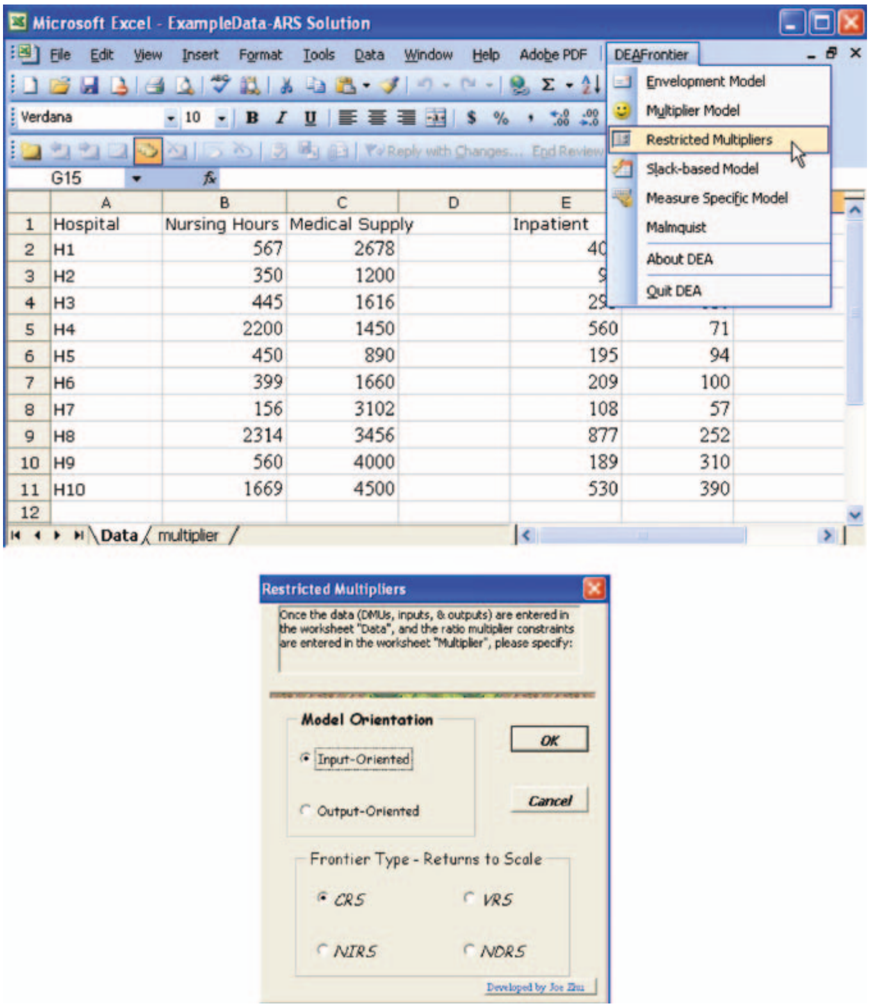
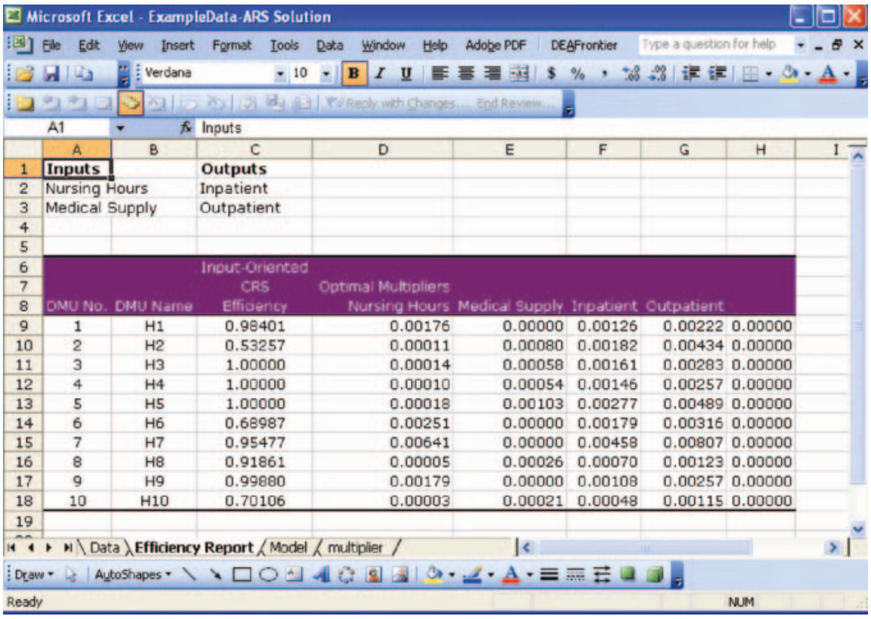


Fig. 4.7 CRS input-oriented restricted multiplier model selection

bound and column D shows the upper bound value calculated earlier. With these set up to run the restricted multiplier model, we choose the appropriate option as shown in Fig. 4.7.

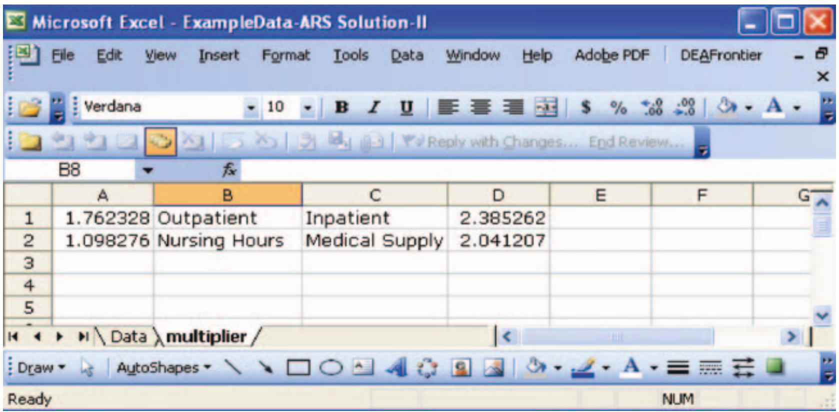
The result of CRS input-oriented restricted multiplier model is shown in Fig. 4.8. One can clearly observe that the number of efficient hospitals (compare to Fig. 2.7) reduced to three hospitals. Hospitals H1, H8, and H9 are no longer at the efficiency frontier due to restrictions imposed on output weights.

After seeing the impact of the outpatient preference to inpatient treatment policy, we can enter an additional constraint to measure the impact of input preferences; namely by restricting the weights on the ratio for nursing hours to medical supplies.



DMU No.	DMU Name	Input-Oriented CRS Efficiency	Optimal Multipliers Nursing Hours	Medical Supply	Inpatient	Outpatient	
1	H1	0.98401	0.00176	0.00000	0.00126	0.00222	0.00000
2	H2	0.53257	0.00011	0.00080	0.00182	0.00434	0.00000
3	H3	1.00000	0.00014	0.00058	0.00161	0.00283	0.00000
4	H4	1.00000	0.00010	0.00054	0.00146	0.00257	0.00000
5	H5	1.00000	0.00018	0.00103	0.00277	0.00489	0.00000
6	H6	0.68987	0.00251	0.00000	0.00179	0.00316	0.00000
7	H7	0.95477	0.00641	0.00000	0.00458	0.00807	0.00000
8	H8	0.91861	0.00005	0.00026	0.00070	0.00123	0.00000
9	H9	0.99880	0.00179	0.00000	0.00108	0.00257	0.00000
10	H10	0.70106	0.00003	0.00021	0.00048	0.00115	0.00000

Fig. 4.8 Restricted multiplier solution – Ratio 1

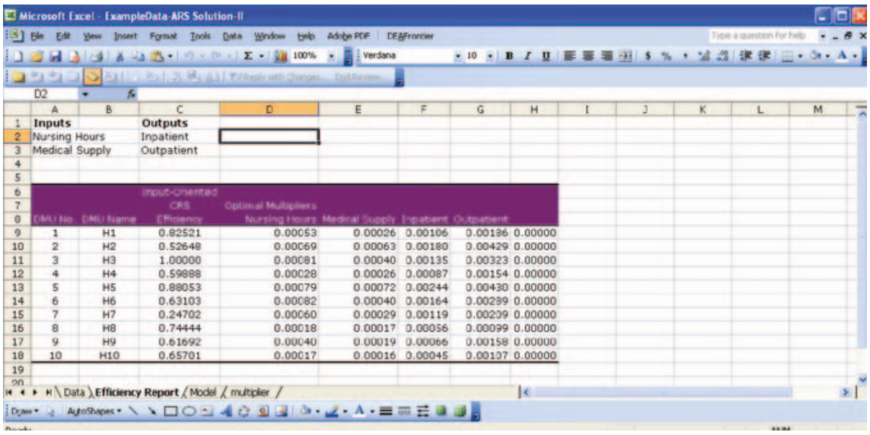


	A	B	C	D
1	1.762328	Outpatient	Inpatient	2.385262
2	1.098276	Nursing Hours	Medical Supply	2.041207

Fig. 4.9 Multiplier sheet for both output and input restrictions

In this second stage, we add the mentioned constraint into the multiplier sheet as shown in Fig. 4.9. Now we have both output and input restrictions in place. Running the model in a similar way, as shown in Fig. 4.7, we obtain the results where both ratios are in effect. These results are shown in Fig. 4.10.

It is interesting to observe that after imposing restrictions on input weights, an additional two hospitals dropped from the efficiency frontier. These hospitals are H4 and H5. Only H3 remains on the efficiency frontier.



DMU No.	DMU Name	Input-Oriented CRS Efficiency	Nursing Hours	Medical Supply	Inpatient	Outpatient	
1	H1	0.82521	0.00053	0.00026	0.00106	0.00186	0.00000
2	H2	0.52648	0.00069	0.00063	0.00180	0.00429	0.00000
3	H3	1.00000	0.00081	0.00040	0.00135	0.00323	0.00000
4	H4	0.59888	0.00028	0.00026	0.00087	0.00154	0.00000
5	H5	0.88053	0.00079	0.00072	0.00244	0.00430	0.00000
6	H6	0.63103	0.00082	0.00040	0.00164	0.00289	0.00000
7	H7	0.24702	0.00060	0.00029	0.00119	0.00209	0.00000
8	H8	0.74444	0.00018	0.00017	0.00056	0.00099	0.00000
9	H9	0.61692	0.00040	0.00019	0.00066	0.00158	0.00000
10	H10	0.65701	0.00017	0.00016	0.00045	0.00107	0.00000

Fig. 4.10 Restricted multiplier solutions: Ratio 1 & Ratio 2

Table 4.2 Comparison of basic and multiplier (weight) restricted models

Hospital	Input-oriented CRS efficiency	Restricted multiplier Ratio 1 Input-oriented CRS efficiency	Restricted multiplier Ratios 1 & 2 Input-oriented CRS efficiency
H1	1.00000	0.98401	0.82521
H2	0.61541	0.53257	0.52648
H3	1.00000	1.00000	1.00000
H4	1.00000	1.00000	0.59888
H5	1.00000	1.00000	0.88053
H6	0.75780	0.68987	0.63103
H7	0.96852	0.95477	0.24702
H8	1.00000	0.91861	0.74444
H9	1.00000	0.99880	0.61692
H10	0.75297	0.70106	0.65701
Average	0.90947	0.87797	0.67275
Ratio 1	1.76	>=Outpatient/Inpatient<=	2.39
Ratio 2	1.10	>=Nursing hours/Medical supply<=	2.04

Table 4.2 provides a comparison of three models. The first one is the basic model, with no restrictions on input or output weights. The second model is the first stage restricted multiplier model, where we imposed outpatient to inpatient weight restriction, Ratio 1. The final model is the restricted multiplier model which includes the first stage and the second stage weight restriction – imposed by nursing hours to medical supplies, Ratio 2.

It should be further noted that the efficiency scores of individual hospitals can only decrease as more restrictions are imposed on them. The average efficiency score of the unrestricted model where there were six efficient hospitals was 0.91. With output multiplier restrictions (Ratio 1), this average was reduced by 3.5%. However, imposing both output and input weight restrictions reduced the efficiency by 26% compared to basic model. Thus, in this case, the multiplier restricted model provides 26% more pure efficiency evaluation when compared to the basic model, or that the impact of weight restrictions shifts the efficiency frontier by 26%.

4.6 Summary

In this chapter, we introduced the multiplier models and weight restricted models that are also known as assurance region models, or cone ratio models. These models provide additional discrimination compared to the standard DEA models by reducing the number of hospitals that make up the best-practice frontier. The impact of these models in determining truly efficient health care organizations is extremely valuable. In addition, using these models, health care managers and researchers can test the impact of various managerial decisions or policies.

Appendix F

F.1 Input-oriented multiplier model formulation

Model 9

$$Maximize \sum_{r=1}^{s} \mu_r y_{ro} + \mu$$

Subject to:

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} + \mu \leq 0 \quad j = 1, \ldots, n$$

$$\sum_{i=1}^{m} \upsilon_i x_{io} = 1$$

$\mu_r, \upsilon_i \geq 0(\varepsilon)$, in CRS, $\mu = 0$ and in VRS μ is free.

F.2 Output-oriented multiplier model formulation

Model 10

$$Maximize\, m \sum_{i=1}^{m} \upsilon_i x_{io} + \upsilon$$

Subject to: $\sum_{i=1}^{m} \upsilon_r x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} + \upsilon \geq 0$ $j = 1, \ldots, n$, in CRS, and in VRS υ is free.

$$\sum_{i=1}^{m} \upsilon_r x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} + \upsilon \geq 0 \quad j = 1, \ldots, n, \text{ in CRS, and in VRS } \upsilon \text{ is free.}$$

$$\sum_{i=1}^{m} \mu_r y_{ro} = 1$$

$\mu_r, \upsilon_i \geq 0(\varepsilon)$, in CRS $\upsilon = 0$, and in VRS υ is free.

Chapter 5
Non-Oriented and Measure Specific Models

5.1 Non-Oriented (Slack-Based) Models

When the health care manager is able to both reduce inputs and augment outputs simultaneously, a non-oriented model is of great use. The non-oriented model is formulated based on input and output slacks, which, in the DEA literature, is called an *additive model* or a *slack-based* model. The slack-based model assumes equal weights (e.g., 1) for all non-zero input and output slacks, if the health care manager has a priori information on the relative importance of the slacks (in terms of reducing inputs or augmenting outputs). Then this information can be included in the model (see Fig. 5.2 "Weights on Slacks" section of the popup menu).

Figure 5.1 shows the setup for the slack-based model, and Fig. 5.2 displays the selection options for this model. Continuing our example from previous chapters, we select CRS model to demonstrate the slack-based model.

Figure 5.3 provides the solution for the setup shown in Figs. 5.1 and 5.2. It should be noted that since we did not specify any prior values on slack weights, they are assumed to be 1, indicating that all input and output slacks are of equal value. Columns B and E of the Excel worksheet named "Slack Report" showing the solution provides this information.

"Slack-Report" in Fig. 5.3 also displays the input and output slacks as well as other pertinent information relating to the DEA solution. Examining $\Sigma\lambda$ in this *non-oriented* model, we can determine that Hospitals H1, H3, H4, H5, H8 and H9 are efficient, as they were in an *input-oriented* CRS model. However, it is interesting to observe that the magnitude of slacks between these two models is different. Figure 5.4 shows the slacks from an input-oriented CRS model, a non-oriented (slack-based) model, and the differences in slack values from the non-oriented model and the input-oriented model.

For example, examining Hospitals H2 and H10 for the nursing hours input we observe that the slack-based model produced significantly higher values for these hospitals, where nursing hours slack increased from 12.03 to 146.64 (by 134.61) for H2, and from 323.65 to 735.94 (by 412.28) for H10. For the medical supply input, H7 now has to reduce this input to 2,444.82 compared to 2,309.19 (by 140.64).

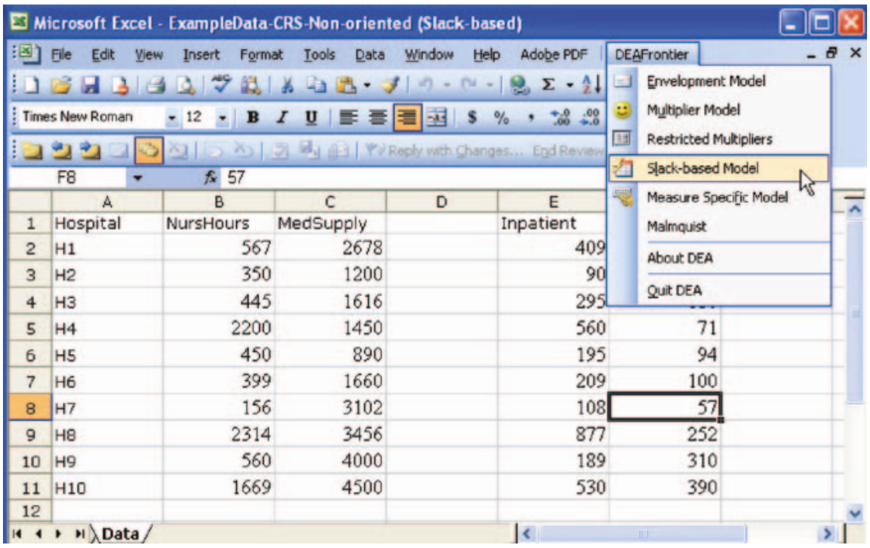


Fig. 5.1 Slack-based model setup

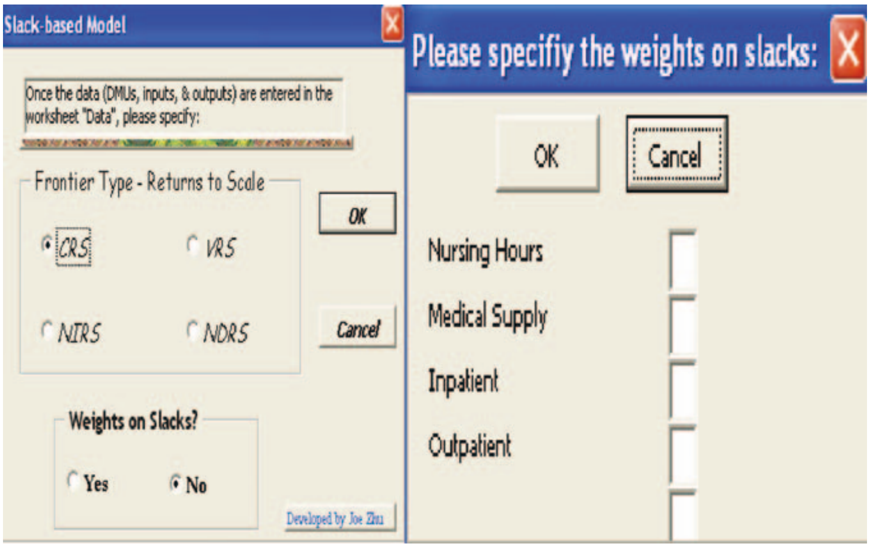


Fig. 5.2 Slack-based model selections

However, Hospitals H2 and H6 that did not have any slacks for the input-oriented model must reduce medical supplies by 461.50 and 629.00, respectively, under the non-oriented model. On output slacks, H6 must increase outpatient visits by 6.35

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Inputs	Weights		Outputs	Weights								
2	NursHours	1		Inpatient	1								
3	MedSupply	1		Outpatient	1								
4													
5	CRS Results		Input Slacks		Output Slacks		Sum of		Optimal Lambdas				
6	DMU No.	DMU Name	NursHours	MedSupply	Inpatient	Outpatient	lambdas	RTS	with Benchmarks				
7	1	H1	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H1			
8	2	H2	146.63978	461.50538	44.81183	0.00000	0.45699	Increasing	0.457	H3			
9	3	H3	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H3			
10	4	H4	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H4			
11	5	H5	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H5			
12	6	H6	0.00000	629.00365	0.00000	6.35048	0.54180	Increasing	0.457	H3		0.084	H8
13	7	H7	0.00000	2449.82849	0.00000	4.60706	0.31262	Increasing	0.138	H1		0.174	H3
14	8	H8	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H8			
15	9	H9	0.00000	0.00000	0.00000	0.00000	1.00000	Constant	1.000	H9			
16	10	H10	735.93548	1111.61290	88.54839	0.00000	2.09677	Decreasing	2.097	H3			
17													

Efficient Target / Slack Report / Model / Data

Fig. 5.3 Slack-based model solution

Input-Oriented CRS Model Slacks

	Input Slacks		Output Slacks	
DMU Name	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	12.03405	0.00000	44.81183	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	0.00000	0.00000	0.00000	19.66368
H7	0.00000	2309.18646	0.00000	0.00000
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	323.65061	0.00000	88.54839	0.00000

Non-Oriented (Slack-based) CRS Model Slacks

	Input Slacks		Output Slacks	
DMU Name	NursHours	MedSupply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	146.63978	461.50538	44.81183	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	0.00000	629.00365	0.00000	6.35048
H7	0.00000	2449.82849	0.00000	4.60706
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	735.93548	1111.61290	88.54839	0.00000

Differences on Slacks between Oriented and Non-Oriented Models

DMU Name	NursHours	MedSupply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	134.60573	461.50538	0.00000	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	0.00000	629.00365	0.00000	-13.31320
H7	0.00000	140.64204	0.00000	4.60706
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	412.28487	1111.61290	0.00000	0.00000

Fig. 5.4 Slack report of input-oriented model

instead of 19.66 (a decrease by 13.31) compared with the input-oriented model. Hospital H7, on the other hand, must increase its outpatient visits by 4.6.

Comparison for solution targets are displayed in Fig. 5.5. Input-oriented and non-oriented (slack-based) solution targets, as well as the differences between the oriented and non-oriented models, are shown in this figure. It is interesting to note that the differences on targets show change only on Hospitals H6 and H7. Most of the adjustments done through simultaneous input reduction and output augmentation

Input-Oriented CRS Model Solution Targets

	Efficient Input Target		Efficient Output Target	
DMU Name	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	567.00000	2678.00000	409.00000	211.00000
H2	203.36022	738.49462	134.81183	85.00000
H3	445.00000	1616.00000	295.00000	186.00000
H4	2200.00000	1450.00000	560.00000	71.00000
H5	450.00000	890.00000	195.00000	94.00000
H6	302.36067	1257.94164	209.00000	119.66368
H7	151.08945	695.16914	108.00000	57.00000
H8	2314.00000	3456.00000	877.00000	252.00000
H9	560.00000	4000.00000	189.00000	310.00000
H10	933.06452	3388.38710	618.54839	390.00000

Non-Oriented (Slack-based) CRS Model Solution Targets

	Efficient Input Target		Efficient Output Target	
DMU Name	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	567.00000	2678.00000	409.00000	211.00000
H2	203.36022	738.49462	134.81183	85.00000
H3	445.00000	1616.00000	295.00000	186.00000
H4	2200.00000	1450.00000	560.00000	71.00000
H5	450.00000	890.00000	195.00000	94.00000
H6	399.00000	1030.99635	209.00000	106.35048
H7	156.00000	652.17151	108.00000	61.60706
H8	2314.00000	3456.00000	877.00000	252.00000
H9	560.00000	4000.00000	189.00000	310.00000
H10	933.06452	3388.38710	618.54839	390.00000

Differences on Targets between Oriented and Non-Oriented Models

DMU Name	Nursing Hours	Medical Supply	Inpatient	Outpatient
H1	0.00000	0.00000	0.00000	0.00000
H2	0.00000	0.00000	0.00000	0.00000
H3	0.00000	0.00000	0.00000	0.00000
H4	0.00000	0.00000	0.00000	0.00000
H5	0.00000	0.00000	0.00000	0.00000
H6	96.63933	-226.94529	0.00000	-13.31320
H7	4.91055	-42.99763	0.00000	4.60706
H8	0.00000	0.00000	0.00000	0.00000
H9	0.00000	0.00000	0.00000	0.00000
H10	0.00000	0.00000	0.00000	0.00000

Fig. 5.5 Solution targets compared

based on efficiency scores plus slacks did not change the target values for the other inefficient Hospitals H2 and H10.

An interested reader can find the mathematical formulations of non-oriented CRS (slack-based) model (Model 11) and its weighted version (Model 12) in Appendix G.

5.2 Measure Specific Models

Health care managers and researchers often find variables that are not at their discretion or over which they have little control. However, inclusion of these variables into the DEA model is often essential to capture the health service production process. The measure specific DEA models incorporate the uncontrollable nature of such variables into the formulation. That is, even in the model, health care managers will not be able to exercise input reduction or output augmentation over these variables. In the DEA literature, the measure specific models are also called models with non-controllable variables or models with non-discretionary variables. Figure 5.6 shows the setup for measure specific models for our ongoing example.

Once the "Measure Specific Model" option is selected from the DEAFrontier menu, depending upon input or output orientation, one can designate the variables that we have control over (or variables that are at our discretion). If the controllable variables constitute a group (set) of inputs then they will be identified by $\boldsymbol{I}$, which is a set of such inputs. Similarly, if the controllable variables constitute a group (set) of outputs then they will be identified by $\boldsymbol{O}$, which is a set of such outputs.

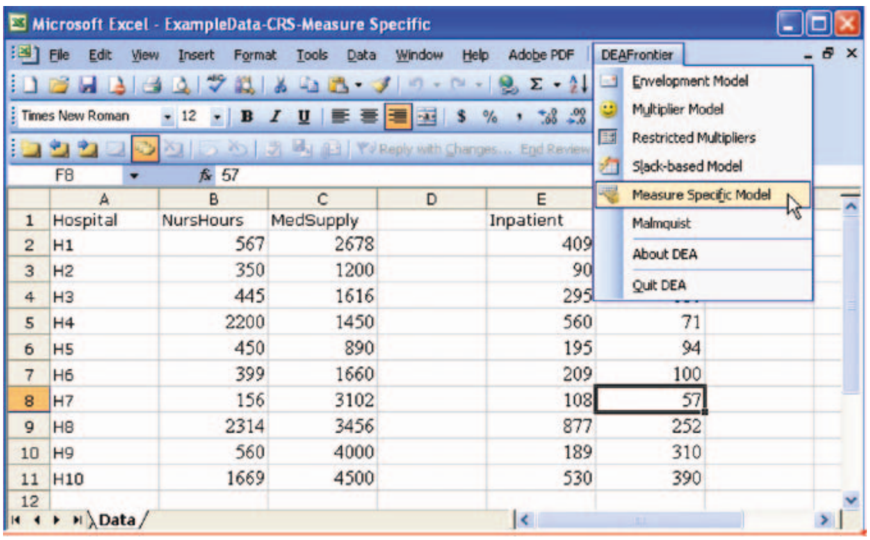


Fig. 5.6 Measure specific model setup

Although both envelopment models and measure specific models will produce the same frontier, the measure specific models will result in different efficient targets.

For the purposes of demonstration, let us assume that "Medical Supply" is a non-controllable variable. Thus, we select an input-oriented model and click on the inputs we have control over (proportional reduction possible), namely, "Nursing Hours". Figure 5.7 displays measure specific model specifications for this example.

Put another way, in this selection we assume that the variable "Nursing Hours" is controllable, and medical supply is a non-controllable input in an input-oriented CRS model. Thus, "Nursing Hours" $\in I$ and "Medical Supply" $\notin I$. Appendix H details the formulation of input-oriented measure specific model where Model 13 specifies the CRS version.

The solution to the measure specific CRS input-oriented model for this example is provided in Fig. 5.8. Note that the efficiency scores for inefficient Hospitals H2,

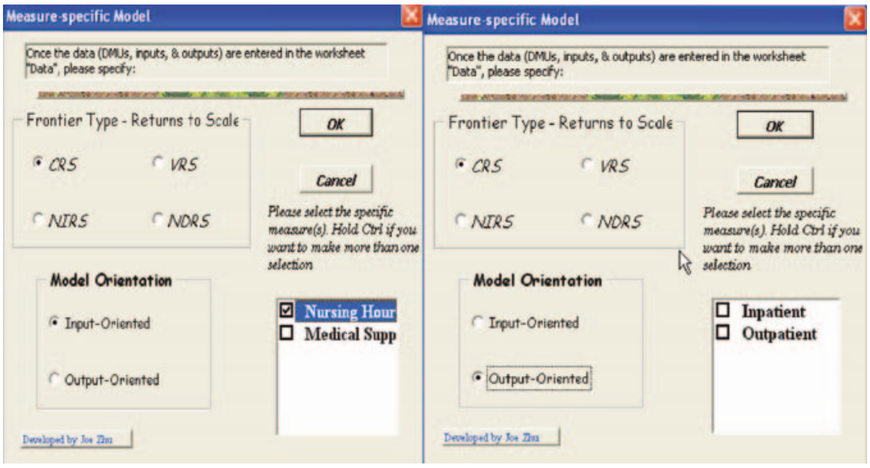
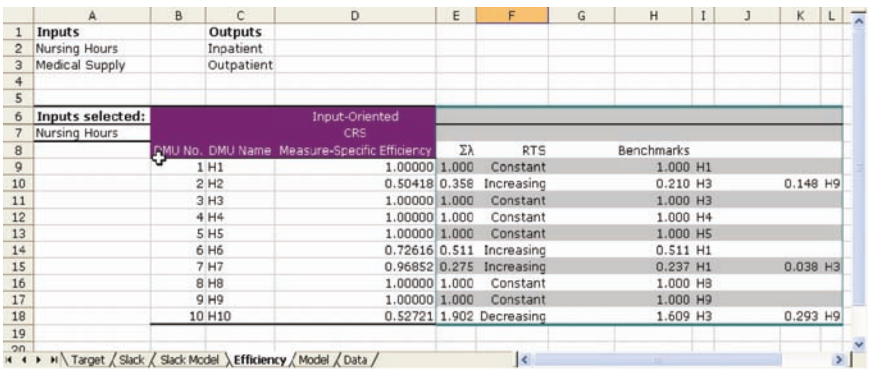


Fig. 5.7 Measure specific model selections



Inputs		Outputs								
Nursing Hours		Inpatient								
Medical Supply		Outpatient								
Inputs selected:			Input-Oriented CRS							
Nursing Hours	DMU No.	DMU Name	Measure-Specific Efficiency	Σλ	RTS	Benchmarks				
	1	H1	1.00000	1.000	Constant	1.000	H1			
	2	H2	0.50418	0.358	Increasing	0.210	H3		0.148	H9
	3	H3	1.00000	1.000	Constant	1.000	H3			
	4	H4	1.00000	1.000	Constant	1.000	H4			
	5	H5	1.00000	1.000	Constant	1.000	H5			
	6	H6	0.72616	0.511	Increasing	0.511	H1			
	7	H7	0.96852	0.275	Increasing	0.237	H1		0.038	H3
	8	H8	1.00000	1.000	Constant	1.000	H8			
	9	H9	1.00000	1.000	Constant	1.000	H9			
	10	H10	0.52721	1.902	Decreasing	1.609	H3		0.293	H9

Fig. 5.8 Solution to measure specific model

H6, and H10 are different than those for the input-oriented CRS model (the reader can verify this by comparing the efficiency scores reported in Fig. 5.8 to efficiency scores in Fig. 2.8).

Similarly, the slack values shown in Fig. 5.9 for the measure specific input-oriented CRS model for the inefficient hospitals are different than those reported in Fig. 2.9 for the input-oriented CRS model. Since "Nursing Hours" is a controllable input variable, the health care manager can reduce its use, and thus the input slack values for this input variable are zero.

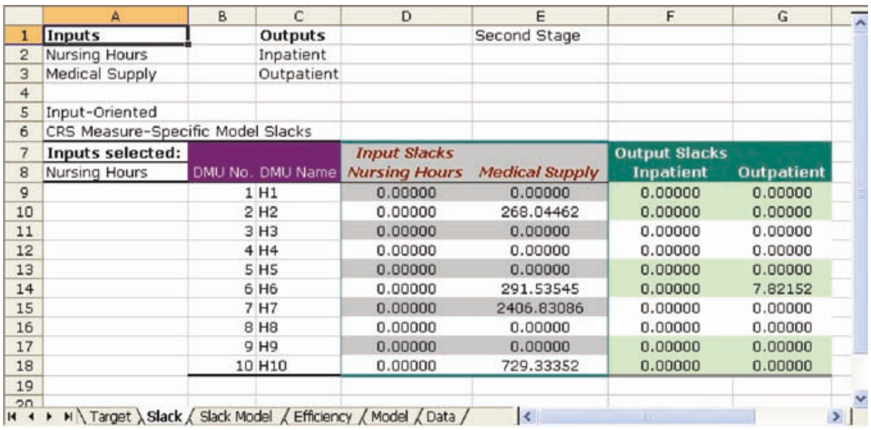
Efficient targets for measure specific models are calculated by taking the controllable nature of the variable (see Appendix H, Part 2). Since there are four inefficient hospitals, we can apply the efficient target formulas for inputs as:

$$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i \in I, \text{ where i} = \text{Nursing Hours (controllable input), and}$$
$$\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i \notin I, \text{ where i} = \text{Medical Supply (non-controllable input).}$$

Applying these equations to inefficient Hospitals H2, H6, H7, and H10, we can summarize their partial original data (from Fig. 5.6), efficiency scores (Fig. 5.8), and slack data values (Fig. 5.9) for both inputs in Table 5.1.

For H2, to calculate the efficient target for Nursing Hours (NH), we can write:

$$\widehat{x}_{NH,\ H2} = \theta^* x_{NH,\ H2} - s_{NH}^{-*} \text{ or } \widehat{x}_{NH,\ H2} = 0.50418 * 350 - 0.00 = 176.4632$$



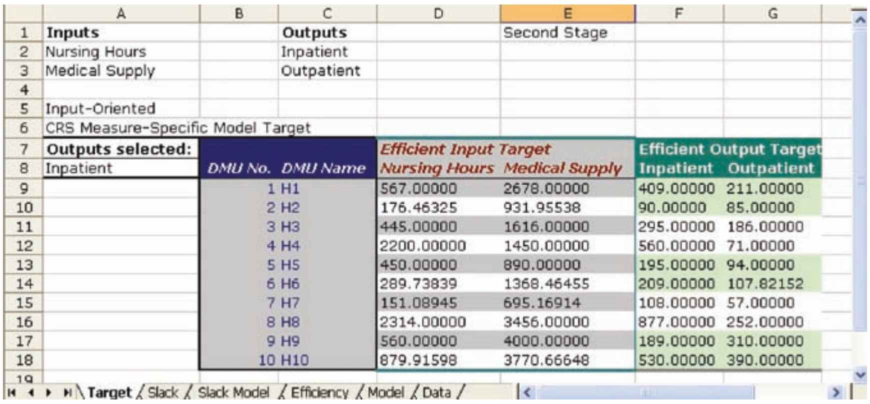
	A	B	C	D	E	F	G
1	**Inputs**		**Outputs**		Second Stage		
2	Nursing Hours		Inpatient				
3	Medical Supply		Outpatient				
4							
5	Input-Oriented						
6	CRS Measure-Specific Model Slacks						
7	**Inputs selected:**			*Input Slacks*		**Output Slacks**	
8	Nursing Hours	DMU No.	DMU Name	*Nursing Hours*	*Medical Supply*	**Inpatient**	**Outpatient**
9		1	H1	0.00000	0.00000	0.00000	0.00000
10		2	H2	0.00000	268.04462	0.00000	0.00000
11		3	H3	0.00000	0.00000	0.00000	0.00000
12		4	H4	0.00000	0.00000	0.00000	0.00000
13		5	H5	0.00000	0.00000	0.00000	0.00000
14		6	H6	0.00000	291.53545	0.00000	7.82152
15		7	H7	0.00000	2406.83086	0.00000	0.00000
16		8	H8	0.00000	0.00000	0.00000	0.00000
17		9	H9	0.00000	0.00000	0.00000	0.00000
18		10	H10	0.00000	729.33352	0.00000	0.00000
19							

Target | Slack | Slack Model | Efficiency | Model | Data

Fig. 5.9 Slacks for measure specific model

Table 5.1 Inefficient hospital data values

DMU name	Nursing hours	Medical supply	Efficiency score θ^*	Nursing hours slack	Medical supply slack
H2	350	1,200	0.50418	0.00	268.04462
H6	399	1,660	0.72616	0.00	291.53545
H7	156	3,102	0.96852	0.00	2406.83086
H10	1,669	4,500	0.52721	0.00	729.33352



	A	B	C	D	E	F	G
1	**Inputs**		**Outputs**		Second Stage		
2	Nursing Hours		Inpatient				
3	Medical Supply		Outpatient				
4							
5	Input-Oriented						
6	CRS Measure-Specific Model Target						
7	**Outputs selected:**			*Efficient Input Target*		**Efficient Output Target**	
8	Inpatient	*DMU No.*	*DMU Name*	*Nursing Hours*	*Medical Supply*	**Inpatient**	**Outpatient**
9		1	H1	567.00000	2678.00000	409.00000	211.00000
10		2	H2	176.46325	931.95538	90.00000	85.00000
11		3	H3	445.00000	1616.00000	295.00000	186.00000
12		4	H4	2200.00000	1450.00000	560.00000	71.00000
13		5	H5	450.00000	890.00000	195.00000	94.00000
14		6	H6	289.73839	1368.46455	209.00000	107.82152
15		7	H7	151.08945	695.16914	108.00000	57.00000
16		8	H8	2314.00000	3456.00000	877.00000	252.00000
17		9	H9	560.00000	4000.00000	189.00000	310.00000
18		10	H10	879.91598	3770.66648	530.00000	390.00000

Fig. 5.10 Efficient targets for measure specific model

Similarly, for H6, H7 and H10, we calculate:

$\widehat{x}_{NH,\ H6} = \theta^{*} x_{NH,\ H6} - s_{NH}^{-*}$ or $\widehat{x}_{NH,\ H6} = 0.72616 * 399 - 0.00 = 289.73839$
$\widehat{x}_{NH,\ H7} = \theta^{*} x_{NH,\ H7} - s_{NH}^{-*}$ or $\widehat{x}_{NH,\ H7} = 0.96852 * 156 - 0.00 = 151.08945$
$\widehat{x}_{NH,\ H10} = \theta^{*} x_{NH,\ H10} - s_{NH}^{-*}$ or $\widehat{x}_{NH,\ H10} = 0.52721 * 1669 - 0.00 = 879.91598$.

The reader can observe and confirm these results for Fig. 5.10 where efficient targets for measure specific model for "Nursing Hours" are shown.

A calculation of efficient targets for the non-controllable input, Medical Supply (MS), for H2, H6, H7 and H10, can be calculated as:

$\widehat{x}_{MS,\ H2} = x_{MS,\ H2} - s_{H2}^{-*}$ or $\widehat{x}_{MS,\ H2} = 1200 - 268.04462 = 931.95538$
$\widehat{x}_{MS,\ H6} = x_{MS,\ H6} - s_{H6}^{-*}$ or $\widehat{x}_{MS,\ H7} = 1660 - 291.53545 = 1368.46455$
$\widehat{x}_{MS,\ H7} = x_{MS,\ H7} - s_{H7}^{-*}$ or $\widehat{x}_{MS,\ H7} = 3102 - 2406.83086 = 695.16914$
$\widehat{x}_{MS,\ H10} = x_{MS,\ H10} - s_{H10}^{-*}$ or $\widehat{x}_{MS,\ H10} = 4500 - 729.33352 = 3770.66648$

The reader can again observe and confirm these results in Fig. 5.10, where efficient targets for measure specific model for Medical Supply are shown.

The formulation of an output-oriented version of this model is shown as Model 14 in Appendix I. The VRS version of both input-oriented and output-oriented models can be easily solved by adding the following constraint to either formulation:

$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots .n$. As shown in Appendix H and Appendix I.

5.3 Summary

This chapter introduced two additional extensions to the envelopment model and illustrated their use for health care managers and researchers. While non-oriented (slack-based) models allow managers and researchers to work on both inputs and outputs to achieve efficiency. On the other hand, measure specific models allow them to work only on those inputs or outputs under their discretion. This way, those variables that do not provide flexibility to managers can be included in the DEA model for control purposes.

Appendix G

Non-oriented CRS (slack-based) model – additive model formulation

Model 11

$$Maximize \ \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots .m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots .s$$
$$\lambda_j, s_i^-, s_r^+ \geq 0 \quad j = 1, \ldots .n$$

Non-oriented weighted (slack-based) CRS model formulation

Model 12

$$Maximize \sum_{i=1}^{m} w_i^- s_i^- + \sum_{r=1}^{s} w_r^+ s_r^+$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots .m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots .s$$
$$\lambda_j, s_i^-, s_r^+ \geq 0 \quad j = 1, \ldots .n$$

For VRS based models of 11 and 12, add the following constraint:

$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots .n$$

Appendix H

H.1 Input-Oriented Measure Specific Model Formulation

Model 13: Input-oriented CRS – measure specific model

$$Minimize \, \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad i \in I, \text{ where } \boldsymbol{I} \text{ represents controllable inputs}$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i \notin I, \text{ for those non-controllable inputs}$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, \ldots, s$$
$$\lambda_j \geq 0 \quad j = 1, \ldots, n$$

For VRS version of Model 13, add the following constraint:

$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots, n.$$

H.2 Efficient Target Calculations for Input-Oriented Measure Specific Model

Inputs:

$$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad i \in I, \text{ for controllable inputs}$$
$$\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i \notin I, \text{ for non-controllable inputs}$$

Outputs:

$$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r = 1, \ldots, s$$

Appendix I

I.1 Output-Oriented Measure Specific Models

Model 14: output-oriented CRS – measure specific model

$$Minimize\, \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$
$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots .m,$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{ro} \quad r \in O, \text{ where } \boldsymbol{O} \text{ represents controllable outputs}$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r \notin O, \text{ where } \boldsymbol{O} \text{ represents non-controllable outputs}$$
$$\lambda_j \geq 0 \quad j = 1, \ldots .n$$

For VRS version of Model 14, add the following constraint:

$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots .n.$$

I.2 Efficient Target Calculation for Output-Oriented Measure Specific Model

Inputs:

$\widehat{x}_{io} = x_{io} - s_i^{-*} \quad i = 1, \ldots .m$

Outputs:

$\widehat{y}_{ro} = \phi^* y_{ro} + s_i^{+*} \quad r \in O$, for controllable outputs
$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad r \notin O$, for non-controllable outputs

Chapter 6
Longititudunal (Panel) Evaluations Using DEA

6.1 Malmquist Index

Monitoring performance over time is essential in health care organizations. The Malmquist index is a method which provides an opportunity to compare the health care facility performance from one period to another. Such a tool was suggested first by Malmquist (1953), then developed as a productivity index by Caves, Christensen and Diewert (1982), and then further developed by Fare, Grosskopf and Lowell (1994) as the Malmquist-DEA performance measure.

The Malmquist DEA calculates DEA efficiency for the following input (or output) oriented CRS models:

[a] Calculating the frontier in time period-1 (time t) and comparing efficiency scores, $\theta_0^{\mathrm{t}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t}})$, of health care organizations at period-1 (time t),
[b] Calculating the frontier in time period-2 (time t + 1) and comparing efficiency scores, $\theta_0^{\mathrm{t+1}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t+1}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t+1}})$, of health care organizations at period 2 (time t + 1),
[c] Comparing efficiency scores of time period-1 (t), $\theta_0^{\mathrm{t}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t+1}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t+1}})$, to frontier at time period-2 (t + 1), and
[d] Comparing efficiency scores of period-2 (t + 1), $\theta_0^{\mathrm{t+1}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t}})$, to frontier at period-1 (t).

Malmquist efficiency is defined as the geometric mean of efficiency scores defined above:

$$M_o = \left[\frac{[a] Period - 1}{[c] Period - 1 \ on \ Period - 2} \quad * \quad \frac{[d] Period - 2 \ on \ Period - 1}{[b] Period - 2} \right]^{\frac{1}{2}} \tag{6.1}$$

or

$$M_o = \left[\frac{\theta_0^{\mathrm{t}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t}})}{\theta_0^{\mathrm{t}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t+1}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t+1}})} \frac{\theta_0^{\mathrm{t+1}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t}})}{\theta_0^{\mathrm{t+1}}(\mathrm{x}_{\mathrm{o}}^{\mathrm{t+1}}, \mathrm{y}_{\mathrm{o}}^{\mathrm{t+1}})} \right]^{\frac{1}{2}} \tag{6.2}$$

where M_o indicates the efficiency change between period-1(t) and period 2 (t + 1).

The efficiency change is observed as:

If $M_o > 1$, efficiency is decreased from period-1 to period-2.
If $M_o = 1$, no change in efficiency from period-1 to period-2.
If $M_o < 1$, efficiency is increased from period-1 to period-2.

An important feature of the DEA Malmquist index is that it can decompose the overall efficiency measure into two mutually exclusive components, one measuring change in technical efficiency (catching-up effect) and the other measuring change in technology (innovation). Since the Malmquist efficiency index is the product of these two components, the decomposition can be shown as:

$$M_o = \underbrace{\frac{[a]Period-1}{[b]Period-2}}_{\text{(EFFICIENCY CHANGE)}} * \underbrace{\left[\frac{[b]Period-2}{[c]Period-1\ on\ Period-2} * \frac{[d]Period-2\ on\ Period-1}{[a]Period-1}\right]^{\frac{1}{2}}}_{\text{(TECHNICAL CHANGE)}} \tag{6.3}$$

or

$$M_o = \frac{\theta_0^{t}(x_o^{t}, y_o^{t})}{\theta_0^{t+1}(x_o^{t+1}, y_o^{t+1})} * \left[\frac{\theta_0^{t+1}(x_o^{t+1}, y_o^{t+1})}{\theta_0^{t}(x_o^{t+1}, y_o^{t+1})} * \frac{\theta_0^{t+1}(x_o^{t}, y_o^{t})}{\theta_0^{t}(x_o^{t}, y_o^{t})}\right]^{\frac{1}{2}} \tag{6.4}$$

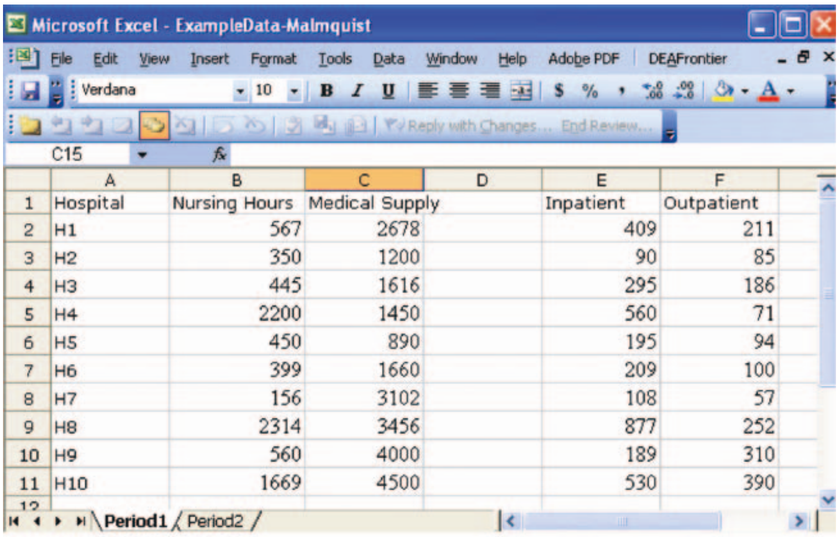
The efficiency component of the index (the first half) measures changes in technical efficiency from period t to period $t+1$. That is, it measures how the units being examined have managed to catch up to the frontier. On the other hand, the technical component of the index (the second half) measures changes in the production frontier (i.e., a shift in best-practice technology) from period t to period $t+1$. In an input-oriented evaluation, if the values of the Malmquist index and its components are less than 1, equal to 1, or greater than 1, they indicate progress, no change, or regress, respectively (Caves, Christensen and Diewert, 1982; Färe, Grosskopf, Lindgren, and Ross, 1994).

CRS output orientation can be handled similarly. However, for VRS the following constraint should be added to the model:

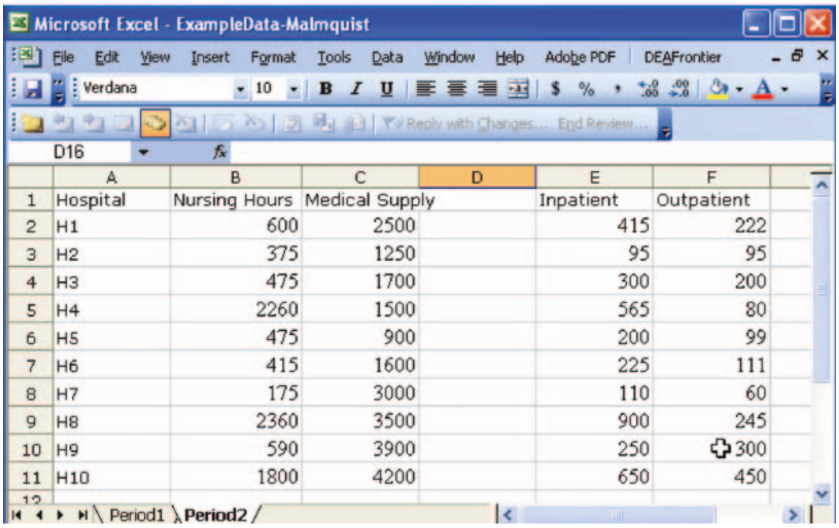
$$\sum_{j=1}^{n} \lambda_j = 1 \quad j = 1, \ldots n$$

6.2 Malmquist-DEA Efficiency Example

To illustrate the use of DEA based Malmquist index, we will use the ongoing example, in which we will consider the existing data belonging to period-1. Additional



Hospital	Nursing Hours	Medical Supply		Inpatient	Outpatient
H1	567	2678		409	211
H2	350	1200		90	85
H3	445	1616		295	186
H4	2200	1450		560	71
H5	450	890		195	94
H6	399	1660		209	100
H7	156	3102		108	57
H8	2314	3456		877	252
H9	560	4000		189	310
H10	1669	4500		530	390



Hospital	Nursing Hours	Medical Supply		Inpatient	Outpatient
H1	600	2500		415	222
H2	375	1250		95	95
H3	475	1700		300	200
H4	2260	1500		565	80
H5	475	900		200	99
H6	415	1600		225	111
H7	175	3000		110	60
H8	2360	3500		900	245
H9	590	3900		250	300
H10	1800	4200		650	450

Fig. 6.1 Malmquist data for the example problem

data from the same hospitals was gathered from another time period (year) and labeled as period-2. The top part of Fig. 6.1 illustrates period-1 and the bottom part of Fig. 6.1 shows the data belonging period-2. As the reader can observe, the data setup is similar to the cross-sectional (single time period) version, however, for each period under consideration a new Excel sheet must be present. Health care managers and researchers can include more than two periods; however, the evaluation of Malmquist-DEA must be carried by choosing any two periods at a time.

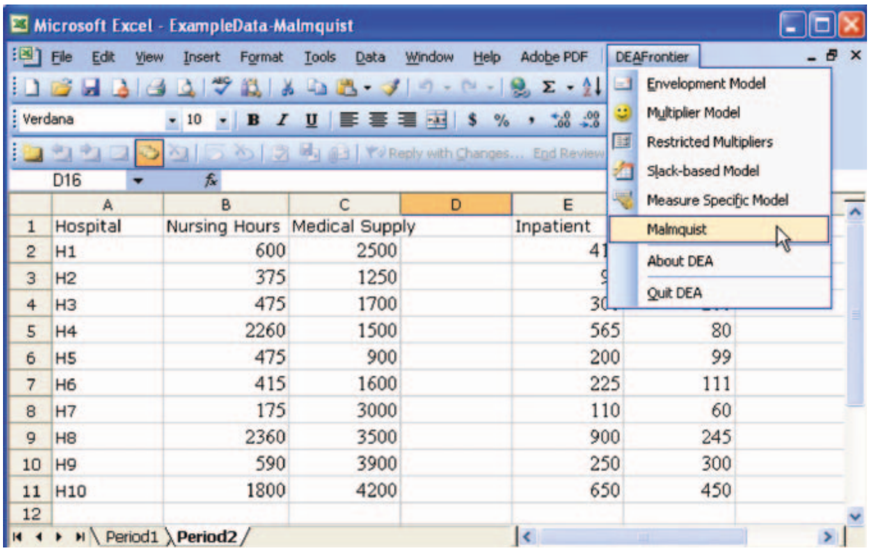


Fig. 6.2 Setup for Malmquist-DEA

To evaluate performance over time using Malmquist-DEA, select the Malmquist option from the DEAFrontier menu, as shown in Fig. 6.2. This will prompt another window for the selection of time periods from the available set. As shown in Fig. 6.3, our example contains only two periods; thus we choose both. In order to select the second period, the user should hold the Ctrl key then click into the designated box. Selection of the model orientation (input or output) completes the selection process, as shown in Fig. 6.3. Click OK to run the model.

Once the model runs, the health care manager and researcher can view a file containing outputs in several spreadsheets. Naturally, the raw data from period-1 and period-2 are the essential parts of this file. The Malmquist-Index file shown in Fig. 6.4 displays the summary information for the Malmquist-DEA. The three columns of information display the results for each hospital, as shown in the formulation earlier in Sect. 6.

The reader can verify that "Malmquist Index=Efficiency Change * Frontier Shift" by multiplying the values in the last two columns of the report shown in Fig. 6.4. As discussed earlier, if $M_o > 1$, efficiency is decreased from period-1 to period-2; hence H1, H3, H4, H7 and H9 exhibit such a decrease. On the other hand, if $M_o < 1$, efficiency is increased from period-1 to period-2; hospitals H2, H5, H6, H8 and H10 all increased their efficiency between these two periods.

To further investigate the components of the Malmquist index, we can observe efficiency independently in each period. Fig. 6.5a,b show the independent efficiency evaluations of period-1 [a] and period-2 [b].

Using these independent evaluations to compare hospitals in Fig. 6.5a,b, we observe that inefficient hospitals H2, H6, and H10 increased their efficiency in the second period, while H7 decreased its efficiency score.

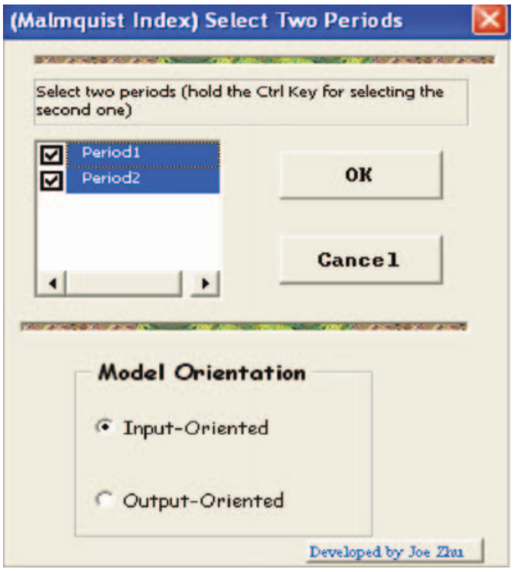


Fig. 6.3 Selection of periods and orientation

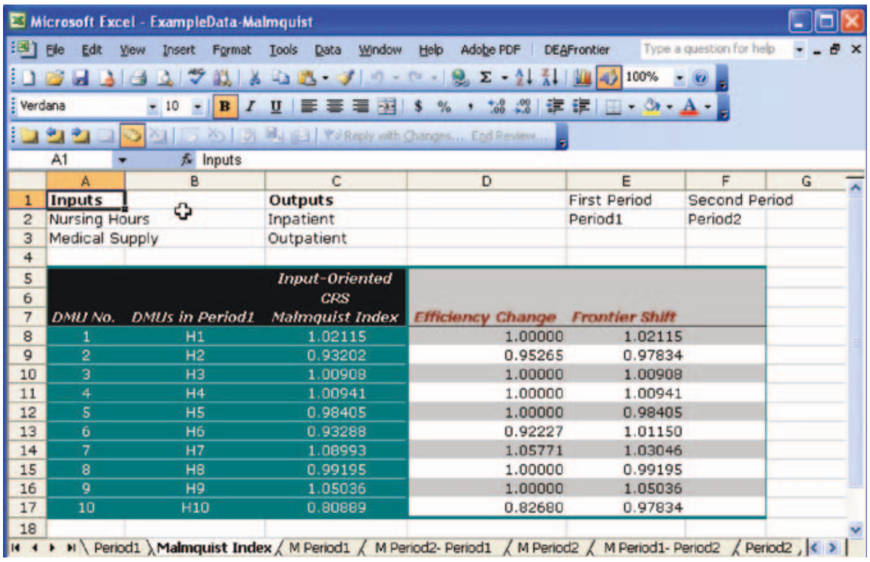


Fig. 6.4 Summary of Malmquist-DEA results for the hospital example

In order to calculate the Malmquist index shown by (6.4), we need to observe period-1 on period-2 and period-2 on period-1, where one period is under evaluation with respect to the other period, and the other period serves as reference. These are the [c] and [d] components of the formula. As shown in Fig. 6.6a “M period1-period2” indicates that period-2 is the reference set, and the Malmquist index for

Inputs		Outputs
Nursing Hours		Inpatient
Medical Supply		Outpatient

DMU No.	DMUs in Period2	Input-Oriented CRS Efficiency	Σλ	RTS	Benchmarks			
1	H1	1.00000	1.000	Constant	1.000	H1		
2	H2	0.64600	0.475	Increasing	0.475	H3		
3	H3	1.00000	1.000	Constant	1.000	H3		
4	H4	1.00000	1.000	Constant	1.000	H4		
5	H5	1.00000	1.000	Constant	1.000	H5		
6	H6	0.82166	0.648	Increasing	0.267	H1	0.380	H3
7	H7	0.91568	0.273	Increasing	0.244	H1	0.029	H3
8	H8	1.00000	1.000	Constant	1.000	H8		
9	H9	1.00000	1.000	Constant	1.000	H9		
10	H10	0.91071	2.250	Decreasing	2.250	H3		

Period1 / Malmquist Index / M Period1 / M Period2- Period1 / M Period2 / M Period1- Period2 / Period2

Fig. 6.5 (**a**) Independent efficiency evaluation of period-1 [a]

Inputs		Outputs
Nursing Hours		Inpatient
Medical Supply		Outpatient

DMU No.	DMUs in Period1	Input-Oriented CRS Efficiency	Σλ	RTS	Benchmarks			
1	H1	1.00000	1.000	Constant	1.000	H1		
2	H2	0.61541	0.457	Increasing	0.457	H3		
3	H3	1.00000	1.000	Constant	1.000	H3		
4	H4	1.00000	1.000	Constant	1.000	H4		
5	H5	1.00000	1.000	Constant	1.000	H5		
6	H6	0.75780	0.609	Increasing	0.258	H1	0.350	H3
7	H7	0.96852	0.275	Increasing	0.237	H1	0.038	H3
8	H8	1.00000	1.000	Constant	1.000	H8		
9	H9	1.00000	1.000	Constant	1.000	H9		
10	H10	0.75297	2.097	Decreasing	2.097	H3		

Period1 / Malmquist Index / M Period1 / M Period2- Period1 / M Period2 / M Period1- Period2 / Period2

Fig. 6.5 (**b**) Independent efficiency evaluation of period-2 [b]

period-1 is under evaluation. Similarly, in Fig. 6.6b "M period2-period1" indicates that period-1 is the reference set, and the Malmquist index for period-2 is under evaluation.

To calculate the "Efficiency Change" and "Frontier Shift" components of the (6.3) or (6.4), we shall reorganize efficiency scores calculated from Fig. 6.5a, from Fig. 6.5b [b], from Fig. 6.6a [c], and from Fig. 6.6b [d]. Figure 6.7 displays the summary of these efficiency scores for each hospital in the respective columns, and also includes a summary of the Malmquist index, efficiency change and frontier shift from Fig. 6.4.

Now, if we customize (rewrite) the (6.4) for this example, let us say for hospital H6, then we get

$$M_6 = \frac{\theta_6^1(x_6^1, y_6^1)}{\theta_6^2(x_6^2, y_6^2)} \quad * \quad \left[\frac{\theta_6^2(x_6^2, y_6^2)}{\theta_6^1(x_6^2, y_6^2)} \quad * \quad \frac{\theta_6^2(x_6^1, y_6^1)}{\theta_6^t(x_6^t, y_6^t)}\right]^{\frac{1}{2}}$$

	A	B	C	D	E	F	G	H	I	J
1	**Inputs**		**Outputs**							
2	Nursing Hours		Inpatient							
3	Medical Supply		Outpatient							
4										
5			*Input-Oriented*							
6			*CRS*							
7	*DMU No.*	*DMUs in Period2*	*Scores*	Benchmarks						
8	1	H1	1.00015	0.519 H1			0.687 H3			
9	2	H2	0.66030	0.511 H3						
10	3	H3	1.02214	1.075 H3						
11	4	H4	1.00630	0.967 H4			0.121 H5			
12	5	H5	1.03196	0.059 H3			0.936 H5			
13	6	H6	0.80332	0.121 H1			0.595 H3			
14	7	H7	0.89120	0.200 H1			0.096 H3			
15	8	H8	1.01038	0.014 H4			1.018 H8			
16	9	H9	0.98679	0.369 H3			0.746 H9			
17	10	H10	0.93088	2.419 H3						
18										

Period1 / Malmquist Index / M Period1 / M Period2- Period1 / M Period2 / **M Period1- Period2** / Period2

Fig. 6.6 (**a**) Malmquist index period-1, period-2 is reference [c]

	A	B	C	D	E	F	G	H	I	J	K
1	**Inputs**		**Outputs**								
2	Nursing Hours		Inpatient								
3	Medical Supply		Outpatient								
4											
5			*Input-Oriented*								
6			*CRS*								
7	*DMU No.*	*DMUs in Period1*	*Scores*	Benchmarks							
8	1	H1	1.04290	0.986 H1							
9	2	H2	0.60208	0.425 H3							
10	3	H3	1.04078	0.069 H1		0.888 H3					
11	4	H4	1.02533	0.991 H4							
12	5	H5	0.99930	0.090 H3		0.679 H5				0.036 H8	
13	6	H6	0.75802	0.499 H1		0.007 H3					
14	7	H7	1.00093	0.260 H1							
15	8	H8	0.99418	0.022 H4		0.335 H5				0.886 H8	
16	9	H9	1.08869	1.033 H9							
17	10	H10	0.73667	1.950 H3							
18											

Period1 / Malmquist Index / M Period1 / **M Period2- Period1** / M Period2 / M Period1- Period2 / Period2

Fig. 6.6 (**b**) Malmquist index period-2, period-1 is reference [d]

DMU No.	M Period 1 [a] Input-Oriented CRS Efficiency	M Period 2 [b] Input-Oriented CRS Efficiency	M Period1-Period2 [c] *Input-Oriented CRS Scores*	Period2-Period-1 [d] *Input-Oriented CRS Scores*	*CRS Malmquist Index*	*Efficiency Change*	*Frontier Shift*
1	1.00000	1.00000	1.00015	1.04290	1.02115	1.00000	1.02115
2	0.61541	0.64600	0.66030	0.60208	0.93202	0.95265	0.97834
3	1.00000	1.00000	1.02214	1.04078	1.00908	1.00000	1.00908
4	1.00000	1.00000	1.00630	1.02533	1.00941	1.00000	1.00941
5	1.00000	1.00000	1.03196	0.99930	0.98405	1.00000	0.98405
6	0.75780	0.82166	0.80332	0.75802	0.93288	0.92227	1.01150
7	0.96852	0.91568	0.89120	1.00093	1.08993	1.05771	1.03046
8	1.00000	1.00000	1.01038	0.99418	0.99195	1.00000	0.99195
9	1.00000	1.00000	0.98679	1.08869	1.05036	1.00000	1.05036
10	0.75297	0.91071	0.93088	0.73667	0.80889	0.82680	0.97834

Fig. 6.7 Summary of efficiency scores

DMU No.	A [a]/[c]	B [d]/[b]	$\sqrt{A*B}$ M_o	C [a]/[b] Efficiency Change	M_o/C Frontier Shift	D [b]/[c]	E [d]/[a]	$\sqrt{D*E}$ Frontier Shift
1	0.99985	1.042902	1.02115	1.0000	1.02115	0.99985	1.04290	1.02115
2	0.93202	0.932018	0.93202	0.9527	0.97834	0.97834	0.97834	0.97834
3	0.97834	1.040778	1.00908	1.0000	1.00908	0.97834	1.04078	1.00908
4	0.99374	1.025328	1.00941	1.0000	1.00941	0.99374	1.02533	1.00941
5	0.96903	0.999296	0.98405	1.0000	0.98405	0.96903	0.99930	0.98405
6	0.94333	0.922543	0.93288	0.9223	1.01150	1.02283	1.00029	1.01150
7	1.08676	1.093097	1.08993	1.0577	1.03046	1.02747	1.03346	1.03046
8	0.98972	0.994179	0.99195	1.0000	0.99195	0.98972	0.99418	0.99195
9	1.01338	1.088690	1.05036	1.0000	1.05036	1.01338	1.08869	1.05036
10	0.80889	0.808889	0.80889	0.8268	0.97834	0.97834	0.97834	0.97834

Fig. 6.8 Detailed calculations of Malmquist-DEA index

and, substituting the respective efficiency values, θ_6^*, from Fig. 6.7, we obtain:

$$M_6 = \frac{0.75780}{0.82166} \quad * \quad \left[\frac{0.82166}{0.80332} * \frac{0.75802}{0.75780}\right]^{\frac{1}{2}}$$

$$M_6 = 0.92227 \quad * \quad [1.022825 \quad * \quad 1.000291]^{\frac{1}{2}}$$

$$M_6 = 0.92227 \quad * \quad [1.023123]^{\frac{1}{2}}$$

$$M_6 = 0.92227 \quad * \quad 1.01150$$

$$M_6 = 0.93288$$

Figure 6.8 shows the correspondence of these calculated scores for all ten hospitals (DMUs). The reader can observe that hospital H6's Malmquist index, M_6, is 0.93288 as shown in column M_0 in Fig. 6.8. The components of this index, efficiency change and frontier shift values, were also obtained while calculating M_6 as 0.92227 and 1.01150, respectively.

Independent calculation of the frontier shift is also demonstrated in Fig. 6.8, in columns D and E, where the square root of the cross product of this calculation yields the frontier shift.

It should be noted that when more than two periods involved in the evaluation, one can perform Malmquist index for any pair of periods given that periods are identified properly on Excel worksheets. Ozgen and Ozcan (2004) study demonstrated seven year evaluation of performance for dialysis centers using Malmquist index (see Chap. 13, Sect. 13.2 for further information).

6.3 Summary

This chapter demonstrated the longitudinal evaluations of performance using the Malmquist-DEA index. In doing so, we can identify changes in efficiency from one period to another, but can also determine whether this change is due to pure efficiency improvement and/or due to technological changes in service delivery, such as medical innovations, which caused a shift in the efficiency frontier. As health care organizations adopt many new technologies, frontier change is expected, provided there is a long enough duration lag to capture this effect.

Chapter 7
Effectiveness and Other Models of DEA

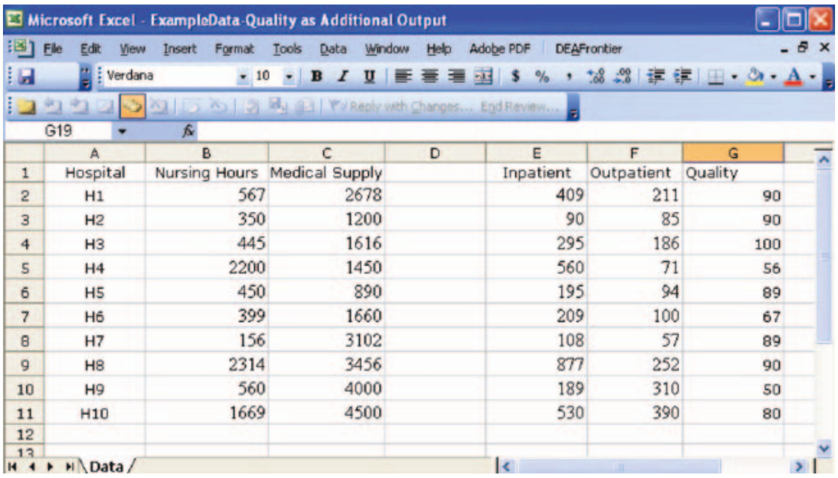
7.1 Incorporation of Quality into DEA Models

The two components of health care facility performance, efficiency and effectiveness quality), were introduced in Chap. 1. In this chapter, a closer examination of the effectiveness component is provided. Sherman and Zhu (2006) introduce quality-adjusted DEA applied to bank branches. In this discussion, they incorporate quality into DEA benchmarking in two different models. The first model adds a quality variable as an additional output into the standard DEA model. They demonstrate that, using this approach, the model may exhibit a quality/efficiency tradeoff. Of course in health care, managers would not welcome such a tradeoff sacrificing quality for efficiency. The second approach, which avoids such tradeoffs, is an evaluation of quality and efficiency independently. Using the hospital example, we illustrate these concepts below.

7.2 Quality as an Additional Output

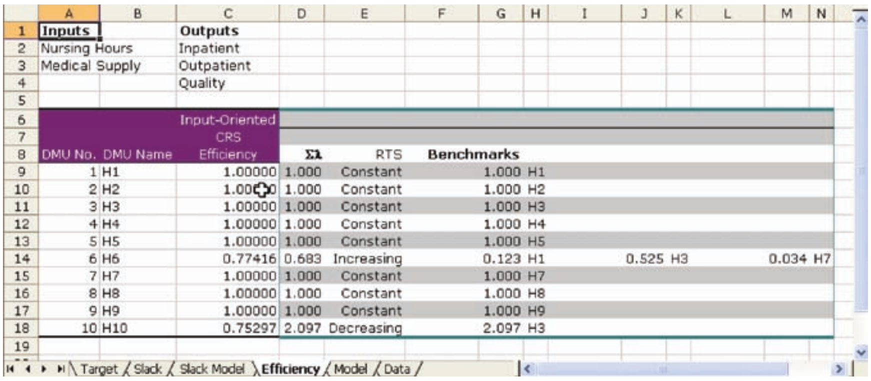
Hospital quality for this example is measured using data from the Hospital Quality Alliance (HQA) for the purpose of public reporting on the Hospital Compare Website. The data include information about clinician adherence to clinical guidelines for patients with three conditions including pneumonia, acute myocardial infarction and congestive heart failure (HQA, 2007). The data was coded to produce a total hospital quality score by providing a dichotomous measure of whether the hospital performed above (1) or below (0) the national average for each individual measure, and then dividing this score by the number of measures the hospital reported. This resulted in the range of scores from zero to 100, with 100 indicating perfect adherence to clinical guidelines in these measures.

The setup for our ongoing hospital example with quality as an additional output is shown in Fig. 7.1. As the number of variables (one additional output) increased in this model compared to the basic CRS model, one can expect more hospitals



Hospital	Nursing Hours	Medical Supply	Inpatient	Outpatient	Quality
H1	567	2678	409	211	90
H2	350	1200	90	85	90
H3	445	1616	295	186	100
H4	2200	1450	560	71	56
H5	450	890	195	94	89
H6	399	1660	209	100	67
H7	156	3102	108	57	89
H8	2314	3456	877	252	90
H9	560	4000	189	310	50
H10	1669	4500	530	390	80

Fig. 7.1 Setup for quality as an additional output



Inputs	Outputs
Nursing Hours	Inpatient
Medical Supply	Outpatient
	Quality

DMU No.	DMU Name	Input-Oriented CRS Efficiency	Σλ	RTS	Benchmarks					
1	H1	1.00000	1.000	Constant	1.000	H1				
2	H2	1.00000	1.000	Constant	1.000	H2				
3	H3	1.00000	1.000	Constant	1.000	H3				
4	H4	1.00000	1.000	Constant	1.000	H4				
5	H5	1.00000	1.000	Constant	1.000	H5				
6	H6	0.77416	0.683	Increasing	0.123	H1	0.525	H3	0.034	H7
7	H7	1.00000	1.000	Constant	1.000	H7				
8	H8	1.00000	1.000	Constant	1.000	H8				
9	H9	1.00000	1.000	Constant	1.000	H9				
10	H10	0.75297	2.097	Decreasing	2.097	H3				

Fig. 7.2 Results of CRS input-oriented model with a quality output

to become efficient while keeping the number of hospitals in this evaluation the same, ten.

Figure 7.2 displays the results of the CRS input-oriented envelopment model with an additional quality variable. As expected, compared to the basic model, two more hospitals became efficient. Compared to the basic model, hospitals H2 and H7 are classified as best performers. In order to examine the performance of the hospitals, it is prudent not only to compare the basic DEA model with the modified DEA model with additional quality output, but also to compare the original raw quality scores of the hospitals.

Figure 7.3 provides this comparison. As can be observed, the average performance of the hospitals increased from 0.909 to 0.953, as an additional variable was introduced to the DEA model. We also may have introduced some tradeoffs between efficiency and quality, as suggested by Sherman and Zhu (2006). However, the more

	Basic Model	Quality as additional output	
DMU Name	Input-Oriented CRS Efficiency	Input-Oriented CRS Efficiency	Raw Quality Score
H1	1.00000	1.00000	90
H2	0.61541	1.00000	90
H3	1.00000	1.00000	100
H4	1.00000	1.00000	56
H5	1.00000	1.00000	89
H6	0.75780	0.77416	67
H7	0.96852	1.00000	89
H8	1.00000	1.00000	90
H9	1.00000	1.00000	50
H10	0.75297	0.75297	80
Average	0.90947	0.95271	80

Fig. 7.3 Comparison of DEA models and quality score

important observation here is whether the additional quality variable provides the needed performance information for managerial decision-making.

Upon closer examination of the last two columns of Fig. 7.3, we observe that the two hospitals, H2 and H7, which are now among the best performers, have raw quality scores of 90 and 89, respectively. This score may be acceptable, assuming that 90 is a good raw quality score, yet with other hospitals, such as H4 and H9, despite their perfect DEA scores, display raw quality scores of 50 and 56, nowhere near acceptable levels.

Thus, this illustration shows one of the shortcomings for inclusion of quality variables into the benchmark model as an additional output.

7.3 Quality as an Independent Output

In this section we examine the impact of quality as an independent output in a separate DEA model and make comparisons between the basic DEA model, quality-adjusted DEA model, and raw quality scores. This way we have two independent DEA evaluations, one for efficiency and one for quality.

Using our example again, Fig. 7.4 shows the setup for quality as an independent output DEA model. As the reader can observe, there is only one output variable, quality.

The result of the CRS input-oriented DEA model, where quality is only output are shown in Fig. 7.5. This model, along with the basic DEA model, will provide two independent dimensions of performance to the health care managers.

	A	B	C	D	E
1	Hospital	Nursing Hours	Medical Supply		Quality
2	H1	567	2678		90
3	H2	350	1200		90
4	H3	445	1616		100
5	H4	2200	1450		56
6	H5	450	890		89
7	H6	399	1660		67
8	H7	156	3102		89
9	H8	2314	3456		90
10	H9	560	4000		50
11	H10	1669	4500		80

Fig. 7.4 Setup for quality as an independent output

	A	B	C	D	E	F	G	H	I	J	K
1	Inputs		Outputs								
2	Nursing Hours		Quality								
3	Medical Supply										
4											
5			Input-Oriented								
6			CRS								
7	DMU No.	DMU Name	Efficiency	Σλ	RTS	Benchmarks					
8	1	H1	0.56340	1.002	Decreasing	0.841	H2			0.161	H7
9	2	H2	1.00000	1.000	Constant	1.000	H2				
10	3	H3	0.86100	1.111	Decreasing	1.081	H2			0.030	H7
11	4	H4	0.38362	0.625	Increasing	0.625	H5				
12	5	H5	1.00000	1.000	Constant	1.000	H5				
13	6	H6	0.61644	0.742	Increasing	0.671	H2			0.070	H7
14	7	H7	1.00000	1.000	Constant	1.000	H7				
15	8	H8	0.26074	1.013	Decreasing	1.013	H5				
16	9	H9	0.27245	0.558	Increasing	0.338	H2			0.221	H7
17	10	H10	0.21111	0.894	Increasing	0.499	H2			0.395	H5

Fig. 7.5 Results of CRS input-oriented model with an independent quality output

The independent quality evaluation using DEA shows that only three hospitals H2, H5 and H7 perform well (at 1.0 level). Of course, this is an independent quality evaluation, and should be compared to raw quality scores for validation of this model. The reader can observe that H5, which was identified as an efficient hospital in the basic-DEA model, is also an excellent performer in quality dimension. On the other hand, hospitals H2 and H7 that were identified as inefficient in the basic DEA model are now identified as excellent performers once quality is considered.

Figure 7.6 provides the comparison of both the basic DEA, independent quality models, and the raw quality scores. While we can validate that hospital H5 is both efficient and effective in both DEA models, it has near acceptable raw quality score. However, we cannot validate a quality DEA score for hospitals H1, H3 and H8.

	Basic Model	Quality as independent Output	
DMU Name	Input-Oriented CRS Efficiency	Input-Oriented CRS Efficiency	Raw Quality Score
H1	1.00000	0.56340	90
H2	0.61541	1.00000	90
H3	1.00000	0.86100	100
H4	1.00000	0.38362	56
H5	1.00000	1.00000	89
H6	0.75780	0.61644	67
H7	0.96852	1.00000	89
H8	1.00000	0.26074	90
H9	1.00000	0.27245	50
H10	0.75297	0.21111	80
Average	0.90947	0.61688	80

Fig. 7.6 Comparison of DEA-models and quality score

These hospitals had good raw quality scores but the quality DEA model resulted in poor performance on quality.

This introduces the dilemma of how to incorporate quality into DEA models. In these examples we used only one quality variable. Other dimensions of the quality certainly would change the results of these evaluations. Because this is a fertile area of research in health care management, and many operations and health services researchers are examining this issue as more public data becomes available in quality of care, better models would be built and validated for health care managers' use.

This begs the question of how to evaluate the two dimensions of performance, efficiency and effectiveness (quality) in the mean time. Actually, this is not that problematic, as long as health care managers have access to quality data.

7.4 Combining Efficiency Benchmarks and Quality Scores

The health care managers can use the power of the DEA benchmarks from the efficiency models and the quality scores as shown in Fig. 7.7. The next step for the manager is to decide cut-off points for high and low efficiency and quality dimensions of the performance. For illustrative purposes, let us suppose that the manager decided to use 1.0 for high efficiency provided by DEA score. Any hospital that did not achieve the score of one will be considered low in efficiency. Similarly, the health care manager can set the high and low values for the quality scores. Let us assume a score of 90 or above (out of 100) represents high quality. With this

DMU Name	Basic Model: Input-Oriented CRS Efficiency	Raw Quality Score
H1	1.00000	90
H2	0.61541	90
H3	1.00000	100
H4	1.00000	56
H5	1.00000	89
H6	0.75780	67
H7	0.96852	89
H8	1.00000	90
H9	1.00000	50
H10	0.75297	80
Average	0.90947	80

Fig. 7.7 Benchmark and quality scores

Efficiency	Effectiveness (Quality): Low <90	Effectiveness (Quality): High >=90
High = 1.0	Improvement Need on Quality **H4, H5, H9**	Best Performance H1, H3, H8
Low < 1.0	Poor Performance H6, H7, H10	**Improvement Need on Efficiency H2**

Fig. 7.8 Combined performance

information we can construct the quadrants of low/high efficiency and quality as shown as combined performance in Fig. 7.8.

Best performing hospitals are shown in the upper right quadrant of the Fig. 7.8.

These include hospitals H1, H3 and H8, which all had a perfect efficiency score, and 90 or better on their quality scores. The other three efficient hospitals H4, H5 and H6 appear on the upper left quadrant, indicating that they need to improve their quality. Although hospital H2 has high quality score, its efficiency is low, thus causing H2 to appear in lower right quadrant, indicating that it needs improvement on efficiency.

The poor performance on both dimensions, efficiency and quality, is identified in the lower left quadrant. The hospitals H6, H7 and H10 are identified as poor performers, hence they not only need to improve their efficiency, but also their quality at the same time.

Using these combined performance models, health care managers of the hospitals lacking performance on efficiency would have information on how to improve efficiency by examining targets provided by DEA solutions. Similarly, health care managers who know the quality scores will be able take the necessary actions to improve that dimension.

7.5 Other DEA Models

The DEA field has grown tremendously during the past three decades. Besides the most frequently used models presented in this book, there are other models of DEA. These more specific models provide solutions to specific conditions. We will briefly describe them here, and the interested reader can further inquire from the following texts listed in the references: Zhu (2003), Cooper et al. (2007). We will list few of them below, which can be applied to problems in health care organizations.

7.5.1 Congestion DEA

If in a situation in which a reduction in one or more inputs generates an increase in one or more outputs (the reverse can also occur), congestion might be present. Fare and Grosskopf (1983) developed models to handle conditions that arise from these situations. Zhu (2003) also provides solutions using slack-based congestion models.

7.5.2 Super Efficiency DEA Models

This model, among other purposes, can identify extreme-efficient DMUs. To evaluate the super efficiency, the DMU under evaluation is not included in the reference set (benchmarks) of the envelopment models. More explanations for these models can be found in Andersen and Petersen (1993), Zhu (2003), Cooper et al. (2007).

7.5.3 Economies of Scope

This DEA model can be used to evaluate whether a health care organization might produce different services by spinning them off as separate organizations. Similarly, one can test whether separate organizations delivering the services might be better off by consolidating under one umbrella. Economies of scope provide some answers to many capacity related questions using DEA. For further details of effects of divestitures and mergers, the interested reader is referred to Fare et al. (1994), and Cooper et al. (2007).

7.6 Summary

This chapter examined the effectiveness (quality) dimension of performance and illustrated how different evaluations can yield unexpected scores. More specifically, DEA models with quality variables may produce results that may not be valid. Thus, it is safer to evaluate efficiency and effectiveness dimensions independently to make managerial decisions in performance assessment and devise necessary improvement strategies.

Part II
Applications

The first seven chapters introduced various models of efficiency and effectiveness that can be solved using DEA. The next seven chapters are devoted to applications of DEA.

Chapter 8 develops a robust hospital DEA model based on these previous studies, while Chap. 9 provides an in-depth look to DEA based physician evaluations. Chapter 10 specifies the DEA based nursing home models. Chapter 11, introduces a few studies on health maintenance organizations (HMOs) and DEA models associated with them. Chapter 12 explores home health, and introduces DEA models for home health agencies.

Chapter 13 examines other health care organizations including dialysis centers, community mental health centers, community based youth services, organ procurement organizations, aging agencies, and dental providers. Chapter 14 provides an insight to other DEA models designed to evaluate health care provider performance for specific treatments including stroke, mechanical ventilation, and perioperative services. This chapter also discusses DEA models for physicians at hospital settings, hospital mergers, hospital closures, hospital labor markets, hospital services in local markets, etc.

Chapter 8
Hospital Applications

8.1 Introduction

In health care, the first application of DEA is dated to 1983 by the study of Nunamaker, measuring routine nursing service efficiency. Since then, DEA analysis is used widely in the assessment of hospital technical efficiency in the United States as well as around the world at different levels of decision making units.

Earlier DEA studies were aimed at specific characteristics or types of hospitals, such as teaching and non-teaching hospitals, studied by O'Neill (1998), Grosskopf et al. (2001, 2004). Harrison et al. (2004) evaluated the technical efficiency of 280 U.S. federal hospitals in 1998 and 245 U.S. federal hospitals in 2001 using DEA methodology. The study found that overall efficiency in federal hospitals improved from 68% in 1998 to 79% in 2001, while at the same time there was a potential for savings of $2.0 billion annually through more efficient management of resources. Harrison and Sexton (2006) evaluated the efficiency of religious not-for-profit hospitals using DEA and found that overall efficiency in religious hospitals improved from 72% in 1998 to 74% in 2001. Wang et al. (1999) evaluated trends in efficiency among 314 metropolitan American hospital markets with 6,010 hospitals. Results suggested that larger hospital size was associated with higher inefficiency. Ozcan (1995) studied the hospital industry's technical efficiency in 319 U.S. metropolitan areas and found that at least 3% of health care costs in the gross domestic product (GDP) are due to inefficiencies created by the excessive buildup of providers.

Changes in hospitals' technical efficiency resulting from impact of policy, technology and environment issues also were studied in literature. One of the areas of application of DEA to the hospital industry was an assessment of hospital mergers (Harris et al. 2000; Ferrier and Valdmanis, 2004). Lee and Wan (2004) used DEA in the study of relationship between information system (IS) integration and efficiency of 349 urban hospitals, measured in 1997 and 1998. Chu et al. (2004) examined effect of capitated contracting on hospital efficiency in California and found that less efficient hospitals are more likely to participate in capitated contracting and that hospital efficiency generally increases with respect to the degree of capitation involvement. Mobley and Magnussen (2002) assessed the impact of managed care penetration and hospital quality on efficiency in hospital staffing in California using DEA production function model, including ancillary care among the inputs and outputs. The study found that market share and market concentration were the major determinants of excess staffing and poor quality was associated with less efficient staffing. Chirikos and Sear (1994) studied technical efficiency and the competitive behavior of 189 acute Florida hospitals and found that inefficiency ratings were systematically linked to the competitive conditions of local health care markets. A study by Brown (2002) used the HCUP sample of hospitals for 1992–1996 for estimation of hospital technical efficiency and found that increased managed care insurance is associated with higher technical efficiency.

Different studies used different levels of DMUs (Ozcan and McCue, 1996; Ozcan et al. 1996a, b). While most of researchers used hospital level, there are also applications of DEA at managerial level. O'Neill (2005) compared multifactor efficiency (MFE) and non-radial super-efficiency (NRSE) for operating room managers at an Iowa hospital. These techniques lead to equivalent results for unique optimal solutions and a single output. MFE incorporates the slack values from multiple output variables and can be easier for managers because it does not require additional steps beyond the DEA. O'Neill and Dexter (2004) developed and validated a method to measure "market capture" of inpatient elective surgery using DEA for Perioperative Services at 53 non-metropolitan Pennsylvania hospitals, demonstrating DEA's potential as a valuable tool for managers' decision-making.

Data envelopment analysis for estimation of different aspects of health care services and hospitals' technical efficiency was used in Spain (Pina and Torres, 1996; Sola and Prior, 2001; Dalmau-Atarrodona and Puig-Ju, 1998), Taiwan (Chang, 1998), Thailand (Valdmanis et al. 2004), Turkey (Ersoy et al. 1997; Sahin and Ozcan, 2000), Greece (Giokas, 2001; Athanassopoulos and Gounaris, 2001), Germany (Helmig and Lapsley, 2001), Canada (Ouellette and Vierstraete, 2004), United Kingdom (Field and Emrouznejad, 2003; McCallion et al. 2000), Belgium (Creteur et al. 2003), Kenya (Kirigia et al. 2004), Botswana (Ramanathan et al. 2003), and Sweden (Gerdtham et al. 1999). Biorn et al. (2003) studied the effect of activity-based financing on hospital efficiency in Norway. DEA also was used for international comparison (Mobley and Magnussen, 1998; Steinmann et al., 2003). For more in-depth evaluation and a summary of health and hospital applications of DEA, the reader is referred to papers by Hollingsworth (2003) as well as O'Neill et al. (2007).

8.2 Defining Service Production Process in Hospital Sector

The various studies mentioned above defined hospital service production in varying models. Sherman and Zhu (2006) identified the variations in hospital production models and suggested that it is hard to compare outcome of efficiency studies due to a lack of standard conceptualization of inputs and outputs in this process. O'Neil et al. (2007), in a recent taxonomy of DEA hospital studies, illustrated various inputs and outputs used by different researchers in service production process.

Ozcan et al. (1992), Ozcan (1993), Ozcan and Luke (1993) and later studies by Ozcan identified three major categories of inputs as capital investment, labor and other operating costs. Similarly, O'Neill et al. (2007) taxonomy provide categories of inputs and outputs and identify three broad categories of inputs; namely capital investment, labor and other operating expenses. These categories of inputs through the research over the years emerged as the standard for hospital service production. On the output side, Ozcan and associates (in early 1990s) introduced the following output measurements: case-mix adjusted discharges for inpatient side, outpatient visits for ambulatory activities, and teaching for those hospitals engaged in medical education. O'Neill and associates taxonomy also includes outpatient visits, admissions or discharges, and teaching. Although inpatient days are also identified as another output category in this taxonomy, O'Neil and associates also provide trends that shape the usage of inputs and outputs in hospital studies. More specifically, they show that the use of "inpatient days" measuring inpatient activities is replaced by adjusted admissions or discharges as DRG-based reimbursement took place both in the USA and some European countries.

While conceptualization of service production using these input and output categories is very important for robust DEA modeling, it is equally important to operationalize these variables with available measurements from the field via existing data bases.

American Hospital Association (AHA) data, http://www.aha.org, is the main source for operationalization of the DEA input and output variables in the United States. However, the AHA database alone cannot provide all the necessary components for a robust model. Thus, other databases such as the Centers for Medicare and Medicaid Services (CMS), http://www.cms.hhs.gov, are necessary to identify the nature of the outputs, especially for inpatients through determination of case-mix for the hospitals. It should be also noted that, data elements collected by AHA changes overtime. For example, until the 1990s financial data that could determine the operational costs were reported. However, in later years, researchers could only obtain such data from the CMS database. Furthermore, reporting of some variables was also substituted with their variants, as is the case with the AHA, which no longer reports discharges but reports admissions.

These idiosyncrasies challenge practicing administrators and researchers to operationalize the inputs and outputs for a robust DEA model of hospital service production. However, culmination of the research to date demonstrates that most commonly agreed to and available variables from the mentioned databases are used to evaluate general hospital efficiency throughout the United States. Non-US examples appear to follow similar steps.

Based on this discussion, it is possible to create a nomenclature for performance evaluation and a robust DEA model that is operationalized for hospital sector in general.

8.3 Inputs and Outputs for General Hospitals

As it is briefly introduced in previous section, inputs of hospitals can be categorized in three major areas as: capital investments, labor, and operating expenses. Outputs, on the other hand, should reflect both inpatient and outpatient activity. Those hospitals which provide teaching function would be considered as extension to this model.

8.3.1 Hospital Inputs

Operationalization of three broad categories of inputs using AHA and CMS databases requires construction of variables and proxies. For example, the capital investment is a variable that not directly available from these data bases. State wide databases or hospitals in their accounting books may report this variable as "assets," however, value of assets depends on their recorded or acquisition time and their depreciation. Thus, using the book values of such investments do not reflect what is on the ground as a health service plant.

8.3.1.1 Capital Investments

Ozcan and Luke (1993) showed that one can estimate capital investments in a hospital using two indicators: (1) plant size, measured by number of operational beds, and (2) plant complexity, measured using number of diagnostic and special services provided exclusively by the hospital. These two proxy variables were tested using Virginia data to assess their approximation to actual assets of the hospitals in the state. Their assessment found significant association between the two proxies and hospital assets, thus validating these measures for capital investment. Although we will use same variables in defining our model, we will choose more commonly used names that correspond to current literature. For example, plant complexity will be referred as service-mix.

Beds. AHA database routinely provides operational beds in their annual survey reports, thus the measurement of this variable is readily available.

Service–mix. AHA database currently identifies up to 80 services that are offered by a hospital and provides coding that indicates whether these services are offered by the hospital or through the hospital by others. The key to the coding is whether the services are offered by the hospital, thus appropriate investment is in place. If the service is not offered or offered by others for this hospital, then it can be coded as zero (0), otherwise code would be one (1) indicating the service offering. By adding the number of services offered by the hospital, service-mix variable is created. The value of this variable technically can change from 0 to 80, however, 2004 AHA survey report we calculated the median number of service-mix for small, medium, and large hospitals as 9, 14, and 18, respectively.

8.3.1.2 Labor

Labor is the second major category for hospital inputs. Operationalization of this variable would be different in USA and other countries, especially in those where socialized medicine is practiced and physicians are the part of the labor force for the hospitals. In the USA, however, physicians generally are not hospital employees with an exception of chiefs and department heads. Thus, in evaluating the performance, it is prudent to attribute the labor as non-MD labor or their full time equivalents (FTEs). The number of non-physician FTEs employed by a hospital would cover all nursing, diagnostic, therapy, clerks and technical personnel. It is also prudent to remind the reader that some of the DEA studies used labor costs to measure this variable. Depending upon the location of the hospital and the availability of skill-mix, labor salaries may not accurately reflect this input variable. Thus, the labor costs would require regional or even state or city based adjustments. However, using FTEs overcomes this weakness.

FTEs. AHA database provides the total FTEs as well for various categories. Part time labor is converted to FTE by multiplying ½ of their numbers.

8.3.1.3 Operating Expenses

Operating expenses for hospitals can be obtained from CMS data base, however, to eliminate double counting, labor expenses and expenses related to capital investments such as depreciation should be subtracted from this amount. Ozcan and Luke (1993) labeled this variable as supplies indicating all necessary non-labor resources in provision of patient care. We label this variable as other operational expenses.

Other operational expenses. This variable provides the account for medical supplies, utilities, etc. to provide the services to patients.

8.3.2 Hospital Outputs

Inpatient and outpatient services constitute the majority of outputs for general hospitals that do not provide teaching function. Thus, each type of service needs to be accounted for in the hospital service production with appropriate measurements.

8.3.2.1 Inpatient

Inpatient services are easy to account for through admissions or discharges. However, not all patients arriving at the hospital require same level of attention and service. Some come for a day for a minor ailment, yet others go through major medical or surgical procedures. In order to account for this diversity in health service demand or its provision, we must account for severity for the admissions. CMS publishes case-mix index for hospitals each year. The case-mix indexed is calculated based on patient diagnostic related groups (DRGs) providing relative weight for acuity of the services provided by a hospital. For instance, if case-mix for a hospital is equivalent to 1.2, this means the hospital served 20% more acute patients than a standard hospital (compared to hospital with case-mix index value of 1). This measure is calculated based on Medicare and Medicaid patients, and since a good portion of the hospital revenues come from this source, we could extrapolate the case-mix index for the other patients of the hospital.

Case-mix adjusted admissions. This variable is created using admissions from AHA data base and multiplying them by CMS case-mix index. This way a hospital with 10,000 admissions a year and case-mix index of 1.2 would be reflected as 12,000 adjusted admissions. Similarly, a hospital with case-mix index of 0.9 and 10,000 admissions would be reflected as 9,000 adjusted admissions.

8.3.2.2 Outpatient

Outpatient visits are a readily available variable from AHA data base. Unfortunately it does not have case-mix adjustments as in inpatient, since the payment systems are not in a similar vein. Here, health care managers and researchers have options to differentiate the visits, indicating whether these are day surgery, emergency or routine visits. Unfortunately, most general databases do not differentiate the visits.

Outpatient visits. This variable is available from AHA data base as described. The ongoing identification of input and output variables for a robust hospital sector service production via DEA model is summarized in Fig. 8.1. This model includes two outputs and four inputs and encompasses the majority of the hospital service production processes.

In this model, hospital managers are in control of the assets of the hospital, its labor, medical supplies and associated operational expenses. Admitted patients and visits to clinics (outpatient) constitute its final outputs. Of course, in order to produce these outputs given inputs, many intermediate processes are to occur, and these processes involve clinical decisions largely controlled by physicians or other clinicians. The aim of the proposed model is to capture the managerial performance (although often affected by clinical decisions) that can be attributed to hospital management.

Using the model and its variants described in this section, various studies were conducted to date. Most of these studies were applied to acute and general hospitals while others targeted federal government run institutions such as veterans administration (VA) hospitals as well as department of defense (DoD) hospitals. Furthermore, hospitals with a teaching mission or Academic Medical Centers were also considered in various studies where outputs or inputs of the model adjusted accordingly. Ensuing sections of the chapter provide brief discussions of these studies, starting with acute general hospitals (8.4), government hospitals (8.6), and Academic Medical Centers (8.7).

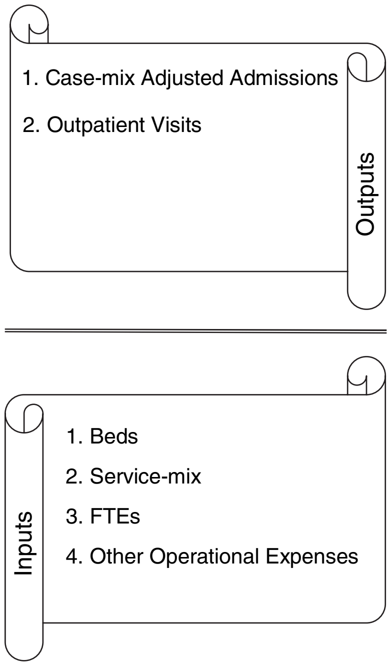


Fig. 8.1 Outputs and inputs for a robust hospital DEA model

8.4 Acute and General Hospital Applications

Acute and general hospital applications are the most frequently reported application area in health institution performance measurement. These studies can be grouped by their profit and non-profit, public comparisons as well as religious affiliations.

Grosskopf and Valdmanis (1987) conducted the first study comparing 82 public and not-for profit hospitals. This study showed that public hospitals were slightly more efficient (96%) than non-profit counterparts (94%). The results of Valdmanis (1990) study with 41 hospitals showed 98% efficiency for public hospitals compared to 88% for not-for-profit hospitals. Similarly, using 1989 AHA data base, Ozcan et al. (1992) and Ozcan and Luke (1993) found public hospitals were more efficient (91%) than church (87%), not-for-profit (88%), and for-profit (83%) hospitals.

These studies also intrigued further investigation of religious affiliation, and White and Ozcan (1996) examined the non-profit hospitals further by examining ownership by church and secular dimensions. This study examined 170 California hospitals using the variant of the robust model described above, and found that church based hospitals were more efficient (81%) than secular (76%) hospitals.

Using the DEA techniques learned in earlier chapters, and the robust hospital performance model presented in this chapter, we will show a hospital application example.

8.5 Large Size General Hospital Performance Evaluation

It is prudent to illustrate the robust model with recent data. This example follows the model presented in Sect. 9.3 for large acute and general hospitals in US. The data is drawn from 2004 AHA and CMS data bases. Few hospitals were deleted from consideration because of important missing information. This yielded 131 hospitals with 600 or more beds for evaluation of their efficiency. Table 8.1 summarizes the descriptive statistics for this group of hospitals.

Large US hospitals considered in this example have an average 805 beds and average 20 different services offered. They employ equivalent of 4,786 full time employees and spend over 311 million on their operational expenses not including labor. On output side, on average 61,767 adjusted (due to high severity) inpatient admissions and over one half million outpatient visits occurred to each hospital.

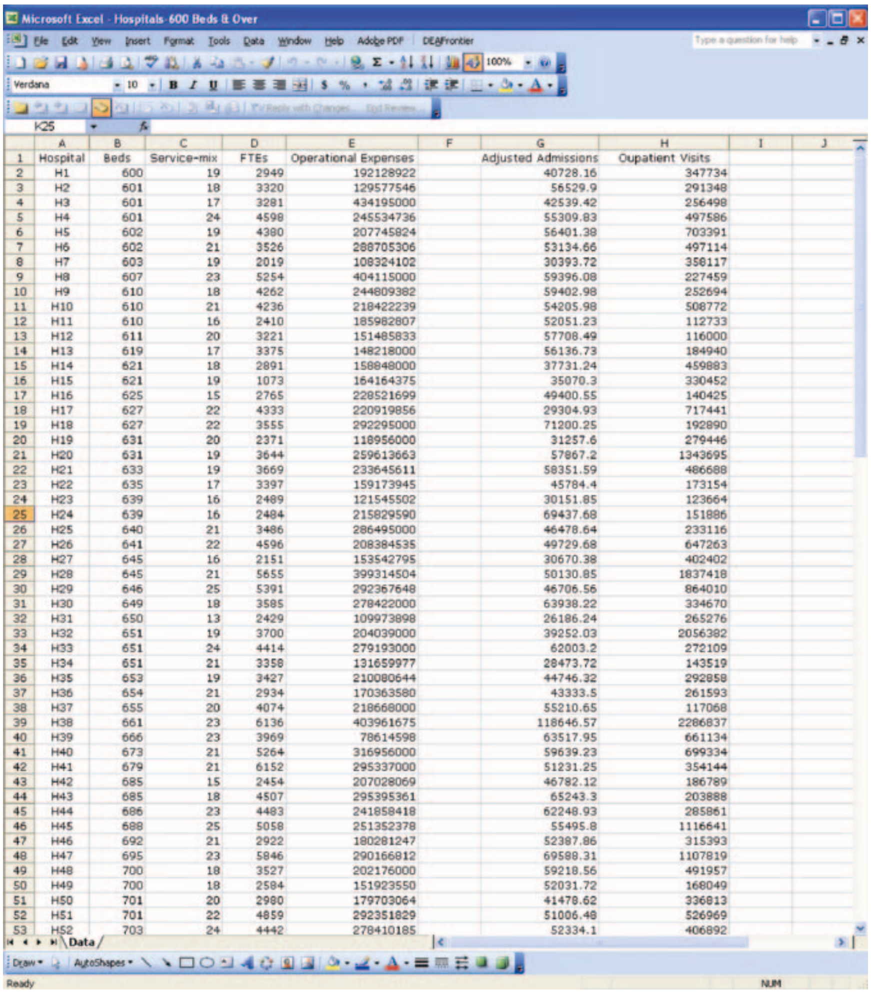
Although these 131 large hospitals account for about 2.6% of the non-federal hospitals, the total number of beds in these hospitals represents approximately 13.2% of all US non-federal hospital beds. Similarly, outputs of these 131 large hospitals constitute approximately 23% of all inpatient admissions and 12.6% of all outpatient visits in the US. Thus, evaluation of performance for large hospitals is important and may shed some light on health care performance, as well as identify excessive resources spent in this country.

Figure 8.2 displays a partial view of data input and set up for 131 hospitals with 600 or more beds for DEAFrontier software. Figure 8.3 provides also a partial view of the results of the efficiency evaluations for these hospitals. The reader can note that four inputs and two outputs are shown at the top of the results spreadsheet in this figure. The results are summarized in Table 8.2. Large hospitals' average efficiency scores were about 0.685, indicating on average 31.5% overall inefficiency. One hospital reported 66%, the worst inefficiency. Further description of efficiency is displayed in Table 2.4, where range of efficiency, number of hospitals and percentage of hospitals are reported. Only ten hospitals (7.6% of large hospitals) achieved a perfect efficiency score of one among their peers. Another five hospitals achieved

Table 8.1 Descriptive statistics for US hospitals with 600 or more beds (n = 131)

Statistics	Inputs				Outputs	
	Beds	Service-mix	FTEs	Operational expenses (in million $)	Adjusted admissions	Outpatient visits
Mean	805.2	20	4,786	311	61,767	556,350
St. Dev.	239.6	3	2,362	171	22,866	448,902
Min	600	13	1,073	5	15,268	101,581
Max	2,095	25	15,570	1,021	171,563	2,875,388
Total	105,476	2,628	626,924	39,542	8,091,472	72,881,823
US total[1]	800,000		4,000,000		575,000,000	35,000,000

[1]Approximate values based on AHA 2004 data.



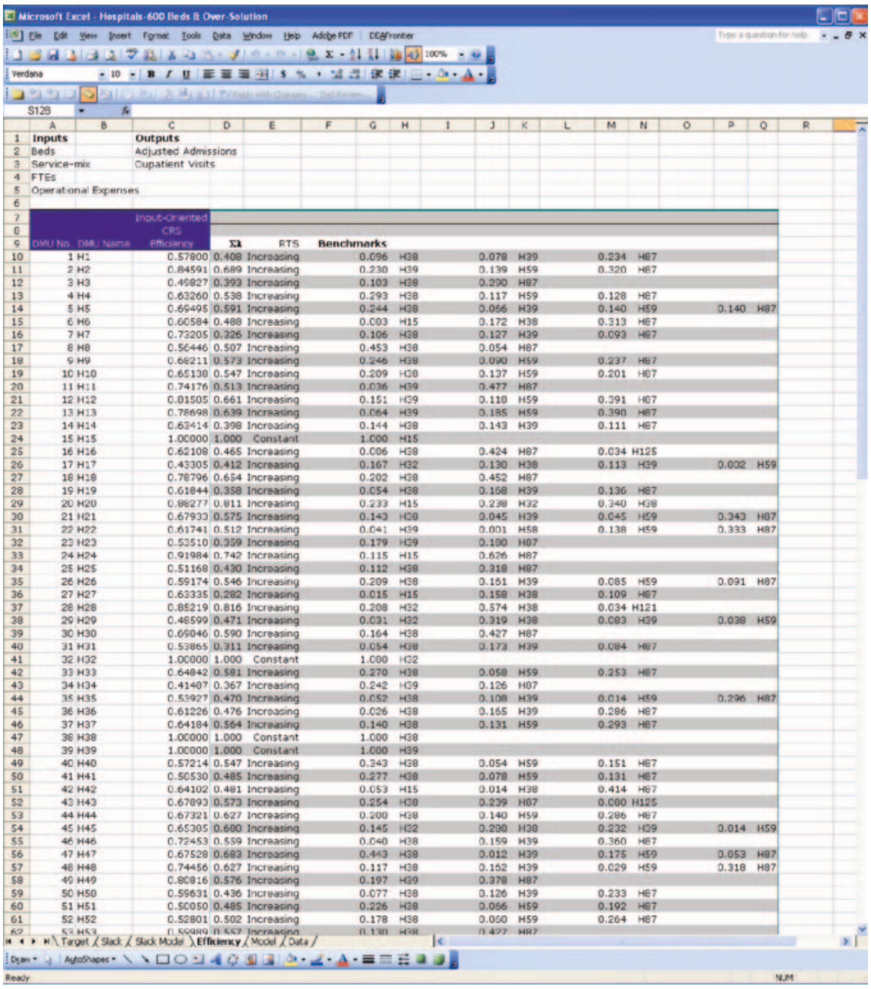
Hospital	Beds	Service-mix	FTEs	Operational Expenses	Adjusted Admissions	Oupatient Visits
H1	600	19	2949	192128922	40728.16	347734
H2	601	18	3320	129577546	56529.9	291348
H3	601	17	3281	434195000	42539.42	256498
H4	601	24	4598	245534736	55309.83	497586
H5	602	19	4380	207745824	56401.38	703391
H6	602	21	3526	288705306	53134.66	497114
H7	603	19	2019	108324102	30393.72	358117
H8	607	23	5254	404115000	59396.08	227459
H9	610	18	4262	244809382	59402.98	252694
H10	610	21	4236	218422239	54205.98	508772
H11	610	16	2410	185982807	52051.23	112733
H12	611	20	3221	151485833	57708.49	116000
H13	619	17	3375	148218000	56136.73	184940
H14	621	18	2891	158848000	37731.24	459883
H15	621	19	1073	164164375	35070.3	330452
H16	625	15	2765	228521699	49400.55	140425
H17	627	22	4333	220919856	29304.93	717441
H18	627	22	3555	292295000	71200.25	192890
H19	631	20	2371	118956000	31257.6	279446
H20	631	19	3644	259613663	57867.2	1343695
H21	633	19	3669	233645611	58351.59	486688
H22	635	17	3397	159173945	45784.4	173154
H23	639	16	2489	121545502	30151.85	123664
H24	639	16	2484	215829590	69437.68	151886
H25	640	21	3486	286495000	46478.64	233116
H26	641	22	4596	208384535	49729.68	647263
H27	645	16	2151	153542795	30670.38	402402
H28	645	21	5655	399314504	50130.85	1837418
H29	646	25	5391	292367648	46706.56	864010
H30	649	18	3585	278422000	63938.22	334670
H31	650	13	2429	109973898	26186.24	265276
H32	651	19	3700	204039000	39252.03	2056382
H33	651	24	4414	279193000	62003.2	272109
H34	651	21	3358	131659977	28473.72	143519
H35	653	19	3427	210080644	44746.32	292858
H36	654	21	2934	170363580	43333.5	261593
H37	655	20	4074	218668000	55210.65	117068
H38	661	23	6136	403961675	118646.57	2286837
H39	666	23	3969	78614598	63517.95	661134
H40	673	21	5264	316956000	59639.23	699334
H41	679	21	6152	295337000	51231.25	354144
H42	685	15	2454	207028069	46782.12	186789
H43	685	18	4507	295395361	65243.3	203888
H44	686	23	4483	241858418	62248.93	285861
H45	688	25	5058	251352378	55495.8	1116641
H46	692	21	2922	180281247	52387.86	315393
H47	695	23	5846	290166812	69588.31	1107819
H48	700	18	3527	202176000	59218.56	491957
H49	700	18	2584	151923550	52031.72	168049
H50	701	20	2980	179703064	41478.62	336813
H51	701	22	4859	292351829	51006.48	526969
H52	703	24	4442	278410185	52334.1	406892

Fig. 8.2 Data input and setup for hospitals with 600 and more beds for DEAFrontier

less than perfect efficiency, with an efficiency score above 0.9 but less than 1.00 (Table 8.3).

Figure 8.4 displays the efficient targets for the input-oriented CRS model. As the reader can observe, the target values for efficient hospitals are equivalent to their original input and output values (see hospitals H15, H32, H38, and H39 from the figures). Calculation of targets is the same as in the CRS model and they can be found in Chap. 2. For detailed formulation of these calculations, the reader is referred to Appendix B, Part 3.

One of the aims of DEA evaluation of performance is to find out how much unnecessary resources are used by each hospital and how much they lack in attracting patients to their facilities. Elimination of the excessive resource use and production



Microsoft Excel - Hospitals-600 Beds & Over-Solution

Inputs	Outputs
Beds	Adjusted Admissions
Service-mix	Outpatient Visits
FTEs	
Operational Expenses	

DMU No.	DMU Name	Input-Oriented CRS Efficiency	Σλ	RTS	Benchmarks							
1	H1	0.57800	0.408	Increasing	0.096	H38	0.078	H39	0.234	H87		
2	H2	0.84591	0.689	Increasing	0.230	H39	0.139	H59	0.320	H87		
3	H3	0.49827	0.393	Increasing	0.103	H38	0.290	H87				
4	H4	0.63260	0.538	Increasing	0.293	H38	0.117	H59	0.128	H87		
5	H5	0.69495	0.591	Increasing	0.244	H38	0.066	H39	0.140	H59	0.140	H87
6	H6	0.60584	0.488	Increasing	0.003	H15	0.172	H38	0.313	H87		
7	H7	0.73205	0.326	Increasing	0.106	H38	0.127	H39	0.093	H87		
8	H8	0.56446	0.507	Increasing	0.453	H38	0.054	H87				
9	H9	0.68211	0.573	Increasing	0.246	H38	0.090	H59	0.237	H87		
10	H10	0.65138	0.547	Increasing	0.209	H38	0.137	H59	0.201	H87		
11	H11	0.74176	0.513	Increasing	0.036	H39	0.477	H87				
12	H12	0.81505	0.661	Increasing	0.151	H39	0.118	H59	0.391	H87		
13	H13	0.78698	0.639	Increasing	0.064	H39	0.185	H59	0.390	H87		
14	H14	0.63414	0.398	Increasing	0.144	H38	0.143	H39	0.111	H87		
15	H15	1.00000	1.000	Constant	1.000	H15						
16	H16	0.62108	0.465	Increasing	0.006	H38	0.424	H87	0.034	H125		
17	H17	0.43305	0.412	Increasing	0.167	H32	0.130	H38	0.113	H39	0.002	H59
18	H18	0.78796	0.654	Increasing	0.202	H38	0.452	H87				
19	H19	0.61844	0.358	Increasing	0.054	H38	0.168	H39	0.136	H87		
20	H20	0.88277	0.811	Increasing	0.233	H15	0.238	H32	0.340	H38		
21	H21	0.67933	0.575	Increasing	0.143	H38	0.045	H39	0.045	H59	0.343	H87
22	H22	0.61741	0.512	Increasing	0.041	H39	0.001	H58	0.138	H59	0.333	H87
23	H23	0.53510	0.359	Increasing	0.179	H39	0.180	H87				
24	H24	0.91984	0.742	Increasing	0.115	H15	0.626	H87				
25	H25	0.51168	0.430	Increasing	0.112	H38	0.318	H87				
26	H26	0.59174	0.546	Increasing	0.209	H38	0.161	H39	0.085	H59	0.091	H87
27	H27	0.63335	0.282	Increasing	0.015	H15	0.158	H38	0.109	H87		
28	H28	0.85219	0.816	Increasing	0.208	H32	0.574	H38	0.034	H121		
29	H29	0.48599	0.471	Increasing	0.031	H32	0.319	H38	0.083	H39	0.038	H59
30	H30	0.69046	0.590	Increasing	0.164	H38	0.427	H87				
31	H31	0.53865	0.311	Increasing	0.054	H38	0.173	H39	0.084	H87		
32	H32	1.00000	1.000	Constant	1.000	H32						
33	H33	0.64842	0.581	Increasing	0.270	H38	0.058	H59	0.253	H87		
34	H34	0.41407	0.367	Increasing	0.242	H39	0.126	H87				
35	H35	0.53927	0.470	Increasing	0.052	H38	0.108	H39	0.014	H59	0.296	H87
36	H36	0.61226	0.476	Increasing	0.026	H38	0.165	H39	0.286	H87		
37	H37	0.64184	0.564	Increasing	0.140	H38	0.131	H59	0.293	H87		
38	H38	1.00000	1.000	Constant	1.000	H38						
39	H39	1.00000	1.000	Constant	1.000	H39						
40	H40	0.57214	0.547	Increasing	0.343	H38	0.054	H59	0.151	H87		
41	H41	0.50530	0.485	Increasing	0.277	H38	0.078	H59	0.131	H87		
42	H42	0.64102	0.481	Increasing	0.053	H15	0.014	H38	0.414	H87		
43	H43	0.67893	0.573	Increasing	0.254	H38	0.239	H87	0.080	H125		
44	H44	0.67321	0.627	Increasing	0.200	H38	0.140	H59	0.286	H87		
45	H45	0.65305	0.600	Increasing	0.145	H32	0.208	H38	0.232	H39	0.014	H59
46	H46	0.72453	0.559	Increasing	0.040	H38	0.159	H39	0.360	H87		
47	H47	0.67528	0.683	Increasing	0.443	H38	0.012	H39	0.175	H59	0.053	H87
48	H48	0.74456	0.627	Increasing	0.117	H38	0.162	H39	0.029	H59	0.318	H87
49	H49	0.80816	0.576	Increasing	0.197	H39	0.378	H87				
50	H50	0.59631	0.436	Increasing	0.077	H38	0.126	H39	0.233	H87		
51	H51	0.50050	0.485	Increasing	0.226	H38	0.066	H59	0.192	H87		
52	H52	0.52801	0.502	Increasing	0.178	H38	0.050	H59	0.264	H87		
53	H53	0.59989	0.557	Increasing	0.130	H38	0.427	H87				

Target / Slack / Slack Model / Efficiency / Model / Data

Fig. 8.3 Efficiency results for hospitals with 600 and more beds using DEAFrontier

Table 8.2 Summary of efficiency results

Statistic	Efficiency
Mean	0.685
St. Dev.	0.145
Min	0.340
Max	1.0

of more health services with given resources will improve efficiency of each hospital. In order to find the exact amount of the excess resource (input) use and lack of outputs, we can subtract the target values of each input and output variable presented

Table 8.3 Magnitude of efficiency

Efficiency level	Hospitals	Percent
1.0	10	7.6
$\geq 0.9 - < 1.0$	5	3.8
$\geq 0.8 - < 0.9$	9	6.9
$\geq 0.7 - < 0.8$	22	16.8
$\geq 0.6 - < 0.7$	48	36.6
$\geq 0.5 - < 0.6$	29	22.1
$\geq 0.4 - < 0.5$	7	5.3
< 0.4	1	0.8
Total	131	100

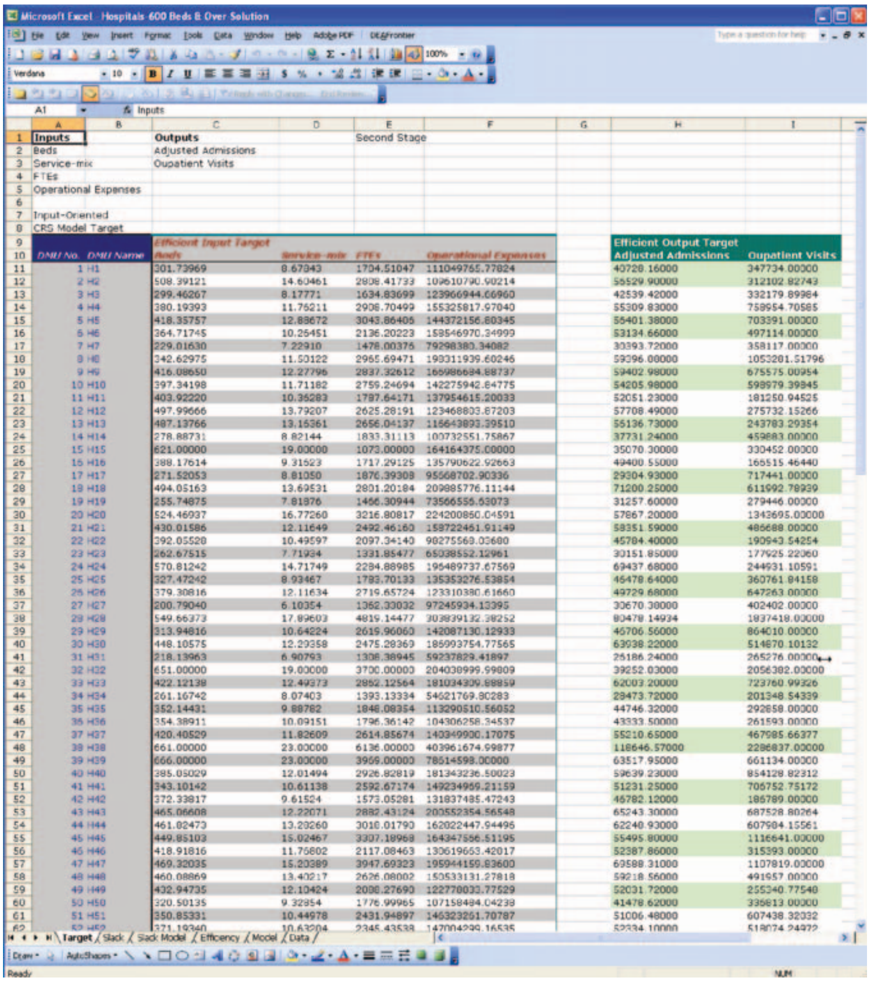


Fig. 8.4 Efficient targets for hospitals with 600 and more beds using DEAFrontier

				Inefficiencies		
		Excessive Inputs			Shortage of Outputs	
Hospital	Beds	Service-mix	FTEs	Operational Expenses	Adjusted Admissions	Oupatient Visits
H1	-298.3	-10.3	-1244.5	-81079156.2	0.0	0.0
H2	-92.6	-3.4	-511.6	-19966755.1	0.0	20754.8
H3	-301.5	-8.8	-1646.2	-310228055.3	0.0	75681.9
H4	-220.8	-12.2	-1689.3	-90208918.0	0.0	261368.7
H5	-183.6	-6.1	-1336.1	-63373667.2	0.0	0.0
H6	-237.3	-10.7	-1389.8	-130158335.7	0.0	0.0
H7	-374.0	-11.8	-541.0	-29025721.7	0.0	0.0
H8	-264.4	-11.5	-2288.3	-205803060.4	0.0	825822.5
H9	-193.9	-5.7	-1424.7	-77822697.1	0.0	422881.0
H10	-212.7	-9.3	-1476.8	-76146296.2	0.0	90207.4
H11	-206.1	-5.6	-622.4	-48028191.8	0.0	68517.9
H12	-113.0	-6.2	-595.7	-28017029.1	0.0	159732.2
H13	-131.9	-3.8	-719.0	-31574106.6	0.0	58843.3
H14	-342.1	-9.2	-1057.7	-58115448.2	0.0	0.0
H15	0.0	0.0	0.0	0.0	0.0	0.0
H16	-236.8	-5.7	-1047.7	-92731076.1	0.0	26090.5
H17	-355.5	-13.2	-2456.6	-125251153.1	0.0	0.0
H18	-132.9	-8.3	-753.8	-82409223.9	0.0	419102.8
H19	-375.3	-12.2	-904.7	-45389443.4	0.0	0.0
H20	-106.5	-2.2	-427.2	-35412803.0	0.0	0.0
H21	-203.0	-6.9	-1176.5	-74923149.1	0.0	0.0
H22	-242.9	-6.5	-1299.7	-60898377.0	0.0	17789.5
H23	-376.3	-8.3	-1157.1	-56506949.9	0.0	54261.2
H24	-68.2	-1.3	-199.1	-19339852.3	0.0	93045.1
H25	-312.5	-12.1	-1702.3	-151141723.5	0.0	127645.8
H26	-261.7	-9.9	-1876.3	-85074154.4	0.0	0.0
H27	-444.2	-9.9	-788.7	-56296860.9	0.0	0.0
H28	-95.3	-3.1	-835.9	-95475371.6	0.0	0.0
H29	-332.1	-14.4	-2771.0	-150280517.9	0.0	0.0
H30	-200.9	-5.7	-1109.7	-91428245.2	0.0	180200.1
H31	-431.9	-6.1	-1120.6	-50736068.6	0.0	0.0
H32	0.0	0.0	0.0	0.0	0.0	0.0
H33	-228.9	-11.5	-1551.9	-98158690.1	0.0	451652.0
H34	-389.8	-12.9	-1964.9	-77038207.2	0.0	57829.5
H35	-300.9	-9.1	-1578.9	-96790133.4	0.0	0.0
H36	-299.6	-10.9	-1137.6	-66057321.7	0.0	0.0
H37	-234.6	-8.2	-1459.1	-78318099.8	0.0	350917.7
H38	0.0	0.0	0.0	0.0	0.0	0.0
H39	0.0	0.0	0.0	0.0	0.0	0.0
H40	-287.9	-9.0	-2337.2	-135612763.5	0.0	154794.8
H41	-335.9	-10.4	-3559.3	-146102030.8	0.0	352608.8
H42	-312.7	-5.4	-880.9	-75190583.5	0.0	0.0
H43	-219.9	-5.8	-1624.6	-94843006.4	0.0	483640.8
H44	-224.2	-9.7	-1465.0	-79035970.1	0.0	322123.2
H45	-238.1	-10.0	-1750.8	-87004811.5	0.0	0.0
H46	-273.1	-9.2	-804.9	-49661583.6	0.0	0.0
H47	-225.7	-7.8	-1898.3	-94222652.2	0.0	0.0
H48	-239.9	-4.6	-900.9	-51642868.7	0.0	0.0
H49	-267.1	-5.9	-495.7	-29145516.2	0.0	87291.8
H50	-380.5	-10.7	-1203.0	-72544580.0	0.0	0.0
H51	-350.1	-11.6	-2427.1	-146028567.3	0.0	80469.3

Fig. 8.5 Calculation of inefficiencies

in Fig. 8.4 from the original data of input and outputs shown in Fig. 8.2. Figure 8.5 displays partial view of results for the inefficiencies. As the reader can note, the negative values in inputs indicates that they must be reduced by that amount. Shortage of outputs, on the other hand, requires augmentation of the outputs by the indicated amount.

Although Fig. 8.5 provides an excellent prescription for individual hospitals for their course of action towards efficiency, we can also study the impact of these efficiencies for a larger economy. As indicated before, these 131 large hospitals account for approximately 13.2% of all US non-federal hospital beds, 23% of all inpatient admissions and 12.6% of all outpatient visits in the US. Thus, improvement of overall inefficiency for the large hospitals in the health care industry would contribute

Table 8.4 Excessive inputs and shortage of outputs for US hospitals with 600 or more beds

Statistics	Excessive inputs				Shortage of outputs	
	Beds	Service mix	FTEs	Operational expenses (in million $)	Adjusted admissions	Outpatient visits
Mean	304	7	1630	111	0	103,712
St. Dev.	183	4	1217	104	0	191,205
Total	39, 867	931	213,516	14,566	0	13,515,586

significantly to this sector. To view this from a macro perspective, we can summarize the values obtained from Fig. 8.5.

A summary of excessive inputs and lack of outputs for all 131 large hospitals is shown in Table 8.4. As the reader can note, a total value on the last row indicates the total excessive input or total shortage by all 131 hospitals. Results show that collectively large hospitals can reduce beds by 39,867 from 105,476 existing beds shown in Table 8.1. Additionally, 931 services can be curtailed while FTEs can be reduced from 626,924 by 213,516 (a 34% reduction). Furthermore, large hospitals must reduce non-labor operational expenses by 14.5 billion dollars. These findings are similar to Ozcan (1995), who determined that at least 3% of health care costs in the GDP are due to inefficiencies created by the excessive buildup of providers.

Although there is no shortage of inpatient admissions, to achieve efficiency the large hospitals must attract 13.5 million more outpatient visits (augmentation of output). This way outpatient visits should increase from current 72.9 million visits to 86.4 million visits. This means more care should shift to outpatient by some hospitals (see H2, H3, H5 and so on in Fig. 8.5).

8.6 Federal Government Hospitals (VA and DoD)

A study by Burgess and Wilson (1993) evaluated 32 veterans administration (VA) hospitals and compared them to non-federal hospitals (n = 1445). Ozcan and Bannick (1994) compared VA hospitals to DoD hospitals (n = 284). A Burges and Wilson study showed that VA hospitals were more efficient (91.8%) than their non-government counterparts (84.9–88.0%). On the other hand, Bannick and Ozcan (1995) showed that defense hospitals (n = 126) were generally more efficient (87%) than VA (n = 158) hospitals (78%). Due to different size and comparison groups, it is hard to generalize the results on a comparison of government to non-government hospitals. Even within a government hospital framework, there might be idiosyncrasies that should be accounted for in the comparisons. Bannick and Ozcan (1995) provide useful discussion on the homogeneity and heterogeneity of DoD vs. VA hospitals. Nevertheless, due to funding and administration differences, comparison of non-government hospitals to non-governmental acute care hospitals may produce misleading results. Thus, the VA or DoD hospitals should be only compared among themselves.

Ozcan and Bannick (1994) in an earlier study used DEA to evaluate trends in DoD hospital efficiency from 1998 to 1999 using 124 military hospitals, with data from the American Hospital Association Annual Survey. This study used the model described earlier, and included army, air force and navy hospitals in the comparison. They found that average efficiency ranged from 91 to 96% among these three services.

Coppola (2003) conducted a DEA study of military hospitals using 1998–2002 data. In his study, he selected the following input variables: costs, number of beds in the military facility, FTEs, and number of services offered. For output variables, he included surgical visits, ambulatory patient visits (APVs), emergency visits, case mix adjusted discharges (CMAD), and live births. Data was obtained from the US DoD and 390 facilities were included in the study. Cappola's study found that 119 (31%) of the hospitals were efficient. Air Force hospitals were leading with 92% efficiency while Navy hospitals were recorded at 87%. Average efficiency gradually declined from 91% in 1998 to 89% in 2002.

Up to this point, the studies were conducted at the strategic level under a different operational paradigm prior to the large-scale adoption of managed care. In the most recent work in the area of MTF, Fulton (2005) analyzed the performance of 17 U.S. Army Community Hospitals and seven Army Medical Centers over a 3-year period, 2001–2003. Fulton's model, however, uses different approach than Coppola's and evaluates from the managed care perspective by including quality, patient satisfaction, readiness measure, relative value units (RVUs) and relative weighted product (RWP), and GME training as outputs. His inputs include cost and enrollment/population measures as a non-discretionary input. The VRS input-oriented model yielded 97.6% efficiency while an output-oriented VRS model showed 98.9% efficiency. According to Fulton, the results suggest that about $10 million reduction in cost could have been achieved in 2001.

Depending upon the purpose of the efficiency evaluation, models deployed by various researchers utilized the variants of the essential inputs and outputs presented in the robust model shown in Fig. 8.1.

8.7 Academic Medical Center Applications

Academic Medical Center application of DEA is another variant of the model presented above. The only difference in this model is capturing the training or teaching output (Morey et al. 1995). This particular variable can be captured in terms of resident MD and dentist FTEs from AHA data base. This begs the question, then, of if this variable should be considered just as output (teaching function of the Academic Medical Centers)? Others may also argue that these FTEs provide an immense resource for the hospitals, thus they can also be considered as input. To test these assertions, in separate studies Ozcan (1992) and Valdmanis (1992) performed sensitivity analysis to test the impact of using teaching variable (FTEs) as input, output or

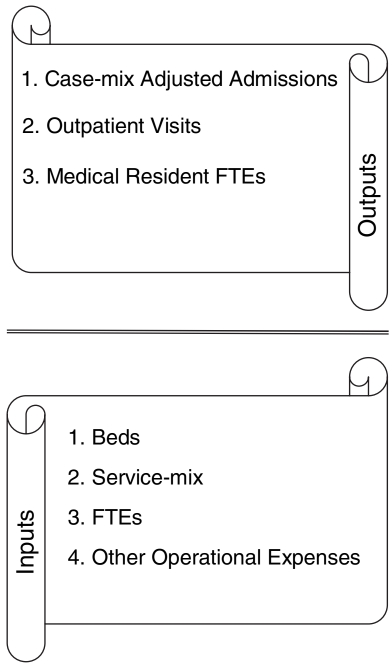


Fig. 8.6 DEA model for Academic Medical Centers

both. Both studies showed that using input, output, or both did not affect efficiency scores dramatically, other than having the effect of the additional variable. Thus, not to over inflate efficiency scores, a more prudent approach would be including the variable only one time. Since the teaching is an important output for Academic Medical Centers, using the variable as output seems a more reasonable approach. Hence, we can identify medical resident FTEs as teaching output for Academic Medical Centers as shown in Fig. 8.6.

8.8 Summary

This chapter provided general guidance for a robust hospital performance model and its operationalization using generally available data basis. Furthermore, development of these models is connected to research conducted during the past several decades. Using the robust model presented, efficiency of large size US hospitals is also examined. Variation of the models for federal government hospitals and Academic Medical Centers are also discussed.

Chapter 9
Physician Practice and Disease Specific Applications

9.1 Introduction

Physician practice applications to date were limited due to the complicated nature of accounting the performance in physicians and available data. Physician practice applications are also often referred to as clinical applications or primary care physician (PCP) models in the literature. Although physician practice on specific disease is often the main focus of the applications in this area (Chilingerian, 1995; Ozcan, 1998; Ozcan et al., 2000), more generic models of physician production were also modeled (Chilingerian and Sherman, 1997b).

Starting with diagnostic related groupings (DRGs) in the 1980s for the hospital payments, in the 1990s the US federal government extended the fixed pricing mechanism to physicians' services through resource based relative value schedule (RBRVS) to achieve efficiency in health care delivery. The aim of these pricing mechanisms is to influence the utilization of services and control the payments to hospitals and professionals. However, the effective cost control must be accompanied by a greater understanding of variation in physician practice behavior and development of treatment protocols for various diseases (Ozcan, 1998).

Patient outcomes research and studies of variations in clinical practice eventually resulted in development of guidelines to disseminate information to practitioners for diseases which are common and/or costly for overall treatment of the condition (AHCPR, 1994). Over the past several decades, researchers have demonstrated differences in the patterns of care being delivered for the same disease by physicians in the US. One of the most probable causes for this variation in the use of health care resources is differing physician practice styles. There is a growing concern about the efficiency in which health care services are delivered, thus inefficiencies emanating from the varying practice styles should be identified. DEA methodology helps us not only to identify the efficient practices, but also using multiplier (weight restricted) models, one can further evaluate the impact of specific policy decisions (such as payment mechanisms to enforce utilization patterns) in health care.

DEA has also been used in healthcare for evaluation of physician practice patterns. Although limited research has been fielded, considerable potential is available to healthcare leaders. Chilingerian and Sherman (1997a) employed DEA to benchmark physician practice patterns as a potential approach for cost containment. They were able to demonstrate that some specialists practicing as primary care providers (PCPs) were more efficient than some general practitioner PCPs. In addition, Chilingerian and Sherman (1997a) were able to use DEA modeling in the identification of opportunities to manage high cost groups as a means of controlling costs. They estimated potential resource savings of about 30% if all PCPs in the health maintenance organization (HMO) studied were to adopt the best practice patterns associated with the efficient PCPs.

As shown in the previous chapter for hospitals, conceptualization of a model for production of services needs to be identified for physician practices. This model will identify service production for this sector of providers and operationalize inputs and output measurements from available databases.

There are many challenges for practicing administrators and researchers to operationalize the inputs and outputs for a robust DEA model for physician practice service production. Culmination of research to date demonstrated most commonly agreed and available variables from claim based data bases to evaluate physician efficiency for common diseases such as otitis media (Ozcan, 1998), sinusitis (Ozcan et al. 2000), asthma (Ozcan et al. 1998), cardiac surgery (Chilingerian et al. 2002), and overall primary care (Chilingerian and Sherman, 1997b).

9.2 Production of Services in Physician Practice

Inputs and output of physician practice follow the same logic used in hospital production, where patient treatments are measured as outputs, and the resources used to produce these treatments as inputs. The only difference in production of the services between hospitals and physician practice is that we will be modeling the physician as DMU rather than the organization (either solo, or group practice). In addition, this model can be applied to a specific disease that is under evaluation or to type of practice, such as primary care.

Physicians make decisions for each patient visit. These decisions include ordering various diagnostic tests, therapeutic interventions and medications. Thus, depending upon the disease, patients' condition and physicians training, the magnitude of diagnostic, therapeutic and prescription orders will vary. Hence, evaluating performance of a physician who treats only a specific disease to a generalist physician should be avoided. However, this does not preclude evaluation of specific disease treated by specialist and generalists (say PCPs). As long as a patient panel represents the treatment of a specific disease by different types of practitioners, one should be able to make comparisons.

When a specific disease is targeted for physician evaluation, the next step is to identify the inputs or the resources used to treat the patient. Patient treatment generally occurs over time. We may call these episodes or encounters.

In order to analyze the practice behavior of physicians, claims data must be converted to an episode base for each patient. This way, one can detect the patterns of services by each physician provider. Since episodes of patients are different in terms of severity, one also has to identify those patients in various severity categories, retrospectively, at this stage. These severity categories will serve as a case-mix adjustment for the model outputs, as they will be explained later in discussion of outputs.

9.2.1 Physician Practice Inputs

An episode of a common disease starts with a visit to the physician's office, and various laboratory and radiological tests may be ordered. Some episodes of the diseases may be concluded in short time with a follow-up visit, say 3–4 weeks, yet others may take up to 3–6 months or longer. Depending upon the test findings, therapy and/or medications would be ordered. Some cases would be referred to a specialist. Again, depending upon the condition of the patient, other ambulatory clinics or hospitalization may be required. During the episode of the disease, the patient's condition may worsen, and emergency room interventions may be required. Utilization (variation) of these services also depends on practice behavior and training and experience of the physician, and his or her approach to risk (malpractice concerns). To simplify the unit of analysis, physician would be identified as a DMU, and all resource consumption occurred during an episode attributed to his/her credit as a PCP.

9.2.1.1 PCP Visits

One of the main ingredients in the service production of physician practice is the patient visit to physician office. Depending upon the definition of the episode length of a disease, patients may have multiple visits either requested by their PCP or their self initiatives. Every visit claim made by PCP's office to insurance companies (public or private) would register as an encounter in the claims database.

9.2.1.2 Specialists Visits

A patient referred to a specialist by a PCP or patient initiated specialist visit occurred during an episode is considered as resource consumption attributable to PCP's practice. Each of these would register as specialist visit encounters in the database.

9.2.1.3 Ambulatory Clinic Visits

Some physicians refer their patients to ambulatory clinics which are more technologically equipped than their offices. Thus, when this occurs, the number of ambulatory clinic visits by patients during the episode would be attributed to PCP.

9.2.1.4 Emergency Room (ER) Visits

When medical emergency situation arise such that PCP or the PCP office is not equipped to handle, they refer the patient to emergency room; this could happen during office hours or when a patient goes to the ER when the office is closed (nights and weekend or vacation). If the patient's condition is sub-acute, and does not require hospitalization, the patient is discharged from the ER after appropriate care. When the patient's condition is acute and requires hospitalization after initial care in the ER, the patient is admitted. If these occurrences are connected to the ongoing disease episode, the number of ER visits would be attributed to PCP.

9.2.1.5 Hospitalization

If the patient's condition is acute, the PCP may decide to admit the patient to a hospital for treatment, or the patient may be admitted through the ER. When such an occurrence is connected to the ongoing disease episode, the number of patient hospitalizations would be attributed to PCP.

9.2.1.6 Laboratory Tests

The number of diagnostic tests, including various blood chemistry tests, culture tests, etc., ordered by the PCP connected to the ongoing episode of care would be accumulated and attributed to the PCP.

9.2.1.7 Radiology

The number of diagnostic or therapeutic radiology encounters ordered by the PCP connected to the ongoing episode of care would be accumulated and attributed to the PCP.

9.2.1.8 Medications

The cost of medications prescribed for the condition during the episode of care would be accumulated and attributed to PCP.

9.2.1.9 Durable Medical Equipment

If the patient's condition requires durable medical equipment such as portable oxygen units, wheel chairs, etc., ordered by the PCP and connected to the ongoing disease episode, cost of these would be attributed to the PCP.

9.2.2 *Related Costs for Visits, ER, Hospitalizations, Lab and Radiology, Medications, and Durable Medical Equipment*

Although visits, emergency room encounters, hospitalizations, and lab and radiology tests can be used as count variables in the physician performance model, having their associated costs provides more enhanced information to observe the economic differences between efficient and inefficient providers. These additional cost variables would be used in a post-hoc analysis to assess impact of efficiency. Ozcan (1998) showed that average total cost of otitis media treatment of an episode by efficient providers amounted to $357. On the other hand, for inefficient providers, the same treatment cost was $492; the cost was about 38% higher for inefficient PCPs.

9.2.3 *Physician Practice Outputs*

Physician practice outputs are the patients that are in varying acuity conditions. Thus, it is prudent to differentiate the patients who seek health care for the particular disease or condition.

To accomplish this task procedure, codes for the physician claims need to be reviewed and categorized into severity groups based on categories from the current procedural terminology (CPT) manual. CPT coding incorporates level of complexity in medical decision-making for outpatient and inpatient services. Based on the complexity level of decision-making, one can associate severity of the patient. A typical example of this is low, medium and high decision-making complexity as a guide to identify the severity of each patient encounter as severity 1–3, respectively (Ozcan, 1998). However, we must recognize that there may be a problem regarding the encounter severity scores due to CPT upcoding (CPT code creep) by physicians. Further discussion about this possibility and suggested solution is shown in the Appendix at end of this chapter.

Chilingerian and Sherman (1997b) and Sherman and Zhu approached case-mix and severity adjustment using a simpler approach. They classified the patients based on gender and age groups and the sheer counts of patients in these age-gender based categories formed their seven outputs. In another study, Chilingerian et al. (2002) used DRG 106 and DRG 107 to identify low and high severity coronary by-pass graft (CABG) discharges with and without catheterization in four outputs.

The ongoing identification of input and output variables for a physician practice service production via DEA model is summarized in Fig. 9.1. This general model includes three outputs and nine inputs and encompasses the majority of the physician service production processes.

This model can be applied to various diseases to evaluate groups of physicians' performance for a particular disease. In the next section, three examples from literature will be shown.

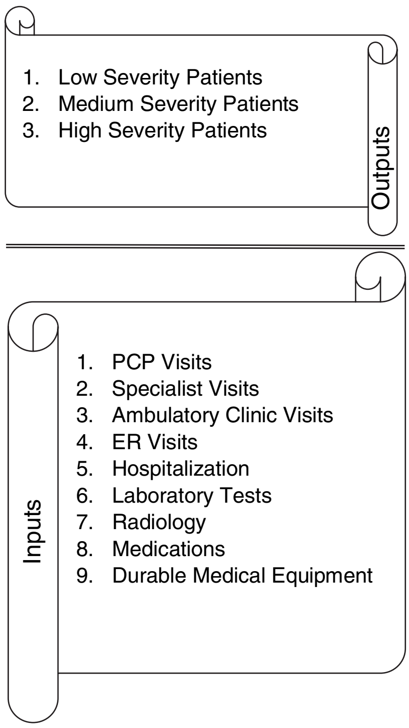


Fig. 9.1 Outputs and inputs for a physician practice DEA model

9.3 Physician Practice Applications

The three applications of the physician practice model shown in Fig. 9.1 are applied to the specific diseases of: (1) otitis media, (2) sinusitis, and (3) asthma. Each disease's episode time and input (resource) usage may vary. Thus, for each disease, the model needs to be adjusted.

9.3.1 Measuring Physician Performance for Otitis Media

While there may be several different ways of treating patients, there is a growing emphasis on the effectiveness and efficiency of health care services, and these variation studies illustrate that there is an opportunity to identify best care practices, which optimize resource use while obtaining acceptable outcomes.

To illustrate this point, let us assume, in a very simple manner, that otitis media can be treated with a combination of primary care (PCP) visits and medications. Of course, there are many other resources (e.g., specialist visits, laboratory tests, hospitalization for severe cases) that may be needed to complete treatment. Furthermore,

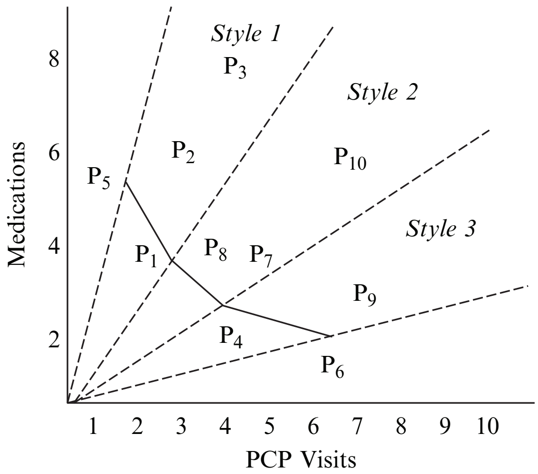


Fig. 9.2 Physician practice styles (source: Ozcan, 1998)

there may be differences in outcomes for otitis media treatment (e.g., cured cases, partially cured cases). There are multiple inputs to treatment and multiple outputs of outcome. These issues will be addressed after we introduce the concept. To assist in the conceptualization of practice styles using a combination of inpatient and primary care visits, we will first assume a uniform outcome, and we will later relax this assumption.

In order to fully explore best physician care practices, let us consider a hypothetical situation shown in Fig. 9.2, which depicts ten physicians who use varying combinations of the two resources to treat a specific disease. For example, physician P_5 utilizes five units of medications in conjunction with two primary care visit. Physician P_8 utilizes these resources in a different way, with four units of medications and four primary care visits, while physician P_6 uses two units of medications and six primary care visits. Based on each physician's preference (or practice behavior/style) of medications vs. primary care visits in the treatment of this disease, one can group physician practice styles.

In this case, Fig. 9.2 displays three different possible styles based on these practice behaviors. Given a practice style, let us say style 2, we observe variation in resource utilization within the practice pattern. For example, physician P_{10} treats a condition by utilizing six units of medications and seven primary care visits, while physician P_1 achieves the same result with four units of medications combined with three primary care visits. Given practice style 2, one can argue that physician P_{10} is practicing less efficiently when compared to physician P_1. Similar arguments can be made for physicians P_7 and P_8 for style 2. The same concept can also be extended to other styles. This conceptualization of practice styles recognizes historical variations, but it seeks reduction in inefficiencies once the style is identified. Although the reduction of inefficiencies is the primary goal when reducing the consumption of costly resources, one must identify all the efficient physicians from each practice style in order to achieve this reduction. With the physicians who are identified as efficient practitioners, we can form a "treatment possibilities frontier." Figure 9.2 illustrates such a frontier with physicians P_5, P_1, P_4, and P_6. This frontier is the efficiency frontier. Given their practice styles, there is no other physician who can practice with fewer resources than those on the frontier. The remaining physicians could change their practice behaviors in order to become more efficient.

To further develop this concept, one can challenge the more extreme or costlier practice styles. For example, from the cost perspective, style 1 would be preferred to style 2. From another perspective, style 1 and style 3 might be considered as outlier styles (one as risky, the other one as costly), and style 2 might be accepted as the standard. Thus, style 2 can be called the "quality assurance region" of practice behavior. The reader should note that reference to cost implies payments made by third party payers (e.g., government or private insurance) for the services, not the actual cost of producing the services.

In our discussions there will be two main areas of focus. The first is simply looking at physicians involved in the treatment of otitis media and determining which physicians are indicated as efficient and inefficient in regards to input consumption and output production. The second examination will look at weigh restricted DEA models and the ability to direct physician behavior towards practice styles found to be technically efficient.

9.3.1.1 Efficiency Focus

The measures for the otitis media evaluation include the number of treated patient episodes categorized to three distinct (low, medium, and high) severity levels (outcome measures) as outputs. The number of PCP visits, specialist visits, hospitalizations, laboratory tests, and medications (prescriptions) consists of the input measures. Separately, the costs of inputs were tracked. The unit of analysis is the physicians who treated at least 100 cases of otitis media. The DMUs for the evaluation was 160 PCPs. Figure 9.3 displays the outputs and inputs for a physician practice for otitis media.

Analysis of 160 PCPs showed that indeed there is a practice variation for those PCPs with a panel of 100 and more patients. Of the 160 PCPs, 46, or 28.8%, were classified as efficient. The remaining 114, or 71.2%, were classified as inefficient compared to efficient PCPs. Given the levels of comparable inputs, the inefficient PCPs, on average, could have treated an additional 21.6 low severity, 4.4 medium severity and 0.3 high severity otitis media episodes. Similarly, compared to efficient producers of otitis media treatment, the inefficient PCPs, on average, used excessive amount of inputs. For example, an average inefficient PCP's patients collectively use 118.2 PCP visits, 4.5 specialist visits, 94.6 hospitalizations, 324.3 prescriptions and 91.9 lab procedures in excess than the benchmark created by efficient frontier PCPs.

Since physicians do not have control over who is going to appear in their office for diagnosis and treatment, we could set aside the issues related to outputs that could have been produced. However, it is necessary to examine the factors that

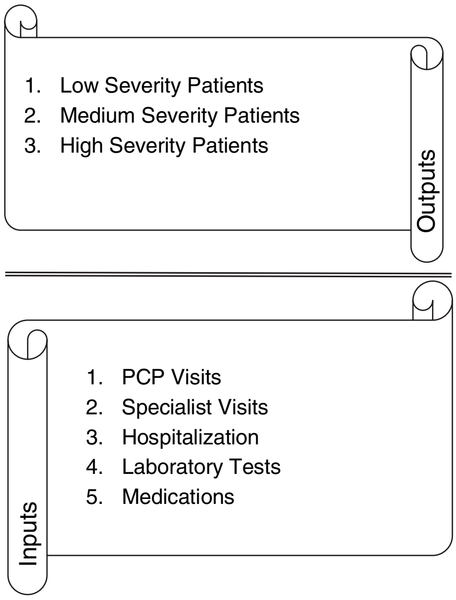


Fig. 9.3 Outputs and inputs for a physician practice – otitis media model

the PCPs have control over, given the patient's condition of severity. For detailed discussion of these, the reader is referred to (Ozcan, 1998).

To gain a better understanding of efficient and inefficient practices, resources consumption per patient among efficient and inefficient PCPs was analyzed for three severity panels. The inefficient providers, irrespective to severity panel, tend to use higher amounts of PCP visits, hospitalization, and prescriptions. PCPs with low and medium severity panels use more lab procedures per patient than efficient ones. Only one inefficient PCP with a high severity panel used less lab procedures per patient than its comparable efficient peers.

To examine the service production differences between efficient and inefficient PCPs, overall output production and resource consumption can be analyzed. In this evaluation, efficient PCPs treated, on average, more medium and high severity patients. On the other hand, inefficient PCPs treated, on average, more low severity patients, although the difference is insignificant. In sum, there is a clear pattern in excessive resource consumption by inefficient PCPs, which suggests that their clinical practice for otitis media needs re-tooling by examining the practice patterns of the efficient providers, or by continuing education and adherence to established clinical guidelines.

Similar to analysis of input consumption, examination of the cost of the inputs used by PCPs indicates that payments made by third-party payers (insurers) to PCPs, specialists and pharmacies are significantly higher for inefficient PCPs. The payments made to hospitals and laboratories for those patients treated by inefficient PCPs were also higher but not significant. In general, an insurance company or network provider who is seeking cost efficient and effective care providers for inclusion/exclusion of such providers to their panel of PCPs would generally look to total cost of treatment. In this case, average total cost of otitis media treatment of an episode by efficient providers amounted to $357, whereas it was $492 for inefficient providers, a $135 (38%) difference. With over 25 million otitis media related visits in a year, this is not a sum that can be ignored by the health care industry.

9.3.1.2 Behavior Focus

In our previous example, illustrated in Fig. 9.2, there are ten PCPs and three practice styles. Practice style 3 can be defined as a PCP strictly preferred model (Fig. 9.4). Here primary care visits are designated as the preferred type of treatment, taking preference over everything else, especially over medications. This particular style's ratio constraints can be defined as PCP visits over specialty visits, PCP visits over hospitalization, PCP visits over medications, and PCP visits over laboratory tests. When restricted by these preferred ratio constraints the efficiency frontier would only include that section, creating the desired practice style.

Style 2 can be defined as a balanced primary otitis media model as shown in Fig. 9.5. This style of behavior has ratio constraints that prefer PCP visits over specialty visits, PCP visits over hospitalization, medications over specialty visits, laboratory test over specialist visits, and specialist visits over hospitalization. Again, implementing these constraints comparisons of physician behaviors are done in respect to the frontier within style 2.

To create the preferred ratio constraints that are used to define the practice styles, DEA weights (also referred to as prices or multipliers) are utilized. The desired ratio(s) are calculated using the input or output weights from each DMU. Then,

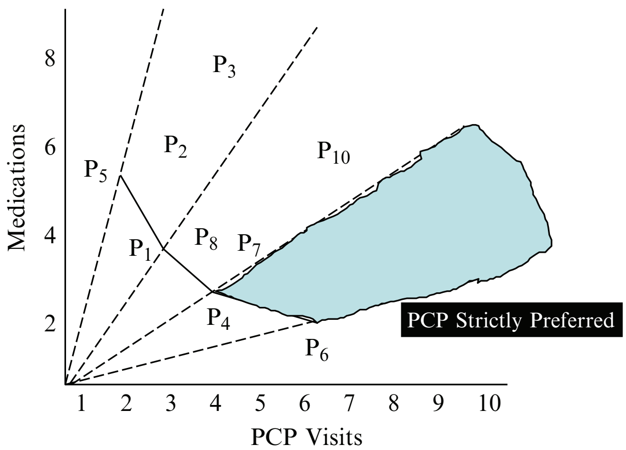


Fig. 9.4 PCP strictly preferred otitis media model (source: Ozcan, 1998)

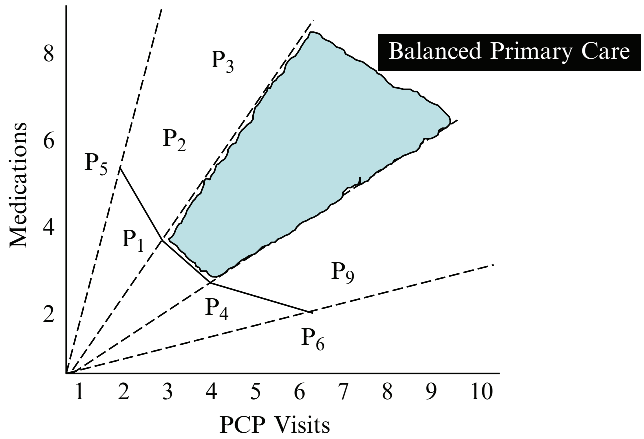


Fig. 9.5 Application of weight restrictions through multiplier model: (source: Ozcan, 1998)

for each ratio created the minimum, first quartile, median, third quartile, and maximum values should be calculated. These values illustrate the distribution of the ratio and give the researcher options on what level to restrict it. How much restriction is placed on a particular ratio depends on the distribution level selected (usually median or third quartile values are selected initially); this application used median values. These newly restricted ratios can be plugged back into the DEA model and restrict the use of those certain inputs and outputs needed to reach the efficiency frontier.

9.3.1.3 Implication of Weight Restricted Practice Styles

It is seen that the cost for treatment of an otitis media episode for both efficient and inefficient providers decreases as the models shift from practice as usual to a strict PCP style, and finally to a balanced primary care model. By restricting particular inputs and outputs, and directing all physicians to treat otitis media through a balanced primary care model, physicians would be able to provide the same quality care at a average savings of $93.10 per efficient and $21.53 per inefficient provider episode compared to the average cost achieved in the treatment of otitis media as usual.

The key is getting physicians to change their practice behavior so it falls within the output and input ratios that such a preferred style needs. This can be done by providing education to physicians on the necessary changes and creating financial incentives for those physicians that maintain ratios within practice style specifications.

Further studies can be conducted using such data sources that do not only evaluate a PCPs performance on one disease category but also a majority of the PCP's practice yielding an overall report card for the PCP in a given year. Using the 20/80 rule, one can determine for a given type of PCP 20% of the diseases which encompass 80% of the PCP's business. In this manner, a solid report card system generation mechanism can be established. This report card would provide more sincere and reliable measurement of physician efficiency since the foundation of the methodology relies on optimization (Ozcan, 1988).

9.3.2 Measuring Physician Performance for Sinusitis

Sinusitis is another common health complaint with high treatment expenses. Thus, it is prudent to evaluate physician practice efficiency in managing patient care for this disease. Evaluations by researchers shed some light on physician practice in this area by examining the generalist vs. specialist care, as well as regional variations. Past research has indicated that specialty care is more expensive, since they have adopted clinical protocols that result in higher utilization of services. In addition, specialty training has also been associated with more intensive care than generalist care.

Whether PCPs or specialists provide more efficient care is investigated by Ozcan and associates (Ozcan et al. 2000). Physician-level data was obtained from 1993 Medicaid claim files. Several decision rules were used to eliminate cases that did not meet study criteria (i.e., if a non-MD claim preceded a MD claim by more than 2 months, or if no MD claim was encountered during 1993). DEA was used to examine the utilization of PCP visits, specialist visits, ER visits, laboratory test, and medications in the treatment of sinusitis, which is the inflammation of our sinuses that often presents initially as a common cold. PCPs were generalists and specialists were otolaryngologists and they comprised the DMUs in this evaluation.

There were five input and three output variables as detailed in Fig. 9.6. The three output variables were organized into the three levels of severity based on CPT codes while adjustments made for the potential for up-coding (see Appendix for details). Physician level data was constructed from claim files and those physicians with less than ten treatments of sinusitis in a year were removed from evaluation. These yielded 176 physicians (DMUs) of 152 were generalist and 24 were otolaryngologist for the final evaluation.

CRS-input oriented model results showed that 38 (25%) of the generalist were providing efficient care based on this model with an average cost of $442 per episode. Only five (21%) of the 24 otolaryngologist were efficient and cost of their treatment per episode averaged $720. More interestingly, cost per episode for inefficient generalists and otolaryngologist was much higher than their efficient counterparts. The inefficient generalists' cost of treatment per episode was $693 (57% higher than efficient generalist) and their average efficiency score was 0.71. The inefficient otolaryngologist provided services at average cost of $769 (only 7% higher than efficient otolaryngologist) and their average efficiency score was 0.73. It should be noted that about two-thirds of these costs were medication costs.

The main conclusion was that there are no differences in technical efficiency between generalists and specialists in the treatment of sinusitis. However, specialists tend to use more resources and hence, incur higher service costs. A possible explanation for the specialist's using more resources was the higher acuity of their patients compared to generalists.

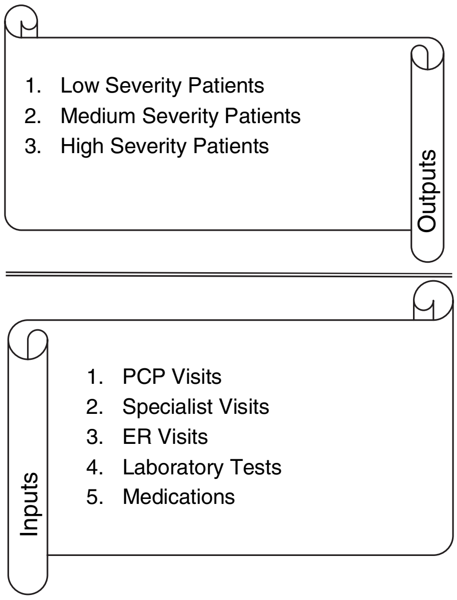


Fig. 9.6 Outputs and inputs for a physician practice – sinusitis model

In a separate evaluation, using the same group of physicians (n = 176) and the same model presented in Fig. 9.6. Pai et al. (2000) evaluated the effect of practice variation in sinusitis treatment for metropolitan vs. rural locations across the four regions of State of Virginia. About 55% (98) physician practices were in metropolitan areas, others were in rural locations.

Results showed that 24 (32%) of the physicians located in metropolitan areas were providing efficient care with an average cost of $340 per episode. Only 19 (32%) of the 77 rural physicians were efficient and cost of their treatment per episode averaged $644. On the other hand, the cost per episode for inefficient metropolitan and rural physicians was much higher than their efficient counterparts. The inefficient metropolitan physicians' cost of treatment per episode was $603 (77% higher than efficient physician) and their average efficiency score was 0.75. The inefficient rural physicians provided the services at average cost of $830 (38% higher than efficient metropolitan physicians) and their average efficiency score was 0.66. It should be noted that the 61% of the costs were for medication for efficient metropolitan physicians, but 71% for efficient rural physicians. The percentages of costs for medication for inefficient metropolitan and rural physicians were, 69 and 73%, much higher than their efficient counterparts. Inefficient physicians located in Southwest region of the state were in most dire need for improving performance. The observed regional differences were attributed to lack of laboratories and competition (for medication dispensing) in rural regions of the state.

9.3.3 Measuring Physician Performance for Asthma

Community variation in treating asthma, as with many other medical conditions, has been noticed by researchers. In the Boston, Massachusetts area, evaluation of pediatric bronchitis/asthma admission rates was noticed by Payne and associates (Payne et al. 1995). They determined approximately 4.4% of admissions for bronchitis/asthma is inappropriate. In addition, sharp decreases in admission rates were experienced once the key hospital-staff were notified of the research findings. Community variation leads many medical researchers and health care leaders to question the components of medical care and search for what constitutes the best practice of medicine. In addition, many healthcare leaders begin to think of potential cost savings if best practices are adopted.

Coventry, Weston, and Collins compared costs of treating asthma patients across different treatment settings (Coventry et al. 1996). Using CPT codes and a database consisting of payments made under the Civilian Health and Maintenance Program for the Uniformed Services (CHAMPUS), the authors evaluated the cost of pediatric asthma care in four treatment settings: physician office, emergency room, hospital outpatient, or unknown. The cost of treating patients in each of the settings varied dramatically. For example, the amount paid for a physician office visit was $36, while the amount paid for treatment of pediatric asthma in a hospital outpatient setting was $153, and in the emergency room, the payment was $182.

A study by Ozcan and associates (Ozcan et al. 1998b) using 1995 Medicaid claims from Virginia conducted an evaluation of PCP performance. The claim files contained all related visits, hospitalizations and other resources used to treat the asthma patients. Files also contained detailed information regarding the date of service, identifier codes for provider and patient, procedure and diagnoses codes, as well as charge and payment information for each of the services provided. Descriptions of variables and measures used in this evaluation are shown in Fig. 9.7. As mentioned earlier, related costs for each of the input variables were available.

All diagnosis (ICD-9-CM) codes from 49,300 to 49,391 were used to extract providers who treated patients for asthma in 1995 (American Medical Association, 1995). The extraction of data generated 309,240 claims which can be classified as follows:

- 38.43% were for office visits,
- 1.12% were for emergency room visits with subsequent hospitalization,
- 4.73% were for emergency room visits without subsequent hospitalization,
- 0.90% were for hospitalization without immediately preceding emergency room visits,
- 2.37% were for clinic visits, and
- 52.44% were for medications.

A Current Procedure Terminology, 1995 (CPT-1995) manual was used to categorize patient severity. CPT coding incorporates three complexity levels for the medical decision-making process. For example, low decision-making complexity occurs in

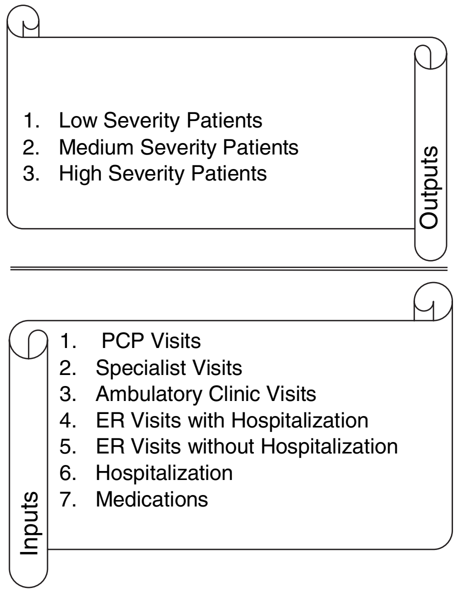


Fig. 9.7 Outputs and inputs for a physician practice – asthma model

a quarterly follow-up office visit for a 45-year-old male established patient, with stable chronic asthma, on steroid and bronchodilator therapy. Such a visit might require 15 min of face-to-face time with the patient, whereas in moderate complexity cases 25 min of face-to-face time might be required. In contrast, high complexity decision-making typically requires 40 min of face-to-face time with the patient. Based upon the complexity of the medical decision-making process, three categories of severity were developed:

- Low, with a severity score equal to 1;
- Medium, with a severity score of 2; and
- High, with a severity score of 3.

The following decision rules were employed to construct an episode of asthma care:

1. The chronology of the events. If the first claim filed in 1995 was not for physician service, it was excluded from the current episode of treatment since it could be included in an earlier (1994) episode.
2. If a non-physician claim preceded a claim for a physician by more than 2 months, it was classified as the end of a previous episode.
3. If no physician claim was encountered in 1995, then such a recipient was deleted from the study database.
4. If a patient changed their PCP and was subsequently treated by a different PCP in a new time window without any referral during 1995, a new episode of care was created and subsequent claims were attributed to the second PCP.

By employing decision rules, all multiple claims to a specific provider were aggregated. The aggregated provider based recipient claims constituted 110,209 utilization records classified as follows:

- 67.93% for PCP visits,
- 2.65% for specialist visits,
- 1.66% for emergency room visits with subsequent hospitalization,
- 4.56% for emergency room visits with no subsequent hospitalization,
- 1.02% for hospitalization with no immediately preceding emergency room visit,
- 1.69% for clinic visits, and
- 20.48% for medications.

A PCP is defined as a general practice, internal medicine, and/or pediatric physician who treated asthma patients as evidenced in the data files. In addition to PCPs, a specialist might behave as a PCP when providing health care to asthma patients. In either case, all claims filed in chronological order for the patient were attributed to that particular physician. Reference to claims files was previously made. PCP use of a specialist referral was attributed when a specialist filed a claim for compensation subsequent to a compensation claim filed by a PCP. For the aggregated physician claims, 29.84% were filed by general practitioners, 40.21% by internists, 19.68% by pediatricians, and 10.27% by specialists.

PCPs who treated less than 50 asthma patients in a year were considered infrequent providers of asthma services and were deleted from the final database. The rationale for this cut-off point is simply that the performance of a physician may not be representative of physician capabilities when adequate numbers of patients are not treated. As a consequence, medical decision-making skills related to diagnosis and treatment of asthma may be sacrificed at the expense of a different practice pattern for the physician. After removing infrequent physicians from the database, 277 physicians remained for final analysis. Of the physicians remaining, 274 physicians were classified as PCPs and three physicians were classified as specialists. Analyses were carried out using only PCPs.

Table 9.1 presents the descriptive statistics for both outputs and inputs when treating asthma patients. On average, in 1995 PCPs in the final database were attributed with:

- Treating 767 patient visits to PCPs,
- Referring 48 patient visits to specialists,
- Four patients who had emergency room visits with subsequent hospitalization,
- Fifteen patients who had emergency room visits only,
- Seventeen patients who were seen in the ambulatory clinics,
- Five patients who were admitted to hospital directly, and
- Prescription of 1,205 medications in 1995.

These activities were for a panel of 135 patients consisting of 106 classified as low severity, 19 classified as medium severity, and ten patients who were classified as high severity. Costs associated with treatment of asthma patients in this evaluation were higher than those identified by Coventry et al. (1996) in their study, however,

Table 9.1 Descriptive statistics for asthma episodes

Variables	Mean (std. dev.) N = 274
Outputs	
Low severity patients	107.36 (103.79)
Medium severity patients	19.36 (22.76)
High severity patients	10.53 (14.19)
Inputs	
Primary care physician visits	767.33 (1005.22)
Specialist visits	48.54 (94.06)
Emergency room visits followed by subsequent hospitalization	4.51 (6.98)
Emergency room visits only	15.70 (22.43)
Hospitalizations with no immediately preceding emergency room visits	4.82 (12.56)
Clinic visits	16.85 (52.69)
Prescriptions	1205.82 (1367.95)
Average Costs (in $)	
Primary care physician visits	139.40 (117.76)
Specialist visits	486.00 (1658.55)
Emergency room visits followed by subsequent hospitalization	2579.03 (4076.26)
Emergency room visits only	241.80 (375.32)
Hospitalizations not immediately preceding emergency room visits	2611.47 (5267.38)
Clinic visits	228.43 (690.26)
Prescriptions	1206.03 (1417.73)
Total average cost	1070.31

pattern was nearly identical – physician office treatment was least costly, followed by hospital clinic visits, emergency room, and admission. Within this database, the average PCP cost paid for the respective visits is broken down as follows:

- \$139.40 for a PCP office consultations,
- \$486.00 for specialist visits,
- \$2,579.03 for emergency room visits followed by hospitalization,
- \$241.80 for emergency room visits only,
- \$2,611.47 in charges for patients admitted to hospital directly,
- \$228.43 for clinic visits, and
- \$1,206.03 for medications.

Input-oriented CRS DEA model was evaluated, and the results of the average CRS efficiency score was 0.86 (Table 9.2). The model identified 156 (56.93%) physicians as efficient, whereas 118 (43.06%) were considered inefficient. The efficiency score for inefficient DMUs averaged 0.68. In the model, 79 DMUs were categorized as providing constant returns to scale (CRS), 141 DMUs were classified as providing decreasing returns to scale (DRS) and 57 DMUs were classified as providing increasing returns to scale (IRS).

The inefficient physicians, on average, treated 8.68 fewer low severity patients, 4.41 fewer medium severity patients, and 2.36 fewer high severity patients less than their efficient physician counterparts. The inefficient physicians tended to use more

Table 9.2 Efficiency results

Efficient DMUs		n = 156	56.93%
Inefficient DMUs		n = 118	43.06%
Variables	n	Mean	Std. Dev.
Efficiency			
Efficient DMU included	274	0.861	0.232
Efficient DMU excluded	118	0.677	0.257
Output shortages			
Low severity patients	20	8.68	5.66
Medium severity patients	50	4.41	3.69
High severity patients	45	2.36	1.95
Input excess			
PCP visits	4	415.52	237.38
Specialist visits	50	62.65	88.86
ER visits with hospitalization	45	3.86	5.04
ER visits only without hospitalization	35	7.6	8.04
Hospitalization without ER visits	50	6.77	15.08
Ambulatory clinic visits	34	29	54.02
Medications	52	783.1	1064.1

Table 9.3 Total increase and reduction in outputs, inputs and cost for inefficient PCPs

Variable	Increase	Reduction	Savings ($)
Outputs			
Low severity patients	1,024		
Medium severity patients	520		
High severity patients	278		
Inputs			
PCP visits		49,031	6,850,121
ER use with hospitalization		455	1,166,738
ER use without hospitalization		897	214,724
Cost			
Medications			53,201
Total Potential Savings in $			8,284,784

resources compared to efficient physicians. For example, the excesses (in comparison to efficient physicians) included:

- 415.52 PCP visits,
- 62.65 specialist visits,
- 3.86 emergency room visits followed by hospitalization,
- 7.60 emergency room visits only,
- 6.77 direct hospitalization,
- 29.00 clinic visits, and
- 783.10 prescriptions.

Table 9.3 presents the number of asthma patients in three categories of severity the inefficient PCPs should increase in order to bring their practice to the efficiency frontier; 1,024 for low severity; 520 for medium severity; and 278 for high severity.

It can be further broken down to a reduction in inputs of 49,031 PCP visits, 455 emergency room visits followed by hospitalization, and 897 emergency room only visits.

As for the costs associated with caring for asthma patients, there were no significant differences for most input variables except for medication payments. Inefficient PCPs tended to generate charges (payments) higher than their efficient peers. However, the use of medications was not determined to be a significant variable. This implies that inefficient PCPs tended to prescribe more expensive medicines for the patients they see. The inefficient physicians may, for example, prescribe at the same rate as their efficient peers; however, the inefficient providers may be prescribing more expensive medications when less expensive medications will afford the same outcome. One possible explanation for this is that inefficient physicians may be prescribing medications, for which there are no commercially available generic substitutes, thus resulting in higher payments for brand-name medications. If the inefficient PCPs were brought to the efficiency frontier, there could be a potential saving of $53,201 in payments for medications. The figures are derived by multiplying the number of inefficient providers (118) with the mean values discussed above.

Although payments made for treatments did not vary significantly between efficient and inefficient providers, is easy to see that a reduction of inputs previously identified would save considerable sums of money for the Medicaid program. The savings would potentially come from reduced numbers of payments made for office visits. For example, if the inputs for PCP visits could be reduced by 49,031 and the Medicaid program saved the cash payment average of $139.71 (Table 9.1) for each visit, the resulting savings would theoretically exceed $6,850,000. Similarly, a reduction of 455 emergency room visits with subsequent hospitalization at a savings of $2,564.26 per reduction would result in a potential net savings of $1,166,738.30. Finally, if a reduction of inputs for emergency room only visits could be reduced by 897 visits, a hypothetical savings of approximately $215,000 could be realized. In total, the potential savings would be $8,284,784. Obviously reaching the best-practice frontier would be extremely difficult, if not impossible, though substantial room for improvement is evident and potential exists for significant savings from current program expenditures.

9.3.3.1 Limitations

A difficult issue to address in many healthcare studies which rely on secondary, or administrative data, is that relating to adjusting the data for differences in patient severity of illness. Patient severity is an important adjustment to be made due to differences in resource consumption, mortality, etc., and is generally performed on the basis of the patient mix considering age, gender, race, or other readily available methods. Typically, sicker patients consume more resources than patients who are not as severe. Asthma patient severity is clinically gauged based largely upon the patient's peak expiratory flow rate (PEFR). According to the NIH, chronic mild asthma results in PEFRs that are $\geq$80% of the individual's personal best or individual norms. Chronic moderate asthma results of PEFRs in the 60–80% of patient personal best (or individual norms) and chronic severe asthma is indicated when PEFRs are <60% of personal bests/individual norms (National Institutes of Health, 1991). In consideration of resource consumption, a truly severe asthma patient, as determined by clinical indicators, may initially be seen in the emergency room, and failing satisfactory progress with treatment, might be admitted to the intensive care unit. Less clinically severe patient may be treated in the emergency room and released. Yet another patient diagnosed with asthma may be able to perform regular daily living activities or compete in world-class athletic events with only a few regular follow-up visits with their physician to discuss any problems they may have noticed and perhaps receive a medication refill. These examples of three patients with three clearly different levels of resource consumption poignantly identify the need for an accurate method of adjusting data for severity of illness when comparing resource utilization across physicians. In addition, the same patient can, on diverse occasions, present either asymptomatic or as experiencing mild, moderate, or severe asthma attacks.

In most administrative databases, however, such as the data employed in this evaluation, clinical measures of illness severity are not readily available. As a consequence, using CPT codes as an indicator of the level of decision-making required to determine the severity of the patient may not accurately reflect physiological conditions of a patient in terms of their severity. Furthermore, it is thought that physicians may be tempted to up-code to a higher level of complexity in order to maximize reimbursement for the procedure or office visit. Consequently a patient visit coded as medium severity may actually be low severity in terms of the guidelines found in the CPT coding manual. In a case study by Robinette and Helsel, up-coding rates for 1991 were as high as 7.4%. Specifically, they looked at situations where a 99,245 consultation code was billed when a 99,215 office visit would have been more appropriate (or cases where initial office visits were charged for established patients). Following review, the authors noted a precipitous drop in up-coding rates, and by the fifth quarter, found only. 1% up-coding (Robinette and Helsel, 1992). On the other hand, a patient with a tendency to experience severe episodes of acute asthma may only require a brief (low severity) office visit (due to their past experiences with asthma (and education) for expensive medications to prevent acute exasperation of the disease.

Coding visits to the emergency room for severity and coding hospital admissions for severity becomes a bit more tedious. CPT codes do not differentiate these areas as to whether or not they consist of a high degree of decision-making expertise or a low degree of decision making expertise. The tendency to consider emergency room visits and hospitalizations as higher severity treatment than a standard office visit might initially appear logical; after all, a patient must be pretty sick to present to the emergency room. In consideration of the data obtained, this may not be a valid assumption, since many Medicaid patients do not have PCPs who follow the patient on a regular basis in a physician office setting. Instead, the Medicaid patient may have a tendency to be seen in the emergency room, even if only for a medication refill. Albeit an inefficient delivery mechanism for routine care, many Medicaid patients simply do not have the benefit of an assigned PCP. Admittedly, this may be changing with the implementation of capitated payment mechanisms for Medicaid patients which require their enrollment on the practice panel of a PCP. Despite the difficulties associated with using CPT codes, patient severity as identified in our study did meet our expectations that the majority of patients would be classified as low severity, followed by a smaller number of medium severity patients, and an even fewer number of high severity patients.

9.3.3.2 Summary of the Asthma Evaluation

Overall, 57% of the physicians were efficient and 43% were inefficient in this study. We found that inefficient PCPs in Virginia who treated 50 and above Medicaid asthma patient encounters treated fewer patients visits and prescribed medications, which resulted in higher payment for medications than the efficient PCPs did during 1995. Moving inefficient physicians to the efficiency frontier as practiced by their peers has the potential of considerably decreasing Virginia's annual expenditure for treatment of patients diagnosed with asthma.

In order to improve their efficiency, the inefficient PCPs should increase their production function, i.e., increase the number of patient encounters they treat. In addition, all physicians should be encouraged to engage in comprehensive patient education/health education programs as an effective preventive measure. Perhaps when a system of reimbursement is fully implemented which encourages providers to educate the patient, thus reducing the need for service utilization, educational programs will play a more vital role in physician practice patterns for treatment of asthma. In addition, physicians and other practitioners who prescribe medications should always actively consider providing medications that provide the desired physiological response while considering the financial impact of their prescribing habits.

Further consideration should be given to the study of asthma treatment practice efficiency. Especially in the area of patient education, based on the amount of education provided to patients, one can assess how much practice efficiency could be achieved. It is also suggested that future studies risk adjustment based upon clinically valid measures of disease severity, rather than on complexity of the medical decision making process. In addition, an interesting area for further research would be to compare provider efficiency based how frequently they follow clinical practice guidelines (e.g., all the time, some of the time, or never).

9.4 Summary

This chapter provided general guidelines for a physician practice performance model, and its operationalization using generally available claim databases. Furthermore, development of these models connected to research conducted in the past. Using the presented model, several applications of disease specific physician practice models were discussed including: otitis media, sinusitis, and asthma.

Appendix J: CPT Based Claim Processing and Data Development (Source: Ozcan, 1998)

J.1 Procedures for Development of an Episode

The development for CPT based severity classification requires structuring multiple visits to a particular provider within the time frame (i.e., year). For example, a patient could have two visits to one provider, and six months later he/she can go to another provider. Thus, all multiple claims to a specific provider should be aggregated to single level claim file for the PCP.

In the subsequent stage of data structuring, claims would be sorted based on the recipient's age (in terms of calendar days) at the time of service and the claim patterns would be examined. In the chronology of events based on aggregated provider claims, different patterns would be identified to develop decision rules for the identification of episodes, hence the inclusion/exclusion of various claims to the final database. Decision rules associated in this stage include:

- In the chronology of the events if non-physician claims were preceded by a physician claim, and they were more than usual episode time apart (2 months for otitis media), they can be ruled out as the end of an earlier episode which the provided time window did not have sufficient information to build as part of the current episode.
- If no physician claim is encountered, then the whole claim stream for the particular recipient can be deleted.

These decision rules enabled physician claims to serve as the trigger for the start of an episode. On the next level, the decision rules assessed whether the encounter with the physician was with a PCP or a specialist. One can also observe that there could be instances when specialists are acting as PCPs.

Once the PCP is identified in the claim stream, all claims should be followed in the chronology of the claims for the recipient that were attributed to that PCP. These should include referrals to specialists, ER, inpatient hospitalization, pharmacy, and lab claims. The same patient, however, could change his/her PCP in time and go to another PCP in a different time window within the evaluation period. Claims following such instances can be attributed to those PCPs who were taking care of the new patient, hence a start of a new episode. If a claim was filed by a specialist following a claim by an internist, pediatrician or family/general practitioner, this particular claim can be attributed to a PCP as part of specialist use in the treatment of care.

Since the unit of analysis for the evaluation is PCP, the final aggregation of the data should be conducted by identifying a number of recipients for each physician who acted as the PCP for the patient's episode. This way, for the relevant disease, patient panels for each PCP during an evaluation period can be identified (Ozcan, 1998).

J.2 CPT Code Creep

The prospective payment system (PPS) has always depended on the accurate reporting of clinical diagnoses and procedures. If errors are present in the reporting process, over-reimbursement or under-reimbursement of services can occur. Since the implementation of the PPS, there have been increases in the average case mix index. Because each percent increase in the case mix index corresponds to large growth in revenue for providers (Carter et al. 1990) this increase has been closely examined.

Payers of health care services are concerned that a majority of this change is due to upcoding. Upcoding, or code creep, is when a provider bills for services that are more extensive or intensive than the ones really performed; services are coded as higher weighted diagnoses, tests, or procedures, when there is no change in the actual resources needed or used. Payers believe that much of the case mix increase has occurred because the PPS gives providers an incentive to code more completely, and in cases of ambiguity, to assign the most highly or complex weighted diagnosis or procedure as principal. On the other hand, providers have argued that most of the change in the case mix index is correct, and reflects a mix of more complex cases. They believe the increase has transpired because with the implementation of managed care, the less complex, lower weight cases have been moved outside the traditional medical setting.

Recent evidence tends to illustrate that most of the rise in the case-mix index is true (Carter et al. 1990). Studies have found that on average, only one-third of claims are found to have coding errors (Bailey, 1990; Hsia et. al. 1992; Siwolop, 1989; Shwartz et al. 1996) and that this number can fall below ten percent when dealing with some CPT codes (Javitt et al. 1993). Providers may have under-coded prior to PPS because it made little difference in their payment. The implementation of PPS may have promoted doctors to be more accurate about diagnosing and classifying procedures in order to get the proper reimbursement. Nevertheless, in order to overcome the possibility of CPT code creep we devised an adjustment algorithm so that the severity of the patients was near to actual occurrences.

J.3 Adjustment Algorithm

The number of PCPs identified needs to be clustered for post-hoc evaluation based on the severity weight class of the patient panels they have seen during the year. The clustering can be done using an index of severity measure which incorporates a weighted volume of patients from each severity class. More specifically, it is assumed that the PCP's workload for the patients in the second tier of severity would be three times as much, relative to the first peer. Similarly, the PCP's workload for patients in the third tier would be three times that of the second tier's severity or nine times those of the first tier's severity. Using the following weighing formula, each PCP's volume/severity workload can be indexed (I_i), and the cluster weight (C_j) for each PCP can be calculated as follows:

$$I_i = \frac{w_i}{\sum_{i=1}^{n} w_i / n} \quad i = (1, \ldots, 3)$$

$$C_j = \sum_{j=1}^{m} P_{ij} * I_i \quad (i = 1, \ldots, 3;\ j = 1, \ldots,\ m)$$

where P_{ij} represents the number patients in the ith class of severity for the jth PCP.

As an example, the index values (I_i) calculated in Ozcan (1998) using 160 PCPs were 0.23, 0.69, and 2.08 for respective severity categories. Cluster weight distribution (C_j) ranged from 0.2016 to 0.7479. Results of the adjustment algorithm showed six PCPs were classified in the high severity/volume cluster, 22 PCPs in the medium, and the remaining 132 PCPs were designated to the low severity/volume cluster. This representation fit reasonably well to expectations.

Chapter 10
Nursing Home Applications

10.1 Introduction

"Nursing home facilities provide care to people who can't be cared for at home or in the community and for most people this care generally is to assist people with support services such as dressing, bathing, and using the bathroom, for people who can't take care of themselves due to physical, emotional, or mental problems" (http://www.medicare.gov).

Nursing homes are significant health care providers in developed nations. As the life expectancy of the population has increased over the years, demand for nursing home services has also increased. The population of the US over 65 years old has increased to about 10% during the past decade. The number of people over 85 years old increased by more than 1/3 (36.8%). The percentage of persons with out-of-pocket expenses was the largest in age group over 65 years; more than 96% of persons over 65 had out-of-pocket expenses that were more than $1,000 (Health, United States, 2005).

There are over 1.5 million residents of nursing homes over 65 years old, and more than half of them are over 85 years old. In US national health expenditures, nursing home care expenditures amounts to $110.8 billion in 2003. Kemper et al. (2005/2006) noted that as the leading edge of the baby boom generation turns 65 in 2011, the country will have to deal with a retirement boom and an increasing need in long-term care for at least the next 2 decades. In 2005 the average time lived after age 65 was 17.8 years, while the average time of long-term care needed was 3 years (2.2 for men and 3.7 for women), when 69% of people will need any type of long-term care (Kemperh et al. 2005/2006). According to the Medicare CMS website, in 2005 about nine million people over 65 years currently need long-term care and by 2020, 12 million older Americans will need long-term care.

There are many different types of long term care, such as community-based services, home health care, in-law apartments, housing for aging and disabled individuals, board and care homes, assisted living, continuing care retirement communities and nursing homes with different levels of costs depending on geographic location and services provided. While long-term care can be provided at home, in the community or in assisted living facilities, Medicaid is the major purchaser of long-term services, paying for ∼50% of all nursing homes expenditures and 70% of all bed days (Grabowski, 2001).

Increased demand for long-term care will require higher efficiency of institutions providing such care, as well as knowledge about the particular characteristics of efficient nursing homes.

10.2 Nursing Home Performance Studies

The question of efficiency of nursing homes is studied in the US as well as around the world. Ozcan et al. (1998c) used data envelopment analysis (DEA) to determine technical efficiency of skilled nursing facilities in the United States. The study used a 10% national sample of 324 skilled nursing facilities and led to the conclusion that non-profit/for-profit status affects the mode of production. The study shows that greater efficiency is associated with higher occupancy and a larger percentage of Medicaid patients, and lower efficiency is associated with higher percentage of Medicare patients.

Other studies examined the relationship between efficiency and particular characteristics of nursing homes. Gertler and Waldman (1994) analyzed managerial efficiency and quality in for-profit and non-for-profit nursing homes and found that for-profit nursing homes have ∼15.9% lower costs, but not-for-profit homes do provide 3.9% higher quality. Kleinsorge and Karney (1992) examined causes of inefficiency within a nursing home chain; the authors mentioned that the inclusion of quality measures affected the evaluation of home efficiency. Hicks et al. (1997) used Missouri Medicaid cost reports for 403 nursing homes to examine contributors to cost of care. The study found that mid-sized facilities with 60–120 beds reported the lowest resident-related PRD costs, PRD expenses for aides and orderlies were higher in tax-exempt facilities, and investor-owned facilities showed significantly greater administrative costs PRD. Fizel and Nunnikhoven (1993) examined efficiency of NHs chains on a sample of 163 Michigan nursing homes and found that chain nursing homes have a higher mean level of efficiency than independent facilities.

Knox et al. (2004) examined the link between compensation and performance in for-profit and nonprofit nursing homes in Texas. To measure facility performance (resource allocation efficiency by firm management) the study used cost and profit functions. The results of the study show that the highest paid administrators allocate their firm's resources in the most efficient way and generally compensation of management is strongly influenced by firm size and capacity utilization. Vitaliano and Toren (1994) analyzed cost and efficiency in 164 SNF and 443 combination Skilled and Health Related Facilities, using a stochastic frontier approach. The study did not find a change in efficiency between 1987 and 1990 or any difference between for-profit and not-for-profit homes.

Fried et al. (1999) used a sample of nursing homes in a nonparametric, linear programming, frontier procedure study to assess managerial efficiency that controls external operating environment.

Banks et al. (2001) studied strategic interaction among hospitals and nursing facilities, links between payment system structure, the incentive for vertical integration and the impact on efficiency. The study used a static profit-maximization model of the strategic interaction between hospital and nursing facility, and proposed that a reimbursement system affects efficiency and vertical integration of nursing homes. The authors suggested that prospective payment to nursing facilities would keep the incentive to vertically integrate with transferring hospitals, and would not increase efficiency without integration. At the same time, bundled payments would stimulate efficient production if nursing facilities are reimbursed for services performed.

Chattopadhyay and Ray (1998) used output-oriented model of DEA to assess size efficiency of nursing homes, using 140 nursing homes from Connecticut, USA during the year 1982–1983. The study suggested that in some cases, for proper analysis a nursing home may be divided into smaller DMUs. The study also compared the efficiency levels of for-profit and non-profit nursing homes. Christensen (2003) noted that nursing homes vary widely by size and used quantile regression to estimate cost functions for skilled and intermediate care nursing homes in order to account for this heterogeneity. The study found a relationship between cost functions of nursing homes and output mix and variation of cost function across the cost distribution.

There are a number of studies of relationship between quality of care and efficiency. Schnelle et al. (2004) studied nursing home staffing and quality of care of 21 California nursing homes and found that the highest-staffed facilities reported significantly lower resident care loads on all staffing reports and provided better care than all other homes. Weech-Maldonado et al. (2003) analyzed the relationship between quality of care and costs of 749 nursing homes in five states and found a non-monotonic relationship between quality (pressure ulcer and mood decline) and cost (total patient care cost). Cawley et al. (2006) studied factor substitution (materials for labor) in nursing homes. The study found that higher wages are associated with greater use of psychoactive drugs and lower quality.

Castle (2006) analyzed characteristics of 607 nursing homes that closed from 1992 to 1998. He found a list of characteristics associated with a higher likelihood of closing, such as being in state with lower Medicaid reimbursement, high competition, low number of beds, for-profit status, lower resident census, higher Medicaid occupancy, and a lower quality of care. Rosko et al. (1995) used 461 Pennsylvania freestanding nursing facilities to analyze ownership, operating environment and strategic choices in terms of labor efficiency. The study found that major factors of efficiency are ownership, occupancy rate, size, wage rate, payment source, and per capita income rather than quality. Non-for-profits respond to environment by increasing efficiency; for-profits operate at high efficiency levels all time. Aaronson et al. (1994) examined behavioral differences between for-profit and not-for-profit nursing homes and found that self-pay residents and Medicaid beneficiaries received better care in non-for-profit than in for-profit facilities.

In Europe, Laine et al. (2004) have examined the association between productive efficiency and clinical quality in institutional long-term care for the elderly in Finland in 2001. The study used cross-sectional data from 122 wards in health-center hospitals and residential homes using data envelopment analysis to create a production frontier. In this case, technical inefficiency in the production function was specified as a function of ward characteristics and clinical quality of care. According to the authors, there was no systematic association between technical efficiency and clinical quality of care. At the same time, technical efficiency was associated with a prevalence of pressure ulcers that is one of indicators of poor quality. Another study of Laine et al. (2005) provided conflicting evidence. The study examined the association between quality of care and cost efficiency in institutional long-term care in Finland using stochastic frontier cost function and found that average cost inefficiency among the wards was 22%. The authors found an association between the clinical quality indicators and cost inefficiency. A higher prevalence of pressure ulcers was associated with higher costs, and higher prevalence of depressants and hypnotics drugs increased inefficiency. Crivelli et al. (2002) studied a cross-sectional sample of 886 Swiss nursing homes operating in 1998 to assess the relationship between cost efficiency, the alternative institutional forms and the different regulatory settings. Björkgren et al. (2001) used DEA to measure the nursing care efficiency (in terms of cost, technical, allocative, and scale efficiency) of 64 long-term care units in Finland and found large variation in efficiency between units. The study shows that larger units operated more efficiently than smaller units and that allocative inefficiency is the result of using too many registered nurses and aides with too few licensed practical nurses. Blank and Eggink (2001) studied 110 Dutch nursing homes to examine a quality-adjusted cost function and found that quality was (partly) endogenous and was negatively related to input prices of nurses and other personnel, as well as the number of daycare patients and market concentration. Another study of Dutch nursing homes by Kooreman (1994) assessed technical efficiency with respect to the use of labor inputs and found that 50% of NHs were efficient, while the study also found some evidence of a trade-off between labor input efficiency and the quality of care. Farsi and Filippini (2004) surveyed a sample of 36 public and private nonprofit Swiss nursing homes studying cost efficiency and found similar efficiency of public and private nursing homes.

10.3 Performance Model for Nursing Homes

DEA base nursing home studies are summarized in Table 10.1 to gain perspective on nursing home production process. Based on these studies, as in hospital studies, labor is the main common input. Many studies also included beds into inputs of the nursing home service production (Ozcan et al. 1998c; Fried et al. 1998; Björkgren et al. 2001; Dervaux et al. 2006; Laine et al. 2005). Non-payroll expenses in addition to FTEs and beds were included into inputs of DEA model by two of the studies (Ozcan et al. 1998; Fried et al. 1998).

Table 10.1 Measures of inputs and outputs for nursing home DEA models

Authors, year	Inputs	Outputs
Sexton et al. 1989 (in Rosko et al. 1995)	6 labor inputs	Medicaid, non-Medicaid days
Nyman and Bricker, 1989 (in Rosko et al. 1995)	4: Total nursing hours, total social workers hours, total therapists hours, total other workers hours	5: SNF patients, ICF patients, limited care patients, personal care patients, residential care patients
Nyman et al. 1990 (in Rosko et al. 1995)	11 labor inputs	Number of ICF patients
Fizel and Nunnikhoven, 1993	RN hors, LPN hours and aids-orderlies hours	SNF patients days and ICF patients days
Kooreman, 1994	Physicians, nurses, nurse trainees, therapists, general staff and other personnel	Patients classified as physically disables, psycogeriatrically disables, full-care and daycare
Rosko et al. 1995	RN FTE, LPN FTE, NA FTE, rehabilitation personnel FTE and other personnel	SNF days and ICF days
Ozcan et al. 1998	Beds, FTE, non-payroll operational expenses	Self-pay inpatient days, government-pay inpatient days
Dervaux et al. 2006	FTE auxiliary personnel and beds	6 groups of patients, by case-mix severity (from independent to requiring full-time surveillance)
Fried et al. 1998	FTE RN, LPN, other (OEMP), and non-payroll expenses (NEXP).	Inpatient days of skilled care (SKD) and inpatient days of intermediate care (ICD)
Björkgren, et al. 2001	RN FTE, LPN FTE, aides FTE, beds (proxy for capital)	Case-mix adjusted patient days
Laine et al. 2005	RN FTE, LPN FTE, aides FTE, unit size (beds)	Case-mix weighted patient days

Conceptualization of outputs in these studies varied based on the access and the availability of the data. Nevertheless, outputs were based on what type of patients cared for or patient days produced based on skilled or intensive care. The latter serves as a proxy for case-mix adjustment for the service outputs (Sexton et al. 1989; Nyman and Bricker, 1989; Nyman et al., 1990; Fizel and Nunnikhoven, 1993; Rosko et al. 1995). On the other hand, other studies used case-mix adjusted patient days (Björkgren et al. 2001; Dervaux et al. 2006; Laine et al. 2005), which capture the service outputs in more appropriate way.

Based on the literature, we can define a generic nursing home service production model to measure their performance. The inputs and outputs of this model can serve as the guidance to develop future evaluations of nursing home performance. Based on availability, variables in databases or their proxy measures can be used in the evaluation. Figure 10.1 displays the generic nursing home performance model. It should be noted that based on the intent of the evaluation, capital expenses, FTEs,

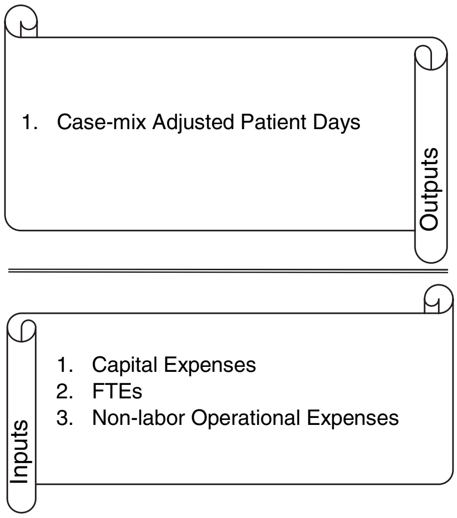


Fig. 10.1 Outputs and inputs for a generic nursing home DEA model

and non-labor operational expenses can be further broken down to categories for detailed evaluation of excessive input usage for inefficient facilities. For example, beds can be used as a proxy for a portion of the capital expenses; amortization, depreciation, and other capital expenses can be used for the reminder of this category. If the source of patient days is important in the evaluation, output can also be categorized into groups for that purpose. For example, patient days can be broken down by third party insurance payers (government or private), or by self pay.

10.4 Data for Nursing Home Performance Evaluations

There are few sources of data to evaluate nursing home performance in the US. CMS database is one of these sources. Ozcan et al. (1998c) used this database to evaluate skilled nursing home facilities. The CMS database contains fields to identify the provider type, thus enabling researchers to extract appropriate information for nursing homes.

There is also state based information available. States require periodic submission of provider information which includes patient level based data, as well as organizational data. Hospitals, long-term care facilities such as nursing homes, and other providers file this information with the appropriate state agency that administers these databases. For example, in the State of Virginia, Virginia Health Information (VHI) is responsible for health care data on hospitals, nursing facilities, physicians, and other health care providers (http://www.vhi.org). A Fizel and Nunnikhoven (1993) study used comparable database from the State of Michigan; a Chattopadhyay and Ray (1998) study used the State of Connecticut database.

10.5 An Example of Performance Model for Nursing Homes

In order to operationalize the model shown in Fig. 10.1, the example evaluation uses VHI data for fiscal year 2004. To obtain the efficiency score, this example uses CRS input-oriented DEA model, because nursing homes usually have more control over their resources (inputs), rather than outputs. As most of DEA studies used beds as proxy for capital investments, FTEs for labor component, and the other expenses for operations, we operationalize the model with these measurements for the inputs. The choice of outputs was based on the facts that Medicaid is a major payer for long-term care and that self-paid patients are important and valuable resource for nursing homes. Patient-days paid by other sources were included in the analysis as a third output. The detailed description of the input and output variables is provided below.

10.5.1 Inputs and Outputs of the Nursing Home Model

Inputs

Beds. Total number of Medicare, Medicaid, Dual Certified beds, Non-certified and Adult care residence or other non-nursing facility beds.
Medical FTEs (RN and LPN). Full-time equivalents of registered nurse (RN), director of nursing, and licensed nurse practitioners (LPN) on staff.
Support FTEs (NA). Full-time equivalents of certified nursing assistants.
Other FTEs. Full-time equivalents of administrator/assistant administrator, food service personnel, occupational therapists, dieticians, occupational therapy assistants/aides, physical therapists, physical therapy assistants/aides, speech therapists, activities personnel, social service personnel, other health professional & technical personnel, housekeeping personnel, maintenance personnel, other non-health and non-technical personnel.
Non-labor operational expenses. Contracts, home office, leases, medications, physician fees and/or medical director, and other expenses.

Outputs

Medicaid patient-days. Medicaid and Medicaid specialized care.
Self-pay patient-days. Self-paid patient days.
Other patient-days. Medicare (Part A), HMO, PPO, other insurance, VA and other government not listed above, other patient days.

Figure 10.2 displays the output and inputs for the DEA model of the example nursing evaluation.

The reader should note that the FTEs of nurse assistants were included in analysis as separate inputs. This labor category does not provide specific medical function

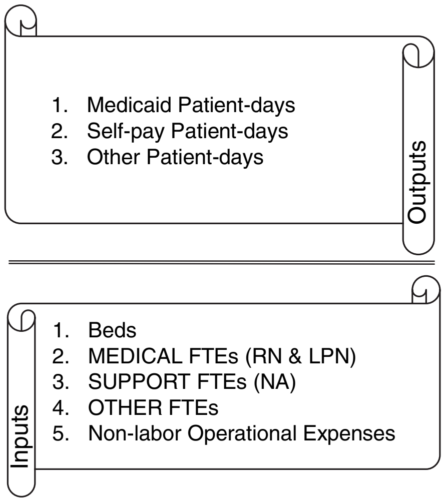


Fig. 10.2 Outputs and inputs for the example nursing home evaluation

for nursing home residents, but they play an important support role for the medical personnel. This categorization of labor was also used in number of other studies (Rosko et al. 1995; Björkgren et al. 2001; Laine et al. 2005).

The values of the certain measures were scaled to ease the computation; non-labor expenses were measured in million dollars and outputs were measured in thousands of patient-days. At the same time, full-time equivalents and the number of bed were used without scaling.

10.5.2 Homogeneous Groups and Descriptive Statistics

In order to create a robust homogeneous evaluation based on the scale of the nursing home operations, nursing homes were grouped by number of beds (Christensen, 2003). Facilities were divided into groups by size (less than 50 beds, 50–99, 100–149, 150–199, 200 and more) as they were divided by CDC. Out of 259 nursing facilities in Virginia 240 facilities have more than 50 beds, 22 have more than 200 beds, with the smallest nursing home having 8 beds and largest one having 373 beds. At the same time, all nursing homes with less than 26 beds are hospital-based (long-term care units).

Descriptive information on Virginia nursing homes by group and their inputs and outputs are shown in Table 10.2.

Table 10.2 Descriptive statistics of input and output measures for nursing homes by bed size

	Nursing homes by bed size				
	<50	50–99	100–149	150–199	200>
Sample size	19	71	99	48	22
Minimum beds	8	54	100	150	200
Maximum beds	49	97	145	198	373
Non-profit	11	13	30	9	10
Hospital based	12	2	2	1	0
Average beds	29	70.7	120.8	180.2	260.5
Average medical FTEs	9	13.5	24.1	34.1	52.2
Average support FTEs	10	23	40.1	59	91.8
Average other FTEs	13.2	25.9	40	55.3	86.6
Average Medicaid patient days	3,145	14,276	24,694	38,730	55,502
Average self-paid patient days	2,935	4,260	7,115	7,499	14,913
Average other patient days	2,514	3,548	6,277	9,007	12,144

Table 10.3 Comparison of DEA results for nursing homes by bed size

	Nursing homes by bed size				
	<50	50–99 beds	100–149	150–199	200>
Number of efficient/total DMU	15/19	47/71	54/99	30/48	16/22
Percent of efficient DMUs (%)	79	66	55	63	73
Average efficiency	0.96	0.98	0.98	0.98	0.99
St. dev.	(0.092)	(0.050)	(0.040)	(0.037)	(0.013)
Minimum efficiency	0.63	0.73	0.77	0.86	0.95

10.5.3 DEA Results

DEA results are presented in Table 10.3. It is interesting to observe that the average efficiency score is increasing as number of beds in a facility increases. Proportion of efficient DMUs across the size groups varies first in a decreasing pattern with lowest percentage of efficient nursing homes in the middle groups, but then increases in larger size group nursing homes.

Another interesting issue in analysis of nursing homes efficiency is the difference between for-profit and non-for-profit facilities. According to Ozcan (1998), for-profit status affects the mode of production; Rosko et al. (1995) found that while non-for-profit nursing homes tended to respond to environmental changes by increasing efficiency while for-profit facilities operated at higher level of efficiency irrespectively to environment.

Among Virginia nursing homes 186 facilities are for-profit and 73 are non-for-profit. A separate DEA was run for the group of nursing homes of 100–149 beds as group with the highest number of for-profit nursing homes. Among 99 facilities, 54 were efficient both in combined and separate analysis; 11 others were inefficient, but they had the same or similar (with difference of 0.001–0.002) efficiency score in both analyses. All facilities have a higher score being analyzed separately by

Table 10.4 Excessive use of inputs and shortage of outputs by inefficient nursing homes grouped by bed size

Nursing home groups and efficiency scores	Excessive inputs					Shortage of outputs/thousands of patient-days		
	Beds	Medical FTEs	Support FTEs	Other FTEs	Non-labor expenses	Medicaid	Self-pay	Other
Up to 50 beds, average efficiency score 0.83 ($n = 4$)								
Avg. inefficiency	1.298	1.420	0.924	1.668	0.181	0.074	0	0.095
50–99 beds, average efficiency score 0.98 ($n = 22$)								
Avg. Inefficiency	1.162	0.814	1.090	2.677	0.084	0	0.458	0.037
100–149 beds, average efficiency score 0.95 ($n = 45$)								
Avg. Inefficiency	0.279	3.336	3.193	6.265	0.082	0.319	0.239	0.250
150–199 beds, average efficiency score 0.95 ($n = 18$)								
Avg. Inefficiency	0.740	2.803	5.790	6.399	0.114	1.672	0.979	0.189
More than 200 beds, average efficiency score 0.98 ($n = 6$)								
Avg. Inefficiency	4.299	6.187	1.844	9.352	0.318	1.677	0	0

for-profit status. An average increase in the efficiency score among for-profit nursing homes was 0.016 and among non-for-profit it was 0.040 of efficiency score.

One of the advantages of data envelopment analysis is its ability to estimate changes necessary for increasing the efficiency score for each of the inefficient DMUs. Summary information by groups is provided in Table 10.4.

Among all size groups of nursing homes, the lowest efficiency score of 0.83 is in the group with up to 50 beds. Almost all nursing homes except the group of 150–199 beds have the highest excess of labor inputs in other FTEs compare to medical FTEs and Support FTEs. The average number of excessive beds ranges from mere 0.3 beds to 4.3 beds, or from 1 to 25 in individual facilities and can reach up to 10% of current capacity. Excessive non-labor expenses range from 4 to almost 1.5 million dollars. Shortage of patient-days as output ranges from 116 to more than 30,000 days. At the same time, the output shortage may require additional analysis, as different nursing homes may have different specialization. For instance, long-term care units of hospitals may be more involved in care for Medicare-paid patients.

10.5.4 Conclusion

The question of nursing homes efficiency is widely discussed in the literature in its various aspects. As the population is getting older, the demand for long-term care, including care provided by nursing homes, will be increasing. In the situation of rapidly growing healthcare expenditures it is important to use scarce resources in the most efficient way, and analysis of technical efficiency allows comparison of inputs to outputs ratios among different facilities. Analysis in this example shows that most nursing homes in Virginia operate efficiently; at the same time the average efficiency score is increasing with size of the facilities. The groups of smallest and largest nursing homes have highest proportion of efficient facilities, while only about half of facilities are efficient in the group of nursing homes with 100–149 beds. While the efficiency score obtained through DEA estimates overall technical efficiency of decision-making units information on inefficiency, shortage of outputs may require additional analysis on base of individual nursing homes.

This evaluation has its limitations. First of all, it is based on the sample of Virginia nursing homes only and therefore the results cannot be expanded to all nursing homes in the country. In addition, although the analysis used reports from 2004 fiscal year, these reports were submitted from March to December 2004. The evaluation has used only 1-year data and did not incorporate quality data.

Future evaluations of the subject may include the questions of interrelationship of quality of care and technical efficiency of nursing homes. Previous research on this issue provided mixed results. According to Schnelle et al. (2004) higher amount of inputs (staff) used by a nursing home is associated with higher quality of care, while Weech-Maldonado et al. (2003) found a non-monotonic relationship between cost and quality. Laine et al. (2004) found no systematic association between technical efficiency and clinical quality of care. The quality models presented in Chap. 7 can be applied to nursing homes if appropriate quality data can be found. Another interesting issue relates to the changes in efficiency of nursing homes in response to changes in the environment, such as a change in demand for care, presence of substitute for care or increased quality requirement. This type of research would require a longitudinal study, and can be carried out using Malmquist model presented in Chap. 6.

10.6 Summary

This chapter provided a general guidance for a nursing home performance model, and its operationalization based on extensive literature review. Using generally available databases from either federal (CMS) or state databases nursing home or other long-term care provider performance can be evaluated. An example nursing home performance model was presented using the database from the State of Virginia. Limitations of the past studies, and suggestions for future evaluations are also provided.

Acknowledgment

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Chapter 11
Health Maintenance Organization (HMO) Applications

11.1 Introduction

Health Maintenance Organizations (HMOs) are a form of health insurance combining a range of coverage in a group basis. Physician groups and other medical professionals offer care through the HMO for a flat monthly rate with no deductibles. HMOs influenced financing and delivery of health care in the United States during the past several decades. By 1999, there were 643 HMO Plans covering over 80 million people throughout the U.S. (U.S. Census 2000 on http://www.Allcountries.org).

There are very little empirical evaluations of HMO performance. Most of the studies in this area concerned with whether hospitalizations rates decreased, increased ambulatory-preventive services, or lowered health care costs. A significant study by Wholey et al. (1996) examined the scope of economies among various HMO types over a 4 year period (1988–1991) using the Health Care Investment Analysts (HCIA) database. The HCIA database includes all HMOs operating in the U.S. Similarly, Given (1996) conducted an evaluation of a sample of California HMOs. Both evaluations found as enrollment increased scale economies decreased due to labor intensiveness of the services. The Wholey study used translog multi-product cost function to explain divestitures and mergers of HMOs. They used the number of commercial, Medicare, and Medi-Cal enrollees as outputs. Inputs consisted of costs related to hospitalizations, physician visit, clerical and facility costs. Rosenman et al. (1997) evaluated output efficiency of 28 Health Maintenance Organizations in Florida.

11.2 HMO Performance Studies

The initial HMO efficiency study by Rosenman et al. (1997) showed clearly the reasons why studying the efficiency of HMOs is important. As indicated, managed care played the key role in health care financing and delivery of health care. Comparing to other insurance plans, HMOs provided relatively cheap and cost saving products for the enrollees. The study explored the efficiency of HMOs and investigated whether efficiency varies across types of plans and ownership status.

Through existing literature review, several factors associated with HMO efficiency were discussed, including ownership (i.e., hospital, physician, and insurance company), an HMO's model type (i.e., staff model, group/network model, independent practice arrangements (IPAs)), tax status (for profit and non-profit) and market power.

The study was a cross-sectional design using 1994 HMOs report data from the Florida Department of Insurance. A total 28 HMOs were samples as DMUs. Output variables included the total number of enrollees in the plan. This study further disaggregated enrollees by three kinds of payer-mix: Medicare, Medicaid, and Commercial. The reason for doing this was to crudely adjust for the differences associated with the age and income of enrollee due to control for variations in health care utilization patterns among enrollee types. Input variables included total assets as a proxy for capital input, and total administrative and medical care expenses as proxy for labor inputs.

Factors that may influence input efficiency included structure (model type), profit status, ownership, mix of enrollees (age, acuity level) and external market characteristics (competition, available physicians, and excess hospital capacity). The functional form used in this study is different from others, but the concept is the same.

Overall, 67% of the HMOs were efficient. There were little differences among HMO type or ownership. Staffed models are most efficient. For-profit HMOs appear to be more efficient. Large HMOs are more efficient in terms of economic of scale. Plans with more homogeneous enrollment were more efficient with respect to economic scope. The number of Medicaid patients enrolled in the HMOs may be associated with inefficiency.

The first nationwide DEA evaluation of HMOs conducted by Draper et al. (2000) using stratified random sample of 249 HMOs that were operating in U.S. in 1995. The Draper et al. study using HCIA data employed three outputs including physician ambulatory encounters, non-physician ambulatory encounters, and hospital patient days. Inputs of their model captured major group expenses for the HMOs including hospitalization, physician, other health care services, and administrative. They also divided HMOs into three different sizes based on enrollment. Those HMOs that had less than 40,000 enrollees consisted of the low enrollee group; while the HMOs with 40,000–59,999 enrollees were identified as the mid-size group; and those more than 60,000 enrollees consisted of the high enrollee group.

There were significant differences in efficiency scores between the HMO size groups. The low enrollee group ($n = 115$) and high enrollee group ($n = 102$) efficiency score averaged 0.46 and 0.43, respectively. However, the mid-size enrollee group ($n = 32$) had an efficiency score of 0.31. Furthermore, those HMOs with no Medicaid enrollees ($n = 47$) had the lowest average efficiency score of 0.307.

Rollins et al. (2001) conducted a multi-year follow up evaluation to Draper et al. study. This study used the same inputs and outputs and the HCIA data base over 5 years. The study evaluated 36 HMOs that were in business from 1993 to 1997.

The number of efficient HMOs increased from 21 (58%) in 1993 to 29 (81%) in 1997. The average efficiency score increased from 0.80 in 1993 to 0.94 in 1997. IPA type HMOs were the best performers followed by other types of HMOs. Of the 36 HMOs, 10 were IPA type, and all of them achieved perfect efficiency by year 1996 and sustained that in 1997.

11.3 Performance Model for HMOs

Based on Given (1996) and Wholey et al. (1996), one can discern that HMOs produce both health care services and health insurance coverage. On the other hand, evaluation of the production of the services provided by HMOs should capture the health care services. These health services include physician ambulatory encounters, non-physician ambulatory encounters and the inverse of the hospital inpatient days. As HMOs try to contain the costs, they would encourage the use of ambulatory encounters but discourage hospitalization by emphasizing preventive care. Thus, good performing HMOs would like to reduce inpatient days. Hence, to reflect this goal in the DEA model, the inverse of the patient days is included as an output variable. Thus, when the DEA model attempts to optimize this variable by increasing this output, due to inverse nature of the variable, it will be reduced. Consequently, those HMOs with less inpatient hospitalization would be considered efficient.

There are different categories of HMOs. Most common categories of HMOs are staff, Independent Provider Association (IPA), network, group, and mixed. Depending upon the type of HMO, data availability may differ. For example, staff HMO employs their own physicians, and may even have their own hospitals and clinics. Under such circumstances more specific input schemes shown for hospitals (Chap. 8) and physician practices (Chap. 9) can be considered. However, for a general evaluation of all type of HMOs, one should only rely on the common inputs for these organizations. Draper et al. (2000) and Rollins et al. (2001) studies provide such common inputs by examining expenses of different resources consumed to produce HMO services. Based on limited HMO studies one can conceptualize the outputs and inputs of DEA model for HMOs as shown in Fig. 11.1.

11.4 Data for HMO Performance Evaluations

HCIA, Inc. was acquired by Solucient, which is an information products company serving the health care managers with data and analytical products to improve the performance of their organizations. Solucient provides comparative measurements of cost, quality and market performance (http://www.solucient.com). Hence, future HMO evaluation can be conducted by using their database. Another data source would be CMS. Using CMS database, patient level data needs to be organized at HMO organizational level. Furthermore, encounters needs to be constructed by the evaluators.

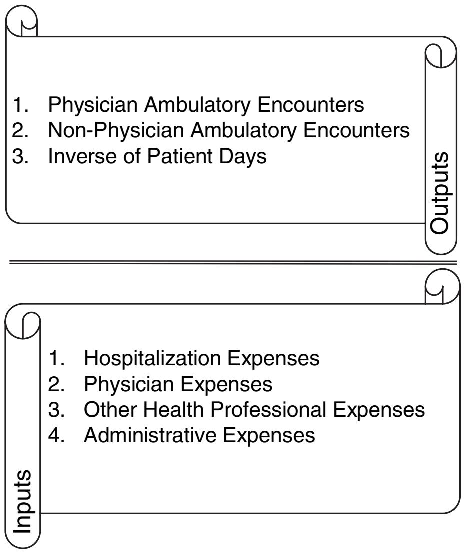

Fig. 11.1 Outputs and inputs for a HMO DEA model

11.5 Summary

This chapter provided a general guidance for a HMO performance model, and its operationalization based on available literature. Using generally available databases from either federal (CMS) or propriety databases, such as Solutient, HMO performance can be evaluated.

Chapter 12
Home Health Agency Applications

12.1 Introduction

The home health care industry has been growing steadily in the United States. Home health care is defined as “skilled nursing, therapy, aide service, or medical social work provided to beneficiaries in their homes” (MedPAC, 2005a, p 106). The beneficiaries must be confined to the home and need intermittent, part-time home health care services. In the early to mid 1980s, the Center for Medicare and Medicaid Services (CMS), then Health Care Financing Administration (HCFA), had very strict eligibility criteria and annual limits on coverage for home health care. Annual spending only increased at a rate of 1% from 1985 to 1988. A court decision broadened the guidelines for home health coverage in 1989, and it was transformed from a benefit primarily for short-term post acute hospital care to a longer term chronic disease care. Afterward, home health care spending grew at an annual rate of 30% from 1989 to 1997 (Government Accounting Office (GAO), 2000).

A few factors contributed to this growth. Hospitals were discharging patients earlier and more surgeries were being done on an outpatient basis, requiring professional assistance at home. HCFA reviewed fewer claims for medical appropriateness, and since home health agencies were paid fee-for-service, they increased the services provided to maximize revenues. Finally, many patients preferred to remain in their home instead of being institutionalized (GAO, 2000; Han et al., 2004).

In 1997, home health agencies were paid through an interim payment system (IPS) while CMS determined the prospective payment system appropriate for home health. The IPS had more stringent per-visit costs, and it initiated a Medicare revenue cap per beneficiary served. In order to make sure that their revenues covered their costs, the home health agencies had to become more efficient. After the IPS, spending for home health dropped dramatically from 1997 (12.8 billion dollars) to 1999 (8.4 billion dollars), which was an annual rate of decrease of 32%. In 2000, the PPS for home health was implemented, which changed the per-visit limits to a 60-day episode of care payment. Home health agencies that were able to provide appropriate care efficiently with fewer visits became more profitable. After PPS,

Table 12.1 Medicare home health care use 1997 and 2002

Measure	1997	2002
Number of beneficiaries served	3,558,000	2,550,000
Average visits per person served	73	31
Average visits per episode	36	19
Average minutes per episode	1,500	940
Average length of stay	106	56
Percent therapy visits	9%	26%

Source: A Data book: Healthcare spending and the Medicare program, MedPAC (2005a, b)

Medicare spending for home health care slowly increased from 2001 (8.7 billion dollars) to 2004 (11.2 billion) (GAO, 2000; MedPAC, 2005b).

The number of Medicare certified home health agencies dropped markedly after the introduction of the IPS in 1997, going from a high of about 9,800 in 1996 to a low of about 6,900 in 2002. Since 2002, the number of home health agencies has steadily increased to about 7,900 in 2005 (MedPAC, 2005a, b). One third of Medicare beneficiaries discharged from a hospital use post acute care, and home health care is the second most common care after hospitalization, accounting for 11% of hospital discharges.

Table 12.1 displays the changes IPS and PPS has induced in home health care use. The number of beneficiaries served, visits per person served, visits per episode, average minutes per episode, and average length of stay all decreased from 1997 to 2002. The mix of visits have changed toward more therapy (physical therapy, occupational therapy and speech therapy) and less home health aide services because the system rewards therapy services.

12.2 Home Health Agency Performance Studies

Research on home health agencies has existed for a little over a decade, and most research focused largely on the impact of the Balanced Budget Act (1997) on utilization. McCall et al. (2003) and colleagues found that the percentage of eligible Medicare population utilizing home health services declined 22% from 10.1% in 1997 to 7.9% in 1999. They also found that beneficiaries aged 85 and older were less likely to use home health services after the Balanced Budget Act (1997). Many other studies have examined the impact of ownership status on home health care agencies' performance relative to cost, quality, access to care and charity care, and they found that either there was no difference between for-profit and non-profit home health agencies, or they found that non-profit home health agencies performed better (Rosenau and Linder, 2001). Non-profit home health agencies tend to have lower average visits per patient and shorter length of stay, thereby using resources more efficiently. No plausible research to date has attempted to measure relative efficiency of home health agencies using DEA.

12.3 Performance Model for Home Health Agencies

Although performance (efficiency) of many other health care organizations (e.g. hospitals, dialysis centers, and nursing homes) has been evaluated using data envelopment analysis, no researcher has tackled home health agencies' efficiency. One of the issues with home health agencies is the variability of the organization. Capacity cannot be measured in the traditional way of employee FTEs because the home health agencies expand or reduce their services to meet demand by contracting with other entities for skilled nursing or physical therapy.

Home health agencies do not have many capital investments to take into account. Most of the activities for home health agencies are based on visits; one can adapt a performance model similar to one in physician practice. This means visits from various professionals involved in home care of the patient during an episode of disease. These professionals include nurses, therapist, nutritionists, speech pathologist, social workers, aides, and so on. Visits by these professionals then would constitute the resources used by home health agency to produce the services for a variety of patients with various needs of post hospitalization care. Although inputs can be accounted for this way, outputs of the model require the patient episode of home health care, however, these episodes would vary from patient to patient. Hence, depending upon the complexity of the post hospitalization, case-mixes will vary and need to be accounted.

Based on these conceptualizations, a generic home health agency performance model can be constructed as shown in Fig. 12.1.

Depending upon available data, variables or their proxies may be used to operationalize the model.

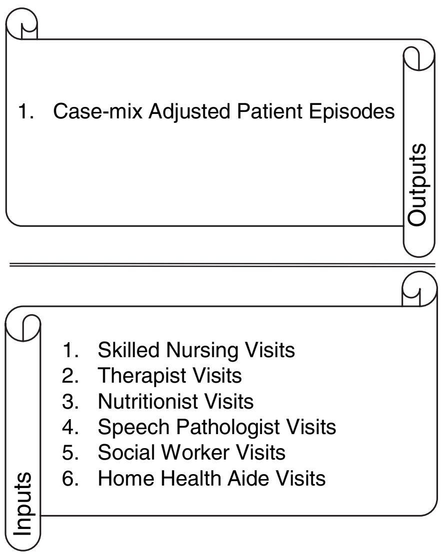

Fig. 12.1 Outputs and inputs for home health agency DEA model

12.4 Data for Home Health Agency Performance Evaluations

CMS database is the main data source for home health agency data. As discussed in previous chapters, CMS keeps track of patient level data by provider in the United States, thus enabling evaluations of home health agencies as a unit of analysis, or as DMU. Another data source for these evaluations would come from State based systems. For example, the Office of Statewide Health Planning and Development (OSHPD) collects annual utilization data for all home health agencies and hospices in California, and the data are available on their website.

12.5 An Example of Performance Model for Home Health Agencies

In order to operationalize the model shown in Fig. 12.1, the example evaluation uses Office of Statewide Health Planning and Development (OSHPD, 2006) annual utilization data for all home health agencies and hospices for year 2004. The 2004 home health and hospice utilization file from OSHPD contained 1,035 organizations. The analysis was limited to organizations that categorized themselves as offering only home health services. Organizations that offered hospice only or home health and hospice were removed from the sample. The sample was further whittled down by removing home health agencies that closed during the year or had zero patients in all age groups. The final sample consisted of 727 home health agencies.

12.5.1 Inputs and Outputs of the Home Health Agency Model

Inputs

The production of the services depends on resource utilization. For home health agencies in this evaluation, the inputs, or resource utilization, are visits by different staff members. Most common visits for various patient episodes in OSPHD were as follows:

- Skilled nursing visits
- Physical therapist visits
- Occupational therapist visits
- Nutritionist visits
- Speech pathologist visits
- Social worker visits
- Home health aide visits
- Other staff visits

Outputs

There is no clear way of adjusting the case-mix for home health episodes. Chilingerian and Sherman (1997a, b), in their primary care physician evaluation, used gender and age groups to account for the case-mix of the patients. It is known that as age increases, so does the severity of the cases. Thus, the outputs of this model consist of the age group of the patient requiring home health care. Ten year intervals on age were used to create age grouped patient outputs as follows:

- Patients age <10 years
- Patients age 11–20 years
- Patients age 21–30 years
- Patients age 31–40 years
- Patients age 41–50 years
- Patients age 51–60 years
- Patients age 61–70 years
- Patients age 71–80 years
- Patients age 81–90 years
- Patients age >90 years

Figure 12.2 displays the output and inputs for the DEA model of the example nursing evaluation.

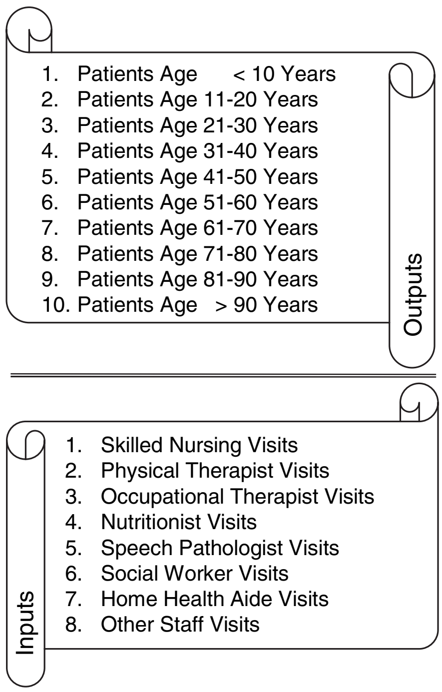

Fig. 12.2 Outputs and inputs for the example home health agency evaluation

This evaluation uses a VRS input oriented DEA model since home health agencies have more control over their inputs versus their outputs.

12.5.2 Homogeneous Groups and Descriptive Statistics

Only 8 counties out of 58 did not have a home health agency, but the majority of home health agencies, 51%, were clustered in Los Angeles County. Over half of the recipients of home health services were over 70 years old, and the average number of visits per individual was 25 (Harrington and O'Meara, 2004).

Since DEA analysis measures relative efficiency, the development of a peer group is very important. By limiting the analysis to one state, some variation is reduced because Medicaid eligibility for home health services differs from state to state. In 2003, over half of the home health agencies were in Los Angeles County. These home health agencies would be exposed to more competition than agencies located in rural counties. Also, the larger the population and smaller the service area, the more patients home health agencies could possibly service. Use of peer groups based on local markets follows previous research (Ozcan et al. 1992; White and Ozcan 1996); however, due to many counties having only one or two home health agencies, pure local markets would have produced too few DMUs for comparison. Therefore, based on the population of the county of the home health agency, the California home health agencies were divided into three peer groups. Peer group one consists of all home health agencies located in Los Angeles County. Peer group two consists of all home health agencies located in large counties with populations over 1 million: Alameda, Contra Costa, Orange, Riverside, Sacramento, San Bernardino, San Diego and Santa Clara. Peer group three consists of home health agencies located in small counties with populations less then 1 million. The descriptive statistics for input and output variables by peer group are displayed in Table 12.2

12.5.3 DEA Results

The results of the DEA analysis are presented in Table 12.3. There were 105 efficient home health agencies in Los Angeles County with a mean efficiency score of.665. The inefficient home health agencies in Los Angeles County should have been able to use 33.5% fewer inputs to create the same outputs. Among large counties, there were 78 efficient home health agencies with a mean efficiency score of.691. Among small counties, there were more efficient ($n = 105$) home health agencies than inefficient ($n = 69$) ones. The mean efficiency score for home health agencies in the small county peer group was.872.

Table 12.2 Descriptive statistics of DEA model variables by peer group

	Los Angeles county $n = 342$		Large counties $n = 211$		Small counties $n = 174$	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Output variable						
Patients age (years)						
<10	10.43	58.09	68.12	321.49	45.05	166.65
11–20	4.27	16.07	21.19	64.21	16.95	47.47
21–30	8.44	39.39	39.57	148.80	41.22	151.31
31–40	12.57	41.65	46.73	135.85	34.30	79.17
41–50	21.49	50.79	58.49	84.64	45.63	57.86
51–60	34.38	84.38	88.50	134.68	74.47	78.26
61–70	63.19	133.64	122.67	193.60	100.99	99.63
71–80	109.11	170.22	190.28	306.97	159.55	160.41
81–90	105.30	167.09	180.66	283.05	160.91	167.72
>90	29.23	43.74	42.72	65.78	41.58	44.33
Input variables						
Skilled nursing visits	10,674.39	17,075.57	8,162.36	9,826.83	6,470.35	10,251.71
Physical therapist visits	1,436.39	2,129.00	2,536.23	4,143.25	2,287.52	2,419.43
Occupational therapist visits	156.51	380.38	466.09	759.66	448.99	623.00
Speech pathologist visits	27.59	75.81	100.08	193.88	115.28	163.49
Nutritionist visits	0.93	10.46	5.88	29.45	3.25	16.21
Social worker visits	92.85	253.90	176.09	316.30	180.78	285.80
Home health aide visits	901.40	1,691.08	843.81	1,685.99	986.56	1,842.88
Other staff visits	5.91	52.40	52.03	474.77	91.44	704.39

Table 12.3 Performance by efficient and inefficient home health agencies by peer group

	Los Angeles county		Large counties		Small counties	
Mean efficiency score	0.665		0.691		0.872	
	Efficient $n = 105$	Inefficient $n = 237$	Efficient $n = 78$	Inefficient $n = 133$	Efficient $n = 105$	Inefficient $n = 69$

The average inefficiency in resource utilization by peer group is presented in Table 12.4. The mean inefficiency for utilization or service production can identify how inefficient hospitals may decrease excess inputs or increase shortfall outputs to move to the efficiency frontier. The fewest number of home health agencies were inefficient in skilled nursing inputs across all three peer groups, but they would have to decrease skilled nursing visits by huge amounts to become efficient. For example, among small county home health agencies, only one home health agency is inefficient in skilled nursing visits, but it would have to decrease skilled nursing inputs by 2090 visits in order to reach the efficiency frontier.

Table 12.4 Magnitude of inefficiencies for home health agencies

	Los Angeles county			Large counties			Small counties		
	Number inefficient	Mean slack	St. dev. slack	Number inefficient	Mean slack	St. dev. slack	Number inefficient	Mean slack	St. dev. slack
Output shortages									
Patients of age group (years)									
0–10	223	10.62	10.55	105	26.65	55.69	48	13.18	15.84
11–20	224	9.95	12.38	87	17.30	41.68	34	4.23	8.24
21–30	227	18.50	24.31	101	32.13	92.69	67	27.02	37.64
31–40	223	26.71	33.20	122	28.30	49.76	50	19.40	23.65
41–50	217	35.68	45.63	101	18.59	25.71	62	22.80	21.47
51–60	194	39.10	45.86	101	23.53	27.57	40	17.83	17.73
61–70	150	22.58	23.51	99	21.43	25.91	41	16.87	20.48
71–80	153	22.99	25.98	59	13.72	26.19	46	17.76	17.86
81–90	128	15.37	17.31	63	18.74	28.50	39	16.98	18.36
>90	88	4.25	6.11	73	5.72	8.59	36	6.51	7.42
Excessive inputs									
Skilled nursing visits	11	11, 372.39	14, 302.22	16	3, 138.51	4, 159.09	1	2, 090.42	N/A
Physical therapist visits	52	249.81	370.62	35	580.12	665.39	17	428.04	906.13
Occupational therapist visits	99	62.03	138.14	81	141.73	258.79	40	170.50	249.30
Speech pathologist visits	84	12.35	35.92	39	30.80	63.48	39	71.59	84.58
Nutritionist visits	70	0.41	1.76	45	12.90	43.51	16	8.92	18.05
Social worker visits	138	24.26	43.94	72	60.02	105.32	36	63.81	68.13
Home health aide visits	124	475.92	862.75	100	234.51	349.17	37	563.59	636.43
Other staff visits	62	7.15	28.85	16	190.68	723.16	3	0.28	0.48

12.5.4 Conclusion

This evaluation measured technical efficiency of home health agencies in serving different age groups. There are other measures of resource utilization in home health besides number of visits, such as length of stay and direct care time (Adams and Michel, 2001). However, one limitation of the study was that the data set used in this study did not have length of stay and direct care time. Another limitation is that this evaluation only assessed efficiency of Californian home health agencies. These results might not be generalizable outside California. This evaluation also measured efficiency by peer groups based on population and competition. These peer groups might not have created desired homogeneous groups. A final limitation is the lack of case mix information to adjust for patient severity. As insurers demand more return for their investments, efficiency in health care production will become more salient.

Since Medicare provides rewards for therapy services, weights can be considered for preferring physical therapy, occupational therapy and speech pathology over home health aide services using multiplier models presented in Chap. 4.

12.6 Summary

This chapter provided a general guidance for a home health agency performance model, and its operationalization. Using generally available databases from either federal (CMS) or state databases, home health agency provider performance can be evaluated. An example home health agency performance model was presented using the database from the state of California. Limitations of the past studies, and suggestions for future evaluations are also provided.

Acknowledgment

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Chapter 13
Applications for Other Health Care Organizations

13.1 Introduction

In earlier chapters, models of performance evaluation for major health care providers were presented. These included hospitals, physician offices, nursing homes, health maintenance organizations, and home health care. There are many other health care providers that serve the patient needs, sometimes in conjunction with major providers, and sometimes independently. The literature shows that a variety of performance models were developed for providers such as dialysis centers, community mental health centers, community based youth services, organ procurement organizations, aging agencies, dental providers, pharmacies, ophthalmology centers, diagnostic and screening centers, and so on (Hollingsworth, 2003). In this chapter, performance models for selected health service providers are presented.

13.2 Dialysis Centers

End-stage renal disease (ESRD), a life threatening disease, cost 2.3 billion dollars in 2000 for 378,862 people. Medicare ESRD program provides coverage of over 93% of the costs regardless of the patient age. Due to the scope of this problem, evaluation of performance for dialysis centers, the organizations that provide treatments for ESRD, is a significant issue. Ozgen and Ozcan (2002) evaluated dialysis centers in a cross-sectional analysis using DEA. Their study was focused on free-standing dialysis facilities that operated in 1997. The data for Independent Renal Facility Cost Report Data (IRFCRD) was utilized to obtain information on the output and input variables and market and facility features for the 791 renal dialysis centers analyzed in this evaluation. IRFCRD is a national data and maintained by the CMS (the Center for Medicare and Medicaid Studies). This study, interestingly, combined both DEA and logistic regression. Technical efficiency scores were determined using DEA. The binary variable of efficiency was then regressed against its

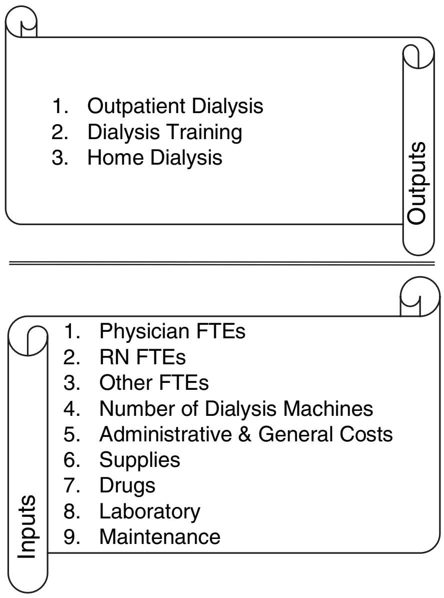

Fig. 13.1 DEA model for dialysis centers

market and facility characteristics and the control factors in a multivariate logistic regression analysis.

The output variables included outpatient dialysis, dialysis training and home dialysis treatments. The input variables included labor inputs (FTEs of physicians RNs and other medical staff), capital inputs (i.e., total number of dialysis machines), and dialysis costs (i.e., administrative and general, supplies, drugs, laboratory, equipment and machine maintenance), as shown in Fig. 13.1.

Overall, it was found that the majority of the dialysis centers are functionally inefficient. The intensity of market competition or a policy of dialyzer reuse did not impact the facilities' efficiency. However, technical efficiency was found to be significantly associated with the type of ownership, the interaction between the market concentration of for-profits and ownership type, and the affiliations with chains of different sizes. In terms of ownership, for-profit counterparts were less likely than nonprofit and government owned facilities to become inefficient producers of renal dialysis outputs.

A follow up evaluation of dialysis centers was also conducted by Ozgen and Ozcan (2004). This evaluation used a longitudinal approach to analyze the efficiency because a previous cross-sectional study provided limited information to answer whether and how influences from the payer and from the provider sides may affect provider efficiency over time. Thus, the Malmquist index based DEA model was used to analyze the dialysis centers.

Data were derived again from Independent Renal Facility Cost Report Data Files from 1994 to 2000. A total 140 facilities were selected based on those operating throughout the study years and with nonzero inputs. Malmquist index was calculated to compare pairs of 7-year periods including: 1994–1995, 1995–1996, 1996–1997, 1997–1998, 1998–1999, 1999–2000, and 1994–2000.

The mean efficiency score for the 7 years was 0.918 and an average 41% of freestanding facilities were efficient. Mean efficiency scores were the lowest in 1995 (0.89) and increased to a high of 0.94 in 2000. Technical efficiency improved by 6%.

The DEA Malmquist index (MI) is a product of technical efficiency and technology change. Using a CRS input-oriented model one can observe that dialysis centers over time were progressive if $\mathrm{MI} < 1$; had no change if $\mathrm{MI} = 1$; and regressive if $\mathrm{MI} > 1$. The overall 1994–2000 Malmquist index was 1.07, meaning that the productivity regressed over time. Some of the interesting results of this evaluation are noted as:

- Outpatient outputs increased but training and home dialyses outputs decreased. Overall output averages fluctuated, resulting in 11% increase. Inputs use has been conservative. For operating costs there was a total average increase of 9%.
- Comparing three cost items, supply cost declined (33–9%), drug costs steadily increased by 13%, representing 43% of total average costs in 2000. Administrative and general costs fluctuated from 29 to 25% in 1994 and 2000, respectively.
- The overall MI and its components (efficiency change and technology change) showed loss of productivity (MI) influenced by technological change (TC). Technical efficiency was slightly positive with very little regression.

This study further examined whether system affiliation and size of dialysis organizations would have different outcomes. From the results, chain affiliations have a positive difference in technical efficiency. The size of a dialysis chain did not have a significant role in technical efficiency. Freestanding dialysis facilities improved their technical efficiency over time, but may have regressed in technology, thus having the potential to improve the quality of care.

13.3 Community Mental Health Centers

While the cost of health care in the United States was approaching 1 trillion dollars in 1996, ~10% of that money ($99 billion) was spent on behavioral health care. Mental health disorders consumed 7% of the health care costs, with Alzheimer's disease/dementias and addiction disorders consuming 2 and 1% of total costs, respectively (U.S. Department of Health and Human Services (1999)). About 18% of the expenditures on mental health went to multi-service mental health clinics, which include community mental health centers. From 1986 to 1996, mental health costs rose 1% less than overall health costs did. Twelve percent of the United States population is covered under Medicaid for their health care. Medicaid's cost for behavioral health amounts to 19% of its expenditures; per capita Medicaid mental health expenditure is ~$481 (U.S. Department of Health and Human Services (1999)). These costs justify examination of efficiency in the provision of the mental health services by community mental health organizations.

One of the early evaluations of DEA in mental health programs was by Schinnar et al. (1990), who assessed the efficiency and effectiveness of 54 of the 80 mental health partial care programs operated in New Jersey during the fiscal year 1984/1985. Schinnar et al. using DEA, created various productivity, efficiency and effectiveness indices. These indices included service-mix, client-mix, fiscal intensity, fiscal distribution, and program effectiveness. Depending upon the purpose and the nature of the index various inputs and outputs were employed. Staff hours or salaries and other costs were part of the inputs for productivity and efficiency indices. Outputs in many indices constituted the young and old high; low functioning clients categorized in four groups. Mean efficiency scores for the indices ranged between 0.62 and 0.67.

Tyler et al. (1995) assessed the technical efficiency of community mental health centers (CMHC) in production of case management services. They compared 39 CMHC programs in Virginia using data from fiscal year 1992/1993 annual statistical reports. Two outputs of the evaluation were case management clients with SMI and case management clients without SMI. Thus, SMI designation served as a case-mix for the patient outputs. The inputs were FTEs of direct service staff, FTEs of support staff, and non-labor operating expenses. An average efficiency score was 0.44. Only six (15%) of the CMHCs were efficient.

A more recent study by Ozcan (2004) used DEA to study technical efficiency of community mental health providers to improve their productivity. This was essentially a pilot investigation using DEA to examine 12 community mental health centers, all receiving traditional fee-for-service (FFS) Medicaid reimbursement in years 1–2 and switching to mandatory, capitated Medicaid managed care in years 3–5. The measures of efficiency were longitudinal patterns of provider efficiency over 5 years before and after implementation of the mandatory Medicaid managed care plan.

In 1996, a mandatory Medicaid managed care program was implemented in the Tidewater region of the state of Virginia. The Ozcan (2004) evaluation focused on care provided by these community mental health centers (CMHC) in Virginia to seriously mentally ill (SMI) patients. The care was limited to those reimbursed by Medicaid between 1994 and 1998. The CMHCs that treated less than 100 SMI cases were excluded to ensure proficiency. The CMHCs were located in two different regions: four in Richmond (control group) and eight in Tidewater (experimental group). The SMI patients were identified using diagnosis codes ranging from 295.00 to 298.99 (schizophrenia, major affective psychosis, paranoid states, and other non-organic psychoses).

The output variables included the number of SMI patients in supplemental security income (SSI), considered as more severe, and the number of SMI patients not in SSI (less severe). The six input variables were use of non-emergency crisis support, use of outpatient assessment, use of outpatient therapy, use of outpatient medication management, use of clubhouse, and use of case management. The DEA model for this evaluation is shown in Fig. 13.2.

Over the 5 years, from 1994 to 1998, 31 out of the 60 DMUs were efficient. The DMUs in the Tidewater region had a higher average efficiency score of 0.895

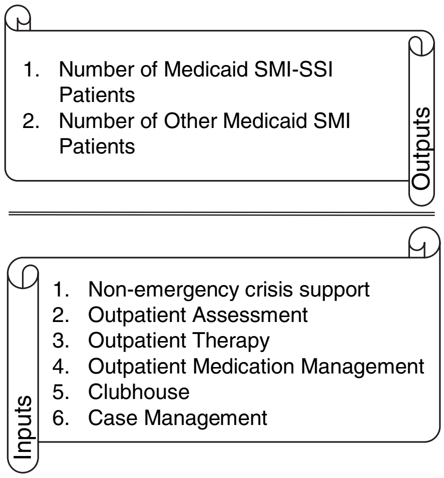

Fig. 13.2 DEA model for community mental health centers

compared to Richmond's score of 0.753. The differences in the efficiency score of the two regions were statistically significant after managed care was implemented. An increasing trend in scores over time for Tidewater area, the region for implementation of Medicaid managed care programs, was observed. On the other hand, the Richmond area CMHCs' scores remained level.

Ozcan (2004) extended their evaluation using a multiplier model (weight restricted) with preferred ratio constraints. The preferred ratio was designated as case management over non-emergency crisis support. This restriction based on this ratio constraint creates an efficiency frontier that only includes the section creating the preferred practice style. The authors added an additional preferred ratio of outpatient medication management over outpatient therapy. The number of efficient DMUs decreased in both the Richmond and Tidewater regions when a more stringent efficiency outcome is utilized.

The results of the multiplier model showed that the efficiency of CMHCs in Richmond is significantly less than in the base model. The Tidewater CMHCs' efficiency scores were reduced during the pre-managed care era and they were significantly higher after managed care. A perfect efficiency score is a score of 1.0. Richmond had only three perfectly efficient CMHCs in the multiplier model, as compared to seven in the base model, yielding a 57.1% reduction in perfect efficiency. On the other hand, the number of instances of perfectly efficient CMHCs in Tidewater dropped to 20 in the multiplier model from 24 in the base model. This model extension showed the power of the multiplier model, which produces more stringent efficiency outcomes (Ozcan, 2004).

The methods shown in this evaluation offer a replicable, objective methodology that can be used to compare the operational efficiency of different types of providers who care for similar populations of clients. The methodology identifies consistent measures for comparison – numbers of patients treated – and provides a means of aggregating information on different numbers of patients to serve as a measure of organizational performance.

This methodology could be useful to public mental health systems as well as to private and public managed care companies, because it can identify the combinations of services that result in the most efficient care. That information can be used to change the mix of services that a managed care company will reimburse, and/or those that a provider chooses to use (Ozcan, 2004).

13.4 Community Based Youth Services

Providing comprehensive mental health services to children is another important issue. Community based youth services is a fully integrated, less expensive alternative for children and adolescents as a substitute for hospitalization. Many states, including Virginia, have established comprehensive community-based youth services (CBYS). Virginia's program started in July 1993.

Yeh et al. (1997) evaluated CBYS using DEA among 40 Virginia communities that reported their data on regular basis to Virginia department of Mental Health, Mental Retardation, and Substance Abuse Services (DMHMRSAS). Financial data for the same fiscal year 1993/1994 was obtained from Virginia Department of Education, the agency that handles the financial aspects of the CBYS program.

The CBYS model considered two outputs based on services provided, namely residential and non-residential services. Inputs included a budget for the services and a budget for the administration of the programs. In addition, the number of youths who received the services and the percentage of youth in poverty were the other inputs. Figure 13.3 illustrates this model. Analysis were carried out to evaluate the effect of the size of CBYS (large-15,000 or more youth population, small

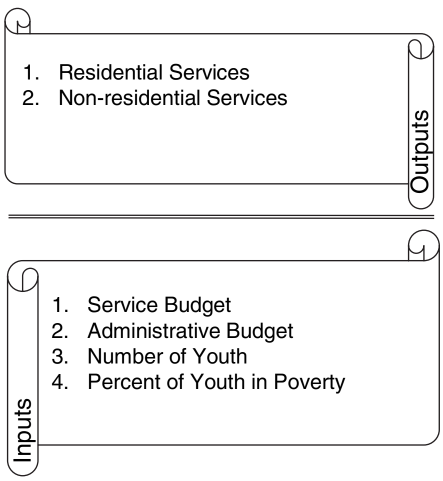

Fig. 13.3 DEA model for community based youth services

otherwise), location (urban vs. rural), and community type (poor if poverty $>8\%$, rich otherwise).

Output-oriented DEA model results showed that ten (25%) of the CBYS were efficient. CYBS programs in large communities, in rich communities, and in urban communities were more efficient than their counterparts. The inefficient CBYS, with their current level of inputs, could have served 164 more youths for residential services and 487 more youths for non-residential services.

13.5 Organ Procurement Organizations

The United Network for Organ Sharing (UNOS) lists about 97,000 individuals on the waiting list for organs as of July 2007, and there were over 9,000 transplants during the period of January-April 2007 (http://www.unos.org). On average, several patients daily die while waiting for organs. UNOS coordinates the placement and distribution of donated organs, collects, analyzes, and publishes transplant data, and educates health professionals about the donation process. Organ procurement organizations (OPOs) coordinate the organ procurement and transplantation process in designated service areas (Ozcan et al. 1999). Thus, evaluation of OPO performance is an important issue, especially when many thousands of individuals are waiting for appropriate organs to be recovered and hopefully matching one transplanted from them to save their lives.

Ozcan et al. (1999) developed a DEA model to evaluate the performance of OPOs. They indicated that the usual measure of performance by ratios, such as kidneys recovered per million population, is limited by itself due to existence of multiple inputs and outputs related to different resources, activities and other factors.

Their evaluation assumes that OPOs would want to know how much shortfall in outputs they have with given resources as compared to other OPOs, and so an output-oriented DEA model was used.

The researchers surveyed the Executive Directors of the 66 OPOs in U.S. who were asked to provide information on OPO hospital development activities, expenditures, and staffing for the 1994 calendar year (McKinney et al. 1998). Sixy-four of the OPO questionnaires were useful for the analysis. Secondary data from Association of Organ Procurement Organizations (AOPO) and UNOS were also utilized for this evaluation.

The most recognized output of OPOs is organs recovered, and the DEA-OPO model employs kidneys and extrarenal organs recovered as outputs. On input side, the measure of hospital development formalization index (0–3 scale accounts for whether an OPO has a hospital development director, department, and written standards for effectiveness) developed in this study provides a proxy for the capital/structure dimension of the input resources, as it reflects the degree to which the OPO has formal structures in place to produce outputs. The other categories of inputs include hospital development labor FTEs, hospital development personnel FTEs, other labor FTEs, and operating expenses not devoted to hospital development (measured by non-FTE operating expenses). One additional nondiscretionary

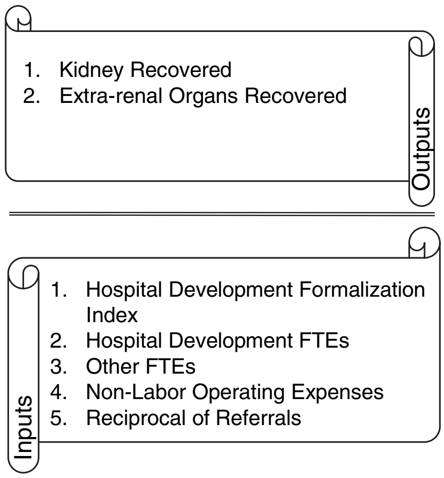

Fig. 13.4 DEA model for organ procurement organizations

input is used, referrals, and are classified as nondiscretionary because OPO managers do not have control over this input. Outputs and inputs of the DEA model for OPO performance is illustrated in Fig. 13.4 (Ozcan et al. 1999).

Based on a two-output, five-input, variable returns to scale, output-oriented model they estimated two peer-grouped (larger and smaller OPOs) DEA models with measures calculated from the survey data obtained from OPOs and secondary data mentioned above. Overall, 55% of the OPOs ($n = 35$) were classified as efficient in comparison to their peers in the two-frontier (larger versus smaller) approach. In the smaller OPO frontier, the average efficiency of the 42 OPOs was 0.79, whereas in the larger OPO frontier the average efficiency score of the 22 OPOs was 0.95. The authors found that OPOs classified as efficient recover significantly more kidneys and extrarenal organs, have higher operating expenses, and have more referrals, donors, extrarenal transplants, and kidney transplants. Furthermore, it is noted that efficient OPO hospital development FTEs, other FTEs, and hospital development formalization indices do not significantly differ.

The role of referrals is interesting in this model; for the large group, none of the inefficient facilities had a lower quantity of referrals than the efficient facilities. But for the small group, inefficient facilities need approximately 92 more referrals to be classified as efficient. These findings indicate that the OPO's in the larger group have greater technical efficiency.

13.6 Aging Agencies

After the Older Americans Act of 1965, states have designed local area agencies to provide aging service for older persons. There are diverse structures and programs among different states, including nonprofit corporations, governmental units, and regional authority of local governments. These agencies, based on their governmental types, may receive funding from different sources, such as the Older Americans Act Funds, non-federal resources, client donations and other federal funds. These agencies provide aging services, including accurate needs assessment (i.e., nutrition service, supportive, community-based services), planning and leadership in service development.

Little evaluation of the efficiency of area agencies on aging exists. Researchers often found some difficulties when evaluating these organizations. Those difficulties included an ambiguous focus, wide-ranging goals, provision of multiple services, and lack of uniform input and outcome data. Specifically, the data collection included bias and inaccuracy problem. Regarding this issue, it is inappropriate to use cost-effectiveness or ratio analysis to evaluate the performance among agencies. Hence, the evaluation of these agencies by Ozcan and Cotter (1994) using DEA allowed the full considerations of multiple outcomes and multiple inputs.

The Ozcan and Cotter (1994) evaluation was a cross-sectional design using 25 Area Agencies on Aging for 1991 in Virginia. The annual performance report data by these agencies was used and this report received accounting audits. Therefore, the quality of the data was satisfactory and consistent.

The outputs of the evaluation consisted of meal services and support and community based services. Meals, however could be delivered either in congregate settings such as at senior centers, or directly delivered to homes of the seniors. In Virginia, the scope of supportive services could amount to 26 different services, including case management, dental services, home care, geriatric day care, residential repair and renovation, etc. Since not all agencies provide all services, using these services as individual outputs would be prohibitive in any model. Thus, a support service index was developed by determining the proportional value of the unit cost of each service relative to the average of unit costs for all services. The support services index score was then used to make adjustments. This provided a combination of the intensity of the service with the total amount of production (Ozcan and Cotter, 1994). The index puts a lower intensity to telephone based services compared to legal services, however, magnitude (number) of telephone services might be far larger than legal services. Outputs and inputs for aging agency evaluation are shown in Fig. 13.5.

This evaluation employed an output-orientation DEA model, since inputs are modestly determined by external factors and decisions often occur with output variables. This study expected that the area agencies with more control over their operations would perform at a higher level of provision of service. Three factors were also considered to affect the results of inputs into outputs, including size (i.e., small, medium, and large), organizational type (i.e., governmental, joint exercise, and private nonprofit), and geographic (i.e., rural, and urban).

Fifteen (60%) out of 25 area agencies are found to be efficient. Governmental units had the highest proportion (80%) of efficient operations. Area agencies in large-size areas were more likely to be efficient. Area agencies covering urban areas were also more likely to be efficient. For inefficient agencies, using the benchmark

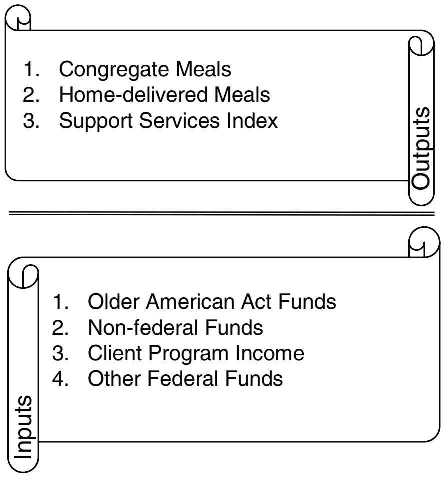

Fig. 13.5 DEA model for aging agencies

targets, the analysis indicated the variety of changes needed to improve greater efficiency and provided information on where intervention efforts offer the most potential.

13.7 Dental Providers

There are very few evaluations of dental services using DEA. A rear study by Buck (2000) evaluated the efficiency of the community dental service in England where they evaluated 100 dental services and found that the average efficiency of community dental services was 0.635. Another study by Linna et al. (2003) examined the technical efficiency of oral health provision in 228 Finnish health centers. The average efficiency score ranged from 0.72 to 0.81, depending upon type of facility.

In a more recent study by Coppola et al. (2003) performance of dental providers were evaluated on posterior restorations. Dental evaluations focus on the survivability of amalgam and composite materials. However, the experience of the provider in restoration longevity must be factored in these evaluations.

Data for this evaluation was obtained from the Washington Dental Service (insurance claims data base) with 650,000 subscribers, 1.5 million patients (updated monthly), and 23,103 total dentists. Dentist who provided more than 100 encounters of dental restoration services from 1993 to 1999, inclusively, were included in the evaluation, hence there were 1,240 such dental providers.

The evaluation employed severity of amalgam or composite restoration (two, three, or four surface), and provider experience as inputs. The single output was restoration longevity. Figure 13.6 displays the DEA model inputs and output for dental provider performance on restoration.

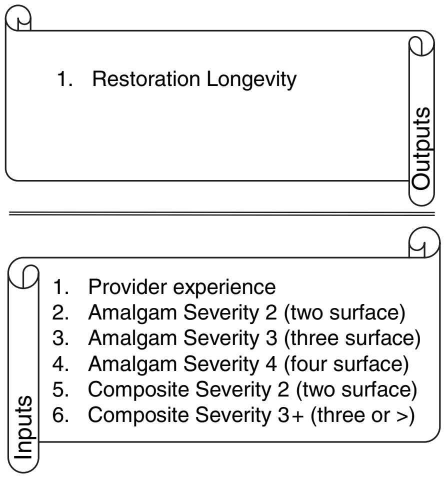

Fig. 13.6 DEA model for dental providers performance on restorations

The result showed that only 122 (9.8%) dental providers were efficient in their restoration work with an average longevity of 46.5 months. The longevity of restorations by inefficient dental providers was only 41.8 months. An average efficiency score for all dental providers was 0.788. The evaluation also found that the efficient dentists have more experience, as efficiency peaks at 14 years provider experience and begins to decrease after the 15th year of practice. Efficient providers have amalgams or composites that last 4.7 months longer. The average age for efficient providers is 40.4 years, and the average age for inefficient providers is 46.8 years. Providers who work on amalgams are less likely to be efficient than providers who work on composites.

This study showed how DEA can be used creatively to evaluate not only performance of providers, but also the quality of the service provided as measured by the longevity of the service product.

13.8 Summary

This chapter provided an overview of 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. The evaluation of each provider type is unique and variables and databases are also unique. We hope these examples serve as guidance to evaluate other traditional and non-traditional health provider service evaluations in the future.

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

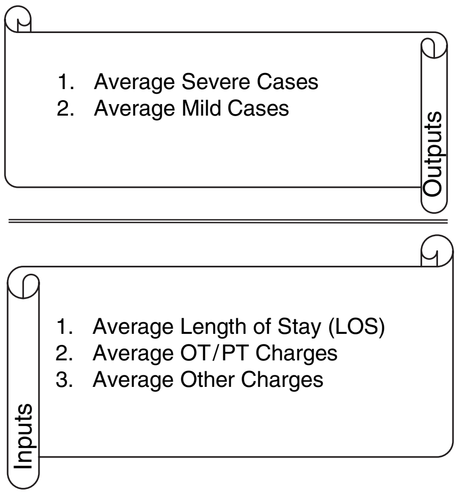

Fig. 14.1 DEA model for stroke treatment

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).

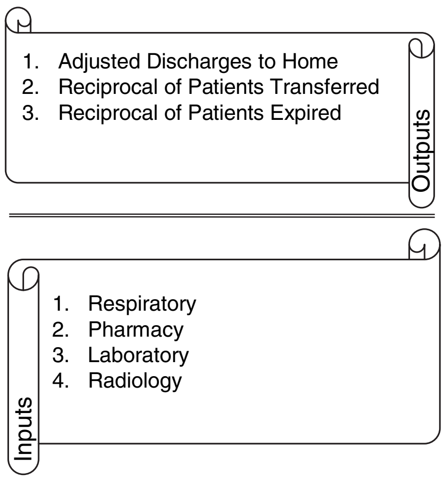

Fig. 14.2 DEA model for mechanical ventilation

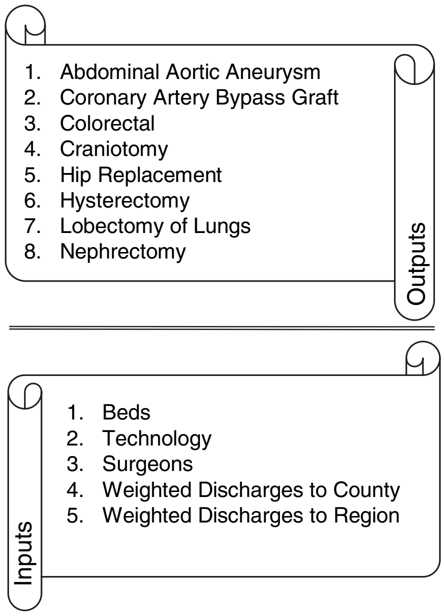

Fig. 14.3 DEA model for perioperative services (Source: O'Neill et al., 2007)

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 ∼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.

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Running the DEAFrontier Limited Version

www.deafrontier.com

Before you run the DEAFrontier software

Before you load the DEAFrontierFree software, the Excel program must be open/loaded first. And then the Solver Parameters dialog box must at least be displayed once in your Excel session. Otherwise, an error (shown in Figure 1) may occur when you run the software. This error message means that the Excel Solver is not found by the DEAFrontier software. (*If the DEAFrontier software is installed in the directory where the Excel Solver is installed, you may not need to load the Excel Solver first.*)

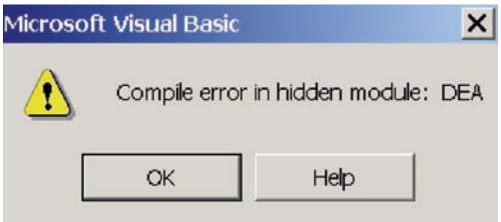
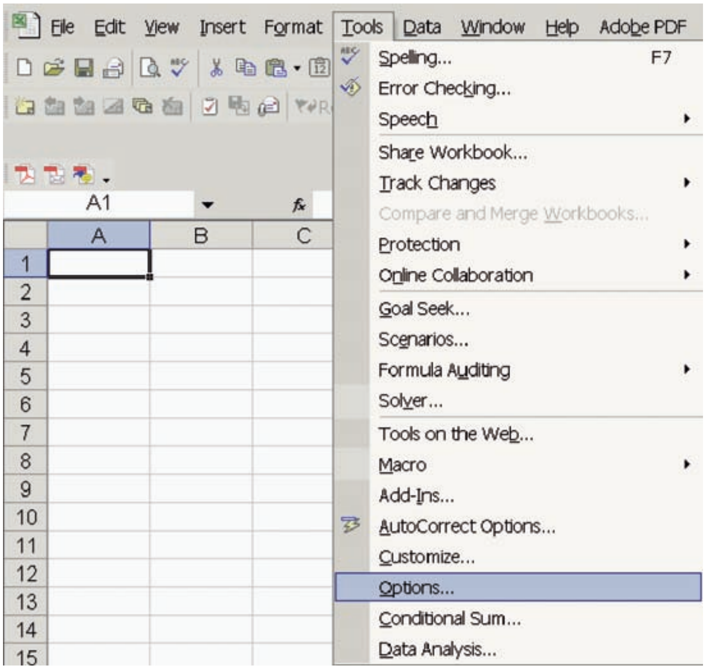
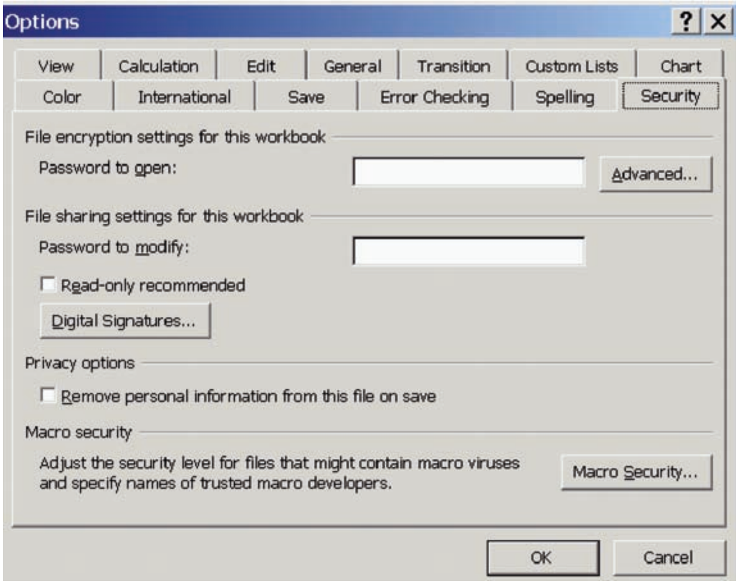


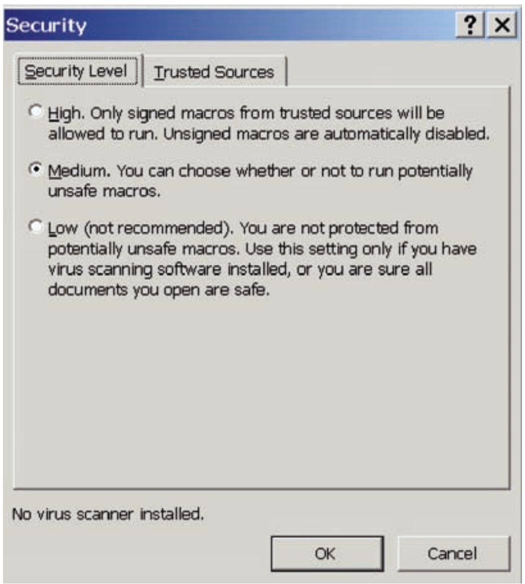
Figure 1

Please also set the Macro Security to Medium Level in the Excel. This can be done by selecting the Tools/Options menu item as shown in the following

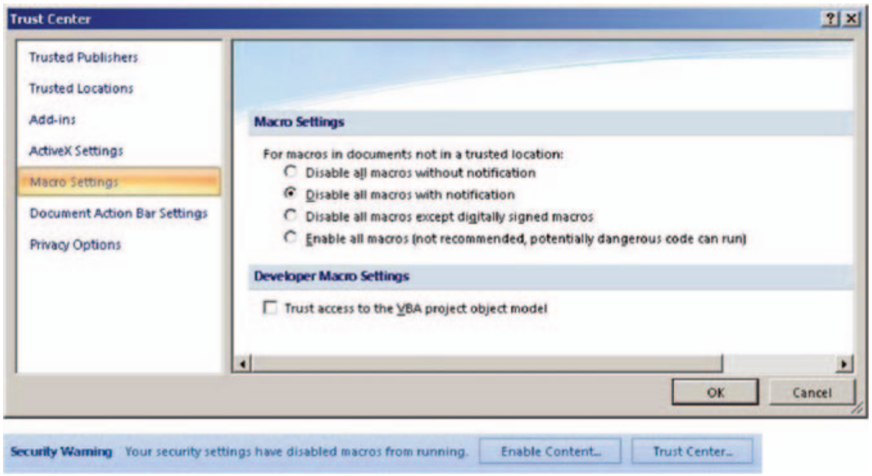


In the Option menu item, click the Macro Security button and then select the "Medium" option.





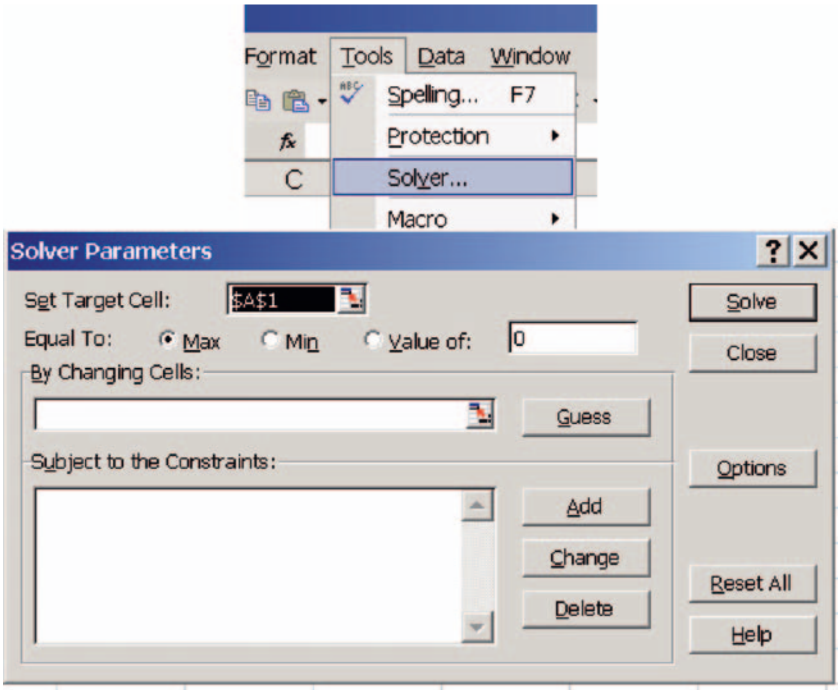
If you are using Excel 2007, you need to do this in the Trust Center: check (1) enable all macros and (2) Trust access to the VBA project object model. You may also need to specify the directory where the DEAFrontier software is located as "Trusted Locations".



Load Excel Solver in Excel 97, 2000 and 2003 (XP)

You may use the following steps. (Close the DEAFrontier if it is already opened using the "Quit" menu item.)

Step 1: Open Excel, and then load Solver parameters dialog box by using the Tools/Solver menu item.



Step 2: Click Close to close the Solver parameters dialog box. Now, the Solver has been loaded.

If Solver does not exist in the Tools menu, you need to select Tools/Add-Ins, and check the Solver box, as shown in Figure 2. (If Solver does not show in the Add-Ins, you need to install the Solver first.)

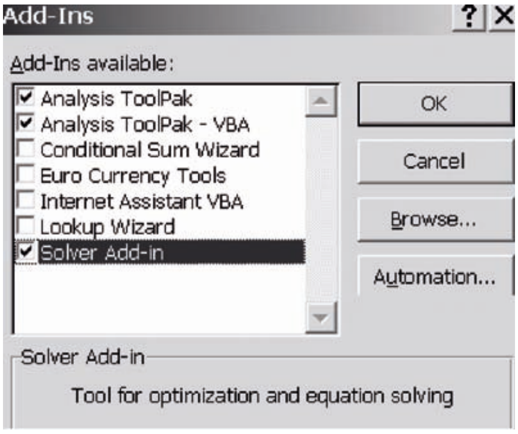


Figure 2

Load Excel Solver in Excel 2007

1. Click the **Microsoft Office Button** , and then click **Excel Options**.
2. Click **Add-Ins**, and then in the **Manage** box, select **Excel Add-ins**.
3. Click **Go**.
4. In the **Add-Ins available** box, select the **Solver Add-in** check box, and then click **OK**.
   Tip: If **Solver Add-in** is not listed in the **Add-Ins available** box, click **Browse** to locate the add-in.
   If you get prompted that the Solver Add-in is not currently installed on your computer, click **Yes** to install it.
5. After you load the Solver Add-in, the **Solver** command is available in the **Analysis** group on the **Data** tab.

Run the DEAFrontier Software

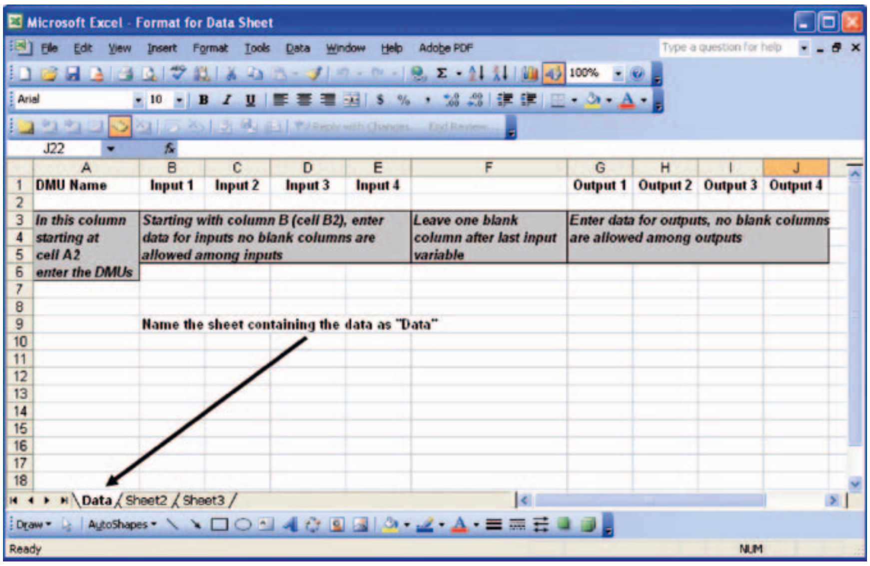
Load the DEA software by opening (i) "DEAFrontier Limited.xla" for Excel 97, 2000 and 2003, or (ii) "DEAFrontier Limited2007.xlam" for Excel 2007.

You will see a new Menu item “DEA” at the end of Excel Menu. Now, the software is ready to run. (Please see the Format for Data Sheet for proper setup of data sets.)

For Excel 2007: to locate the DEA Menu, Office 2007 users select the Add-Ins tab and navigate to the DEA menu option. The DEA menus will not always be visible, as they were in Office 2003. Users can move individual commands to a small Quick Access bar in Office 2007 to make them visible all the time.

Please make sure that the Excel Solver works properly. One can use the file “solvertest.xls” to test whether the Excel Solver works. This test file is available at www.deafrontier.com/solvertest.xls.)

Organization of the Data



About the Author

Yasar A. Ozcan, Ph.D.
***Professor*,**
Department of Health Administration
Virginia Commonwealth University
Richmond, Virginia USA
ozcan@vcu.edu

Yasar A. Ozcan, Ph.D. is a Professor in the Department of Health Administration, Virginia Commonwealth University (VCU), where he has served as faculty member over 28 years. He teaches quantitative health care management courses in graduate professional programs in health administration, and methodology courses at the doctoral level, including data envelopment analysis (DEA).

Professor Ozcan's scholarly work is in the areas of health systems productivity, technical efficiency, financial efficiency, and effectiveness. Specifically, he has applied DEA to measure efficiency across the range of health care facilities including hospitals, nursing homes, health maintenance organizations, mental health care organizations, physician practices, and other facilities. He has presented numerous research papers at professional meetings and published extensively. His work has been published in journals such as *Health Services Research, Medical Care, Health Care Management Science, Health Services Management Research, Journal of Medical Systems, Socio-Economic Planning Sciences, Annals of Operations Research, Journal of Operational Research Society* and the *Journal of Operational Research*. Professor Ozcan authored another text book *Quantitative Methods in Health Care Management: Techniques and Applications* (Jossey-Bass/Wiley, 2005) that is geared toward practicing health care managers and health care management students at the master's level.

He has served twice as President of the Health Applications Section in the Institute of Operations Research and Management Science (INFORMS). Professor Ozcan is the founding Editor in Chief of a highly regarded journal, *Health Care Management Science*, and co-editor of the *Journal of Central Asian Health Services Research*. He has been principal and co-principal investigator on various federal, state grants and international contracts. He has also provided management consultancy services to health care facilities and managed care organizations including: hospitals, physician practices and HMOs on reengineering and lean management. For further information on his research, please visit http://www.had.vcu.edu/∼ozcan/.

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