MATHEMATICAL TOOLS AND BUDGETARY MECHANISMS FOR HOSPITAL COST CONTROL

by

Josep Valor Sabatier

Ingeniero Industrial,
Universidad Politécnica de Barcelona (1976)

Ph.D. in Operations Research,
Massachusetts Institute of Technology (1981)

SUBMITTED TO THE HARVARD-MIT DIVISION OF HEALTH SCIENCES AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF SCIENCE

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 1985

Signature of Author _____
Harvard-MIT Division of Health Sciences and Technology
June 3, 1985

Certified by _____
Barbara J. McNeil
Thesis Supervisor

Certified by _____
Regina E. Herzlinger
Thesis Supervisor

Accepted by _____
Ernest G. Cravalho
Chairman, Departmental Graduate Committee

MATHEMATICAL TOOLS AND BUDGETARY MECHANISMS FOR HOSPITAL COST CONTROL

by

Josep Valor Sabatier

Submitted to the Harvard-MIT Division of Health Sciences and Technology on June 3, 1985 in partial fulfillment of the requirements for the degree of Doctor of Science.

Abstract

This thesis is concerned with hospital cost containment, in particular, how variance-based budgeting (arrived at via mathematical optimization) can be used to introduce incentives for cost containment and standardization of care without putting the institutions at an inordinate level of risk. The importance of the variance-based allocation techniques introduced in this thesis is highlighted via numerical illustrations that use real hospital cost data. The methodology relies on the probabilistic characterization of the resources needed to treat patients, and produces budgets that offer the decision maker a set of options related to the maximization of utility functions. The probabilistic characterization of resource consumption is approached by evaluating several patient classification techniques that have been recently developed and that have not been compared using real cost data. This thesis presents numerical evidence for the great variability of resource usage within DRGs and for the power of severity-based subclassifications as variance reducers.

The problem of multi-facility resource allocation is also addressed. Two multi-facility efficiency measures are compared and evaluated with data from a nonprofit chain. Also, a model describing the effect of medical teaching programs on the staffing loads is developed and evaluated with data from the same nonprofit chain.

The research uses real-life examples to show that the risk profiles of different clinical services in a hospital (and of different hospitals in a system) vary widely. Consequently, it is proven that classical budgeting methodologies used as cost-control mechanisms seriously deviate from goals of overall minimum risk and utility maximization. These objectives are achieved with the use of the variance-based algorithms developed in this thesis.

Thesis Supervisor: Barbara J. McNeil
Title: Professor of Radiology and Clinical Epidemiology
Thesis Supervisor: Regina E. Herzlinger
Title: Professor of Management

ACKNOWLEDGMENTS

I am indebted to my two thesis supervisors professors Regina Herzlinger and Barbara McNeil. With their expertise and knowledge of the health-care system, they provided the guidance necessary for this project to be completed. Dr. Frank Holden gave me help as a reader beyond the call of duty and provided encouragement and support whenever necessary. Professor Stan Finkelstein, who also served as a reader, helped to determine the scope of the project and provided valuable sources of information. Professor Gabriel Bitran helped on development of the efficiency section in chapter six.

The program director, Professor Ernest Cravalho, and the administrative officers of the HST Division, Keiko Oh in particular, have been instrumental in getting me through the financially and bureaucratically troubled waters of MIT.

This thesis is only a partial fulfillment of the requirements to get a degree. A number of people from the Division of Health Sciences and Technology have been essential in making the fulfillment of the other requirements possible. In particular, Debbie Burstein, Joe Smith, Paul Albrecht and Howard Bernstein have been instrumental in making the preclinical courses and the clinical rotations enjoyable. I am also grateful to the staff of the Boston Development Center: Debbie Luisi, Steven Kendall and Mike Mahar.

Also, without the cooperation of the staffs of the hospital and the hospital-chain who provided the data and who must go unnamed, I would have not been able to carry out this research.

The support and understanding of my wife Montserrat have been essential to makeing my four years in HST survivable.

Table of Contents

List of Figures

Chapter 1

Introduction

Hospital costs have skyrocketed in recent years, increasing annually on the average of 17.5% since 1979, three times faster than the rate of inflation. In 1982, hospital costs accounted for two thirds of the $50.9 billion expended by Medicare, amounting to a bill of more than $3 billion per month. This level of spending has brought the Medicare fund to the edge of bankruptcy. Congress has reacted to this grim situation for hospital costs by enacting legislation that mandates a prospective payment method for Medicare (the so-called Diagnosis-Related Group prospective method). The major effect of this legislation is that hospitals must now care for a patient within a limited budget, because they are not able to bill for individual services provided on the basis of the costs incurred.

In the light of this budgetary crisis, the purpose of this thesis is to develop a strategy for resource allocation that takes into account factors that have previously been ignored by classical budgeting methodologies.

These factors are:

- Randomness of the patient-care process. Two patients seemingly alike may use different amounts of resources. Accounting for different resource usage was not important in the past because hospitals could bill whatever costs they incurred while taking care of a patient.

- Lack of reliable cost data. Under a fee-for-service reimbursement policy, hospitals adjusted their charges to meet "bottom line" requirements, not necessarily in accordance to real costs.

- Lack of a coherent unit to measure hospital output, therefore making it impossible to perform productivity studies. Traditional measures used have been bed-days of care and total number of discharges, clearly ignoring issues of intensity of care and diagnosis.

- Few measures of the efficiency of the units budgeted. In a fee-for-service reimbursement system it was not necessary to consider the global efficiency of the hospital as long as it could produce tests and services cheaper than the reimbursement fee.

- Lack of recognition of budgeting as a cost-control measure.

The resource allocation methodology developed in this thesis will be first introduced with mathematical rigor and then applied to two real-life situations: (1) a teaching hospital, where the services of the Division of Medicine will be budgeted, and (2) a noprofit chain, where resources across 160 hospitals will be allocated.

Although all the above factors have influenced the general structure of the methodology, its value with respect to hospital management and cost control is stressed throughout the thesis by discussions regarding its implications on the following issues: (1) Inherent variability of resource usage in the patient care process, (2) Importance of physician behavior in cost control, (3) Multi-institutional budgeting, and (4) Patient classification techniques.

Inherent variability of resource usage in the patient care process: The variability of the resources needed to perform a given task is one of the most challenging aspects of hospital management. In contrast to other industries where usage (and therefore costs) can be predicted with accuracy, a hospital cannot predict the costs of "producing" an item like an appendectomy.

The two numerical examples presented in this thesis demonstrate how budgets vary from intuitive allocations when the budgeting process benefits from information related to the randomness inherent to the health-care process. The insights gained from these examples will help the understanding of how to introduce incentives for cost containment without putting the hospitals at inordinate levels of risk.

Importance of physician behavior in cost control: One of the implications of DRG-based reimbursement is that managers will need to be involved in the cost-benefit analysis of patient management and that physicians will have to get involved with the financial aspects of hospital management. This can be done by properly using the budgeting process within the hospital. When properly applied, budgeting is the instrument that brings together financial aspects of the hospital and patient management issues.

Multi-institutional budgeting: When finite resources have to be allocated among hospitals that use different combinations of inputs and discharge different numbers of patients from different Clinical Services, decision makers are faced with the problem of determining the relative efficiency of each institution. This is a problem known in the Operations Research literature as multiple input - multiple output efficiency measurement.

Measuring efficiency in hospitals is particularly difficult because institutions that have multiple outputs and multiple inputs are very difficult to compare. This thesis will evaluate two different measures of efficiency, based on mathematical programming, recently introduced in the literature. The evaluation will be made both at the theoretical level and at the practical level using real data from a nonprofit chain of 160 hospitals.

Another aspect of the budgeting of systems of hospitals is the impact of medical education in the productivity of the institutions. This thesis will analyze, with a simple model, the effect of medical-school affiliation on the staffing levels of our chain of 160 hospitals, and will make recommendations for extending the study to areas of hospital management other than staffing.

Patient classification techniques: Defining measures of hospital output that are consistent with resource usage is essential for resource allocation and

productivity measurement. A number of techniques have appeared in the literature in the last few months that attempt to define classes of patients with uniform resource usage per admission. This thesis will evaluate the effectiveness of two of the more frequently used systems (Severity of Illness Index and Disease Staging) as variance reducers.

PLAN FOR THIS MANUSCRIPT

Chapter 2 is the bibliography review. Chapter 3 introduces the data that are used for the numerical examples. These data come from two different sources, a teaching hospital and not-for-profit chain. In order to preserve confidentiality, we will refer to the single hospital as Hospital X, and to the chain as Chain Y.

Chapter 4 develops the mathematical model for resource allocation and evaluates different patient classification methodologies. Chapter 5 presents the numerical example allocating resources to the different Clinical Services of the Division of Medicine of hospital X. Chapter 6 deals with multi-institutional budgeting, and examines two different efficiency measures. It also develops a model for the relationship between teaching loads and productivity, and presents the numerical results of using the techniques introduced in chapter 4 with data from the Y chain. Finally, chapter 7 has a summary of the results and topics for future research.

Chapter 2

Literature Review.

2.1 Reimbursement in Health Care

This section will survey the methodologies used to reimburse health care institutions: reimbursement of charges, establishing fixed rates for each service provided, establishing fixed rates per diagnosis, and global budgeting. Particular emphasis will be devoted to the newly developed fixed-price Diagnosis-Related System adopted by Medicare.

2.1.1 Classical Methods

In this chapter, the term "classical methods" is used to denote two distinct reimbursement strategies (1) fee-for-service, either hospital charges or predetermined fixed fees, and (2) global budgeting.

Fee for Service: In a conventional fee-for-service environment, the hospital bills the patient or the insurer for each service provided. When the actual amount paid is the full bill, the reimbursement method does not provide any incentive for real cost control by the provider and it is highly inflationary [9]. To counteract these effects, policy makers developed the *a priori* rate setting strategy.

The concept of *a priori* rate setting for hospital services was introduced in the late sixties, and from 1970 to 1975, the number of rate setting programs grew from two to twenty five [9]. This reimbursement methodology is presently in operation in most states. It differs from conventional fee-for-service form of reimbursement in that providers are not necessairly paid the costs they actually incurred; in addition

they are not allowed to freely adjust their charges to cover their costs. Rather, an external authority decides the maximum prices that providers are allowed to charge for a specified service. This method provides some incentive to health care professionals to operate efficiently within a given medical procedure or test, but it does not make any attempt to reduce the number of medical acts performed during an admission, be they necessary or not. From a financial optimization point of view, if a given medical procedure can be performed with a cost below the reimbursement rate by a physician in the office, he or she may have a tendency to carry out such procedure without necessarily throughly evaluating its potential benefit. The same phenomenon is also true for hospital-based procedures and tests.

There are a number of publications that deal with issues related to prospective reimbursement. One is the book edited by William L. Dowling [28]; it provides a number of examples of prospective rate setting in different states, as well as an analysis of the responses and reactions of administrators and providers. The book also details the management implications of fixed rates as well as underlines the need of bottom-up information flow. Unfortunately, reference [28] (as well as all other literature in this particular area), does not undertake the problem of resource utilization. It examines only how regulators can set prices for medical acts and how fixed rates influence the daily operation of the hospital[1].

---

[1]The effects of fee-for-service reimbusement are numerous. A number of studies have been recently published on the subject of excessive utilization of ancillary tests and hospital days. Studies ranging from 1966 to 1985 have highlighted the different practice patterns observed in the use of tests and hospital resources [20], [29], [30], [43], [70]. Of interest is that none of these articles mention the fact that one of the major incentives toward test overutilization may be purely economical. For example, [43] goes as far as stating "three of the four hospitals reviewed were found to have more than 30% inappropriate use of selected tests...", but does not make a judgment regarding the causes of such a striking finding.

2.1.2 Global Budgeting

Global budgeting is a strategy used by governments in countries with very regulated health sectors. Under this strategy, regulators assign to each health care institution a fixed budget, under which the hospital must operate and provide services during the budgeting period. Examples of this reimbursement policy span all political systems, and can be found in socialist counties, traditional Western democracies (Canada - Ontario [25]), right-wing dictatorships (Spain's General Franco [3]) and U.S. agencies (Department of Medicine and Surgery, Veterans Administration [62]). Particularities of the system vary across different countries, but usually (1) there is a mechanism for appealing the fixed budget, and (2) yearly "standard" adjustments are made to reflect the increase in prices of the different inputs of the hospital.

Recently, Detsky *et al.* [25] compared the evolution of health care costs between the United States and Canada's Ontario province and looked at the evolution of hospital inputs from 1964 to 1981 in both countries. The results indicate that the real inputs[2] devoted to each admission increased 81% in the States during that period whereas they increased only 13.9% in Ontario. A similar result was found for the ratio inputs/bed day of care. The aothors concluded that **if there is no decrease in quality of care**, global budgeting does efficiently reduce the total health-care direct expense. However, they acknowledged that Ontario lags behind the States in the traditional measures of quality like the number of latest-technology apparatus; the authors state: "Differences in health status would be very difficult to demonstrate, given the problems associated with the current indexes for measuring the health status of populations."

---

[2]Inputs were calculated as total costs in constant dollars, adjusting for different inflation rates in each country.

2.1.3 Prospective Methods.

Strictly speaking, both fixing rates for specific services and *a priori* budgeting described in the previous sections are prospective reimbursement methods. Nevertheless, in practice in the USA today, prospective reimbursement is used to denote the methodology by which a hospital is paid as a function of the discharge diagnosis of the patient, regardless of the number or kind of medical acts performed during the hospital stay. The available literature in this area can be divided into at least two distinct areas: (1) studies of different alternatives for classifying patients, and (2) studies of the impact of such reimbursement methodologies on hospital management and financing. These areas will be discussed separately.

Different methodologies for patient classification. Before attempting to pay hospitals as a function of patient characteristics, (e.g. discharge diagnosis) a rigorous method for assigning those characteristics (labeling) must exist. This is clearly the most important problem that a reimbursement method based on a single price for a common type of patient faces. A detailed literature review of the most commonly researched classification methodologies is presented later in this chapter.

Impact on clinical practices and management in the hospital. Stern and Epstein [60] have recently reviewed the effects and incentives introduced by the DRG prospective reimbursement system on medical practices. The authors conclude that low payment rates per case foster, but do not guarantee, efficiency.

Omenn and Conrad [53], have discussed diseases for which both clinical and surgical management protocols are available. They conclude that since reimbursement for surgical DRGs seems to be more profitable at the current Medicare rates than for surgical DRGs, the kind of therapy that hospitals will provide may not be necessarily towards the less expensive DRGs.

Other descriptions of the system have appeared in both specialized (medical) and general periodical publications. Examples of the average level of such discussions can be found in [44] in Medical Economics and in [45] in the New England Journal of Medicine.

Of particular interest in the context of DRG-based reimbursement is the topic of readmission rates. From a theoretical perspective Stern and Epstein [60] foresee a great increase in the readmission rate of DRG reimbursed patients and a deterioration of the quality of care, and suggest that a redefinition of the DRG classification should be undertaken in order to attain more uniformity in resource usage. In a recent empiric study, Anderson and Steinberg [5] show that during the period 1974-1977, 22% of Medicare patients were readmitted within 60 days of discharge. Readmission accounted for 24% of the total Medicare expenditures. If this proportion were also true in 1984 (there are no data available yet) it would represent a total of $8 billion for readmissions within 60 days of a previous discharge. Similar results were found in a cross-sectional sample of patient discharges in the state of Massachusetts [71]. Since the data in these studies came before prospective-payemet was in place and hence before there were economic incentives for readmission there is potential concern for worry as small increases in readmission rates may not be detected by statistical analysis but will nevertheless involve large sums of money.

Another possible change in hospital practices has been identified by Wennberg *et al.* in [65], who reported that in the State of Maine there is a 3.5 fold variation in the hysterectomy rates (1982 data)[3] . With such a wide variation in "common medical practices," the authors argue that the DRG system is bound to move the

[3]Similarly striking differences in the rate of some surgical procedures have been found in other states and periods of time [64].

average toward the high-end of the spectrum unless some controls on admission rates for specific diagnosis and procedures in terms of accepted practice patterns are put in place.

An interesting concept of health care policy, related to the incentives introduced by prospective reimbursement, is that of *cost shifting*, [19], [37], [50]. The cost-shifting phenomenon occurs when governmental agencies fail to fully pay for the medical expenses of the medically indigent and underpay the services reimbursed by Medicare/Medicaid. When hospitals see their income reduced, they shift the cost of their operations to the "paying customer", the patient and, to a large extent, the private insurer. This phenomenon, the references argue, is nothing but a hidden tax on the people who hold private insurance, mostly the worker[4].

To conclude the analysis on the effects of DRG-based prospective reimbursement, one can say that some of the effects which may be seen in the near future are:

- Reduction of length of stay.
- Minimization of the number of procedures carried out within a given diagnosis group.
- Minimization of the number of procedures per admission.
- Moving the admitted case mix towards better reimbursed diagnoses, therefore, avoiding admission of expensive, long stay patients. Another expression of this is a tendency to move hospitals toward specialization, avoiding "unproductive" patients altogether.
- Increasing the number of admissions of the same patient for the same

[4]It should be mentioned here that since patient-specific real-cost data are rarely available, there are no hard data supporting the fact that Medicare reimbursement rates are in fact below the marginal costs of treating their patients. In fact, it may be possible that Medicare is supporting hospital activities other than patient care. When patient-specific cost data from a number of institutions become available, these issues will be able to be rigorously explored.

illness.

- Moving patients toward more "rewarding" diagnosis related groups, even if this implies the performance of elective surgery.

- Performing cost-shifting to non-prospective paying clients.

Nevertheless, it is clear that the expected benefits of a diagnosis-related prospective reimbursement plan are enormous. Until the appearance of such strategies, there had been no other mechanisms that provided any incentive to reduce the length of stay in the hospital or the number of procedures performed [54]. It is also clear that we may be replacing the "overtreating / overtesting" syndrome with the "overadmitting / undertreating" syndrome, and mechanisms have to be devised in order to monitor the operation of the hospitals heavily influenced by the new reimbursement policy. As R. Platt [54] recognizes, these "bad" incentives are going to be minimal if the dollar amounts that hospitals receive are close to the real costs of their operation.

Summarizing the recommendations of the articles referenced above, we can say that for the DRG-based reimbursement system to perform as expected, it is critical to:

- Know the true costs of a given DRG both across patients and across hospitals.

- Obtain "good" DRG-based classifications that have low variance.

- Move to an all-payers system to avoid cost-shifting.

- Have the proper mechanisms to reimburse teaching institutions the costs incurred by teaching programs (optimally, these mechanisms should be disconnected from the reimbursement of medical care per se).

- Develop appropriate mechanisms for the payement of capital expenditures, so that quality of care and technological innovation are maintained.

2.2 Resource Usage, Accounting, and Budgeting in Hospitals

2.2.1 Background

Health care institutions are notorious for their lack of product-related usage and accounting data. This state may be the result, in large part, of the fact that hospital administrators did not need to know in detail the use of their resources on a patient population basis. Charged costs were routinely shifted (usually up) to match the real cost of the operation of the hospital as a whole. Moreover, the presence of rate setting and the establishiment of maximum prices for the "products" sold, and protection from competition as a result of certificate of need further decresed the incentives for developing accurate cost accounting systems.

2.2.2 Estimation of Resource Utilization in Hospitals

Keeping reliable information about the real resources that patients have used is essential for the production of case-mix based reports and for tight management control [7]. Unfotunately, published empirical literature on resource consumption on a DRG basis is sparse.

C.T.Wood [66] in describing the system at the Massachusetts Eye and Ear Infirmary illustrates the kind of organizational structure and information system that has to be developed in order to perform adequate management control. The paper stresses the point that it is essential not only to record the counts of each test and service rendered to a patient, but also that it is necessary to have a set of weights (called Relative Value Units -RVUS) that allow the comparison of different tests and services. These comparisons must be made in terms of the real resources needed to perform such tests and services; therefore, these weights are based on all direct costs chargeable to each test [52], [66].

In the context of resource utilization, the notion of standards of practice should be mentioned. Except in very specialized fields, (such as Oncology, where treatment protocols are published in the literature), there is no readily available information regarding what tests and procedures are acceptable for each particular medical problem. Blue Cross and Blue Shield have started to addressed this issue via their Medical Necessity Program [10], [11]. Under this program, guidelines for the use of diagnostic imaging and respiratory therapy were recently established. Blue Cross and Blue Shield, as stated in [10] and [11], will implement these guidelines via "the initiation of educational programs to familiarize health care professionals with them. There will be no reduction in benefits or immediate denial of claims for suscribers". These guidelines were developed in collaboration with the American Colleges of Physicians, Surgeons and Radiologists.

2.2.3 Accounting and Budgeting

The literature is prolific with books related to hospital accounting. A very good example is the two-volume text by Robert Broyles [17]. The first volume is devoted to financial accounting. The second introduces managerial cost accounting, and a number of examples of disease costing are provided. In this work, it is implied that in order to allocate costs to diseases, all data regarding every procedure and resource utilization (as it relates to a cost center) must be available.

Both the medical and managerial literature, [53], [69], have started to stress the necessity of incorporating physicians into the hospital management control system as the key to cost-containment efforts. In an article by Young and Saltman in the Harvard Business Review, [69], the following disaggregation of hospital costs is suggested: (1) case mix, (2) number of cases, (3) inputs per case, (4) inputs unit price, and (5) input efficiency (i.e. how efficiently a test or procedure can be used

for patient diagnosis and/or management). Physicians, the authors argue, can exert some control over all components, and have exclusive control over some of them, particularly 3 and 5. Therefore, it will be necessary to incorporate physicians into any cost-containment program that the hospital is going to undertake[5].

Physician involvement and decentralized management have been incorporated into a novel hospital-management structure adopted by Johns Hopkins Hospital [40]. Under this system, Hopkins shifted operating responsibilities and financial accountability to the clinical departments. These departments (such as medicine and gynecology) behave as independent centers inside the hospital, which acts as a corporate holding. Each functional unit is headed by a physician chief to whom a nursing director and an administrator report. These three people function as a management team and are responsible for the financial accountability of the unit, including services purchased from other units such as the ancillaries and housekeeping. This system has been effective involving physicians in budgeting and management. The process is now evolving to budgeting both revenue and expense by case or DRG [40].

Also worthy of mention is the effort by the American Hospital Association [4] to introduce cost accounting into the hospital management scene. In this publication, building from very elementary accounting definitions, the necessity of good cost accounting is emphasized, and a methodology for implementing it proposed.

---

[5]Incorporating physicians into management decisions is in complete accordance with traditional management control practices. As early as 1975, Anthony and Herzlinger [6] wrote: "The responsibility structure should correspond to the formal organization units; i.e. the responsibility centers that carry out the programs," therefore implying that physicians (the heads of the responsibility centers) should be involved in managerial decision making.

2.3 Effect of Teaching Programs in Health Care Institutions.

The effect of teaching programs in health care institutions has been the subject of extensive study in recent years. Before starting to review the literature, it should be recognized that most of the studies that have been published state that it is very difficult to isolate the effect of teaching programs from other factors that affect hospital productivity; eg., urban location, state-of-the-art technology, and sicker patients.

Most published studies attempt to quantify the relationship between costs and the sizes of the teaching programs. In general, researchers have addressed this problem via comparative studies of productivity between teaching and non-teaching hospitals (or teaching and non-teaching floors in the same hospital). The results of most of these studies indicate, as expected, that there is higher consumption of resources in teaching than in non-teaching hospitals [48], [57]. Reported differences in utilization range from 14% to 60%. It must be said, though, that these studies are by and large limited to a few diagnoses and that all use *charges* rather than real costs. The only study that uses real costs comes from the British National Health Service [31]. In this study, it is reported that, in the aggregate (without case-mix adjustment), the increased expense of teaching hospitals compared with non teaching hospitals of the same characteristics ranges from 20% to 100%; these results are consistent with charge-based data from the United States.

A second set of studies is represented by the recent paper by Garber, Fuchs and Silverman [36]. The authors state that even though charges are higher in the teaching compared to the non-teaching floors, most of the variance can be explained by controlling for DRG and severity, and that the residual cost variance is due to

higher lengths of stay and use of ancillaries related in the teaching service[6].

Given that about half of the costs in health care institutions are related to personnel, a basic question that also has to be answered but that has been mostly ignored by the literature is how do physicians, house officers, nurses and other health-care personnel relate to each other during the educational process? Usually, house officers are taught by staff physicians, but the house officers also produce patient care services that would otherwise have to be provided by the teachers. Moreover, house officers do most of the teaching to undergraduate medical students, who in turn produce some nursing services.

Quantifying these relationships is essential in order (1) to be able to have a complete picture of the effect of teaching programs in hospitals, and (2) to be able to perform productivity analyses. HCFA (Health Care Financing Administration) has studied this issue, and preliminary results seem to indicate that, everything else being the same, there is about a 5.79% increase in indirect costs for each 0.1 increase in the number of residents per bed [47]. Staffing aspects of teaching hospitals are addressed in Chapter 6 of this thesis.

Teaching institutions and DRG-based reimbursement: Medicare distinguishes two classes of costs related to graduate medical education: Direct and Indirect. Direct costs are mainly resident salaries and teachers time. Indirect costs are the higher patient care costs incurred by hospitals with medical education programs [47].

The reimbursement of direct costs did not change when the DRG legislation was enacted, and it remains essentially proportional to the size of the teaching

[6]There is one study that concluded that there is no difference in the ancillary use between teaching and non-teaching institutions [12].

programs. The reimbursement for indirect costs is done by Medicare via the *indirect teaching factor*. This factor (an adjustment to the DRG rate) is a number coming out of a complex formula that takes into account the location of the hospital, prevailing wages in the area, and the number of residents per bed. The particular formula was arrived at via a political "adjustment" that doubled it from the statistical analysis that had been performed to estimate it [47]. It is unclear at this point what the future holds for teaching adjustments, since there is a bill before Congress that, if passed, will remove educational adjustments by 1987 [1].

2.4 Efficiency Measurements in the Health-Care Sector

A detailed bibliography and discussion of different efficiency measures that have been used in the health-care sector is presented in the introduction to Section 6.1 later in this thesis.

2.5 Patient Classification Techniques

The literature has been prolific with reviews of various classification methods. Since they have to be used as payment devices, they all attempt to provide uniform resource utilization while maintaining some degree of clinical relevance. The patient classification methodologies that have been developed fit into two categories: (1) those that subdivide the whole patient spectrum (DRG, Medical Illness Severity Grouping "MEDISGRPS[7]" and Patient Management Categories) and (2) those whose major goal is to subdivide patients that may have similar diagnosis into more clinically relevant groups (Disease Staging and Severity of Illness Index).

[7]MEDISGRPS is a trade mark of MediQual Systems Inc.

2.5.1 Diagnosis Related Groups

DRGs were developed by the group of R.B. Fetter at Yale University. Initially, they were intended to be a tool for quality assurance review, and they were modified and expanded under the auspices of the Health Care Financing Administration (HCFA) to be used for Medicare as a form of diagnostic-specific prospective reimbursement, [33], [34], [35]. As they are currently used by Medicare, the DRG classification consists of 470 classes, exhaustive and mutually exclusive with respect to the types of patients seen in an inpatient unit. In order to classify patients, DRGs use a number of variables, both clinical and demographic, like Principal Diagnosis, Surgical Procedures, Presence or Absence of Complication/Comorbidity, Age, and Malignancy.

The design objective for the development of DRGs was the creation of a clinicaly relevant patient classification that would reduce the observed variance in patient care costs and lengths-of-stay. Two data bases were used for the research: 320,000 discharge summaries from the Commission on Professional Hospital Activities (1979) evaluated for lengths of stay, and 334,000 discharges from the New Jersey State Department of Public Health evaluated for individual patient costs. Clustering techniques and variance reducing analyses both interlaced with the clinical judgment of a panel of experts were used to create the current groups.

DRGs have been found only to reduce variance from 20% to 40% in hospital *charges* across various institutions [42]. This is comparable to the results described later in this research, where cost data were used (80% of the institutions are between 20% and 50% Reduction in Variance). Computer programs that perform DRG classification (groupers) from the Uniform Hospital Discharge Data [26] are widely available commercially.

A more detailed description of the Diagnosis Related Groups system is found

in the article [35] in Medical Care.

2.5.2 Medical Illness Severity Grouping "MEDISGRPS"

MEDISGRPS is a method of classifying patients into severity groups on the basis of admission data rather than hospital stay or discharge diagnosis data. MEDISGRPS was introduced by Brewster *et al.* [16], and can be used, according to its developers, to classify the whole patient population across diagnosis for management control purposes, or to refine the DRG system to obtain classes with smaller variances.

As described in [16] the properties of the MEDISGRPS classification methodology are:

- It classifies hospital patients into severity groups based on key clinical findings present at admission (first 48 hours in the hospital).
- It can measure change in severity during hospitalization.
- It uses objective clinical findings (both physical exam and laboratory tests) as the basis for classification and measurement.
- It controls for initial severity, thus demonstrating the effect of medical practice on quality and cost outcomes.

MEDISGRPS has 5 severity categories: (0) no findings, (1) minimal findings, (2) severe or acute findings, (3) severe and acute findings, and (4) critical findings.

When used across all patient diagnoses, the researchers in [16] report that they obtain significant p values when comparing the average charges in each severity. MEDISGRPS severity was used to refine two DRGs (DRG 122 - Circulatory Disorders with Acute Myocardial Infarction without Cardiovascular Complications, and DRG 140 - Angina Pectoris). The results indicate that again, MEDISGRPS

severity is able to differentiate average usages. Also, the reduction in variance[8] obtained when subdividing the 2 DRGs in the study by MEDISGRPS severity was 25.4% and 22.8% respectively.

MEDISGRPS has been computerized, but it requires that the information be entered into the computer in a specific manner, and therefore imposes some burden to the medical staff. To overcome that problem, MEDISGRPS developers recommend the use of an integrated medical information system marketed by the same company.

2.5.3 Patient Management Categories

Patient Management Categories (PMC) is a classification methodology developed by the Health Care Research Department of Blue Cross of Western Pennsylvania under a grant from the Health Care Financing Administration (HCFA) [68]. Characteristics of this patient classification include:

- Patient types were defined within disease or disorder groups by physician panels.
- Levels of severity are incorporated into the definition of the different classes.
- The class in which a patient will fall is not affected by the sequence of diagnoses (primary versus secondary).
- Single disease patients having multiple related diagnoses are differentiated from co-morbid cases (cases with more than one disease or pathological condition).

PMC is a classification which is meant to be applied to the whole patient

[8]Reduction in Variance (RIV) is a measure of the ability of a classification technique to explain some the dispersion of an observed variable. 0% implies that the classification does not explain any of the observed variance, and 100% RIV implies that the classification explains it all. RIV will be formally introduced and used extensively in chapter 4.

population, and it tries to represent clinically distinct patient types, each requiring a different diagnostic and treatment strategy of care.

The definition of the categories was done in two steps: first, physician panels grouped patients in clinical terms; second, the resulting groups were characterized with their International Classification of Disease Code (ICD-9-CM) [27] diagnosis and procedure codes. Statistical considerations were not used in order to obtain minimal (or reduced) variance groups, as the physician panels were not provided with any cost data.

To this moment, there has not been any published report of a comprehensive study on the power of the PMCs as reducers of variance of hospital costs. Research is underway in Pensylvania to evaluate PMCs versus DRGs using this and other measures of classification effectiveness, and some critics argue that the fact that they are based in specific treatment paths may discourage the development of alternative treatment modalities [49].

Patient Management Categories are fully computerized, and patients can be classified using the Uniform Hospital Discharge Data [26].

2.5.4 Disease Staging

Staging is a measure of the severity of a particular clinical episode. It was introduced by J. S. Gonnella in 1983 [38], [39], and it borrows from the concept of staging widely used in oncology[9]. Levels of severity have been developed by Gonnella *et al.* for 420 major disease entities plus 20 residual categories. The 440 classes span all possible diagnoses. The major disease categories have been found to

[9]In oncology, patients are staged as a function of a series of clinical findings specific for each disease or pathological condition. Stage, in oncology, has been found to be very well correlated with prognosis, and is the base for many management decisions.

account for about 80% of all hospital discharges in a mixture of hospitals [8].

The methodology classifies patients in one of four stages (except in oncology where stages range from I to V, V=Death):

- Stage I: Conditions with no complications or problems of minimal severity.
- Stage II: Problems limited to an organ or system; significantly increased risk of complications.
- Stage III: Multiple site involvement; generalized systemic involvement; poor prognosis.
- Stage IV: Death.

Staging has been found to correlate with increased hospital charges and length of stay in several studies (see [8] for a summary), but there has not been a comprehensive study comparing the 440 diagnoses with staging versus the DRG system in terms of cost predictability and reduction in variance.

Patients can be staged automatically by computer as the algorithm only uses data contained in the Uniform Hospital Discharge Data [26].

2.5.5 Severity of Illness Index

The Severity of Illness Index has the same goals as Disease Staging: uniformity of resource usage within each class. This Index was developed and introduced by Susan D. Horn in 1983 [42], [41], and it is a four-level index determined from the values of seven variables related to the patient burden of illness. The variables used to assign severity are:

1. Stage of principal diagnosis (unrelated to the Disease Staging described above).
2. Concurrent interacting conditions that affect hospital course.

3. Rate of response to therapy or rate of recovery.

4. Impairment remaining after therapy for the acute aspect of the hospitalization.

5. Complications of the principal diagnosis.

6. Patient dependency on hospital facilities and staff, and

7. Extent of non-operating room procedures.

The classification can be expanded from four severities to twelve by subdividing each of the four original classes into three, according to the extent of a possible operating-room procedure (no procedure, moderate procedure, and intense procedure). This expansion is called Procedure-Adjusted Severity Index.

The Severity Index has been compared to DRGs, Staging, and Patient Management Categories for some specific diagnosis in several institutions [42]. The results indicate that Procedure-Adjusted Severity has better reduction in variance power that Staging and Patient Management Categories in three out of four hospitals analyzed. The average coefficient of variation[10] obtained by subdividing the patient population by Procedure-Adjusted Severity is reportedly smaller than in any of the other subdivisions, including DRGs.

As can be seen by the description of the variables used in determining the index, Severity is a very subjective variable, and it has to be encoded manually by a rater going through the medical record. This presents a serious drawback for ease of implementation, expense, and cross-institution comparisons.

---

[10] Coefficient of Variation is the ratio between the standard deviation and the mean.

Chapter 3

Data Sources

This chapter presents a summarized description of the data sets used for the numerical examples in chapters 5 and 6. The detail of the descriptions that follow is bound, in large part, by the restrictions of confidentiality imposed by the teaching hospital X and the chain Y in order to make the data available.

3.1 Teaching Hospital X

Hospital X is a 450 acute-care hospital associated with a leading medical school.

Since 1983, hospital X has in operation a computerized management information system that captures all costs for each patient throughout his/her hospital stay. The data made available for this research was directly extracted from the management information system, and can be classified into two categories, (1) clinical information, and (2) usage and cost data.

3.1.1 Clinical Data

The clinical data consists, for each patient discharged in Fiscal Year 83, of an extract of the System for Uniform Hospital Reporting [26] containing the patient's age, sex, hospital service that admitted him/her, hospital service that the patient was discharged from, total length of stay, length of stay in any of the Intensive Care Units, principal and secondary diagnoses (ICD-9-CM coded) [27], and all procedures that the patient had (also ICD-9-CM coded). The DRG, the Severity of Illness Index, and the Disease Stage (all as described in Chapter 2, bibliography review) of

each admission were also provided.

3.1.2 Usage Data

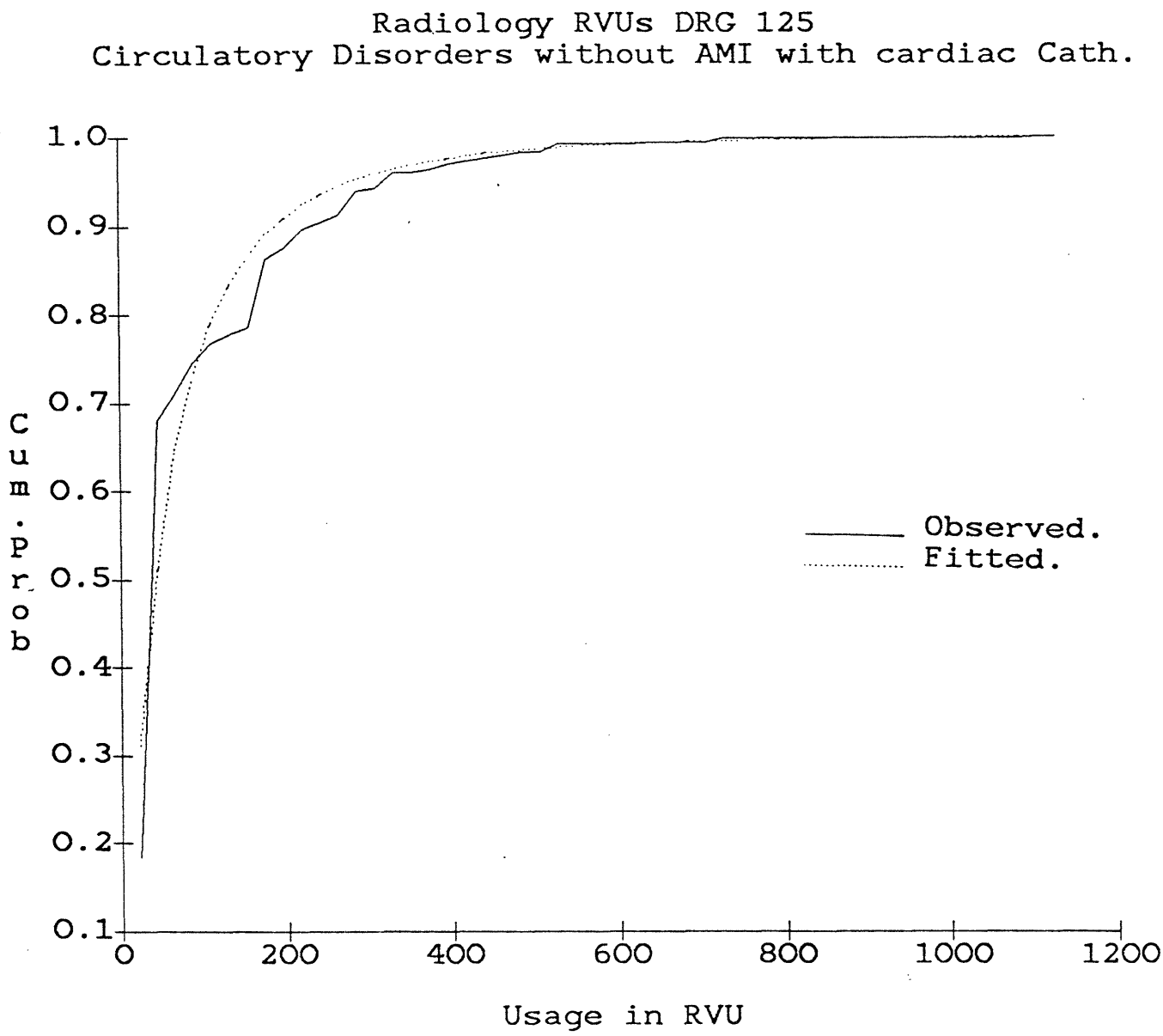
As a result of the integrated medical information system in operation in the hospital, the usage by patient of each ancillary service is recorded in terms of *Relative Value Units* (RVUs). A RVU is a dimensionless quantity assigned to each test or procedure that a laboratory produces, and it is proportional to the real amount of resources spent to perform the test. For example, in the radiology department, RVUs are assigned to each examination as a function of the X-ray film surface, technician time, value of the machine used to perform the exam, and average time that a radiologist needs for the interpretation of the films.

The function of the RVUs is to allow, within each laboratory (or, using hospital's X nomenclature, in each *Intermediate Product Producing Unit* IPPU), the computation of a single number reflecting the different services provided to a patient. RVUs are not necessarily consistent across different laboratories. For the department of nursing (which is an intermediate-product producing unit), the RVUs are the number of bed days in each service or ICU.

At the end of the fiscal year, the RVUs that each IPPU has produced are costed by dividing the total number of RVUs produced by the total expense incurred. This computation allows a true *a posteriori* costing of all patients discharged by the hospital. These costs need not have any relationship with the amounts patients are charged. For billing purposes, the amounts used for each test range from historical inflation-adjusted prices to pre-negotiated Blue-Cross rates. The hospital administrators hope to switch to a cost based pricing scheme in the near future.

Logarithms versus raw data. Hospital resources usage data are inherently

Figure 3-1: Radiology RVUs DRG 125. Data and Lognormal Approximation



skewed. For example, Figure 3-1 presents the cumulative distribution of the Radiology RVUs (solid line) used by patients in DRG 125 -Circulatory Disorders without Acute Myocardial Infarction with Cardiac Catheterization- and its lognormal approximation (dotted line). The X axis is the total number of radiology RVUs, and the corresponding value in the Y axis is the number of patients that had that many RVUs or less. The distribution is quite skewed; while 90% of the patients had 250 RVUs or less, the remaining 10% used as many as 1200 RVUs. Although a simplistic approach would assume that the patients in the high usage range are outliers, and they should not be considered members of the same patient population, a maximum likelihood lognormal model fits the observed data well, as the high users fall inside the tail of the theoretical distribution. Because the data are lognormally distributed, their logarithms are normally distributed[11] [2].

The lognormality of this example is not particular to DRG 125. As a quantitative measure of the lognormality of data distributions we can use a measure of the normality their logarithms. Such a measure is the *normal score* which gives the probability that a sample comes from a normal distribution, [55], [56]. We computed such probabilities for all DRGs in hospital X using as observed variable the logarithm of the Total-Direct Patient-Care Cost (the same tests could have been run for each set of RVUs). From the results we could not reject for 242 DRGs out of the 342 DRGs[12] the hypothesis that total costs come from a lognormal distribution.

---

[11]For many statistical tests where it is assumed that the observed phenomenon is a fixed value modified by a random error, it is necessary that the data follow a normal distribution [23]

[12]Only 342 of the possible 470 DRGs had more than 10 patients; they represented 77% of all discharges.

3.2 Chain Y

The not-for-profit hospital chain Y consists of 160 hospitals located around the United States. The data that were made available to carry out this research from Fiscal Year 1983, and came from two primary sources: (1) discharge abstract summaries (DAS), and (2) general ledger (GL). The chain does not keep patient-specific data at the level of detail described in the previous section for hospital X.

3.2.1 Patient Discharge Summaries

The discharge summaries generated by the medical and administrative staff upon a patient's discharge from a hospital of chain Y are computerized and stored in what is internally called the Discharge Abstract Summary.

Each of the 160 Y hospitals is requested to submit an array of information for each patient who is discharged to the DAS data system. The information that is provided includes all of the data elements in the System for Uniform Hospital Reporting [26], and many other pieces of information.

The following data elements are included in the DAS: Patient Name, Hospital and Service giving the Care, Social Security Number, Age, Sex, Admission and Discharge Dates, Primary, Principal, and Secondary Discharge Diagnoses, Operating Room and other Procedures Done, and DRG. Although all these data elements were made available for this research, only DRG, length of stay and information about the hospital giving the care were used.

The DAS has been traditionally used to prepare National Reports of Y hospital use. More recently, the DAS has become an important source of information for planning and resource allocation purposes. The DAS data system will accept data from the hospitals throughout the year. The corporate data

processing center creates and maintains quarterly and cumulative files for the current year, a complete file for the previous year, and a cumulative history file for all previous years.

The data system has a thorough editing and checking process at the data entry end to insure that data items are consistent with each other; for example, it checks that a date field has a valid date in it, that a diagnosis field has a valid ICD9-CM code in it, or that the discharge date is not prior to the admission date.

The few formal studies of the reliability of the data in the DAS have routinely exposed a 5%-7% transcription error after all checks and edits. They have also shown that a large variation in judgment as to the primary or principal discharge diagnosis. While this variance is large, approximately 30%, it is consistent with other studies performed by similar chains [24], and does not seem to affect the case mix measurement of the facility. Thus, although the principal diagnosis of 30% of the patients may differ among observers, the differences in DRG assignments are much smaller.

3.2.2 General Ledger (GL)

The GL is the data system which reports hospital expenditures for each hospital in the system. The accounting system in Y is build around *programs* and *cost centers*. A program is an organizational unit that provides service to the public. Of all programs, only medical-care programs and educational programs are of interest in this research. Programs use resources from the cost centers. For example, program "Surgical Service" will use some resources from cost center "pharmacy".

There are around 30 medical care programs and 200 cost centers in chain Y. The largest programs are Inpatient Medical Service, Inpatient Surgical Service, Inpatient Psychiatric Service, and Outpatient Medical Care, accounting for $3.9

billion of the $5.5 billion total annual direct and education expenditures incurred in fiscal year 1984.

Cost centers are categorized into direct and indirect. Direct costs centers are those associated with hands-on patient care, while indirect cost centers are associated with the general operation of the hospitals, such as building management.

In order to identify the programs' use of the funds allocated to the cost centers, the managers of the cost centers are asked to report on the distribution of their expenditures across each medical care program at the end of every quarter. These reports account for salary and non-salary expenses, as well as capital acquisition expenditures. The direct cost centers also indicate the proportion of their expenditures which are in support of the education and research missions of the hospital.

For ancillaries, the proportion of dollars spent in each program can be estimated exactly (for example, the radiology chief can determine quite accurately how much of his/her expenses were used to serve Surgery). Ancillaries and pharmacy expenditures account for $0.96 billion, (24%) of the direct care expenditures. Similarly, the Nursing Service can report exactly the distribution of its expenditures because in each hospital the Nursing Services know exactly for which clinical service the nurses are working. Nursing salary costs represent $1.5 billion, (38.4%) of the total direct care expenditures of $3.9 billion.

In contrast, for some cost centers and some types of expenditures it is not possible to have accurate knowledge of the distribution of expenditures. The Department of Medicine, for example, must report the proportion of their salary dollars spent in support of educational programs. Since there is no exact record of the time physicians spent teaching versus taking care or patients, the reported number is only an estimate. These less "accurate" funds accounted for 3.75% of the

direct care expenditures in fiscal 1984.

It is clear from the preceeding discussion that there is some uncertainty as to the accuracy of some of the numbers in the General Ledger. Nevertheless, since the hospital is asked to distribute all of their expenditures, and since this total number can be known accurately, there is a "bottom line" accountability to the GL report.

Chapter 6 will describe in detail the particular data fields from the General Ledger used to develop the model described there.

Chapter 4

Resource Allocation in Hospitals. General Development.

4.1 Introduction

This chapter describes the basic methodology for probabilistic resource allocation in health care institutions. It is divided into two parts. First, it describes how budgets could be used to introduce the necessary incentives for cost-effectiveness when allocated to Clinical Services (section 4.2) and introduces the concepts (1) of probabilistic budgeting with two mathematical formulations and (2) the utility of patient classification schemes which reduce expenditure variations (section 4.3). Then, in sections 4.4 to 4.6, it explores the validity of the DRG system as a method for classifying patient discharges in uniform sets, and uses the Severity of Illness Index and Disease Staging to obtain better patient classifications. The data for the empirical analysis comparing these two patient classifications come from the sources described in the previous chapter.

4.2 Budgeting by Clinical Service versus Budgeting by Ancillary.

Traditionally, hospitals have budgeted their operational resources using as budgeting units the centers that produce tangible patient care services, such as ancillary services, nursing, and pharmacy. Because the cost of taking care of patients depends both on the number and cost of tests and procedures, budgeting these units addresses only half of the problem of cost containment. Even if optimally used, budgeting by ancillary service only applies pressure to the

laboratory to become more cost effective in the production of its tests, which is not sufficient for overall cost control. If reduction in health care costs is to be attained, both components of cost, (1) the number of tests and procedures, and (2) their costs must be controlled.

Alternatively, budgets in health care institutions should be allocated to *Responsibility Centers*[13] which are fully responsible for the care of patients and the use of resources, namely to the Clinical Services. Allocating resources to Clinical Services requires a measure of the productivity of these Services. This production measure has to be equivalent to the resources needed to produce such units of care. Thus, patient discharges would not be a good measure of production because different patients may use different resources, and specifying only the number of patient discharges does not necessarily correspond to the actual activity of the department. It is important to differentiate among classes of patients based upon their different resource requirements. This consideration points toward finding uniform patient classifications.

Switching the budgeting emphasis from the ancillaries to the Clinical Services responsible for patient care and resource-utilization decisions is in full accordance with practices used in all branches of industry, manufacturing as well as service, and for-profit as well as non-profit organizations.

Budgeting by Clinical Services presents several problems not encountered in traditional ancillary budgeting. Most of them are related to the fact that Clinical Services have to reimburse laboratories for the services they provide, and therefore a pricing mechanism for intermediate products must exist. This can be solved by

---

[13] A Responsibility Center is an organizational unit that bears responsibility for certain decisions within an organization. A responsibility center may or may not be considered a cost center or budgeting unit.

adopting a scale of Relative Value Units that would allow tests performed for a given laboratory to be compared with each other in terms of the amount of resources they use. Being able to compare all tests within a laboratory allows a fair pricing strategy, in which the cost of each test is in fact proportional to the real resources involved in carrying it out.

Budgeting by clinical service presents the problem of costing intermediate products. Since laboratories (and services like nursing) have to be reimbursed for the utilization that the Clinical Services "bought" from them, it is necessary to know the prices of these goods a priori.

A result of the cost cutting pressures introduced by having the Clinical Services "pay" for the goods and services used from the ancillary departments is that some Clinical Services could decide to do business with laboratories other that those in the hospital (either independent or from other hospitals). Even though doing business outside the hospital would reduce operating costs in the short run for the clinical service making such a decision, it would introduce a number of interferences to the normal functioning of the institution. Among others, it would (1) reduce the workload in internal laboratories and may threaten their very existence, forcing all services to use outside services, (2) the operating costs of laboratories so affected would have to be shared by the rest of the hospital, and (3) delivery of health care would be impared if emegency laboratory services were not available in house.

To solve this problem, institutions can use a two step pricing procedure for intermediate products [22]. Clinical Services are charged a share of the fixed costs of the laboratories and other intermediate-product producing units, regardless of the number of services they use from them. This ensures that Clinical Services will have an added incentive to "buy" services from the laboratories in the hospital as they

are supporting their fixed costs regarding of volume.

4.3 Probabilistic versus Deterministic Budgeting.

The amount of resources that a given budgeting unit will require in order to perform a given activity can seldom be estimated without error. This is particularly true in the case of hospital budgeting. Costs in hospitals are influenced by the diseases of the patients treated (case mix), the practice patterns of the physicians in charge of these patients, and the costs of performing each of the units of service (tests, operating room procedures, etc.) used to treat each patient. Even within this framework of variability, in practice, managers do allocate resources according to the expenses incurred during the previous budgeting period. This commonly used budgeting technique is equivalent to performing budgeting according to the latest observation of the random variables involved in the process. Another common-practice technique uses historic data from more than one year. If expenses over various past periods are taken into consideration during the budgeting process, the procedure is equivalent to budgeting by expected values.

Budgeting by expected values is in principle a reasonable thing to do. Statistically, if the decision could be made a large number of times, the average dollars spent would be the expected value, but in a budgeting situation where the budgeting decision is made only once, consideration of information other than just averages is of major relevance in the decision criteria. Budgeting by expected values assumes also that the decision maker is unbiased with respect to any particular department who may run out of money.

A number of different approaches are open to the resource allocator when the whole probability distribution functions of the forecasted expenses are available. One plausible strategy would be to allocate resources so that the expected values of

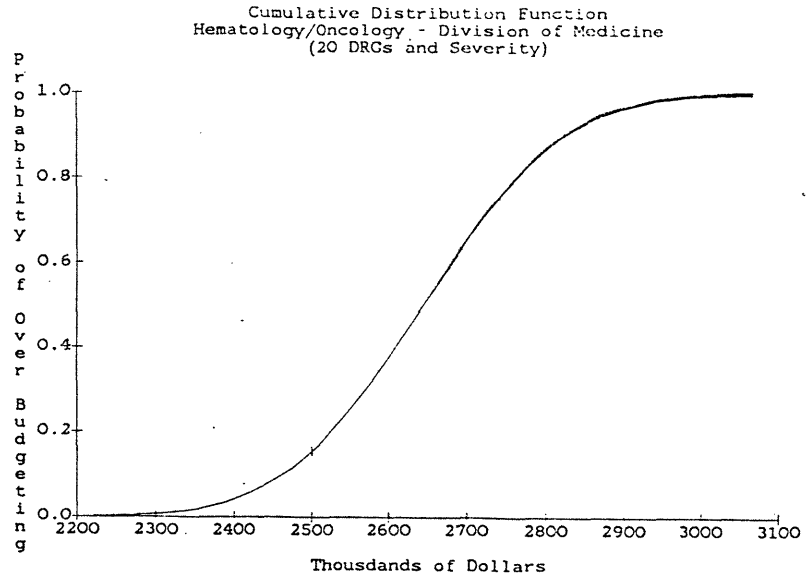
the extra resources needed by each budgeting unit will be the same. Another would be to use a "minimax" technique, by which the maximum chance of needing more money would be minimized. The utility profile and risk aversion profile of the decision maker can be incorporated in all these alternative methods. These strategies are formally introduced as particular cases of a general resource allocation methodology based on value functions in the following sections.

When the budgeting scope is shifted from the hospital level to the multi - institutional level, the issues of lack of bias and risks of underbudgeting gain special significance. If the office in charge of allocating the resources to different institutions has reason to believe that some hospitals are less efficient than others, it could be argued that the inefficient institutions can be penalized by increasing their chances of running out of money. In other words, one can envision a system in which one of the incentives given to inefficient facilities to motivate them to improve their performance is increasing their level of risk. Issues of efficiency measurement are discussed in chapter 6.

Since the total operating money that a given budgeting unit will require for a budgeting period is a random variable, it can be represented by its Probability Distribution Function (PDF) or its Cumulative Distribution Function (CDF). The PDF and CDF for the Hematology/Oncology Service of the Division of Medicine hospital X are presented in figure 4-1[14]. It indicates that the most likely estimate of the total dollars that Hematology/Oncology will need is 2.65 million, the 50 percent point. The probabilities of deviating from this most likely (expected value) total expense can also be read from the plot: the chances that the total budget will be

[14] A Gaussian model has been used to make this plots. This is a reasonable choice since the random variable of interest is the sum of a large number of random variables, the costs of each patient in the service. The parameters of the Gaussian distribution are computed using the methodology described later in this section.

Figure 4-1: Probability and Cumulative Distribution Functions of the Total Budget
Hematology/Oncology Service, Division of Medicine



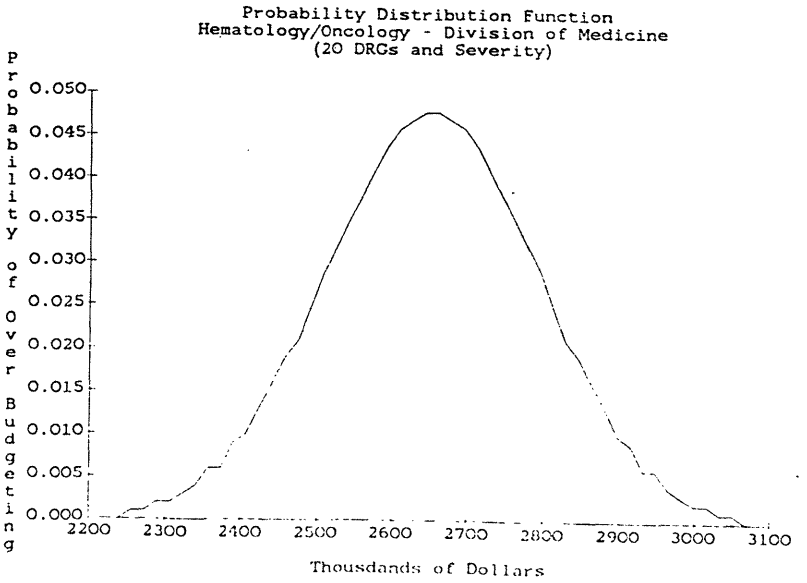
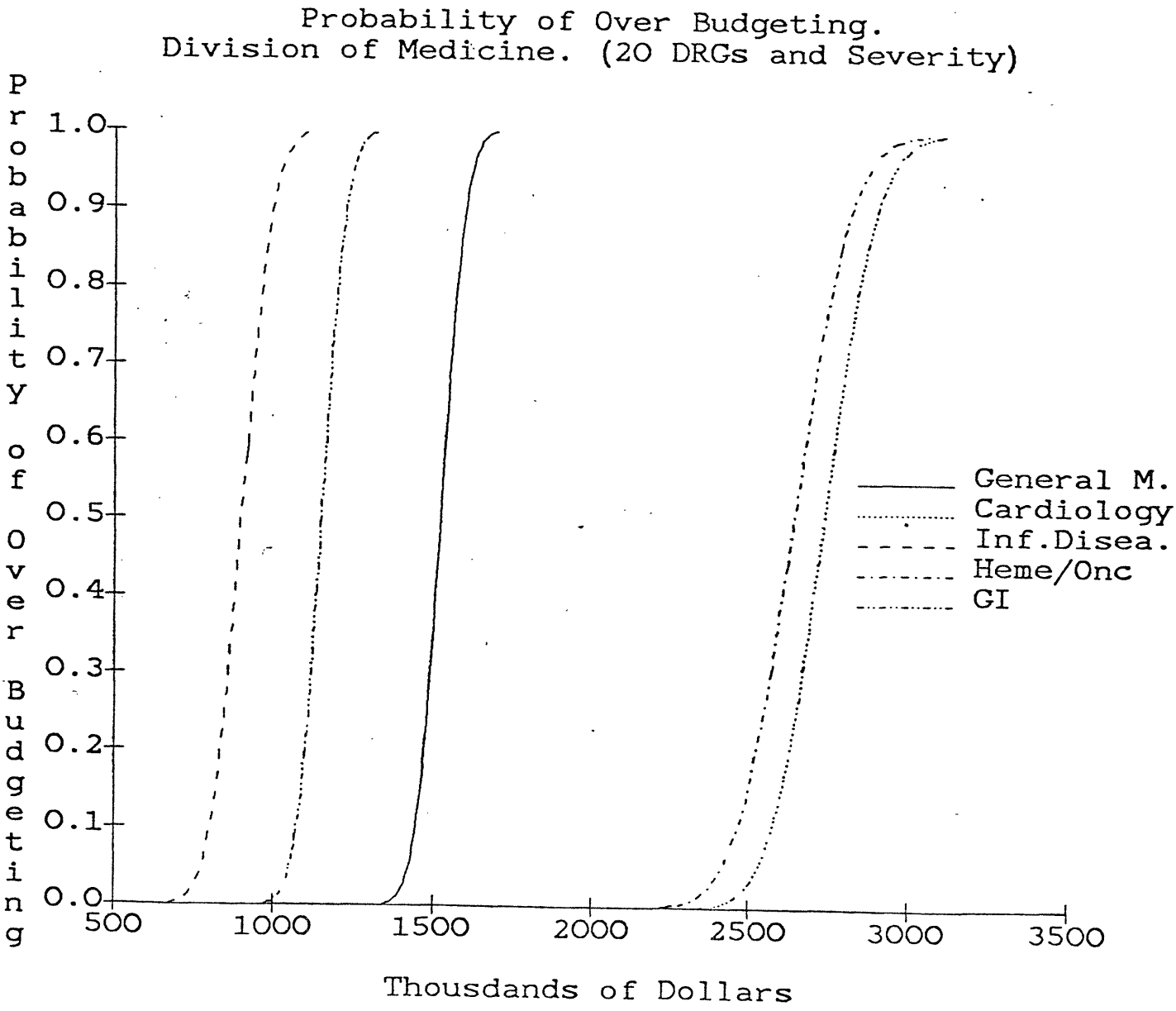


Figure 4-2: Probability Profile (CDF) of the Total Budget
All Services - Division of Medicine



smaller than 2.5 million are only 17%, and that it will be smaller than 2.8 million, 80%. The probability of any other total expense can also be easily derived from figure 4-1.

When curves similar to those in figure 4-1 are available for all budgeting units, resource allocation can be carried out taking into account the risks to which each different unit is subjected. The set of CDFs for the Division of Medicine of the hospital is presented in figure 4-2.

4.3.1 Probabilistic Budgeting. Theoretical formulation.

As a general theoretical introduction to probabilistic resource allocation, the following definitions and assumptions are necessary:

1) There are N budgeting units to which resources have to be allocated. For each unit (i, i=1,2, . . . N), the decision maker has available the a priori probability distribution function of the expected need for resources during the budgeting period f_i. We will use t_i to denote the actual expense incurred (a quantity that will be determined a posteriori and that follows the distribution f_i), and b_i to denote the allocated (budgeted) amount to each unit i.

2) The value to the system (or to society, or to the decision maker) of budgeting b_i dollars to budgeting unit i can be measured by the real valued function $v_i(b_i)$, provided that all resources are used for operational purposes. Assume also that similar functions can be derived for all budgeting units, that is, v_i exist for all i=1,2, $\cdots$,N.

3) If the budgeting unit does not need all the resources allocated to it because the incurred expense, (the realization of the random variable "total cost" t_i) is smaller than the budgeted amount b_i, then the value to the system is not the allocated budget $v_i(b_i)$ but that of the resources in fact used $v_i(t_i)$.

These value functions v_i also have some other names in the utility theory literature - ordinal utility functions, preference functions, worth functions, or utility functions [46]. Note that these value functions, as they may be different for each budgeting unit i, can be adjusted to incorporate the preferences of the decision maker. Subjective preferences will be introduced later in this section in the context of efficiency measures.

Under these assumptions, the statistical expected value of the value function of a particular budget $\{b_i, i=1,2, \ldots ,N\}$ is:

$$\sum_{i=1}^{N} \mathrm{E}\,[v_i|b_i] = \sum_{i=1} [\int_0^{b_i} v_i(t)\, f_i(t)\, dt + \int_{b_i}^{\infty} v_i(b_i)\, f_i(t)\, dt]$$

The left hand side of the equation reads as the expected value to the system given that b_i dollars were allocated to unit i. The right-hand side has two terms, the first one accounts for the possibilities of overbudgeting, and its integral term is the contribution to the expected value of the cases in which the needed resources t were smaller than the allocated b_i. In this case, the argument of the value function $v_i(.)$ is not the allocated dollars but the dollars used. The second integral covers the cases where the observed need is beyond the budgeted amount b_i; here, the argument of the value function is always b_i since all allocated resources are used in all cases of underbudgeting.

If the total resources available for allocation are B, it can be argued that the decision maker will allocate that amount in such a way that the value across all budgeting units is maximized. In other words, he will solve the mathematical programming problem:

$$\text{MAX} \sum_{i=1}^{N} \text{E}\,[v_i|b_i] \qquad \text{P1}$$

subject to:

$$\sum_{i=1}^{N} b_i \leq B$$

$$b_i \geq 0 \quad i=1,2\ldots N$$

In the next section it will be shown how two different choices for the set of functions v_i lead to very plausible resource allocation strategies.

4.3.2 A Risk-Minimization Procedure

An obvious choice for the value functions $v_i(x)$ is the linear function $v_i(x)=x$, the same for all units. In practical terms, this is equivalent to saying that the decision maker gets more utility as the units get more money, independently of which unit gets it, as long as that money is used. In other words, he is indifferent to which budgeting unit gets each dollar if it is used, but dollars in excess have no value to the system.

With this choice of value functions, the expected value for a generic unit i transforms to:

$$\int_0^{b_i} v_i(t)\, f_i(t)\, dt + \int_{b_i}^{\infty} v_i(b_i)\, f_i(t)\, dt = \int_0^{b_i} t\, f_i(t)\, dt + \int_{b_i}^{\infty} b_i\, f_i(t)\, dt =$$

$$= \int_0^{b_i} t\, f_i(t)\, dt + \int_{b_i}^{\infty} b_i\, f_i(t)\, dt + \int_{b_i}^{\infty} t\, f_i(t)\, dt - \int_{b_i}^{\infty} t\, f_i(t)\, dt =$$

$$= \int_0^{\infty} t\, f_i(t)\, dt - \int_{b_i}^{\infty} (t - b_i)\, f_i(t)\, dt = \mu_i - \int_{b_i}^{\infty} (t - b_i)\, f_i(t)\, dt$$

where μ_i is the expected value of the PDF f_i, a constant independent of the budget

decision b_i.

Then, the objective function of the allocation problem (P1) evolves to:

$$\text{MAX} \sum_{i=1}^{N} \text{E}\,[v_i|b_i] = \text{MAX} \sum_{i=1}^{N} [\mu_i - \int_{b_i}^{\infty} (t - b_i)\, f_i(t)\, dt] =$$

$$\text{MAX} \sum_{i=1}^{N} \mu_i - \text{MIN} \sum_{i=1}^{N} \int_{b_i}^{\infty} (t - b_i)\, f_i(t)\, dt$$

Since the first term is a constant, the resource allocation problem reduces to:

$$\text{MIN} \sum_{i=1}^{N} \int_{b_i}^{\infty} (t - b_i)\, f_i(t)\, dt \qquad \text{P2}$$

subject to:

$$\sum_{i=1}^{N} b_i \leq B$$

$$b_i \geq 0 \quad i=1,2,\cdots N$$

Here, each term of the sum in the objective function is the expected lack of resources (risk) to be incurred by each budgeting unit i when allocated b_i, and therefore, this problem is in fact minimizing the expected total risk across the whole set of budgeting units.

$$\text{MIN} \sum_{i=1}^{N} \text{Risk}\,(b_i)$$

subject to:

$$\sum_{i=1}^{N} b_i \leq B$$

$$b_i \geq 0 \quad i=1,2,\cdots N$$

For the case of a Gaussian probability model, the expression of the risk for

budgeting unit i, which total cost has an average of μ_i and a standard deviation of σ_i when allocated b_i dollars is:

$$\text{Risk}\ (b_i) = \int_{x_i}^{\infty} \frac{t - x_i}{\sqrt{2\pi\sigma_i}} e^{-\frac{(t-\mu_i)^2}{\sigma_i^2}} dt$$

This mathematical programming problem is a Knapsak problem with non-linear objective functions. Although the solution of such a problem is generally complex, for the case of convex objective functions efficient algorithms have been developed [15]. This case of probabilistic budgeting, where the objective function is in fact the sum of integrals of Probability Distribution Functions, falls into the class of convex objective functions.

4.3.3 A Mini-Max Algorithm

Another plausible value function $v_i(.)$ to be used in the resource allocation model is the following:

$$v_i(t)=1 \text{ if } b_i \geq t$$

$$v_i(t)=0 \text{ if } b_i < t$$

In other words, the value of a given budget to the system is 1 if enough resources were allocated to the unit, and 0 if the unit did not have enough. A utility function such as this is equivalent to the decision maker trying to minimize the number of units that will need more money, being independent of the actual expected amount of overexpenses; the only relevant fact in this value function is the fact that a unit needed more money, this has value zero; otherwise, the value is one.

With some algebraic manipulations like those in the previous section, it can be easily shown that such a value function reduces the problem of resource allocation (P1) to the following:

$$MIN\{\ MAX\{\ F_i\,(b_i)\ \}\} \qquad \text{P3}$$

subject to:

$$\sum_{i=1}^{N} b_i \leq B$$

$$b_i \geq 0 \quad i=1,2,\cdots,N$$

where the maximum chance of needing more money is minimized.

Here, again, the functions $F_i(.)$ are the Cumulative Distribution Functions of total expenses for budgeting units i, $i=1,2,\ldots N$. The solution of this Mini-Max mathematical program can be obtained in a variety of manners. The simplest, specially in a budgeting application in which the problem only has to be solved a few times (at the beginning of each budgeting period) and therefore solution time is not a major concern, is based in sequential allocation. This algorithm is as follows: one starts by allocating to each budgeting unit the expected value of its total expenses. This gives to every unit a fifty-fifty chance of needing more resources. Then, if the total allocated budget is smaller that the available dollars, one keeps allocating one dollar at a time to the budgeting unit with the largest probability of needing more resources until there are no more dollars to be allocated. In the case of a tie, the dollar in contention goes randomly to any of the units that tied (this will effectively break the tie for the next allocation).

In the case that the base budget (sum of expected values) is larger that the total available dollars ($\sum_{i=1}^{N} b_i \geq B$), one has to remove dollars from the allocated budget until the total budget becomes feasible. This is done by removing the next dollar from the budgeting unit that has the smallest probability of needing it. As before, ties are not an issue, since removing a dollar randomly from any of the tied hospitals breaks the tie for the next step.

Since this algorithm has a "resolution" of one dollar, it will not find the budgets that exactly equate the risks. Nevertheless, one can see that the solution can be as precise as desired, being only a matter of using an allocation step as small as necessary. Clearly, the computational effort needed to solve the problem increases linearly with the accuracy of the solution.

Chapters 5 and 6 present numerical examples of probabilistic budgeting in which this algorithm was used. As it will be detailed there, extremely accurate solutions were attained with steps of one thousand of the difference between the base (expected) budget and the total budget available.

4.3.4 Introducing Preferences and Weights in the Allocation Process

The algorithms described in the previous two sections will effectively allocate resources among the budgeting units according to a predetermined goal such as total risk minimization or equalization of the probabilities of underbudgeting. The decision makers may nevertheless want to use during the allocation process some information regarding their own preferences toward different budgeting units or regarding measures of performance that they may have available.

The use of the value functions described above allows very simply the introduction of measures of efficiency or preferences. As an example, let us assume that using some method the decision maker has calculated the relative efficiency of all the budgeting units[15]. Let these efficiencies be called $e_i \leq 1, i=1,2, \cdots N$. Making the assumption that everything being the same (same PDF), the value to the system of giving an extra dollar to a hospital is affected linearly by its measure of efficiency, the general resource allocation problem (P1) gets modified to:

[15]The numerical implementation that is presented in Chapter 6 introduces and discusses at length how one goes about computing efficiency measures for a hospital system.

$$\text{MAX} \sum_{i=1}^{N} \int_0^{b_i} e_i v_i(t)\, f_i(t)\, dt + \int_{b_i}^{\infty} e_i v_i(b_i)\, f_i(t)\, dt \qquad \text{P4}$$

subject to:

$$\sum_{i=1}^{N} b_i \leq B$$

$$b_i \geq 0 \quad i=1,2 \cdots N$$

When the choices of value functions are the same that have been discussed in the previous sections, the problems reduce to the same risk-minimization and probability-equating methodologies, with the inclusion of the efficiency factors in the objective function. In practice, the allocation will be modified by the efficiency score in the sense that it will be more valuable to give dollars to the efficient facilities than to the non-efficient.

4.4 Measuring Resource Utilization in Hospitals

The problem of resource allocation described thus far relies heavily on the estimation of the operating costs of the different budgeting units for each budgeting period. If a strategy based on the probability distribution functions introduced in section 4.2 has to be used, it is necessary to estimate not only the expected expenses but also other parameters required to define the shape of the distribution, most commonly the variance or second moment. The validity of the budget obtained with PDFs will only be as good as the precision with which the PDFs are estimated.

The cost PDF for each class of patients represents the variability of resource usage of all the patients that belong to that class. If all the patients in a class used exactly the same amount of resources, the PDF of total cost of the service (provided that the case mix could be forecasted accurately) would be a number with zero variance, and the budgeting process would be reduced to assigning the amounts of

dollars equal to the expected (now, without variance) costs.

A good budgeting method will have to be based on PDFs with small variances, which in turn implies that it will require the definition of classes of patients that use similar amounts of resources.

4.5 Estimation of resource usage with minimum variance.

There have been a number of attempts to devise patient classifications that would reduce the variance of the resource usage within each class.

An ideal classification technique for budgeting purposes should have, among others, the following two characteristics: (1) be objective and (2) not depend on the actions of the physicians. Here, objectivity means that the classification should be a function of some variables extracted from the patient record, without room for personal judgment by the encoder. Independence of physician action would ensure that the practitioners could not move patients from one class to another by using more or less laboratory tests and/or procedures. The classification should depend only on clinical and demographic variables.

The next sections describe the effect of DRGs, the Severity of Illness Index, and Disease Staging as variance reducers when applied to cost and usage data from the X hospital. Also, the variance reducing power of the DRG classification is evaluated with multi-institutional data from the Y chain.

4.5.1 DRGs as Uniform Classes of Patients.

In order to design groupings of patients that use similar amounts of resources, a reasonable start is to use those groups adopted by Congress for that same purpose, the DRGs. As mentioned in the literature review, the main objective in the

definition of DRGs was the uniformity of length of stay and total charges within each class [35].

The measure of the goodness of a classification as a variance reduction scheme that has been used in the literature is the Reduction in Variance (RIV). The RIV is a fraction that has as numerator the difference between the total variance and the weighted sum of the variances in each class. The denominator is the total variance (variance of the total population).

$$\text{RIV} = \frac{\text{Variance using whole pop. - Variance using classification}}{\text{Variance using whole population together}} =$$

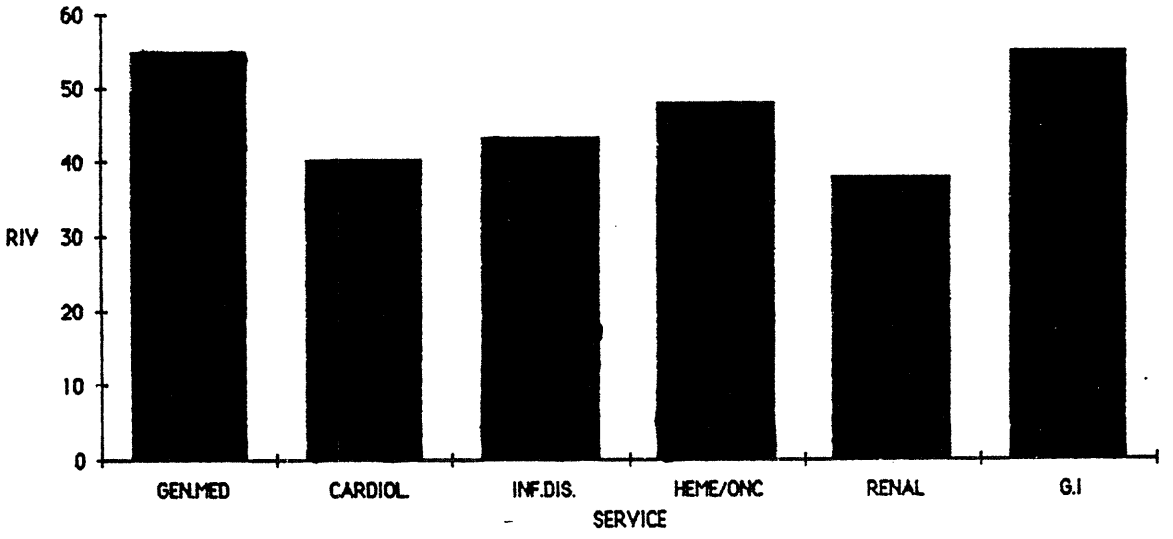
$$= \frac{N \times \sigma^2_p - \sum_{c=1}^{C} n_c \sigma^2_c}{N \times \sigma^2_p}$$

where N is the total number of patient discharges classified in C classes with n_c patients in each ($\sum_{c=1}^{C} n_c = N$), σ^2_p is the variance of the population as a whole and σ^2_c is the variance in class c. Since the weights are the number of patients in each class, the RIV is computing the relative reduction in variance obtained by subdividing the total population in disjoint classes.

The DRG system was used to reduce the variance of the estimates of total cost in the two data sets that were described in Chapter 3. The results are presented in figure 4-3 for hospital X and in 4-4 for the chain of hospitals Y.

The results for hospital X in figure 4-3 show that the maximum reduction in variance in total direct cost when subdividing the patient population by DRG is 55%, obtained in the General Medicine service. The smallest reduction, 40%, is obtained in the Renal service. These results imply that only half of the variance in total-cost observed in the Division of Medicine of hospital X can be explained by DRGs.

Figure 4-3: Reduction of Variance in Total Costs when Subdividing the Patient Population by DRG
Hospital X Division of Medicine - All Services



In contrast with hospital X, we do not have real cost data for each patient from the Y chain. For the RIV studies that follow, the case-mix adjusted length of stay was used as proxy for costs. This patient-cost proxy was calculated as follows:

(1) - It was assumed that for each DRG, the cost of a particular hospital stay was directly proportional to the length of stay in days. This is a very strong assumption, but if we take into account the fact that this proportionality has to hold only within each individual DRG, it is not unreasonable.

(2) - Under this assumption, dividing the total New Jersey Medicaid dollars that the whole system would input by the total number of bed-days provided (per DRG), provides a system-wide average cost of the bed-day of care for a particular DRG. Algebraically:

$$\text{System Average Cost per Day in DRG } i = \text{SC}_i = \frac{N_i \times \text{NJD}_i}{\sum_{p=1}^{N_i} \text{LOS}_p}$$

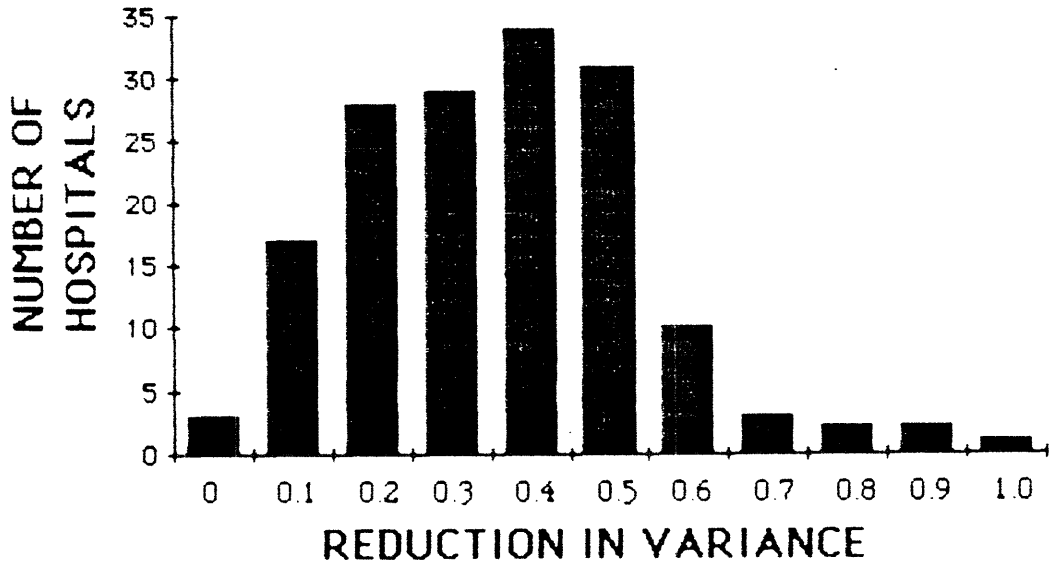
where N_i is the total number of patient discharges in DRG i, NJD_i is the New Jersey reimbursement rate for DRG i, and LOS_p the length of stay of patient p. New Jersey Dollars were used to be able to compare the resource intensity of the different DRGs. The validity of the assumption comes from the fact that we are using the total dollars used by the chain, and since DRG prices were set at the average cost, when using large numbers of patients, differences of particular discharges will tend to cancel each other.

(3) - With this nomenclature, the proxy for cost of a given admission of length of stay LOS days will be $LOS \times SC$. For the remainder of this chapter, we will refer to this proxy as "cost" even that it has to be understood that it is only an approximation.

The results in total cost reduction in variance obtained by classifying the patient discharges by DRG in each of the 160 hospitals of the chain Y are presented in the histogram of figure 4-4. Moat institutions (115) did not reach a 50% reduction in variance. This result, consistent with others reported in the literature ([59] [63]), makes questionable the validity of the DRG classification as a methodology to reduce variance across many institutions.

This heterogeneity induces us to look for more uniform classification

Figure 4-4: Histogram of Reduction of Variance in Total Costs in the 160 Hospitals from Chain Y when Subdividing the Patient Population of each Hospital by DRG



techniques. Disease Staging (DS) and Severity of Illness Index (SII) are studied in the next sections.

4.5.2 Other Variance Reduction Techniques. Applications.

Two problems can be identified with the use of DRGs for budgeting: (1) The within DRG uniformity of resource usage is not very good, and (2) To use DRGs, managers would have to come up with Probability Ditribution Functions for 470 classes of patients. In order to solve these two problems, this section analyzes alternative classifications based in subdividing some DRGs with high volume and

heterogeneity and on aggregating some other DRGs. The value of this alternative system as a variance reducing method is also evaluated.

Severity of Illness Index: As described in the literature review (section 2.6), the severity of Illness Index is an instrument intended to be used for defining case-mix groupings of hospitalized patients.

In order to judge the effectiveness of the Severity of Illness Index as tool in the prediction of resource usage and in the reduction of variance, we performed analysis of variance and reduction of variance studies at two levels: within DRGs and across the whole Division of Medicine. The results indicate that Severity effectively differentiates classes of patients that use significantly different amounts of resources. Figure 4-5 presents the analysis of variance regarding resource usage of the Chemistry and Hematology laboratories and the Routine and Intensive Care Unit (ICU) bed days of care for DRG 14 (Specific Cerebrovascular Disorders except Transient Ischemic Attacks).

The analysis shown in the figure is interpreted as follows: for each category of usage analyzed (i.e. Chemistry laboratory) there are five rows, labeled severity 0 to 4. The column labeled "Number of Patients" contains the number of discharges that the hospital had of the specified severity within DRG 14.[16] The columns labeled Mean and Standard Deviation present the average and standard deviation of the logarithm of the usage of Relative Value Units by each severity class. Logarithms rather than the observed values were used in order to be able to perform statistically correct tests. (See Chapter 3 - Data Sources- for a description of the Relative Value Unit scale and a statistical justification of the Natural

[16]Severity 0 was assigned to those patients that could not be classified by the encoder. The total number of patients that fell into this class was small, only 3% of the patients in the division of medicine. The size of this class was getting smaller during the year due to increase in expertise of the encoders.

Figure 4-5: Analysis of Variance of some Units of Service DRG 14 Classified by Severity of Illness Index.

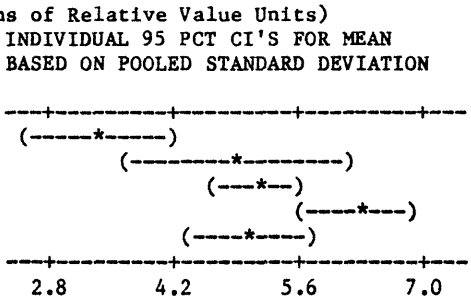
Chemistry Usage (Logarithms of Relative Value Units)

F=7.53

INDIVIDUAL 95 PCT CI'S FOR MEAN
BASED ON POOLED STANDARD DEVIATION

Severity Index	Number Patients	Mean	Standard Deviation
0	12	3.343	2.624
1	6	4.927	0.763
2	45	5.117	0.717
3	24	6.291	0.924
4	21	5.030	2.470

POOLED STANDARD DEVIATION = 1.536



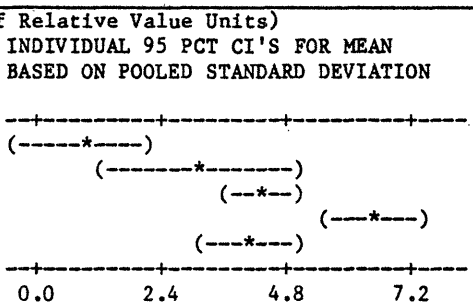
Pharmacy (Logarithms of Relative Value Units)

F=13.14

INDIVIDUAL 95 PCT CI'S FOR MEAN
BASED ON POOLED STANDARD DEVIATION

Severity Index	Number Patients	Mean	Standard Deviation
0	12	0.8907	2.8601
1	6	3.1326	1.2294
2	45	4.2919	1.2708
3	24	6.5087	1.1989
4	21	4.0569	3.9980

POOLED STANDARD DEVIATION = 2.2498



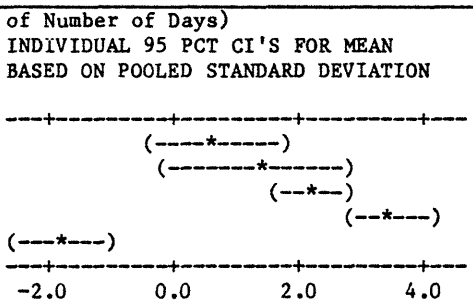
ICU Bed Days (Logarithm of Number of Days)

F=26.11

INDIVIDUAL 95 PCT CI'S FOR MEAN
BASED ON POOLED STANDARD DEVIATION

Severity Index	Number Patients	Mean	Standard Deviation
0	12	0.697	1.798
1	6	1.331	0.770
2	45	2.176	0.785
3	24	3.482	0.796
4	21	-1.756	3.608

POOLED STANDARD DEVIATION = 1.818



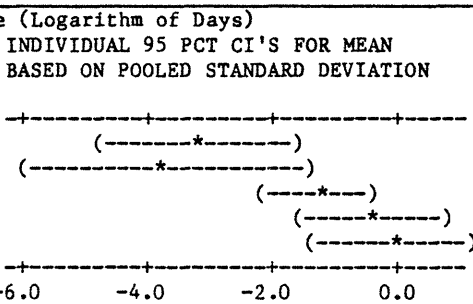
Routine Bed Days of Care (Logarithm of Days)

F=3.95

INDIVIDUAL 95 PCT CI'S FOR MEAN
BASED ON POOLED STANDARD DEVIATION

Severity Index	Number Patients	Mean	Standard Deviation
0	12	-3.212	2.522
1	6	-3.721	2.165
2	45	-1.265	2.935
3	24	-0.374	3.128
4	21	-0.071	2.741

POOLED STANDARD DEVIATION = 2.869



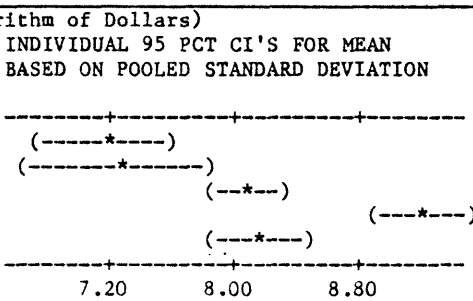
Total Direct Cost (Logarithm of Dollars)

F=19.11

INDIVIDUAL 95 PCT CI'S FOR MEAN
BASED ON POOLED STANDARD DEVIATION

Severity Index	Number Patients	Mean	Standard Deviation
0	12	7.189	0.588
1	6	7.241	0.443
2	45	8.068	0.672
3	24	9.226	0.591
4	21	8.188	1.148

POOLED STANDARD DEVIATION = 0.757



Logarithms as a valid transformation to obtain well behaved distributions of resource requirements.)

The intervals on the right-hand side of figure 4-5 are the 95% confidence intervals of the mean. These intervals are computed using the standard deviation of the whole population being subdivided (the whole DRG). This is necessary in order to be able to draw statistical conclusions on the power of the classification to discriminate between different levels of resource usage. For an in-depth, yet clear explanation of analysis of variance techniques, see [51].

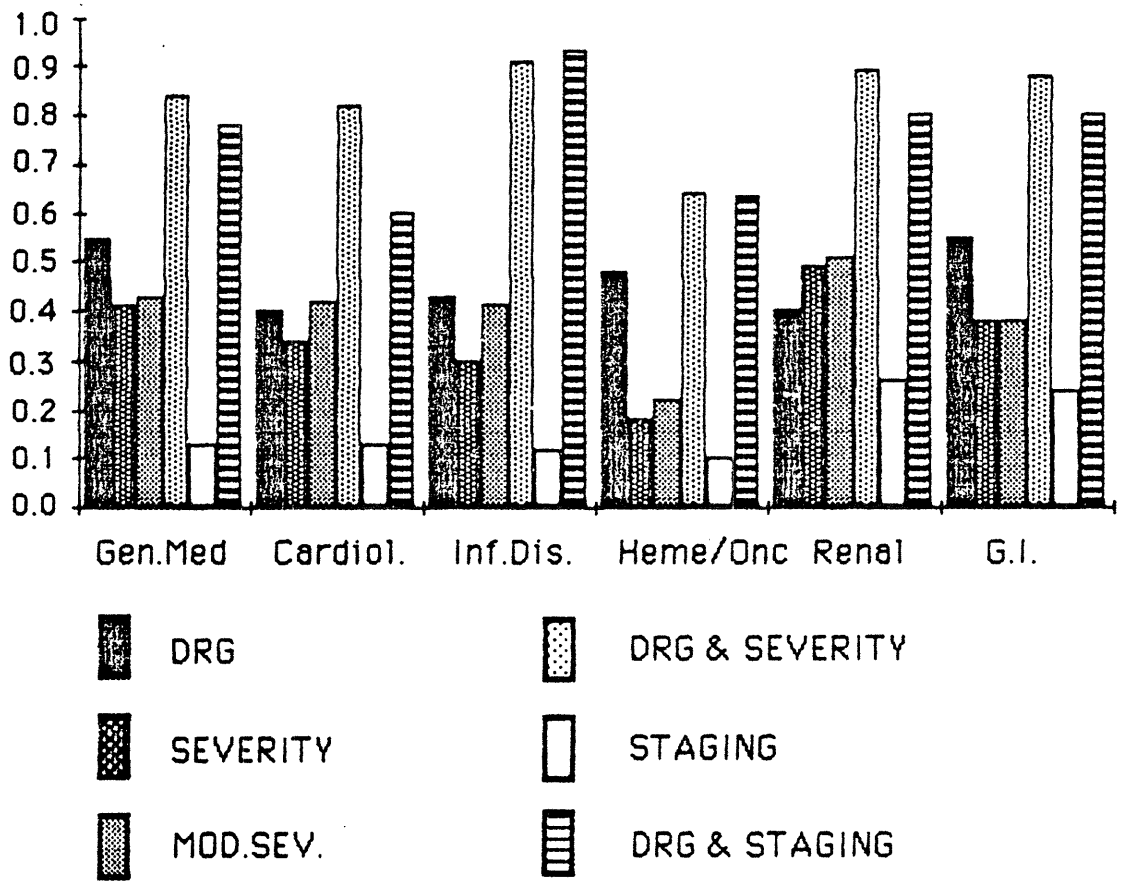
Note that with increasing severity, there is a consistent increase in the average consumption of resources. Severity 4, which corresponds to critically ill patients, does not follow this pattern because of shorter lengths of stay due to death. This fact may explain why severity has failed in a number of instances to explain costs of hospital admissions. When hospital costs are tied to length of stay, a practice still common in the hospital management literature, severity will not be able to differentiate usage. These results are constant throughout most of the DRGs that we analyzed.

Figure 4-6 presents the results of analyzing the power of the Severity of Illness Score and Staging[17] as variance reducers. The efficacy of Severity (bar number 2) versus DRGs (bar number 1) and Procedure-Adjusted Severity (bar number 3) in reducing the variance of the total costs in the Division of Medicine were compared. The measure of the efficacy of the classification is again the Reduction of Variance described in the previous section.

Because since this is the Division of Medicine, only one patient had a procedure of high intensity, and 42 out of 3733 had a moderate procedure. (The

[17] Staging results will be discussed in the next section

Figure 4-6: Severity, Procedure Adjusted Severity, Staging, and DRG as Reducers of Variance



very small numbers of high intensity procedures is typical of any Division of Medicine in most hospitals.) Consequently, the effect of the adjusting the severity score by procedures in negligible.

It can be observed that Severity alone (4 classes maximum) compares quite well with DRGs as a variance reducer. Except for Hematology/Oncology, where the

reduction of variance obtained by the Severity index is only 20%, all other services in the Division of Medicine have RIVs around 40%.

When DRGs are subdivided by Severity, (generating a potential total number of classes of 470×4), the reductions in variance obtained are extremely large, above 80% in all cases. This indicates that the heterogeneity observed within DRGs is due in large part to the clinical situation of the patient. A valid criticism to the subdivision of DRGs into severity classes is the large number of groups generated. Section 4.5 will explore the possibility of using only a few DRGs subdivided into subgroups, and considering all the remaining patients as belonging to a single class.

Disease Staging: The same kind of analysis was carried out for Disease Staging. As an illustration of the methodology, Figure 4-7 presents the analysis of variance for DRG 14 when subdividing the patient population by the Staging Index. Here, we also observe some increase in use at higher (sicker) stages, but the statistical significance is smaller than with the Severity of Illness Index. This lower significance is found through all the DRGs that were analyzed.

Even though Staging does not discriminate as well as Severity among different levels of resource usage within a DRG, figure 4-6 shows that it is a powerful aid to DRGs as a variance reducer. The RIV obtained are almost as high as those obtained with Severity. Note also that Staging alone, does much poorer that Severity alone, because the stages for different basic diagnoses are not comparable. For example, for most diagnoses the scale of Stages goes from 1 to 4, but for Oncology, it spans from 1 to 5.

The conclusion of this RIV exercise with data from the Division of Medicine of Hospital X is that Severity has better discriminatory and variance reducing powers that Staging, but the differences are not large. However, this poorer statistical

Figure 4-7: Analysis of Variance of some Units of Service DRG 14 Classified by Staging.

```
          Chemistry Usage (Logarithms of Relative Value Units)
                                          INDIVIDUAL 95 PCT CI'S FOR MEAN
F=11.99                                   BASED ON POOLED STANDARD DEVIATION
  Stage    Number    Mean    Standard
  Level    Patients         Deviation   -+---------+---------+---------+-----
    1        2     -0.9482    5.1717    (------*------)
    2       41      5.2044    0.9117                            (*-)
    3       47      5.4723    1.1333                             (*-)
    4       18      4.8815    2.5916                          (-*--)
                                        -+---------+---------+---------+-----
 POOLED STANDARD DEVIATION = 1.4976     -3.0       0.0       3.0       6.0
```

```
            Pharmacy (Logarithms of Relative Value Units)
F=1.93                                    INDIVIDUAL 95 PCT CI'S FOR MEAN
                                          BASED ON POOLED STANDARD DEVIATION
  Stage    Number    Mean    Standard
  Level    Patients         Deviation   ---------+---------+---------+-------
    1        2      1.632     1.321     (---------------*--------------)
    2       41      3.969     2.264                       (---*--)
    3       47      4.905     2.305                          (--*---)
    4       18      3.749     4.163                     (-----*----)
                                        ---------+---------+---------+-------
 POOLED STANDARD DEVIATION = 2.678            0.0       2.4       4.8
```

```
            Routine Bed Days of Care (Logarithm of Days)
F=40.31                                   INDIVIDUAL 95 PCT CI'S FOR MEAN
                                          BASED ON POOLED STANDARD DEVIATION
  Stage    Number    Mean    Standard
  Level    Patients         Deviation   --------+---------+---------+--------
    1        2      0.698     0.000            (-----------*-----------)
    2       41      2.146     1.077                              (--*-)
    3       47      2.516     1.544                                (--*-)
    4       18     -2.595     3.079   (---*---)
                                        --------+---------+---------+--------
 POOLED STANDARD DEVIATION = 1.746          -2.0       0.0       2.0
```

```
            ICU Bed Days (Logarithm of Number of Days)
F=6.87                                    INDIVIDUAL 95 PCT CI'S FOR MEAN
                                          BASED ON POOLED STANDARD DEVIATION
  Stage    Number    Mean    Standard
  Level    Patients         Deviation   ---------+---------+---------+-------
    1        2     -4.605     0.000     (------------*------------)
    2       41     -2.514     2.804                     (--*--)
    3       47     -0.470     2.943                          (-*--)
    4       18      0.340     2.464                           (---*---)
                                        ---------+---------+---------+-------
 POOLED STANDARD DEVIATION = 2.801          -6.0      -3.0      -0.0
```

```
            Total Direct Cost (Logarithm of Dollars)
F=4.71                                    INDIVIDUAL 95 PCT CI'S FOR MEAN
                                          BASED ON POOLED STANDARD DEVIATION
  Stage    Number    Mean    Standard
  Level    Patients         Deviation   -----+---------+---------+---------+-
    1        2      6.814     0.087     (------------*------------)
    2       41      7.926     0.855                        (--*--)
    3       47      8.536     0.970                              (-*--)
    4       18      8.130     1.029                        (---*----)
                                        -----+---------+---------+---------+-
 POOLED STANDARD DEVIATION = 0.933        6.0       7.0       8.0       9.0
```

performance of Staging is outweighed by its objectivity and mechanization[18].

4.6 Finding a Good Classification.

As we stated earlier, one of our main objectives is to estimate resource consumption by a given patient case-mix with as little variance as possible. It has already been shown how, by subdividing DRGs by severity or staging, the variance of total costs can be reduced up to 80%. Here, we will explore other subdivisions. The aim is to attain as good a RIV as possible with the smallest possible number of classes.

To introduce our classification mechanism, let us examine two extreme cases: on the one hand, if we take the entire patient population as a whole, without any classification, the variance of the expected total cost is (N being the total number of patients):

$$\sigma^2_{\text{total cost}} = N \times \sigma^2_{\text{cost}}$$

In this expression σ^2_{cost} is the variance of the distribution of costs of all patients, $\sigma^2_{\text{total cost}}$ is the variance of the sum of N random variables with variances σ^2_{cost}. This is a very large number, particularly given the heterogeneity of the total costs in large numbers of patients. For the data from hospital X (14568 patients):

$$\sigma^2_{\text{cost}} = 0.3138 * 10^8,$$
$$\text{and } \sigma^2_{\text{total cost}} = 0.4571 * 10^{12}$$
$$\sigma_{\text{cost}} = 5601, \text{ and } \sigma_{\text{total cost}} = 676129$$

On the other hand, if we decide to classify the patient population in a number of classes, each as homogeneous as possible, the total variance will be:

---

[18] As discussed in the literature review of chapter 2, Severity is considered to be somewhat subjective and an expensive measure to encode [49].

$$\sigma^2_{\text{Total Cost}} = \sum_{c=1}^{C} n_c \sigma^2_c$$

where C is the number of classes, σ^2_c the variance in class c and n_c the number of patients in class c. If the classes in which the population is being subdivided have some homogeneity, the resulting variance will diminish as C increases. Nevertheless, using a large number of classes is not desirable for budgeting purposes, since the resource allocators would have to come up with prices for all classes, many of them with very few patients.

In order to decide what the optimum number of classes would be, one has to weight the obtained reduction in variance versus the added cost of manipulating and costing large numbers of classes. The following strategy was devised to help determine this optimum number:

1. Use only as few DRGs as possible. These DRGs should be those which account for most of the cost of the Division.

2. Divide the rest of the population according to their indexes of severity or staging.

3. Remove from each class, if necessary, those patients that fall into the category of outliers[19] and consider them a different class.

We will comment on these steps separately.

1) In order to determine the reasonable number of classes, the RIVs obtained using a given number of DRGs were plotted against each other. The results for each service are presented in Figure 4-8. DRGs were introduced in the classification according to their relative contribution to the total cost of each clinical service.

2) The remainder of the patients (those that do not belong to any of the 85

[19]Outliers will be defined later in this section.

DRG mentioned above) are classified by their severity index.

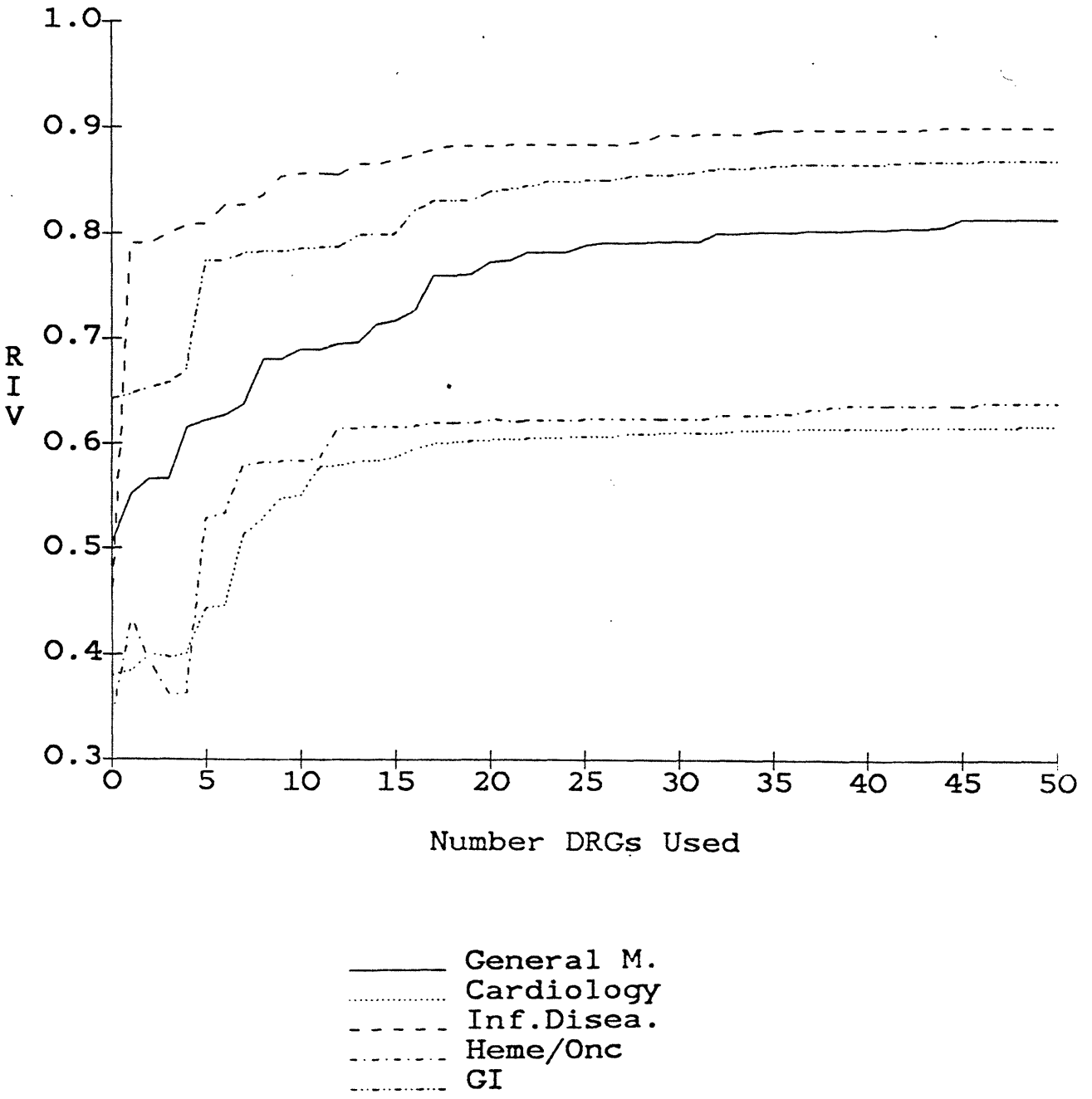
In figure 4-8, each curve represents the evolution of the Reduction in Variance of total costs obtained when introducing one DRG at a time. For example, at the 5 mark in the x axis, the corresponding RIV for each service was obtained using 24 classes: 5 DRGs subdivided by severity ($5 \times 4 = 20$) plus four classes for the rest of patients that do not fall in any of the 5 DRGs. The order in which the DRGs enter the classification is the order in which they contribute to the total cost of each particular service. The effect of classifying by severity the patients that do not belong to any of the selected DRGs (as opposed to just considering them all in a single class) reduced the variance of the estimates of total cost an average of 5% across all bed sections in the Division of Medicine.

One can see that in all services except General Medicine, 10 DRGs are enough to obtain all the reduction of variance that will ever be obtained. This maximum attainable RIV was displayed in the histogram of figure 4-8, which displays the RIV obtained by dividing the population in 470×4 classes.

3) Selecting outliers is not an easy problem. In the health sciences literature it is usually found that an outlier is defined as that observation that is located a given number of standard deviations from the mean of the sample. Since this study is based in Probability Distribution Functions (which by themselves model the whole population, whether the observations are close to the average or far away), it was felt that deciding an a priori cut-off value to consider observations as outliers was inappropriate; instead the method introduced by Tukey [61] based in robust statistics is recommended. This methodology does not require the setting of any cutoff values.

The numerical examples that are presented in Chapers 5 and 6 were performed with all patient discharges, without removing any observation.

Figure 4-8: Reduction in Variance versus Number of Classes.
Division of Medicine.



Chapter 5

Budgeting Within a Single Institution

Chapter 4 has introduced a methodology for accurately estimating the amount of resources needed for a given budgeting period and a procedure for resource allocation. This chapter focuses on applying this methodologies to the Division of Medicine of hospital X. Section 5.1 discusses the relevant inputs and outputs of the budgeting units and section 5.2 presents and discusses the numerical results.

5.1 Inputs and Outputs of a Large Teaching Hospital

5.1.1 Inputs.

For the pupose of our budgeting analysis, the inputs that will be considered are the value of the reimbursement that the budgeting unit would generate during the budgeting period. The numerical example that follows does not deal with the process of defining the actual amount of dollars available for direct patient care in the next budgeting period. Instead, we will assume that the total amount of dollars that has to be distributed among the different budgeting units is a fixed percentage of the sum of the expected expenses. This serves the purpose of focusing the discussion on the differences in budget that various allocation techniques produce.

In a real situation, one would first compute the dollar value of the expected income from the forecasted case mix and volume (the same case mix used to compute the expected expenses), second, one would subtract from this expected income the total indirect costs, and finally, the resulting amount would be allocated using one of the methodologies described in the previous chapter.

5.1.2 Outputs.

The outputs of a large hospital affiliated to a medical school fall into at least three categories, (1) patient care services, (2) teaching activities, and (3) research. These categories will be discussed separately.

Patient Care Services: Although patient care services are the most tangible outputs that the institution produces, they are not necessarily easy to define or quantify. In most hospitals, the services provided are measured by the number of tests, procedures and other medical acts performed. The production of the hospital should be measured by the reimbursable unit, namely, the patient discharged with a given diagnosis. Medical services and ancillaries (called intermediate products in the data-sources chapter) must be recorded for internal accounting and compensation, but the operational units that perform them should not be considered the budgeting units.

Obviously, if hospital X were to sell services (intermediate products) to third parties (as it could be the case of complex laboratory analyses that smaller hospitals were not able to perform due to lack of equipment), then these particular intermediate products would became units of output and the laboratory that performs them could be considered a budgeting unit for the amount of resources that these sales involve. In general these third party sales do not represent any sizable amount of income.

Teaching: Teaching is a complex issue. Traditional criteria to measure this output include the number of residents graduated and the number of undergraduate medical students that took elective clinical curses in the hospital. Unfortunately, there are a number of hidden costs that have to be accounted for when dealing with a teaching institution. Usually, teaching hospitals incur in expenses like having a larger library that they would otherwise have, running seminars, and holding

rounds. These activities have an associated cost of resources and staff time. In hospital X, these costs where all considered indirect, and therefore did not enter our budgeting exercise. This is consistent with our goal of focusing only on budgeting direct patient care resources.

Some health care administrators argue that teaching programs have an associated cost stemming from the fact that some ancillary utilization is done solely for teaching purposes. Since the expected costs in our budgeting example are computed directly from utilization data collected the previous year, this increase from the otherwise purely clinical usage level, if true, will be imbedded in the observed values, and can be ignored provided that there is no change in the medical school affiliation and the intensity of the teaching programs.

Chapter 6, which deals with budgeting a chain of hospitals from the perspective of the corporate management, will analyze the increased personnel costs incurred by teaching institutions. From the point of view of a single institution, though, this problem is less relevant as long as the indirect costs are properly accounted for.

Research: Because its complexity, research is probably easier to deal with than any of the other two outputs. Research resources do not usually come from the patient-care operational budget. In most institutions, as in hospital X, the amount of time that the staff devotes to research is deducted from the total time available for patient care. Similar procedure is followed for costs associated to house keeping and building maintenance, where an overhead is charged to each research project in order to reimburse the institution for these costs. In short, since our concern in this thesis is budgeting for the patient care direct costs, research will not be considered. Therefore, the only output from the Division of Medicine that will be considered are patients discharged.

5.2 Numerical Example

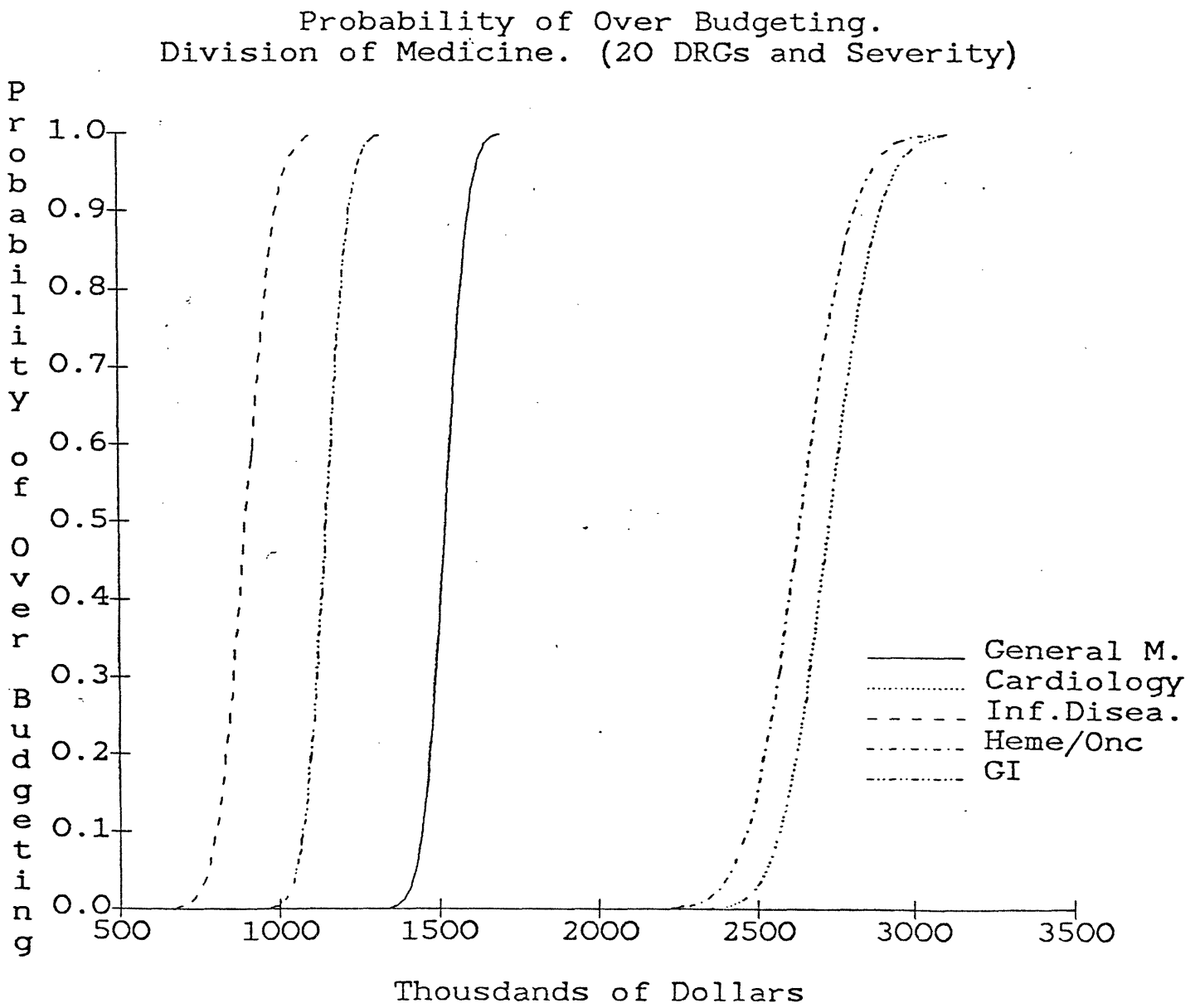
This budgeting example deals solely with the direct-dollars operational budget of the Division of Medicine. It assumes that the manager in charge of the Division has to allocate direct resources among the different Services that belong to the Division (the budgeting units). Figure 5-1 presents the Cumulative Distribution Functions of the expected total direct costs for all clinical services of the Division of Medicine of Hospital X. These curves were computed by costing all patient discharges via the real usage of intermediate products such as X-Rays and laboratory tests. The empirical distribution of costs of each class of patients was then computed, and a Gaussian model fitted. The number of classes of patients used in each service was: 20 DRGs, each subdivided by 4 severity levels, and 4 severity levels for the rest of patients that were not in any of the first 20 DRGs. (See Chapter 4).

We observe that the highest expected total cost is that of the Cardiology Service ($2.75 Million), closely followed by Hematology/Oncology ($2.6 Million). The service with less total expected cost is Infectious Diseases ($0.9 Million).

The different slopes of the curves shoul be noticed. The slopes of the Cumulative Distribution Functions are a function their variances. The distribution with higher variance is Hematology/Oncology whereas general Medicine has the smallest variance. Recall that these variances are computed using the classification procedure outlined in the previous chapter, and therefore, about 80% of the observed original variance within each service has been removed.

In order to illustrate how these curves would be used for allocating resources, the assumption of an increase in budget of 10% over the sum of expected values was made. Figure 5-2 presents the budgets of all services with the aforementioned

Figure 5-1: Cumulative Distribution Functions of Expected Total Costs in the Division of Medicine



increase when the three methodologies introduced in Chapter 4 are applied: (1) Least Total Risk, (2) Equal Probability of Underbudgeting, and (3) Proportional Increase. The differences in allocated resources are better highlighted in the percentual changes presented in figure 5-3. Figure 5-3 shows that services with high variance (Hematology/Oncology, Infectious Diseases and Cardiology) are allocated more resources by the risk and probability minimization algorithms that they would get with fixed percentual increase across the board. The converse is true for services with low variance (General Medicine and GI).

The explanation for this is straightforwardly derived from the definition of the two allocation procedures described in chapter 4: if there is extra money to allocate, as in this example, proportionally larger amounts of it will go to the budgeting units that have larger variances in resource requirement.

If there were less money to allocate than the sum of expected values, then, budgeting units with higher variance would lose more money (in relative terms) than those with more tight expected usages. Again, this is due to the fact that units with a narrow probability distribution function do have a very small chance of deviating from the expected expenses.

This results highlight the point that when decision makers allocate resources deviating from the expected budgets without taking into consideration their inherent variability, they may seriously jeopardize the ability of the units with small variance to function, as they will be more affected during budget cuts.

It should be reiterated at this point that all budget changes and variances that have been mentioned so far refer only to operational budgets[20] and that we have

[20]Operational Budgets are those required for normal operation of the budgeting unit. Capital investment in new machinery and other one-time expenses are excuded from consideration in this numerical example

Figure 5-2: Budgets for Direct Expenses Using Different Algorithms. Division of Medicine (10% Increase Over Expected Value)

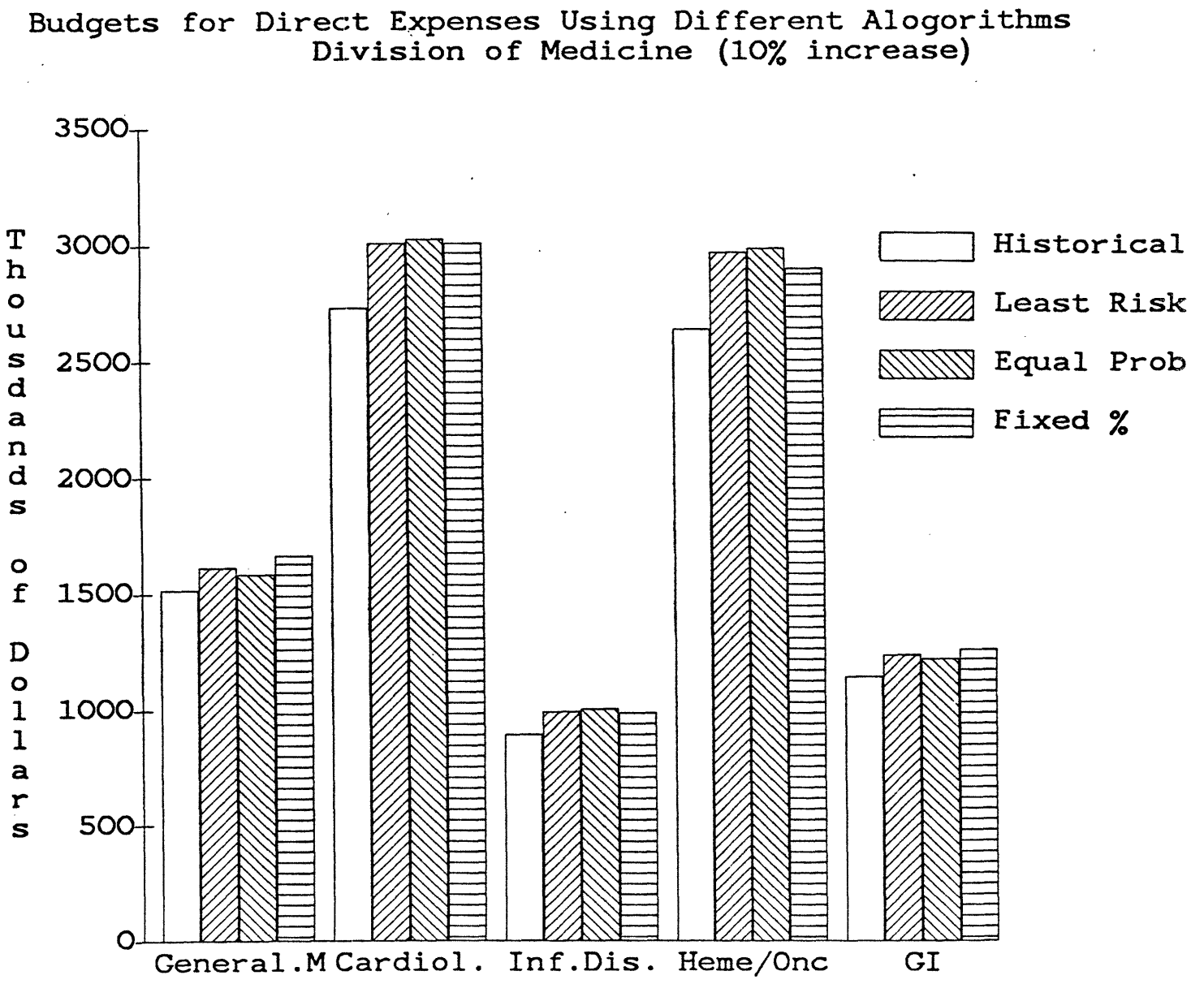
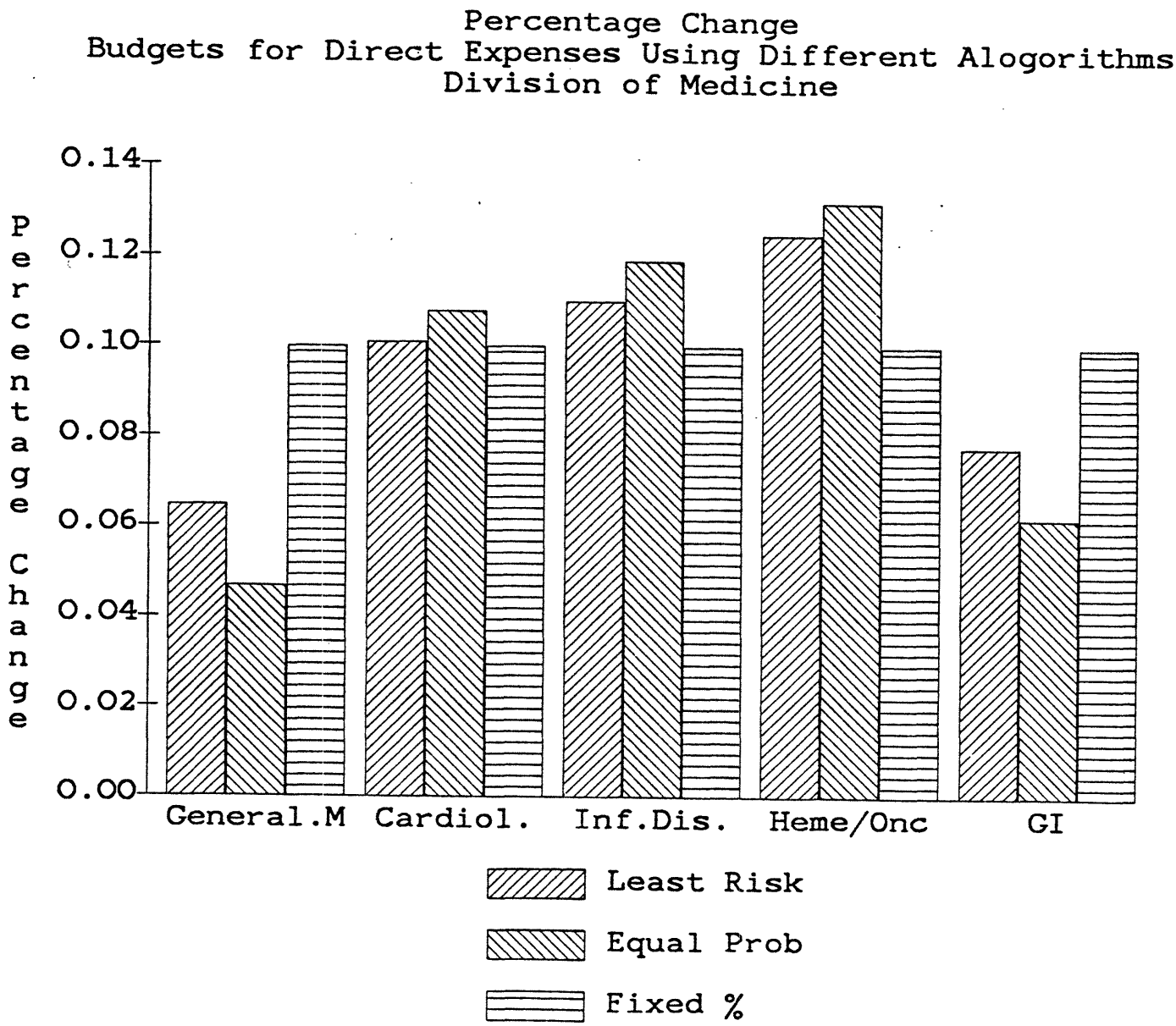


Figure 5-3: Percentage Changes in Budgets for Direct Expenses Using Different Algorithms. Division of Medicine (10% Increase Over Expected Value)



not taken into account at any moment the possibility that the budgeting units could change their internal functioning strategies.

Chapter 6

Budgeting a System of Hospitals

This chapter deals with the problem of resource allocation for direct expenses to the chain of hospitals Y introduced in chapter 3 (Data Sources). The budgeting units that we will encounter in this chapter are the hospitals themselves, and we will take the position of the corporate manager that has to allocate resources to each individual hospital for the next budgeting period. Because there is no available patient-specific cost data, the probability distribution functions of the estimated resource needs for each hospital have been computed using case-mix adjusted length of stay as a proxy for cost. The plan of this chapter is as follows: Section 1 will deal with the issue of the effect of teaching programs in the teaching institutions of the chain Y. Section 2 will describe two measures of efficiency of health care institutions and apply them to the set of hospitals. Section 3 will present the results of using the Risk-minimization and Minimization of Maximum Probability techniques introduced in chapter 4 to the chain Y.

6.1 Efficiency Measures in Health Care Institutions.

6.1.1 Introduction.

Evaluating the performance of a hospital is a task which has been of great interest to health care administrators, multifacility management groups, and government. Since the advent of Diagnostic Related Groups (DRG) as reimbursement methodology, the need for measuring hospital efficiency has been especially important for both government and hospital administrators. A few

performance measures have been developed in the past, specifically, ratios and econometric-regression analyses. For an example see [32], where these classical techniques are applied to the National Health System in England. These approaches, although frequently used in practice, have serious drawbacks (see [58] for a critique). Basically, Ratio Analysis fails to account for differences in Case-Mix, and Cross-Sectional Econometric Regression Estimates provide average cost functions, which are equally influenced by all institutions, efficient and inefficient alike.

The focus of this section is two fold, first, it describes a technique for detecting inefficient facilities called Data Envelopment Analysis (DEA), and second, after analyzing some of DEA's drawbacks, it introduces a variation of DEA based on Multiple Objective Discrete Optimization, which eliminates some of them. Both methodologies are applied to the departments of medicine of a set of 160 hospitals from a not-for-profit chain, and the resulting pairs of efficiency measures are compared. An effort is also made to explain the reasons for the observed discrepancies.

The plan of this section is as follows: Subsections 2 and 3 introduce the basic concepts of Data Envelopment Analysis and Multiple Objective Optimization respectively. Subsection 4 compares both methodologies. Subsection 5 describes the data sources used to evaluate the performance of both approaches. The results are presented respectively in subsections 6 and 7. Subsection 8 discusses the differences obtained in the results of the runs, and subsection 9 has the summary of the conclusions and some final comments.

6.1.2 Data Envelopment Analysis

This methodology was introduced in the late seventies [18] as a tool for measuring the efficiency of decision-making units when faced with multiple inputs and outputs. DEA relies on the very strong assumption that the efficiency of a hospital can be measured as the quotient of a linear combination of the outputs and the inputs. Algebraically,

$$\text{Eff} = \frac{\sum_{i=1}^{\#\text{ outputs}} v_i\, y_i}{\sum_{j=1}^{\#\text{ inputs}} u_i\, x_i} \tag{1}$$

The outputs (the y's) can be the number of patients discharged in a given DRG (case mix), the number of residents trained, or any other "product" that the hospital delivers. Examples of possible inputs (the x's) are Full Time Equivalents (FTE) and Direct and Indirect expenses. The estimate of efficiency can be varied by varying the weights (u's and v's). DEA computes the efficiency of each hospital using <u>the</u> set of weights that MAXIMIZES the estimate of its efficiency.

In order to maintain the efficiency within a common bound, the methodology also requires that for a set of weights to be valid, it should not make the efficiency of any hospital greater than 1. That is,

$$\frac{\sum_{i=1}^{\#\text{ outputs}} v_i\, y_i}{\sum_{j=1}^{\#\text{ inputs}} u_i\, x_i} \leq 1 \text{ For all facilities} \tag{2}$$

One of the major advantages of DEA is that it simultaneously considers the multidimensionality of the input and output spaces, without the need to know a priori the relative weights that are necessary for ratio analysis and most types of regression analysis.

If after running DEA, using a set of data from a group of hospitals, one institution has efficiency smaller than 1, the interpretation is that this facility is relatively inefficient as compared with the others in the group. No matter which other set of acceptable weights this facility had chosen, its efficiency ratio would not increase.

The procedure provides the analyst with relative efficiencies for each facility, rather that absolute measures of inefficiency. The relativeness arises from the fact that all measurements are made with respect to the other hospitals in the sample, and therefore, inefficiencies present in all facilities will never be detected.

For illustration purposes, let us explore the following example: Assume that 7 hospitals have the same amount of each input (Full time equivalents, Dollars, Beds, etc.) and that their outputs are only two types of patients, patients types 1 and 2. Since all the inputs are the same, any inefficiency can be measured by their outputs. We illustrate this example graphically in figure 6-1.

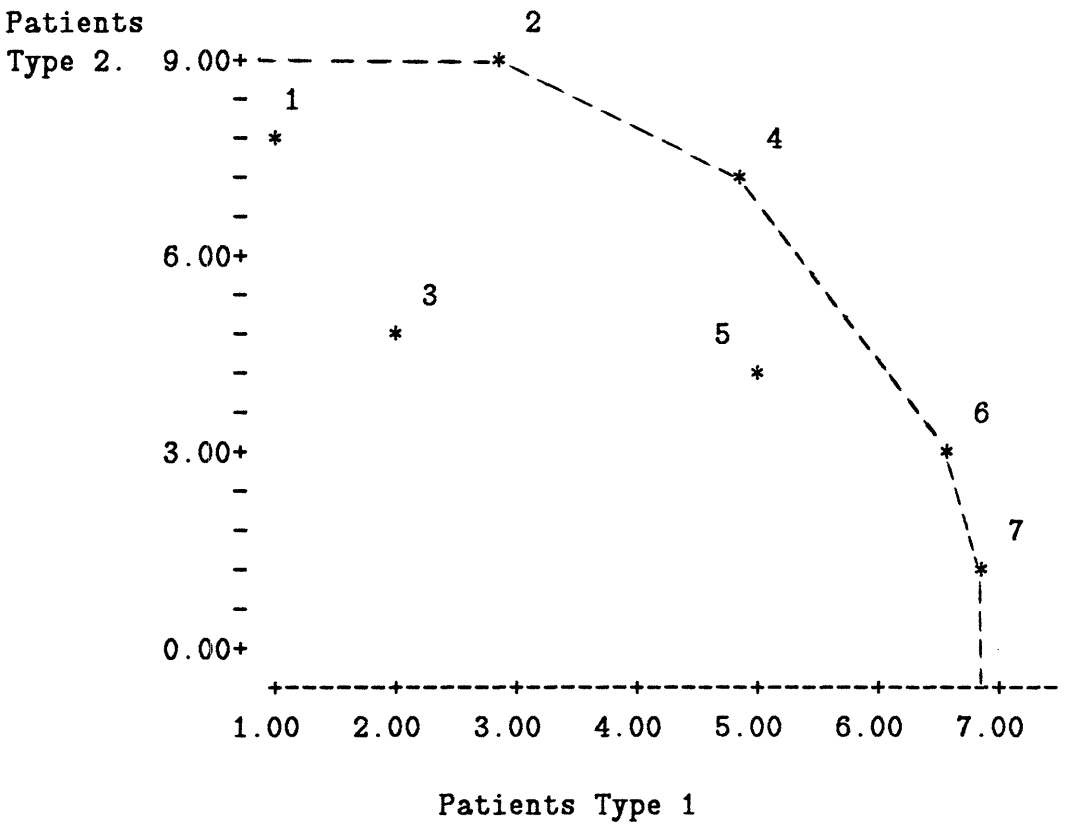
In this simplified case with all inputs the same, the DEA analysis finds the "Envelope" of the points (the dotted line of the figure), and labels the hospitals on the boundary as being efficient and those in the interior as inefficient. The analysis concludes that hospitals 1, 3, and 5, are inefficient when compared to the set 2, 4, 6, and 7. The relative inefficiency of the inefficient hospitals is measured by the distance from the location of the point to the efficient boundary.

6.1.3 Multiple Objective Optimization

Integer Multiple Objective Optimization efficiency measures are based on the following definition [14]:

Let $f_1(x), f_2(x), \ldots f_n(x)$ be n attributes of hospital x. For example, $f_i(x)$ could be the number of patients of type i discharged per full time equivalent of employee

Figure 6-1: DEA Graphic Example



in hospital x, for i=1,2, $\cdots$ n.

A hospital x^1 is said to be efficient with respect to the set of hospitals under consideration if there is no other hospital x^2 such that[21]:

$$\begin{aligned} f_1(x^2) &\geq f_1(x^1), \\ f_2(x^2) &\geq f_2(x^1), \\ &\cdots\cdots \\ f_n(x^2) &\geq f_n(x^1) \end{aligned} \tag{3}$$

with at least one of the inequalities being strict. Loosely speaking, a hospital is inefficient only if there is another hospital that is strictly better in at least one criterion and not worst in all the others.

[21] In this notation, superscrips are the hospital indeces, and subscripts refer to each particular output. For example, $f_1(x^2)$ is the attribute 1 of hospital 2.

Referring back to figure 6-1, where it was assumed that all hospitals in the set of 7 used the same amount of each input, MOO will label as efficient hospitals 2,4,5,6 and 7, and inefficient 1 and 3. Note that in contrast with DEA, hospital number 5 is now efficient, inspite of the fact that it is in the interior on the polygon. This is a direct consequence of the definition of efficiency (3), which requires that in order to label a hospital inefficient, another hospital discharging more of at least one class and not less of each of the other classes must exist. In this case, neither hospitals 4 or 6 satisfy this condition in relation to hospital 5.

When we have multiple outputs and multiple inputs, one can apply MOO by constructing families of functions $f_i(x), i=1,2, \cdots n$ by expressing each of the n outputs on a per unit basis of each of the inputs.

As with DEA, MOO locates pareto inefficiencies comparing hospitals with the most efficient elements in the set, rather than being based on a mean or central tendency relationship, which reflects a mixture of efficient and inefficient institutions.

6.1.4 Contrasting DEA and MOO

DEA, as described in references [13], [18] and [58], does not deal with discontinuities in cost functions; in practical terms, a hospital could be considered inefficient as compared with another that uses the same resources and produces a somewhat different case mix, even though the cost of changing the case mix to the efficient one is enormous.

DEA can label a facility inefficient not only if it is "dominated" (i.e. another facility provides more of at least one output and not less than any other output with the same inputs or the same outputs with less inputs), by another facility, but also if it is only dominated by a linear combination of facilities (what could be called a

"mixture" of hospitals). In the graphic example above, facility number 5 is considered "inefficient" by DEA although both facilities 4 and 6 have less of at least one output. In many cases however, the transfer of resources from treating patients type 1 to patients type 2 is not linear, and therefore, it may not be correct to label facility 5 as inefficient. On the other hand, a facility such as number 3, can be called inefficient since there are in the system other facilities that "produce" more patients of both classes with the same inputs.

The situation of hospital 5 does not occur in MOO since this technique will only label a hospital inefficient if there is another hospital that discharged more patients of one type and not fewer patients of the other type.

However, MOO as described in section 3 can not deal with multiple inputs. The nature of the algorithm does not allow a multidimensional input space. One could circumvent this problem by defining a set of weights for the inputs, and scaling the outputs by dividing them by the weighted combination of the inputs.

Alternatively, one can run MOO as many times as inputs are being considered, dividing in each round the outputs by a different input. This provides the analyst with a series of classifications. Facilities that are consistently efficient for different inputs are candidates to be classified as efficient. For the numerical example that follows we have used this second strategy. The reason is that it is generally very difficult to obtain an appropriate set of weights.

Both DEA and MOO are very sensitive to data. For example, facility 7 is called efficient because it produced the most of patients type 1. In fact, whenever many outputs and inputs are considered, a facility will be considered efficient if it happens to produce more than any other facility of a given output or use less of some input (in DEA), or have the largest ratio output / input for some output and input (in MOO). A facility with this characteristics will be labeled efficient

regardless of its production and consumption relations in all other inputs and outputs.

6.1.5 Description of the data set used.

The data used come from a non-for-profit chain of 160 hospitals. Of all the departments in the hospital, the analysis was performed using data from the Medical Services as opposed to the whole hospital; surgery, psychiatry and the outpatient clinic where excluded because of the different nature of the services they provide.

Inputs Used: Direct Full Time Equivalents (FTE), Direct Salary Dollars and Other Direct Dollars attributed to the Medical Service were used. The data were extracted from the General Ledger from Fiscal Year 1983. Indirect costs were not used since they are often not under the control of the managers of the clinical services [7]. We decided to use both direct salary dollars and Full Time Equivalents in order to explore the effect of differences in the composition of the staff. The variable FTE is not sensitive to different types of employees (physicians, nurses, technicians, etc.) whereas Direct Salary Dollars are likely to reflect such differences whenever they exist.

Outputs Used: The outputs of each hospital (medical services) were measured as the number of discharges in each Major Diagnostic Category (MDC) as reported in the discharge summaries. The MDC classification is a grouping of the DRGs by organ system and/or group of diseases. Examples of MDCs are Number 2, Disorders of the Eye, and Number 10, Endocrine and Metabolic Disorders. In the hospitals analyzed, the DRG encoding is routinely performed by a single organization within the system. This is important to ensure consistency in the assignment of DRG codes.

Figure 6-2: First Quarter Fiscal Year 83 Patient Distribution

ORIGINAL M.D.C.	NEW MDC	NUMBER OF PATIENTS DISCHARGED	
0	1	2603	****** MDC=0 are unclassifiable patients.
1	2	6429	**********
2	3	612	**
3	3	1869	****
4	4	19768	**********
5	5	25627	**********
6	6	10878	**********
7	7	3507	*******
8	8	3942	********
9	9	2731	******
10	10	5405	**********
11	11	3292	*******
12	12	1239	***
13	12	49	*
14	12	0	
15	12	4	*
16	12	980	**
17	13	3850	********
18	14	884	**
19	15	4258	*********
20	15	5873	**********
21	14	707	**
22	14	25	*
23	1	2581	******

Resulting Patient Distribution by MDC after aggregation.

NEW MDC	PATIENTS	
1	5184	**********
2	6429	**********
3	2481	*****
4	19768	**********
5	25627	**********
6	10878	**********
7	3507	*******
8	3942	********
9	2731	******
10	5405	**********
11	3292	*******
12	2272	*****
13	3850	********
14	1616	****
15	10131	**********

We have reduced the number of MDCs from 24 to 15 by collapsing some MDCs with a small number of discharges. The two histograms in figure 6-2 present the distribution of total discharges (Quarter 1 Fiscal Year 83) in the whole system, and detail the collapses made. The first column in the top histogram is the original Major Diagnostic Category in which the patients were discharged, and the second shows the recoding made. As it can be seen, some MDCs (like numbers 13 to 15 and 22 had less that 50 discharges each out of more than one hundred thousand.)

We have excluded the educational components both from the inputs as well as from the outputs in order to compare the hospitals in a more uniform dimension and prevent the problem from becoming overwhelmingly complex. The educational status of a hospital should be taken into consideration before concluding on its degree of efficiency or inefficiency.

6.1.6 DEA Efficiency Results.

Figure 6-3: Efficiencies as computed by DEA.

```
Efficiency        Number of
                  Hospitals
0.00 - 0.25           2          **
0.25 - 0.35           4          ****
0.35 - 0.45           6          ******
0.45 - 0.55           9          *********
0.55 - 0.65          13          *************
0.65 - 0.75          13          *************
0.75 - 0.85           9          *********
0.85 - 0.95           2          **
0.95 - 0.99           0

Efficient:          102          *****************/  /****** (102)
```

A histogram of the efficiency measures as defined in (1) with constraints (2), is shown in figure 6-3. Note that 102 facilities were classified as efficient and 58 as

inefficient[22]. The details of the results obtained by running DEA with these data are presented in appendix A at the end of this chapter.

It should be stressed that the only conclusion that can be drawn from this exercise is that for each of the 58 hospitals with efficiency less that 1 there is no set of weights u_i and v_i that can make any of them efficient. They are either dominated by a single hospital or by a combination of hospitals called efficient.

The Case Mix Effect. As mentioned earlier, DEA as described in [13], [18] and [58], does not take into consideration fixed costs. One of the highest costs in hospital-based health care is that of changing Case Mix since this usually involves one-time large expenditures like new equipment and construction. In DEA practical terms, a hospital labeled as inefficient could become efficient by treating more patients of a given type (and probably could afford treating fewer patients of some other type); in practice, this will only occur in the unlikely case in which the cost of the switch is negligible.

In order to be able to use some of the results from DEA without having to deal with fixed costs of this nature, we have grouped the hospitals according to their case mix: for each inefficient hospital, the efficient hospital with the closest case mix was identified. The measure of closeness (distance) in case mixes was taken to be the Euclidean distance in the 15-dimensional space of the proportion of patients in each MDC. If an inefficient hospital can be closely paired with an efficient one, it can be said that fixed costs (as they refer to case-mix modifications) are probably not a major issue. Appendix B presents the list of inefficient hospitals paired with their closest efficient hospital.

---

[22]Of the 102 efficient hospitals, 18 are in the efficient class due to the fact that they discharged the most patients in one of the 15 MDCs or used the least of one of the 3 inputs. The rest of the hospitals labeled efficient lie in the boundary of the multidimensional polygon as described earlier.

As an example, let us analyze pair number 4, (hospital code 500 with efficiency 0.49 and hospital code 586 with efficiency 1.00), the case mixes are extremely similar (0.054 is the tenth smallest distance in the whole set of pairs efficient-inefficient), and so are the total inputs. Since the case mixes are virtually identical and the consumption of resources very similar, the inefficiency must come from the output volume. It can be readily observed that hospital 500 discharged one third the number of patients.

With this pairing, hospital 500 can not argue that the observed inefficiency is due to different case mixes, since there is another hospital with the same case mix using considerably less resources per patient.

6.1.7 MOO Results.

As stated earlier, Multiple Objective Optimization does not allow for multiple inputs. In order to compute efficiencies in our real life data set, the program was run three times, each time using as outputs the number of discharges in each Major Diagnosis Category divided by each of the three inputs. The results of the three runs are presented in Appendix A. Note that MOO does not give relative efficiency values like DEA. MOO only provides the list of efficient and inefficient facilities. Figure 6-4 shows a summary of the results. The column labeled "Combined" has as efficient the hospitals that are efficient in all three runs.

When using MOO, one does not have to worry about the effect of case-mix differences between hospitals called efficient and those called inefficient. As described earlier, the term inefficient is used only for hospitals for which there is another hospital that produces more of at least one type of output per unit of input and not less of the other outputs per unit of the same input.

The high correlation between the results in the first two runs is to be expected

Figure 6-4: Summary of Multiple Objective Optimization Results

	Number of Facilities when using			
	Discharges/ Direct FTE	Discharges/ Direct Salary $	Discharges/ Direct Other $	Combined
Efficient Hospitals	61	65	34	29
Inefficient Hospitals	99	95	126	131

since the number of full time equivalents is closely related to direct salary dollars.

We have observed the following fact: Of the 29 efficient hospitals, 7 are in the Eastern part of the country, 20 in the Central section, and 2 in the West coast. These numbers represent respectively 12.9% of the hospitals in the East, 31.3% of those in the Central states, and 2.0% of the hospitals in the West. This result coincides with the informal opinion of several specialists in the system under study that North hospitals in the East and West coasts are less efficient than hospitals in other regions.

6.1.8 Comparison of the DEA and MOO results with traditional measures of efficiency.

Case-Mix Adjusted Productivity: A traditional measure of efficiency is the ratio "production" to direct dollars. Since this measure is an output / input ratio, it is often called productivity, and this is the term that we will use for the remainder of this chapter when referring to that measure. In this case, the production of each hospital is defined via the Medicaid reimbursement dollars for the state of New Jersey, sometimes referred as New Jersey Weights. In other words, the units produced by a hospital are the number of dollars the hospital would have been reimbursed if all patients had been Medicaid patients payable via the DRG

system at New Jersey rates. In this measure high numbers refer to efficient facilities, as it means that few dollars were spent relative to the dollars that would have been reimbursed by Medicaid. The ratios were scaled from 0 to 1.. Case-mix adjusted productivity is a measure of performance widely used in practice. Its main drawback is that it assumes that there exists a set of weights that allow to compare different classes of patients. Errors in the computation of these weights greatly diminish the validity of productivity as a measure of performance. The weights used in this chapter (the Medicaid New Jersey DRG weights) are not necessarily accepted by the whole professional community [59], [63]. We have selected them because they are the most used in the literature.

Figure 6-5 presents the histogram of the productivity ratios for the 160 hospitals in the system.

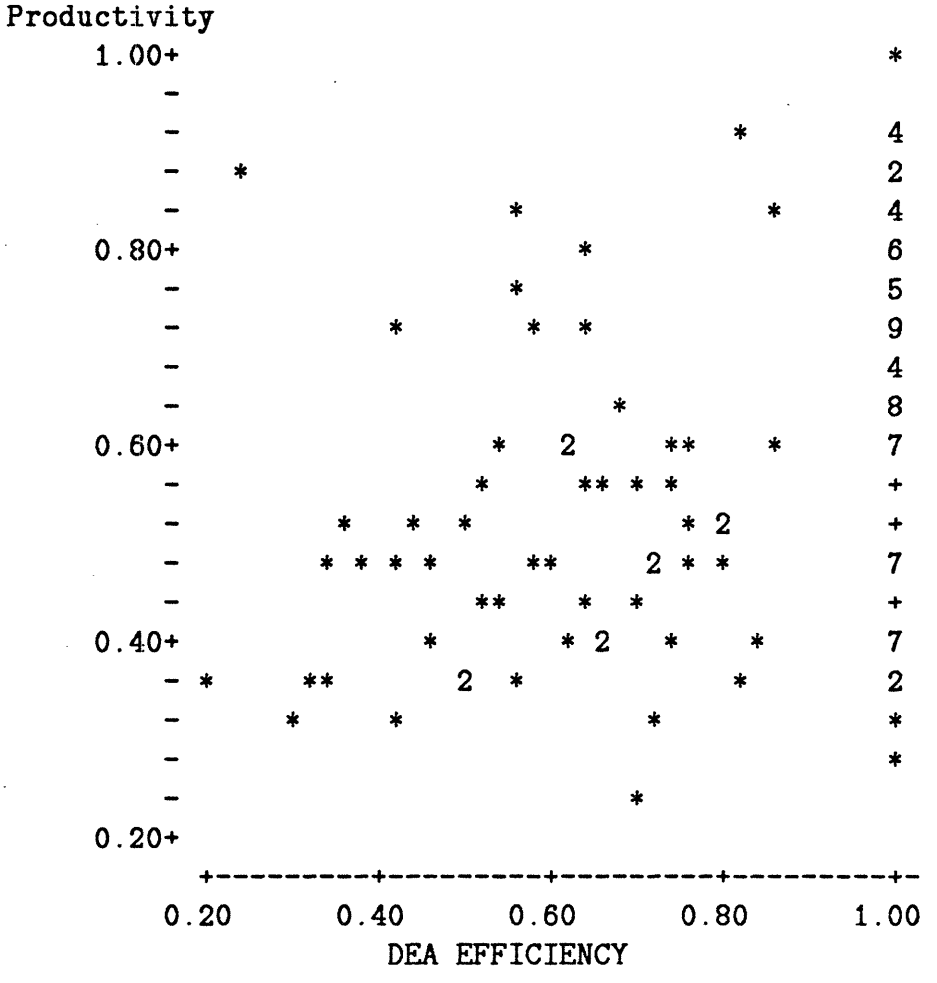
Figure 6-5: Productivity: Histogram of the Productivity scaled from 0.0 to 1.0

```
Productivity  Number of
              Hospitals
    0.2        1    *
    0.3        8    ********
    0.4       30    ******************************
    0.5       43    *******************************************
    0.6       32    ********************************
    0.7       19    *******************
    0.8       14    **************
    0.9       12    ************
    1.0        1    *
```

Figure 6-6 presents the plot of this productivity ratio versus DEA efficiency. One should note that DEA efficiency shows little relationship to this traditional measure of hospital performance.

Figure 6-7 presents the average Productivity measure for the three sets of

Figure 6-6: Production/Direct Cost vs. DEA Efficiency



efficient and inefficient hospitals and in the combined score as computed by MOO. It also shows productivity versus the DEA efficient and inefficient facilities. Note that all four sets of results have statistically significant differences in the averages (the parentheses signal the 95% confidence interval of the estimated mean). This shows that MOO efficiency, at least in this case, is in accordance with this most classical measure of efficiency. Also note that DEA, when used only to select efficient facilities does discriminate well between high and low productivity hospitals. It is when we tried to use the actual value of the inefficiencies that little relationship is found, as described in figure 6-6.

Figure 6-7: Analysis of Variance of Productivity by MOO and DEA Efficiency.

```
                                        INDIVIDUAL 95 PCT CI'S FOR MEAN
Prdctivity/                             BASED ON POOLED STDEV
Dir.FTE        N      MEAN     STDEV   -+---------+---------+---------+--
Non.Eff.      99    0.5510    0.1561    (-------*-------)
Efficient     61    0.6091    0.1627                 (---------*---------)
                                        -+---------+---------+---------+--
 POOLED STDEV = 0.1587                 0.520     0.560     0.600     0.640

                                        INDIVIDUAL 95 PCT CI'S FOR MEAN
Prdctivity/                             BASED ON POOLED STDEV
Sal.D.$        N      MEAN     STDEV   ---+---------+---------+---------+
Non.Eff.      95    0.5431    0.1497    (-------*-------)
Efficient     65    0.6170    0.1671                       (--------*-----)
                                        ---+---------+---------+---------+
 POOLED STDEV = 0.1570                   0.520     0.560     0.600    0.64

                                        INDIVIDUAL 95 PCT CI'S FOR MEAN
Prdctivity/                             BASED ON POOLED STDEV
Oth.D.$        N      MEAN     STDEV   ----+---------+---------+--------
Non.Eff.     126    0.5456    0.1494   (----*---)
Efficient     34    0.6750    0.1622                       (--------*-----)
                                        ----+---------+---------+--------+
 POOLED STDEV = 0.1521                    0.540     0.600     0.660   0.72

                                        INDIVIDUAL 95 PCT CI'S FOR MEAN
                                        BASED ON POOLED STDEV
Combined       N      MEAN     STDEV   ---+---------+---------+---------+
Non.Eff.     131    0.5503    0.1522   (----*---)
Efficient     29    0.6762    0.1600                     (---------*------)
                                        ---+---------+---------+---------+
 POOLED STDEV = 0.1536                   0.540     0.600     0.660    0.72

                                        INDIVIDUAL 95 PCT CI'S FOR MEAN
                                        BASED ON POOLED STDEV
DEA            N      MEAN     STDEV   -----+---------+---------+-------
Non.Eff.      58    0.5168    0.1498   (-------*-------)
Efficient    102    0.6051    0.1585                         (-----*-----)
                                        -----+---------+---------+-------+
 POOLED STDEV = 0.1554                     0.500     0.550     0.600  0.65
```

Comparison of computational results obtained with DEA and MOO: In order to better understand the differences in the efficiency results between the two procedures (DEA and MOO), the average productivity of different sets of hospitals were compared using Student's t-test.

First, the two sets of efficient hospitals were compared (See figure 6-8). The results show that the hypothesis of the average productivity of the two sets being the same would be rejected with a confidence level of 95%. That is, the average productivity of the MOO efficient hospitals is significantly higher than that of the DEA efficient hospitals. Note also that MOO classifies as efficient one third of the number of hospitals classified as efficient by DEA. In other words, MOO chooses as efficient a subset of those hospitals chosen as efficient by DEA that has a statistically significant higher productivity (measured as case-mix adjusted Medicaid dollars divided by direct cost).

Figure 6-8: t-Test of Average Productivity of the Efficient Hospitals

	Count	Mean Product.	Standard Deviat. Product.	Standard Deviation of the Mean
MOO	29	0.676	0.160	0.030
DEA	102	0.605	0.158	0.016

95% Confidence Interval of the difference: (0.003, 0.139)

On the other hand, the two sets of hospitals labeled inefficient by the two algorithms are not statistically different, that is, MOO increases the number of inefficient hospitals without significantly increasing the average productivity of the group. (See figure 6-9, the hypothesis of equal means can not be rejected at the 5% confidence level).

Summarizing, one can say that MOO is more specific than DEA in the sense that its efficient set is smaller than the DEA efficient set, and the statistical

Figure 6-9: t-Test of Average Productivity of the Non-Efficient Hospitals

	Count	Mean Product.	St.Dev Product.	St.Deviation of the Mean
MOO	131	0.550	0.152	0.013
DEA	58	0.517	0.150	0.020

95% Confidence Interval of the difference: (-0.014, 0.081)

comparison of the average productivity of the non-efficient hospitals in both techniques shows no difference at the confidence level of 95%.

The differences between DEA, MOO and productivity do not imply that any of these measures is incorrect or invalid, but certainly should raise caution toward employing any single measure of efficiency without careful consideration of the facts that may influence its result.

6.1.9 Summary and Final Comments

This section has compared two procedures to measure hospital efficiency. They rely on the assumption that efficiency can be measured either as some linear combination of hospital inputs and outputs (DEA), or as the relative position of each facility in the multidimensional space of case-mix discharges (MOO). In both these two methodologies efficiencies are computed without having to specify the a priori weights to combine inputs and outputs respectively. We have applied these methods to a set of 160 hospitals from a non-for-profit chain and we compared the results to the more traditional efficiency measure of case-mix adjusted productivity. In our analysis we have found little relation between DEA measured efficiency and case-mix adjusted productivity. Both DEA and MOO label as efficient sets of hospitals with significantly higher productivity than those they labeled inefficient. MOO was more specific than DEA in the sense that its efficient set was smaller than the DEA efficient set. The average case-mix adjusted productivity of the MOO-

efficient set is significantly higher than the average case-mix adjusted productivity of the DEA-efficient set. The average productivities of both inefficient sets are not statistically different at the 95% level of confidence.

As final comment, it should be said that the mathematical-programming based efficiency measures ignore quality issues, and therefore, one could argue that a facility labeled as inefficient by DEA or MOO can possibly provide much better care than another considered efficient. Also, the reasons for the inefficiencies are not straightforwardly derived from the results of the algorithms, and the analyst should use the results only as a procedure to flag potential problems in the hospital system. Therefore, they should be seen as valuable tools to complement traditional analyses rather that replace them.

6.2 A Model for the Relationship Between Residents and Medical Students and the Production of Health-Care Services.

6.2.1 Introduction

This section describes an attempt to model and quantify the relationships existing between staff, students (residents, medical and non-medical students) and the output of health care institutions. The data used to develop and validate the model come from the hospital chain refered as Y in Chapter 3 (Data Sources).

6.2.2 Description of the model

The philosophy underlying the model is that in teaching hospitals, students will use some staff full time equivalent (FTE) resources in order to be taught, which would otherwise be devoted to patient care. In return, students may provide some patient care service. In other words, the institutional FTE resources used by students are assumed to be non-productive in the sense of generating patient care

(weighted workload units or outpatient visits). On the other hand, the presence of the student in the institution may contribute to the production of some, non-duplicative, patient care services. If a student required as much institutional FTE instructional time as the student equivalently provided in the form of patient care, then the net effect of the student on the institution's productive FTE would be zero. Some kinds of students may have a high demand on staff FTE and a very low productive output, medical students, for example. Others, such as residents, may have a low demand on the institution's FTE and be very productive.

The model does not consider whether a student or staff member is working 40 hours a week or 80. If the pay system registers one full time equivalent then the employee is credited with 40 hours of paid time. An average productive employee who works more than 40 hours (but only gets paid one Full Time Equivalent), will be seen as more productive than his 40 hour a week peers.

For each student type, then, there are at least two numbers which need to be developed. One number is a measure of the patient care services that a student can produce during some fixed period of time like a month[23]. The second number represents the number of teaching hours required from a teacher per student. This latter number could be developed for each kind of teacher, including residents and staff physicians.

The patient care workload output of the institution then can be expressed as the sum of the workload produced by the staff and workload produced by the students.

```
Total Workload = Staff-produced Workload
               + Student-produced Workload.
```

[23]The measure used in this section for patient care production is the same that was used in the efficiency study, namely, New Jersey Weights.

The Staff workload can be estimated by multiplying the available staff time times the staff productivity coefficient (units of output per FTE of staff time). The student workload is the sum of the products of student time and student productivity coefficient. All staff are assumed to be equally productive, and all students of a similar type are assumed to be equally productive.

There are two workload components used in this model, inpatient Weighted Workload Units (WWU) and outpatient visits. The in-patient weighted workload units is the annual weighted sum of all the discharges that the hospital has produced, where the weights are normalized New Jersey non-Physician Direct dollars (for unaffiliated hospitals) that correspond to the discharge DRG of each patient. The workload units include weighting for very long length of stay patients. The outpatient component of production is measured by total number of annual visits.

1. TW = PCS*ps + SFTE*pr

Where:

TW - Total Workload, inpatient and outpatient
PCS - Patient care staff in fte
ps - Staff patient care productivity in wwu's/fte
SFTE - Students in fte
pr - Student productivity in wwu's/fte

Also:

2. PCS = TSFTE - TES

Where:

TSFTE - Total Staff Full Time Equivalents
TES - Teaching staff time in fte
PCS - Patient-care staff time in fte

Also, we assume that the time devoted to teaching by the hospital staff will be proportional to the student body sizes:

3. TES = (SFTE1 * tc1) + (SFTE2 * tc2) + ...

Where:

```
TES - Teaching staff time in fte
SFTEn - Number of type n Students in fte
tcn - Teacher to student ratio (unitless) for student type n
```

Using one type of student, the above simplifies to:

```
4.   TW = ps * [TSFTE - tc * SFTE] + pr * SFTE
        or
        = ps * TSFTE + [pr - ps * tc] * SFTE
```

In the second equation, the quantity inside the parenthesis is the effect of the students on the production of the hospital. It consists of two terms, 1 - the positive (pr) is the student productivity, from which the lost production by the teachers must be subtracted: namely 2 - the student to teacher ratio (tc) times the teachers productivity (ps). If the quantity inside of the parenthesis is close to zero, then the patient care output of the institution can be equated to the staffing load.

6.2.3 The Y data

The Department of Medicine and Surgery of chain Y has various data systems describing the number of students by the level of the student, and the professional FTE and workload output for each institution (for this study, the number of hospitals with reliable data was 158). The department also requires each hospital to identify the amount of professional staff time which is dedicated to the support of educational activities. These data can be combined to estimate the teaching time requirements and the productivity capacity for each class of student. Thus it may be possible to show the effect of medical students upon teaching requirements of residents at various levels of training and the teaching requirements of staff physicians.

The variables and their particular sources used in the analysis that follows are:

<u>Inpatient Workload Production:</u> Measured in Weighted Workload Units

(WWU). This units are computed using data from the Fiscal Year 1983 (FY83) Patient Discharge Abstract file, which summarizes all the discharges in FY83.

Outpatient Workload Production: Measured as Visit Counts.

Staff FTE: Total direct Physician FTE.

Research FTE: This is a self reported figure, each staff physician states at the end of each quarter what percentage of its time was devoted to research. This research time is charged to particular research projects or to a general research account, and therefore, for this study, research FTE were simply subtracted from the total available FTE.

Teaching Staff Time: Measured in FTE, extracted from the self-reported hospitat estimates. Only those reported FTE in Cost Centers directly involved with patient care were used.

Resident FTE: From the position counts provided by the Office of Educational Programs in Y headquarters. This is the office which is responsible for distributing residency positions.

Other Students: From self-reported count from the hospitals. These data are used in the model to estimate teacher to student ratios for medical students, and do not effect the estimates of resident productivity or of the resident to staff ratio.

Affiliation Status: There are several classification strategies that can be used to identify teaching and non-teaching hospitals. Formal medical school affiliation, number of teaching programs and number of residents can all be used and give different results. Preliminary analysis of the several different sources of data describing the affiliation status of the Y hospitals revealed many inconsistencies. Given these inconsistencies, we decided to classify as affiliated all hospitals that according to the Office of Educational Programs had more than five residents. All

other hospitals were considered unaffiliated and their reported counts of teaching FTE, other students etc., forced to be zero. This produces 41 unaffiliated and 117 affiliated institutions.

6.2.4 Results

Staff Productivity:

Staff productivity was estimated by analyzing the data from the unaffiliated hospitals, those which we classified as unaffiliated (non-teaching). Linear regression was used to calculate the estimates. This assumes that the full FTE of the medical staff in unaffiliated institutions is devoted to patient care, either producing WWUs (i.e. inpatient care) or OPC visits (outpatient care.) We ignored the administrative loads on the staff. We argued that the administrative functions of the physician staff will vary in accordance with the intensity of the care provided.

Analytically,

$$TSFTE = a_0 + b_1 * TW + b_2 * OPC$$

TSFTE and TW as described above.
OPC - Total outpatient visit count.
b_1 - Inverse of the staff inpatient WWU productivity

b_2 - Inverse of the staff Outpatient visits productivity

The resulting regression equation is (41 Stations used):

$$Staff.FTE = -3.44 + 0.000061 * TW + 0.000214 * OPC.vis$$

The R^2 was 86.2%, and the analysis of the variance showed that the intercept (-3.44) is statistically non-distinguishable from zero, (t-ratio=-2.0).

This result is equivalent to saying that in the average, a physician annually produces either 16,400 weighted-workload units or 4673 Outpatient Visits, or a linear combination between the two.

Student Productivity.

In order to estimate the productivity of the students, we use the following strategy: First, we computed the total FTE that would be necessary in order to produce the observed WWU in the affiliated hospitals assuming that productivity of staff physicians is constant through the system. In order words, we computed the "theoretical FTE" of the affiliated institutions as if the affiliated hospitals had no students, and all the time of the staff were dedicated to patient care as it is in the unaffiliated hospitals. Second, we subtract from this theoretical FTE the actual patient care FTE of the staff. This difference, must be the "staff equivalent" of the students, that is, the number of staff physicians that would have had to be in the hospital in order to produce what have produced the residents and medical students. This "staff-equivalent" has to be explained by the different counts of students in the system.

Figure 6-10: Staff Equivalent Histogram for Affiliated Institution

```
Middle of Number of
 Interval Observations

     -10   3 ***
       0   6 ******
      10  24 ************************
      20  19 *******************
      30  18 ******************
      40  10 **********
      50  10 **********
      60   4 ****
      70   2 **
      80   3 ***
      90   2 **
```

A histogram of the "staff equivalent" of the students is presented in 6-10. Note that three institutions have negative equivalents, that implies that in those hospitals, the staff alone produces more WWU and OPC visits per FTE than the

average unaffiliated institutions. To evaluate which data set could better explain the "staff equivalent", the following stepwise regression was run:

'Staff.EQU' vs 'Rsfte.aa' 'pd_res' 'woc_res' 'meds34' 'meds12' 'nonmds'

```
Staff.EQU - ''Staff equivalent'' in FTE as defined above.
Rsfte.aa  - Residents FTE.  Data from Educational Office.
pd_res    - Number of paid residents.
woc_res   - Number of non-paid residents.
meds12    - Number of first and second year med students.
meds34    - Number of third and fourth year med students.
nonmds    - Number of non physician students
                (technicians, nurses and social workers)
```

The only explanatory variable that entered the model with any significant explanatory power was Rsfte.aa, the FTE count from the Educational Office. Therefore, the following regression model was fit:

$$\text{Staff.EQU} = a_0 + \text{pres} * \text{Rsfte.aa}$$

pres - FTE equivalent of the residents. Unitless.

The result was:

$$\text{Staff.EQU} = 1.89 + 0.338\ \text{Rsfte.aa}$$

Again, the intercept has no statistical significance (t-ratio = 0.61), and R^2=48%. Note that even that the fit is not very good (we can only explain half of the variance observed in the "Staff equivalents"), the coefficient (.338) estimates that, on the average, for all teaching institutions, it takes three residents in order to produce the same as a staff physician (when production is measured as case-mix adjusted WWU and outpatient visits.)

Student teaching requirement from the faculty.

The amount of time required by the students in order to be taught, was estimated from the student counts and the estimates of the teaching load provided by the institutions in the self-reported part of the general ledger.

Of the various counts of students available, we decided to use the resident count from Corporate Headquarters and the medical and non-medical student counts from the self-reported data. A stepwise regression showed that the medical and non-medical student counts had no relationship with the teaching FTE reported by the hospitals. In consequence, the following model was used:

```
Staff.teaching.FTE = rt * Rsfte.aa

rt - resident teaching requirement from the staff.  Unitless.
```

The result was:

```
teach.fte = -0.54 + 0.253 Rsfte.aa
```

The constant term was not significantly different from zero (t-ratio=-0.89), and R^2=82.0%.

6.2.5 Evaluation of the Model.

In order to have some estimate of the goodness of the prediction of the overall model, we used the observed values of staff FTE, teaching load, residents, OPC visits, etc. to compute the expected hospital production. The relative workload unit differences ([expected - observed]/observed), are displayed in figure 6-11. A positive relative error indicates that a facility is relatively unproductive with regard to the model assumptions. Except for a positive outlier in the Non-Teaching institutions, the Relative errors are unbiased, and reflect a reasonably good fit of the model. Also, errors coming from teaching and non-teaching institutions can not be statistically differentiated.

Another measure of the goodness of the model comes from regressing the predicted versus the observed WWU. The result of such regression is:

Estimated WWU = 50262 + 0.902 Observed WWU

The constant term has t-ratio = 1.51, that is, it can not be statistically

Figure 6-11: Relative Prediction Errors by the Model.

```
Middle of Number of
 Interval Observations

    -0.6  5 *****
    -0.4 12 ************
    -0.2 42 ****************************************
     0.0 48 *****************************************
     0.2 24 ************************
     0.4 13 *************
     0.6  7 ********
     0.8  4 ****
     1.0  1 *
     1.2  0
     1.4  1 *

Mean= 0.018, Stdev=0.338, p for mean not zero = 0.52

                          ------
Teaching            -------I +  I-------- **
                          ------
Non                       -----
Teaching              -----I + I------ *       0
                          -----
         +------+-----------+-----------+------+
        -1.4  -1.0         0.0          1.0   1.4

                    Relative Error
```

differentiated from zero, and R^2=63.3%.

A table with detailed results and data for each hospital is presented in appendix C.

6.2.6 Conclusions.

An additional method for evaluating the model described in the previous section could be done by using data for another year, from the Y chain, or to use the same kind of data from a different set of hospitals, (like a for profit chain, etc.)

Further, it could be possible to design a set of engineering studies which would sample productivity and teaching time from Y hospitals. These data could be used to validate the coefficients calculated here. Without testing the model with different data or with different estimating techniques, we have to limit our conclusions to the Y case, and further yet, to the Fiscal Year 1983.

The results of this study can be summarized as follows:

Staff productivity: One Full Time Equivalent of staff physician produces (in the average, in the non-affiliated Y hospitals for FY83) either 16,400 Case-Mix Adjusted Weighted Workload Units or 4673 Outpatient Visits, or a linear combination between the two.

Resident productivity: Assuming that staff physicians of affiliated and non-affiliated hospitals have the same patient care productivity during the time they do not devote to research or teaching, one Full Time Equivalent of Resident, as counted by the Office of Educational Programs, has one third of the productivity of a Full Time Equivalent of a Staff Physician.

Teaching load: The teaching load that the residents impose on the teaching staff is 0.25 staff FTE for resident FTE. In other words, for each four residents in a Y hospital, there is a loss of one staff FTE from pure production. The medical students have no statistical relationship with the teaching load. This may be due to the fact that staff do medical student teaching during rounds, when they also teach residents, and the real one-to-one teaching of medical students is generally done by residents and interns themselves. The teaching load of the non-medical students (nurses, social workers, etc.) on the staff is also non-statistically significant.

Concluding, we can say that in the teaching hospitals, the net productivity of a resident is 1/12 of that of a staff physician. This comes from subtracting 1/4

from a teacher's production but producing 1/3, net production of 1/12 per FTEE. Note that if the hospital where paying residents 1/12 the salary of the staff members, it would have (as it regards to salary) a teaching program at no cost in terms of personnel. Issues regarding costs incurred in other areas (such as length of stay and ancillary use) are nod addressed here.

6.3 Budgeting the Hospital Chain Y. Numerical Example

Chapter 5 applied the Minimum-Risk and Equal-Probability algorithms to the different clinical services of hospital X. Now, the scope will be moved to multi-institutional budgeting, and in this section, the budgeting units will be the 160 hospitals of chain Y.

The first step in the allocation process is to compute the Probability Distribution Function of the total Direct Patient-Care dollars spent during the previous budgeting period by each hospital. As detailed in chapter 4, chain Y does not keep patient-specific cost data, and therefore it is not possible to compute total cost PDFs in the same manner that was done in hospital X: via the costing of all tests and procedures that each patient had. To circumvent this problem, we used as the cost of each admission the same proxy introduced in section 4.3: the case-mix adjusted length of stay[24].

With the cost of each patient on hand, the expected value and the variance of the cost of an admission in each of the 470 DRGs can be estimated. Assuming that the case mix seen by each hospital will not change, we are able to estimate (1) the expected total cost for each hospital, and (2) its variance.

---

[24]Recall that the case mix adjusted length of stay relies on the assumption that for each DRG the cost of a particular admission is proportional to the length of stay.

For each hospital, the expected total cost is the sum of the total costs of treating the patients in each DRG. If the hospital had grounds to expect changes in its case mix, the expected value of the total cost would not be the same as in the previous budgeting period; instead, the correct expected total cost would be computed using the average cost in each DRG and the forecasted case mix. The variance of the total cost of each hospital is the sum of the variances within each DRG weighted by the expected case mix.

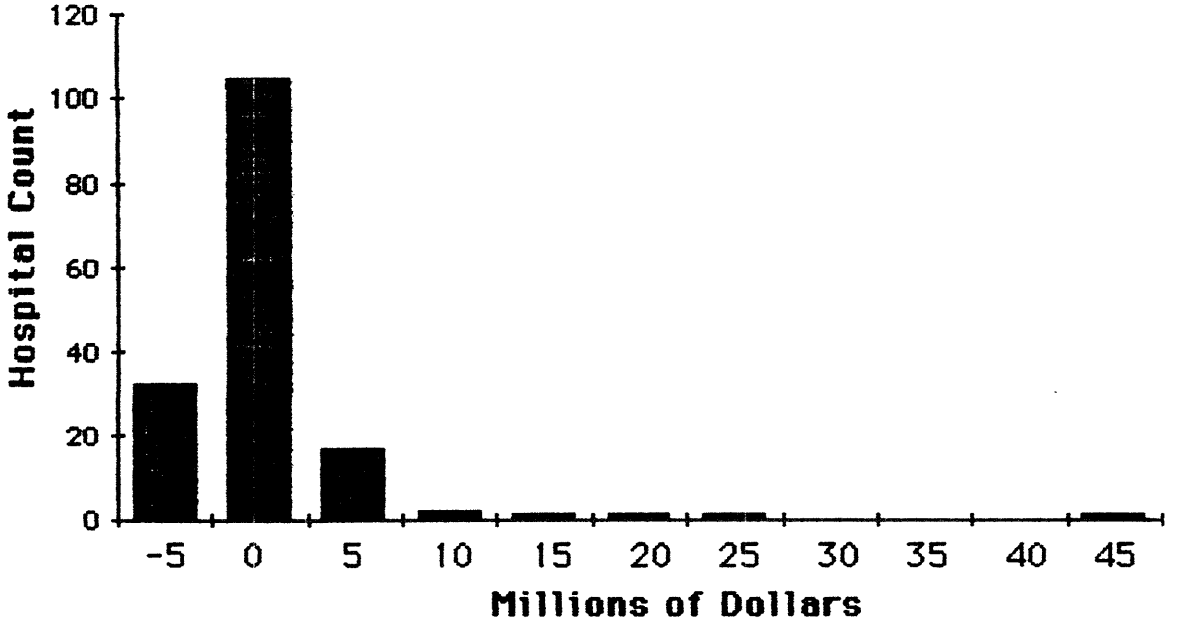
For each of the 160 hospitals, the average and the standard deviation define the PDFs of the total cost, and therefore their budgets can be computed using the two algorithms described in chapter 4. The detailed results of the two allocation runs (under the assumption of a 10% increase on the expected total budget) are presented in Appendix D.

A summary of the budget changes that occur when switching from a fixed percentage increase of 10% to the two variance-based algorithms is presented by the histograms in figures 6-12 and 6-13.

Figure 6-12 presents a histogram of the changes in total budget that are observed when moving from Proportional Allocation to the Minimum Risk strategy. The height of each bar is the number of hospitals that would have the budget change indicated in the X axis. Negative numbers imply that the proportionally allocated budget is larger than the minimum risk budget. The percentage of increase *over the previous year budget* that the total Minimum Risk methodology allocates to each hospital is presented in the bottom histogram of figure 6-12. Note that the same histogram for the Fixed Percentage method would show all hospitals at the 0.1 mark.

As seen in the numerical example of chapter 5, the allocated resources vary considerably for some budgeting units; budgeting units with large variance get

Figure 6-12: Budget Changes from 10% Proportional Increase to Minimum Total Risk



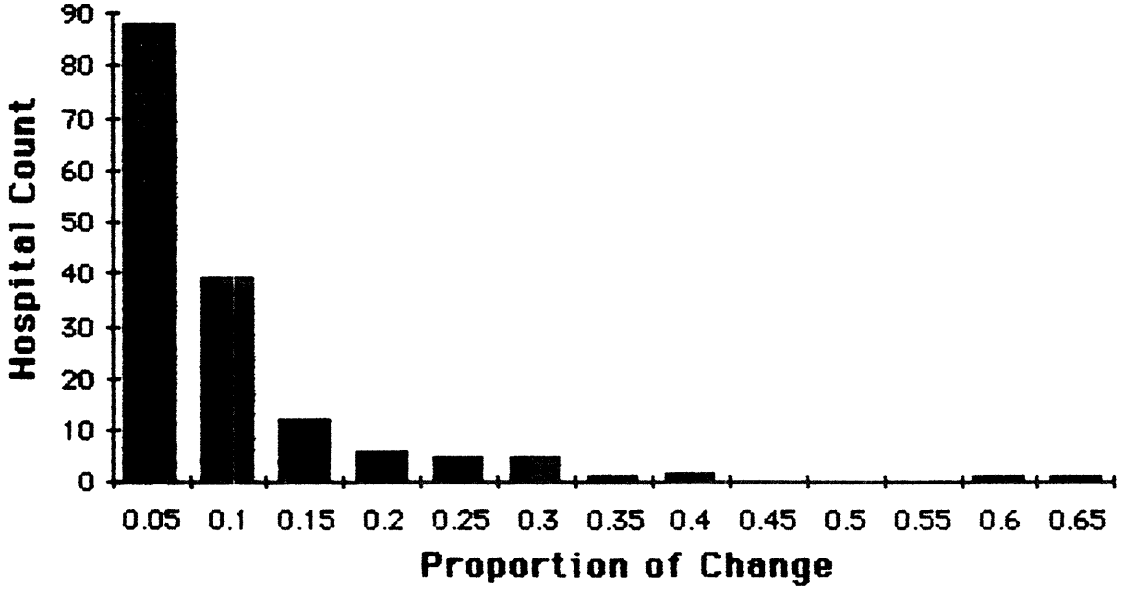
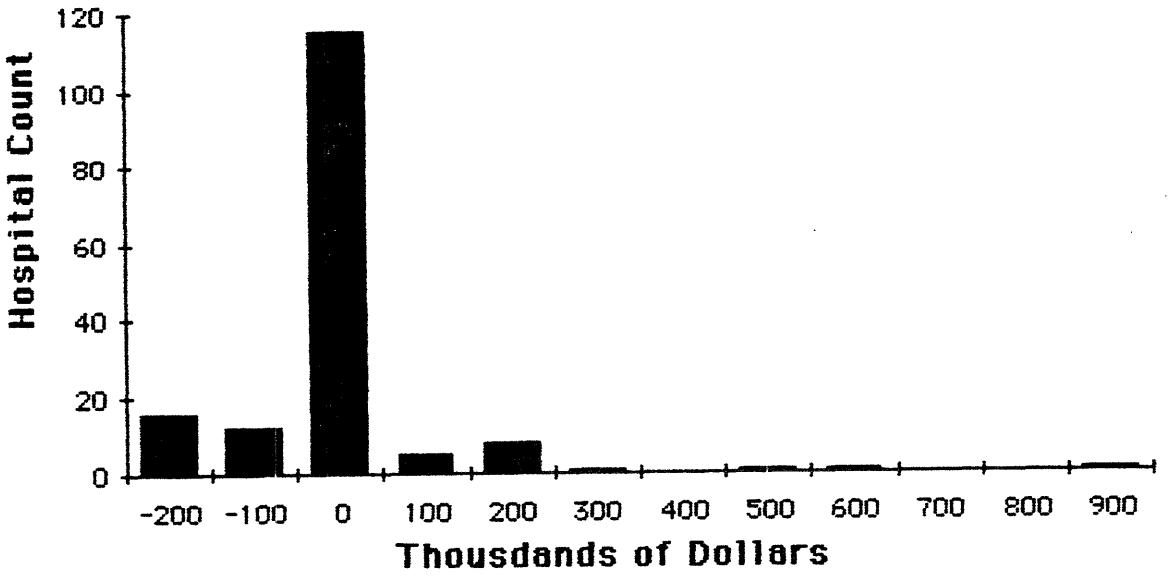


Figure 6-13: Budget Changes from Minimum Total Risk to Equal Probability



larger amounts of money to offset their inherent risk. Again, if the total budget had to be reduced, institutions with large variance would have their budget reduced the most.

Using the methodology of Equal Probability rather than the methodology of Minimum Risk produces similar allocated budgets. The differences, in thousands of dollars, are presented in figure 6-13. These differences in budget between the two strategies, even though they are smaller than between these variance-based strategies and Proportional Allocation, can be as high as $0.9 million.

The hospitals that get more resources with the Equal Probability methodology are those that have high variance but small expected budgets (high coefficients of variation with small total budget). The explanation is that their high variance implies that they will need extra dollars with high probability, but their small volume does not make them big contributors to the total risk.

6.3.1 Using Efficiency Measures.

As described in the theoretical development of chapter 3, one can use the variance-based allocation methodologies in combination with efficiency measures of the budgeting units. In order to do this, one is bound to use the DEA methodology described in the previous sections, as it is necessary to have a quantitative measure of the relative efficiency of all facilities, a measure that is not given by the MOO technique.

Since MOO performed better as a methodology in our example, the following two-step strategy is proposed to incorporate MOO efficiency into the allocation process:

1. Allocate only a percentage of the available funds. The remaining resources will be used for rewarding efficient facilities. Corporate managers have to decide what an appropriate "tax" would be, maybe 5

to 10%.

2. Allocate this leftover money to the efficient facilities.

This procedure has two very important properties: (1) It removes more dollars from facilities with high variance, and (2) It rewards efficient hospitals. Because of these features, this allocation methodology will introduce incentives toward (1) having a narrow distribution of expected costs and therefore striving toward a standardization of care, and (2) becoming MOO efficient.

The last two columns of the table in Appendix D and figure 6-14 show the results of using the Minimum Risk algorithm to allocate a 5% increase in total budget to all facilities (analogously to the allocation described in the previous paragraphs) and another 5% to the MOO efficient facilities only. The total dollars allocated are the same as those in figure 6-12.

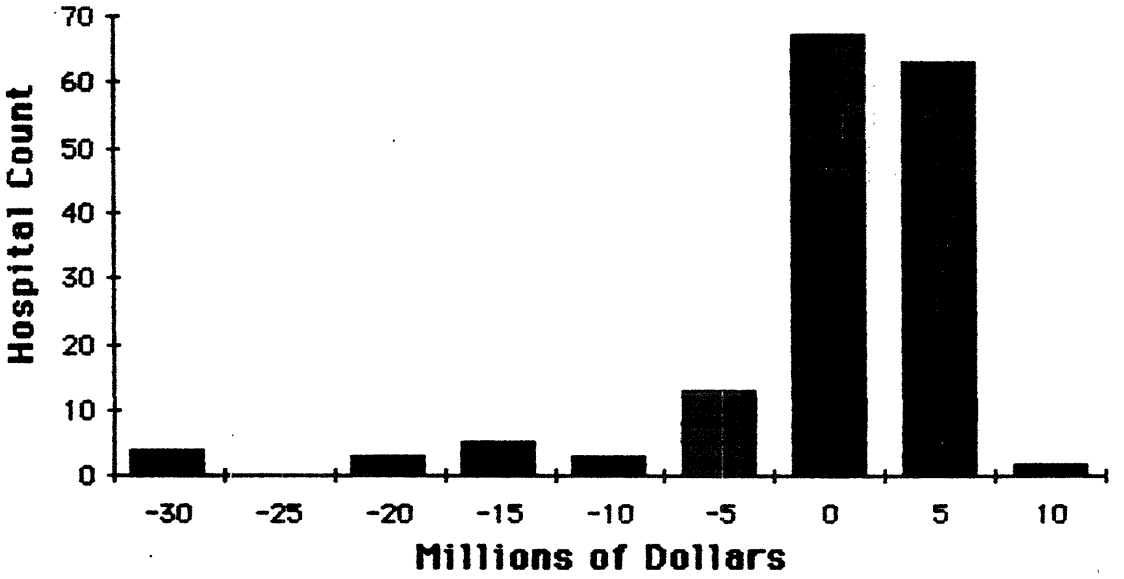
In the first histogram of figure 6-14, each bar is the count of hospitals the had the shift of dollars from a proportional allocation to the efficiency-adjusted allocation expressed by the corresponding X value. Comparing this histogram with that of figure 6-12, one sees that the efficiency-adjusted allocation does penalize more facilities (by budgeting them less resources than the proportional allocation) than the non-adjusted methodology. This effect comes from the fact that only half the initial amount of dollars is available to be allocated to every facility, and that only efficient facilities benefit from the other half.

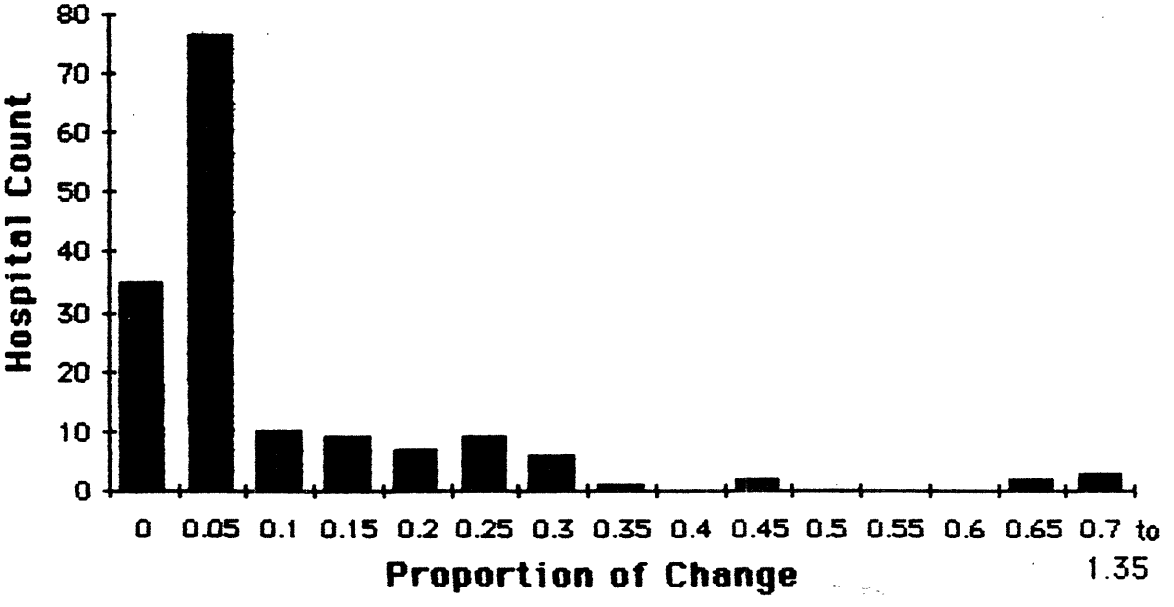
6.3.2 Conclusion

To conclude the discussion on variance-based resource allocation methodologies for systems of hospitals, the following points should be highlighted:

- Variance-based resource allocation produces budgets that are different from those arrived at by proportionally deviating from the expected values. These differences may be large for sets of hospitals with widely

Figure 6-14: Budget Changes from 10% Proportional Increase to MOO Efficiency-Adjusted Minimum Total Risk





different coefficients of variation.

- The inherent randomness of the patient-care process must be taken into account when deviating from the expected value of expenses, especially in the absence of control over volume or if volume changes are undesirable.

- Reducing budgets without taking into account the variance of resource usage puts institutions with small coefficients of variation in a situation of very high risk.

- The variability of resource usage on which to base resource allocation should be the variance unexplained by a patient-classification technique, and not a reflection of the inability to classify patients into homogeneous classes[25].

---

[25]The DRG system alone may not be sufficient to pass judgment on the inherent variability of resource usage in the patient-care process; chapter 4 of this thesis shows that the Severity of Illness Index and Disease Staging reduce by more than 80% the variance unexplained by DRGs in a teaching hospital. In the numerical example of this section we have used DRGs alone because neither of the two subclassifications were available for all 160 hospitals. If a variance-based methodology had to be implemented for routine resource allocation, it would be necessary to use one of the subclassifications in order to differentiate different levels of patient severity.

Chapter 7

Summary and Topics for Future Research

7.1 Summary

This research has dealt with the issue of resource allocation in health care institutions. The thesis revolves around the randomness of the resources needed for the health-care delivery process and how knowledge about such randomness can be used to allocate resources fairly and to introduce incentives for cost containment.

The most important sources of this randomness are (1) case-mix variations from one year to the next and (2) the inherent variability of the resources needed to treat seemingly similar patients. This randomness differentiates resource allocation in the health care industry from many other industries.

This inherent variability in resource usage must be differentiated from another source of variability in resource usage: patients that are considered as belonging to the same category may in fact be different. In order to discriminate between these sources of randomness, one has to be able to discriminate between different classes of patients. Part of this research was devoted to analyzing various methodologies for patient classification. The Severity of Illness Index (SII) and Disease Staging (DS) were compared for their ability to reduce the observed variance in resource usage.

The evaluation was carried out using cost (rather than charges) data from a large teaching hospital. The results indicate that both methodologies effectively reduce the variance of the observed resource usage within DRGs. SII is somewhat better as variance reducer but has the drawback of being a more subjective measure, which cannot be automatically assigned to patients from the Uniform

Discharge Summaries by a computer program.

The analysis also concluded that around 20 properly chosen DRGs subdivided by either SII or DS were enough to obtain more than 85% of the possible Reduction in Variance that can be attained using all 470 DRGs.

This thesis advocates using clinical services as budgeting units, i.e., resources are allocated by management to Clinical Services (for example Surgery), which "purchase" services from the Support Services (for example Radiology.)

This approach is in accordance with a framework that views hospital activity as a two-stage production process. In the first stage, resources are converted into "intermediate products," the individual procedures and services provided in the patient-care areas, such as laboratory tests and nursing-care hours. In the second stage, the intermediate products are grouped in the clinical services and under the supervision of physicians to form "cases." Cases are the "finished products" by which the hospital is reimbursed under the prospective DRG-based reimbursement system.

The generic model for resource allocation that this thesis proposed is based on the maximization of the utility function of the decision maker. When the utility function takes very simple and intuitive forms, the resource allocation problem is transformed into a Minimum Risk and a Mini-Max problem. These mathematical problems can be solved with existing optimization algorithms.

The proposed resource allocation methodologies are used to compute the budgets for (1) the different Clinical Services of the Division of Medicine of a teaching hospital and (2) 160 hospitals of a chain. The results in both cases highlight the fact that budgets do change considerably when variance-based criteria are used.

This research shows that when managers must deviate from the expected

value of the expenses, as is the case when reducing budgets, they should take into account the inherent variability of the health-care process. In the absence of control over volume, budgeting units with narrow distributions of expected costs are much more vulnerable to budget cutting than units with high variance, as the latter still have a fairly reasonable probability of not needing the resources that were removed.

As accessories to resource allocation at the multi-institutional level, two different measures of hospital efficiency were described and evaluated in this thesis: Data Envelopment Analysis (DEA) and Multiple Objective Optimization (MOO). Also, a quantitative approach for the evaluation of the relationships between personnel and productivity in teaching hospitals was developed and applied to data from a chain of 160 hospitals.

The efficiency study showed that there is little relation between DEA measured efficiency and case-mix adjusted productivity. Both DEA and MOO label as efficient a set of hospitals with significantly higher productivity that those labeled inefficient. Comparing the productivity of the hospitals called efficient by DEA with the productivity of the hospitals called efficient by MOO, it was observed that MOO was more specific than DEA in the sense that its efficient set was smaller than the DEA set, and the average case-mix adjusted productivity of the MOO-efficient set was significantly higher than that of the DEA-efficient set, while the average productivity of both inefficient sets were not statistically different.

This thesis also examines the relationship between teaching loads and productivity. The model developed reveals that (under the assumptions detailed in chapter 6) the case-mix adjusted productivity of a resident is, on the average, one third of that of a staff physician. Also, since teachers have one fourth less productivity for each full-time resident present in the hospital, the net productivity of a resident is 1/3 minus 1/4, which is 1/12. Even though this model is imperfect

and only explains about 60% of the variance in productivity that is observed between teaching and non-teaching hospitals, it highlights the fact that quantitative approaches to physician staffing problems are indeed feasible.

7.1.1 Budgeting for Research and Capital Expenditures

Because the focus of this thesis has been on patient-care operational budgets rather than on global budgets for the whole institution, the topic of research budgeting has not been studied with the depth it deserves, and a few comments are appropriate here.

Currently, research involving patients is funded from two sources: drugs and data analysis are paid by research grants, and patient-care costs are paid by the patient or the insurer. These "extra" costs are not small; Yarbro and Mortenson [67] state that in a hospital in New Jersey, under the DRG system, 21 patients in clinical trials represented loses to the hospital of an average of $1,057 per admission, while patients in the same DRG not on the trial carried an average loss of $35 per admission. Not surprisingly, [67] advocated for the creation by Medicare of DRG 471 "NIH-approved clinical trials."

Research performed in hospitals should be funded from sources other than patient-care monies. Even if ultimately the hospital increases its charges to non-prospective payers willing to pay full bills, internal accounting and budgeting should reflect which expenditures are for patient-care purposes and which are for research purposes.

If a clinical department is running an experiment evaluating the effect of some new therapy and has to order tests that would otherwise not be required for routine care of the same patients, the costs of performing such tests should be charged to the research project. Medicare, as other insurance carriers, is not intended to

support clinical research as part of its current mandate [47]. The statutory restrictions of Medicare force the program to pay for the "efficient provision of needed health services to beneficiaries," it covers "established and accepted procedures," of which clinical research is not[26].

Capital-Expenditure budgeting and the budgeting of new programs have not been addressed in this research. For these one-time expenditures, a zero-based budgeting mechanism is appropriate. Such methodology requires that the units needing the resources present to the upper management a plan for implementing the new program and proof of its cost effectiveness in the long run.

7.2 Topics for Future Research

Case-Mix Forecasting: Part of this thesis has dealt with the problem of reducing the observed variance of the resources used by the patient population. This has been done by defining classes of patients as uniformly as possible.

For budgeting purposes, we have to be concerned not only with having defined uniform classes of patients but also with being able to predict how many patients the hospital is going to see in each of the possible classes. In other words, a second component of the variance of the expected total cost of operation is how well the case mix can be forecasted.

Dividing the patient population in a very large number of classes would greatly reduce the variance, since it would be possible to put in the same class only those patients that had very close characteristics. Even though it would ensure a

---

[26]Even with this prohibition of funding clinical research, we can add as an anecdote that Medicaid paid all but costs of 5 days of care of the 114 days (a $254,068 bill) for Barney Clark's artificial heart insertion in 1982 [21]. Now, under the DRG system, there is no automatic reimbursement for heart transplantation, be it human or artificial.

high RIV for the *observed* costs, this would do little to help with the prediction error of the *expected* total costs, as the forecasting problem increases in difficulty as the number of classes increases.

Future research has to analyze the stability of workload forecasting, both as a function of volume and as a function of case mix, and the effect of forecasting errors on the allocation process.

Medical School Affiliation: This thesis has presented a simple model for the study of the effect of residents and medical students on medical staff requirements. The data, even though not fully reliable, shows that such approaches are feasible and produce results consistent with the perceptions of clinicians and hospital administrators.

Future research should expand the model introduced here to include objective measurements of teaching time by staff physicians, and differentiation between specialty and general-medicine residents, as well as different degrees of medical school affiliation.

Appendix A
Efficiencies Using DEA and MOO

Column Definitions

DEA Effic.: Efficiency Computed using Data Envelopment Analysis.

MOO Effic. FTE : Efficiency According to Mult. Objective Optimization, Measure is Discharges/Full Time Equivalents.

MOO Effic. S.$: Efficiency According to Mult. Objective Optimization, Measure is Discharges/Direct Salary Costs.

MOO Effic. O.$: Efficiency According to Mult. Objective Optimization, Measure is Discharges/Other Direct Costs.

MOO Effic. Comb: Efficiency According to Mult. Objective Optimization, Efficient only if efficient in three previous tests.

Productivity : Medicaid Reimbursement Dollars/Total Direct Costs, scaled from 0 to 1.

Hospital Code	DEA Effic.	MOO Effic. (FTE)	MOO Effic. (S.$)	MOO Effic. (O.$)	MOO Effic. (Comb)	Productivity
402	0.615	0	0	0	0	0.58428
405	0.382	0	0	0	0	0.47643
436	0.647	0	0	0	0	0.78979
437	1.000	1	1	0	0	0.57057
438	1.000	0	1	0	0	0.57197
442	1.000	1	1	0	0	0.81916
452	1.000	1	1	1	1	0.53546
455	1.000	0	0	0	0	0.51237
460	1.000	0	0	0	0	0.56724
500	0.491	0	0	0	0	0.52718
501	0.533	0	0	0	0	0.42407
502	1.000	1	1	1	1	0.79418
503	1.000	1	1	1	1	0.71040

504	1.000	1	1	1	1	0.58156
505	0.616	0	0	1	0	0.39042
506	1.000	0	0	0	0	0.28223
508	0.798	0	0	0	0	0.47200
509	1.000	0	0	0	0	0.43918
512	1.000	0	0	0	0	0.45641
513	1.000	0	0	0	0	0.87011
514	0.819	1	1	1	1	0.90086
515	1.000	1	1	1	1	0.53422
516	0.798	1	1	1	1	0.52712
517	1.000	1	1	0	0	0.73993
518	0.298	0	0	0	0	0.32363
519	1.000	1	1	1	1	0.59582
520	1.000	1	1	0	0	0.77925
521	1.000	0	0	0	0	0.45257
522	1.000	1	1	1	1	0.85298
523	0.671	1	1	0	0	0.63232
525	0.559	0	0	0	0	0.84249
526	0.328	0	0	0	0	0.37379
527	1.000	0	0	0	0	0.49868
528	0.532	0	0	0	0	0.58669
529	1.000	0	0	0	0	0.72016
531	1.000	1	1	0	0	0.41620
532	1.000	0	0	0	0	0.60103
533	1.000	0	0	0	0	0.74774
534	1.000	0	0	0	0	0.40479
535	1.000	0	0	0	0	0.53309
537	1.000	0	0	0	0	0.53781
538	1.000	0	0	0	0	0.69025
539	0.734	1	1	0	0	0.40210
540	1.000	1	1	1	1	0.80530
541	0.346	0	0	0	0	0.34259
542	1.000	0	0	0	0	0.44320
543	0.809	1	1	0	0	0.52458
544	0.854	1	1	0	0	0.59604
546	1.000	1	1	1	1	0.42943
549	0.750	1	0	0	0	0.49726
550	1.000	0	0	1	0	0.63007
552	1.000	0	0	0	0	0.62279
553	0.609	0	0	0	0	0.46502
554	0.820	0	0	0	0	0.34853
555	1.000	1	1	0	0	0.48565
556	1.000	0	0	0	0	0.44501

557	1.000	1	1	0	0	0.69999
558	1.000	1	1	0	0	0.41664
561	1.000	0	0	0	0	0.49646
562	0.577	0	0	0	0	0.70585
564	1.000	1	1	1	1	0.77230
565	1.000	1	1	0	0	0.91073
566	1.000	0	0	0	0	0.79404
567	0.231	0	0	0	0	0.86357
568	1.000	0	0	0	0	0.51534
569	1.000	1	1	1	1	0.79625
570	0.560	0	0	0	0	0.37133
573	1.000	1	1	0	0	0.42336
574	1.000	0	0	1	0	0.76840
575	1.000	1	1	1	1	0.62821
578	1.000	0	0	0	0	0.59715
579	1.000	1	1	1	1	0.65441
580	1.000	0	0	0	0	0.62900
581	1.000	0	0	0	0	0.63177
583	0.637	0	0	0	0	0.44819
584	0.497	0	0	0	0	0.35044
585	1.000	1	1	1	1	0.65735
586	1.000	1	1	0	0	0.54727
589	0.456	0	0	0	0	0.38418
590	1.000	0	0	0	0	0.38457
591	1.000	0	1	1	0	0.91599
592	1.000	0	0	0	0	0.72990
594	1.000	1	1	1	1	1.00000
595	0.632	0	0	0	0	0.71053
596	0.699	1	1	0	0	0.43375
597	0.628	0	0	0	0	0.60846
598	0.411	0	0	0	0	0.47143
599	0.334	0	0	0	0	0.49345
600	0.467	0	0	0	0	0.47531
603	0.715	1	1	0	0	0.49555
604	1.000	0	0	0	0	0.55977
605	1.000	0	0	0	0	0.61597
607	1.000	1	1	0	0	0.43208
608	1.000	1	1	1	1	0.70210
609	1.000	1	1	0	0	0.70578
610	0.422	0	0	0	0	0.71925
611	1.000	0	0	0	0	0.87643
612	1.000	0	0	0	0	0.46066
613	1.000	0	1	0	0	0.91139

614	1.000	1	1	1	1	0.85588
617	1.000	1	1	1	1	0.78722
618	1.000	1	1	0	0	0.53512
619	1.000	0	0	0	0	0.69858
620	1.000	0	0	0	0	0.85813
621	0.694	1	1	0	0	0.55334
622	1.000	0	0	0	0	0.30850
623	1.000	0	0	0	0	0.52661
626	1.000	1	1	0	0	0.55104
627	0.837	1	1	0	0	0.41943
629	1.000	0	0	0	0	0.45974
630	0.510	0	0	0	0	0.54847
631	1.000	0	0	0	0	0.66086
632	0.719	1	1	0	0	0.33922
635	1.000	0	0	0	0	0.44039
636	0.756	0	0	0	0	0.53830
637	1.000	0	0	0	0	0.82445
640	1.000	1	1	0	0	0.37321
641	1.000	0	0	0	0	0.51942
642	1.000	0	0	0	0	0.45929
644	1.000	1	1	0	0	0.55944
645	1.000	0	0	0	0	0.70024
646	1.000	0	0	0	0	0.54321
647	1.000	1	1	1	1	0.91498
648	0.588	1	0	0	0	0.48119
649	1.000	0	0	0	0	0.57999
650	0.723	1	1	1	1	0.47012
652	0.196	0	0	0	0	0.37923
653	1.000	0	0	1	0	0.63510
654	1.000	1	1	0	0	0.36783
655	1.000	1	1	1	1	0.73158
656	0.741	0	1	0	0	0.55112
657	0.359	0	0	0	0	0.50301
658	0.502	0	0	0	0	0.34731
659	0.851	1	1	1	1	0.85534
660	1.000	0	0	0	0	0.39520
662	0.709	0	0	0	0	0.24181
663	0.660	0	1	0	0	0.41102
664	1.000	0	0	0	0	0.43738
665	1.000	0	0	0	0	0.39188
666	1.000	1	1	1	1	0.47252
667	0.748	0	0	0	0	0.60836
668	1.000	1	1	0	0	0.71699

670	1.000	1	1	0	0	0.50964
671	1.000	1	1	1	1	0.52136
673	1.000	1	1	1	1	0.47974
674	0.754	1	1	0	0	0.60788
676	1.000	0	0	0	0	0.56245
677	1.000	0	0	0	0	0.59871
678	1.000	0	0	0	0	0.40194
679	0.433	0	0	0	0	0.53873
680	1.000	0	0	0	0	0.77711
685	1.000	0	0	0	0	0.59381
686	0.631	1	1	1	1	0.54632
687	1.000	0	1	0	0	0.56810
688	0.655	0	0	0	0	0.55614
689	1.000	1	1	1	1	0.49745
690	0.657	0	0	0	0	0.40100
691	0.419	0	0	0	0	0.30860
693	0.567	0	0	0	0	0.75663
695	0.526	0	0	0	0	0.45400

Appendix B
Pairs Efficient-Non Efficient

Column Definitions

Ind: Hospital Identification Code.
Eff.: DEA efficiency.
Dist.: Case-Mix Distance to closest efficient hospital.
Case Mix: Proportion of patients in each Major Diagnosis Category.
No.Pat.: Total number of patients discharged in Medical Service.
No.FTE: Total number of direct patient-care Full Time Equivalents.
D.Sal.D: Total direct patient-care salary dollars.
D.Oth.D: Total direct patient-care non-salary dollars.

Ind	Eff.	Dist.	Case Mix															No.Pat.	No.FTE	D.Sal.D.	D.Oth.D
402	0.615	0.067	0.07	0.09	0.03	0.18	0.13	0.12	0.04	0.05	0.03	0.06	0.03	0.01	0.01	0.01	0.08	476	140.4	4.0	1.3
537	1.000	0.000	0.05	0.07	0.03	0.17	0.21	0.14	0.04	0.02	0.01	0.08	0.03	0.03	0.03	0.01	0.08	913	322.3	9.5	2.3
405	0.382	0.078	0.05	0.08	0.05	0.17	0.15	0.17	0.03	0.03	0.02	0.05	0.01	0.03	0.04	0.02	0.09	210	122.2	3.3	1.5
537	1.000	0.000	0.05	0.07	0.03	0.17	0.21	0.14	0.04	0.02	0.01	0.08	0.03	0.03	0.03	0.01	0.08	913	322.3	9.5	2.3
436	0.647	0.049	0.05	0.06	0.02	0.14	0.15	0.10	0.02	0.05	0.02	0.03	0.01	0.01	0.01	0.00	0.33	386	106.1	3.0	0.7
442	1.000	0.000	0.04	0.07	0.02	0.14	0.15	0.09	0.02	0.08	0.01	0.04	0.01	0.01	0.01	0.00	0.29	541	83.8	2.3	0.5
500	0.491	0.054	0.05	0.02	0.02	0.23	0.29	0.13	0.05	0.04	0.02	0.03	0.03	0.01	0.03	0.02	0.04	600	278.2	7.4	2.0
586	1.000	0.000	0.04	0.04	0.02	0.24	0.27	0.11	0.03	0.03	0.02	0.06	0.04	0.03	0.03	0.02	0.03	1501	269.1	7.0	2.4
501	0.533	0.068	0.05	0.06	0.02	0.16	0.29	0.11	0.05	0.03	0.02	0.04	0.03	0.02	0.03	0.02	0.07	544	235.8	6.6	1.6
578	1.000	0.000	0.03	0.02	0.04	0.18	0.30	0.12	0.05	0.04	0.02	0.06	0.04	0.02	0.02	0.02	0.04	740	714.6	20.6	2.9
505	0.616	0.090	0.03	0.08	0.06	0.25	0.14	0.10	0.05	0.04	0.04	0.02	0.03	0.01	0.04	0.01	0.10	336	149.6	3.9	0.7
533	1.000	0.000	0.02	0.07	0.09	0.22	0.21	0.09	0.03	0.03	0.04	0.05	0.03	0.01	0.03	0.01	0.08	352	140.9	3.5	0.7
508	0.798	0.052	0.05	0.06	0.01	0.18	0.33	0.09	0.03	0.03	0.04	0.04	0.03	0.03	0.02	0.01	0.04	1010	268.2	7.4	2.6
614	1.000	0.000	0.03	0.06	0.01	0.20	0.32	0.08	0.04	0.04	0.02	0.06	0.03	0.02	0.03	0.02	0.04	1550	339.3	8.4	0.8
514	0.819	0.069	0.04	0.05	0.04	0.17	0.17	0.04	0.02	0.06	0.03	0.04	0.03	0.01	0.01	0.00	0.30	454	123.3	3.3	0.4
557	1.000	0.000	0.02	0.07	0.02	0.16	0.21	0.04	0.02	0.03	0.01	0.05	0.02	0.01	0.00	0.01	0.33	800	156.2	4.5	0.9

---

516 0.798 0.047 0.11 0.09 0.02 0.17 0.18 0.10 0.03 0.03 0.03 0.04 0.03 0.02 0.04 0.01 0.10 1889 388.2 10.5 2.8

452 1.000 0.000 0.13 0.09 0.02 0.16 0.18 0.10 0.02 0.04 0.01 0.04 0.02 0.02 0.01 0.03 0.12 546 105.2 2.9 0.9

---

518 0.298 0.060 0.05 0.07 0.02 0.17 0.23 0.09 0.01 0.05 0.05 0.06 0.01 0.02 0.01 0.01 0.17 173 112.0 3.2 0.7

538 1.000 0.000 0.01 0.08 0.02 0.19 0.23 0.09 0.01 0.07 0.02 0.06 0.03 0.01 0.01 0.01 0.16 576 188.5 4.6 0.7

---

523 0.671 0.081 0.05 0.03 0.02 0.18 0.19 0.16 0.03 0.03 0.06 0.04 0.02 0.02 0.04 0.01 0.10 1072 352.5 9.6 2.8

527 1.000 0.000 0.02 0.03 0.02 0.20 0.24 0.13 0.04 0.03 0.03 0.07 0.03 0.02 0.03 0.02 0.09 1365 517.5 15.5 4.7

---

525 0.559 0.090 0.03 0.08 0.01 0.13 0.25 0.13 0.05 0.03 0.07 0.02 0.04 0.01 0.02 0.02 0.11 475 267.2 6.7 1.1

620 1.000 0.000 0.00 0.04 0.03 0.17 0.21 0.15 0.05 0.04 0.07 0.05 0.05 0.03 0.00 0.01 0.11 153 169.9 4.5 0.8

---

526 0.328 0.053 0.04 0.02 0.02 0.16 0.30 0.11 0.04 0.02 0.03 0.07 0.04 0.03 0.03 0.02 0.07 676 476.1 13.3 2.4

578 1.000 0.000 0.03 0.02 0.04 0.18 0.30 0.12 0.05 0.04 0.02 0.06 0.04 0.02 0.02 0.02 0.04 740 714.6 20.6 2.9

---

528 0.532 0.060 0.05 0.05 0.01 0.18 0.28 0.10 0.05 0.04 0.02 0.06 0.05 0.01 0.03 0.02 0.05 921 433.7 11.8 3.0

665 1.000 0.000 0.04 0.07 0.01 0.20 0.25 0.12 0.04 0.04 0.04 0.05 0.04 0.03 0.01 0.02 0.05 569 358.8 10.0 2.1

---

539 0.734 0.044 0.07 0.04 0.01 0.24 0.28 0.09 0.03 0.02 0.01 0.04 0.04 0.02 0.03 0.02 0.03 686 186.3 5.5 2.0

586 1.000 0.000 0.04 0.04 0.02 0.24 0.27 0.11 0.03 0.03 0.02 0.06 0.04 0.03 0.03 0.02 0.03 1501 269.1 7.0 2.4

---

541 0.346 0.053 0.04 0.08 0.01 0.20 0.23 0.09 0.04 0.05 0.02 0.06 0.05 0.03 0.02 0.02 0.08 688 432.5 12.5 3.6

646 1.000 0.000 0.03 0.07 0.02 0.21 0.23 0.10 0.03 0.03 0.02 0.08 0.05 0.03 0.04 0.01 0.05 744 271.3 7.7 2.6

---

543 0.809 0.089 0.10 0.06 0.01 0.18 0.28 0.10 0.02 0.06 0.01 0.04 0.02 0.01 0.06 0.01 0.02 846 188.0 5.0 2.3

506 1.000 0.000 0.05 0.03 0.04 0.20 0.29 0.12 0.02 0.04 0.05 0.03 0.04 0.02 0.03 0.01 0.03 797 277.7 7.8 2.2

---

544 0.854 0.071 0.05 0.07 0.03 0.16 0.16 0.10 0.04 0.01 0.02 0.07 0.03 0.03 0.17 0.02 0.05 875 262.9 7.0 2.4

504 1.000 0.000 0.06 0.06 0.03 0.16 0.20 0.08 0.01 0.02 0.02 0.04 0.02 0.04 0.16 0.00 0.08 516 73.5 2.1 0.7

---

549 0.750 0.054 0.03 0.06 0.01 0.23 0.28 0.07 0.05 0.02 0.02 0.07 0.04 0.03 0.03 0.01 0.04 1202 383.0 10.9 2.3

580 1.000 0.000 0.02 0.04 0.01 0.24 0.27 0.08 0.06 0.03 0.04 0.05 0.05 0.02 0.03 0.03 0.03 1354 534.2 14.7 3.1

---

553 0.609 0.062 0.06 0.03 0.01 0.16 0.31 0.12 0.03 0.02 0.02 0.06 0.04 0.02 0.02 0.02 0.06 699 229.5 6.9 1.4

578 1.000 0.000 0.03 0.02 0.04 0.18 0.30 0.12 0.05 0.04 0.02 0.06 0.04 0.02 0.02 0.02 0.04 740 714.6 20.6 2.9

---

554 0.820 0.062 0.04 0.02 0.01 0.28 0.26 0.06 0.05 0.03 0.03 0.03 0.05 0.02 0.07 0.02 0.04 592 178.7 5.3 1.8

521 1.000 0.000 0.03 0.04 0.01 0.26 0.26 0.09 0.03 0.02 0.02 0.02 0.05 0.02 0.05 0.01 0.07 731 286.3 7.4 2.7

---

562 0.577 0.061 0.04 0.10 0.03 0.17 0.28 0.08 0.03 0.07 0.01 0.06 0.02 0.04 0.02 0.01 0.04 368 116.8 3.2 0.9

540 1.000 0.000 0.04 0.09 0.04 0.17 0.28 0.10 0.03 0.04 0.01 0.08 0.02 0.01 0.01 0.01 0.07 732 109.2 3.0 0.8

---

567 0.231 0.116 0.02 0.10 0.01 0.17 0.17 0.06 0.02 0.15 0.01 0.01 0.00 0.00 0.00 0.02 0.23 81 138.3 3.2 0.4

442 1.000 0.000 0.04 0.07 0.02 0.14 0.15 0.09 0.02 0.08 0.01 0.04 0.01 0.01 0.01 0.00 0.29 541 83.8 2.3 0.5

---

570 0.560 0.073 0.03 0.10 0.02 0.24 0.24 0.09 0.03 0.05 0.05 0.03 0.03 0.03 0.02 0.02 0.03 488 173.4 5.2 1.3

531 1.000 0.000 0.04 0.08 0.02 0.22 0.26 0.08 0.02 0.04 0.01 0.03 0.03 0.02 0.03 0.03 0.08 541 101.8 2.8 0.9

---

583 0.637 0.043 0.03 0.04 0.01 0.24 0.27 0.09 0.03 0.04 0.01 0.07 0.05 0.01 0.03 0.01 0.05 906 298.7 8.1 2.7

586 1.000 0.000 0.04 0.04 0.02 0.24 0.27 0.11 0.03 0.03 0.02 0.06 0.04 0.03 0.03 0.02 0.03 1501 269.1 7.0 2.4

---

584 0.497 0.055 0.05 0.07 0.02 0.17 0.30 0.09 0.03 0.02 0.03 0.06 0.02 0.01 0.06 0.01 0.06 524 195.9 5.3 2.6

555 1.000 0.000 0.03 0.08 0.02 0.16 0.27 0.08 0.03 0.03 0.01 0.07 0.03 0.01 0.08 0.03 0.05 893 180.0 4.8 1.2

---

589 0.456 0.061 0.06 0.06 0.05 0.19 0.27 0.11 0.04 0.01 0.03 0.05 0.05 0.02 0.02 0.02 0.03 514 246.5 7.0 2.4

629 1.000 0.000 0.04 0.06 0.01 0.20 0.28 0.12 0.04 0.01 0.01 0.06 0.05 0.03 0.03 0.02 0.02 870 303.4 8.5 2.4

---

595 0.632 0.054 0.06 0.12 0.02 0.17 0.25 0.09 0.06 0.05 0.00 0.07 0.02 0.01 0.01 0.01 0.07 286 123.7 3.3 0.6

565 1.000 0.000 0.03 0.10 0.02 0.17 0.25 0.12 0.05 0.05 0.02 0.07 0.02 0.01 0.01 0.01 0.08 755 138.4 3.8 1.0

---

596 0.699 0.075 0.04 0.06 0.02 0.21 0.30 0.08 0.03 0.01 0.01 0.05 0.02 0.02 0.09 0.02 0.03 875 255.0 7.0 2.9

614 1.000 0.000 0.03 0.06 0.01 0.20 0.32 0.08 0.04 0.04 0.02 0.06 0.03 0.02 0.03 0.02 0.04 1550 339.3 8.4 0.8

---

597 0.628 0.071 0.07 0.08 0.02 0.26 0.22 0.09 0.03 0.03 0.03 0.05 0.03 0.02 0.01 0.01 0.07 264 76.3 2.0 0.6

438 1.000 0.000 0.04 0.10 0.03 0.21 0.22 0.12 0.02 0.04 0.01 0.04 0.04 0.02 0.02 0.02 0.07 504 125.3 3.1 1.2

---

598 0.411 0.050 0.06 0.06 0.02 0.18 0.32 0.09 0.03 0.04 0.01 0.04 0.05 0.02 0.03 0.01 0.04 777 410.2 11.4 3.9

614 1.000 0.000 0.03 0.06 0.01 0.20 0.32 0.08 0.04 0.04 0.02 0.06 0.03 0.02 0.03 0.02 0.04 1550 339.3 8.4 0.8

---

599 0.334 0.049 0.02 0.08 0.03 0.21 0.25 0.13 0.03 0.03 0.02 0.06 0.03 0.01 0.01 0.01 0.08 306 165.1 4.8 1.1

565 1.000 0.000 0.03 0.10 0.02 0.17 0.25 0.12 0.05 0.05 0.02 0.07 0.02 0.01 0.01 0.01 0.08 755 138.4 3.8 1.0

---

600 0.467 0.066 0.03 0.07 0.01 0.16 0.29 0.10 0.05 0.04 0.04 0.05 0.04 0.03 0.03 0.02 0.05 1352 746.7 22.4 4.3

665 1.000 0.000 0.04 0.07 0.01 0.20 0.25 0.12 0.04 0.04 0.04 0.05 0.04 0.03 0.01 0.02 0.05 569 358.8 10.0 2.1

---

603 0.715 0.052 0.04 0.04 0.02 0.20 0.25 0.11 0.04 0.04 0.02 0.06 0.02 0.02 0.04 0.02 0.06 724 209.6 5.8 1.7

665 1.000 0.000 0.04 0.07 0.01 0.20 0.25 0.12 0.04 0.04 0.04 0.05 0.04 0.03 0.01 0.02 0.05 569 358.8 10.0 2.1

---

610 0.422 0.074 0.05 0.08 0.02 0.11 0.12 0.04 0.03 0.07 0.02 0.05 0.03 0.01 0.01 0.00 0.38 251 151.9 3.7 0.5

579 1.000 0.000 0.04 0.05 0.03 0.11 0.13 0.09 0.00 0.05 0.02 0.03 0.03 0.01 0.01 0.00 0.39 635 122.4 3.3 0.5

---

621 0.694 0.063 0.07 0.08 0.03 0.21 0.18 0.10 0.02 0.02 0.02 0.04 0.03 0.03 0.03 0.01 0.13 897 209.1 5.6 2.3

623 1.000 0.000 0.04 0.10 0.01 0.22 0.20 0.07 0.03 0.03 0.02 0.05 0.03 0.02 0.02 0.02 0.13 527 137.2 3.8 0.8

---

627 0.837 0.069 0.07 0.07 0.02 0.20 0.19 0.13 0.04 0.02 0.03 0.05 0.02 0.01 0.04 0.02 0.10 441 100.2 2.7 1.1

537 1.000 0.000 0.05 0.07 0.03 0.17 0.21 0.14 0.04 0.02 0.01 0.08 0.03 0.03 0.03 0.01 0.08 913 322.3 9.5 2.3

---

630 0.510 0.058 0.04 0.01 0.02 0.19 0.31 0.11 0.05 0.02 0.04 0.04 0.05 0.02 0.04 0.02 0.03 959 498.9 14.5 3.4
578 1.000 0.000 0.03 0.02 0.04 0.18 0.30 0.12 0.05 0.04 0.02 0.06 0.04 0.02 0.02 0.02 0.04 740 714.6 20.6 2.9
---
632 0.719 0.064 0.03 0.10 0.02 0.18 0.31 0.06 0.03 0.02 0.01 0.07 0.04 0.02 0.06 0.01 0.02 899 267.9 7.4 1.8
614 1.000 0.000 0.03 0.06 0.01 0.20 0.32 0.08 0.04 0.04 0.02 0.06 0.03 0.02 0.03 0.02 0.04 1550 339.3 8.4 0.8
---
636 0.756 0.049 0.06 0.07 0.03 0.17 0.25 0.15 0.03 0.04 0.02 0.04 0.04 0.03 0.02 0.02 0.04 866 230.2 6.2 1.6
618 1.000 0.000 0.05 0.04 0.03 0.18 0.25 0.15 0.02 0.04 0.02 0.04 0.03 0.03 0.04 0.01 0.06 1800 396.1 11.4 2.2
---
648 0.588 0.064 0.04 0.07 0.02 0.19 0.24 0.11 0.04 0.03 0.02 0.03 0.02 0.03 0.05 0.01 0.10 1526 478.6 13.6 3.6
531 1.000 0.000 0.04 0.08 0.02 0.22 0.26 0.08 0.02 0.04 0.01 0.03 0.03 0.02 0.03 0.03 0.08 541 101.8 2.8 0.9
---
650 0.723 0.119 0.14 0.03 0.01 0.16 0.19 0.17 0.02 0.02 0.02 0.03 0.02 0.02 0.11 0.01 0.06 780 221.0 6.4 1.8
607 1.000 0.000 0.05 0.03 0.02 0.18 0.19 0.20 0.03 0.04 0.01 0.06 0.04 0.04 0.06 0.02 0.05 850 239.9 6.1 1.8
---
652 0.196 0.068 0.06 0.03 0.01 0.18 0.34 0.11 0.05 0.01 0.02 0.05 0.03 0.02 0.03 0.01 0.04 338 430.7 11.3 3.0
509 1.000 0.000 0.03 0.03 0.02 0.21 0.33 0.10 0.02 0.02 0.02 0.07 0.03 0.02 0.03 0.02 0.05 747 272.0 7.7 2.0
---
656 0.741 0.089 0.05 0.10 0.03 0.11 0.13 0.13 0.01 0.03 0.01 0.06 0.02 0.01 0.02 0.01 0.26 187 60.1 1.4 0.2
442 1.000 0.000 0.04 0.07 0.02 0.14 0.15 0.09 0.02 0.08 0.01 0.04 0.01 0.01 0.01 0.00 0.29 541 83.8 2.3 0.5
---
657 0.359 0.059 0.06 0.04 0.05 0.25 0.21 0.08 0.02 0.04 0.03 0.04 0.04 0.02 0.06 0.02 0.05 955 521.1 15.2 3.4
626 1.000 0.000 0.05 0.03 0.02 0.23 0.22 0.10 0.04 0.02 0.04 0.04 0.05 0.03 0.07 0.02 0.04 1219 255.6 7.0 2.9
---
658 0.502 0.069 0.08 0.10 0.02 0.17 0.30 0.09 0.03 0.02 0.02 0.04 0.03 0.01 0.01 0.02 0.05 545 201.4 5.6 1.2
540 1.000 0.000 0.04 0.09 0.04 0.17 0.28 0.10 0.03 0.04 0.01 0.08 0.02 0.01 0.01 0.01 0.07 732 109.2 3.0 0.8
---
659 0.851 0.102 0.11 0.09 0.02 0.25 0.22 0.06 0.04 0.04 0.01 0.05 0.01 0.00 0.01 0.02 0.07 485 128.7 3.4 0.6
623 1.000 0.000 0.04 0.10 0.01 0.22 0.20 0.07 0.03 0.03 0.02 0.05 0.03 0.02 0.02 0.02 0.13 527 137.2 3.8 0.8
---
662 0.709 0.097 0.12 0.03 0.03 0.16 0.29 0.10 0.04 0.03 0.02 0.04 0.03 0.02 0.03 0.02 0.04 742 222.2 6.9 2.4
506 1.000 0.000 0.05 0.03 0.04 0.20 0.29 0.12 0.02 0.04 0.05 0.03 0.04 0.02 0.03 0.01 0.03 797 277.7 7.8 2.2
---
663 0.660 0.065 0.08 0.03 0.02 0.17 0.30 0.14 0.02 0.03 0.03 0.04 0.03 0.01 0.05 0.02 0.02 670 218.4 5.4 1.9
506 1.000 0.000 0.05 0.03 0.04 0.20 0.29 0.12 0.02 0.04 0.05 0.03 0.04 0.02 0.03 0.01 0.03 797 277.7 7.8 2.2
---
667 0.748 0.044 0.05 0.09 0.02 0.17 0.26 0.11 0.03 0.03 0.01 0.05 0.02 0.01 0.01 0.02 0.10 993 244.2 6.3 1.6
565 1.000 0.000 0.03 0.10 0.02 0.17 0.25 0.12 0.05 0.05 0.02 0.07 0.02 0.01 0.01 0.01 0.08 755 138.4 3.8 1.0
---
674 0.754 0.049 0.04 0.08 0.03 0.21 0.20 0.09 0.03 0.04 0.02 0.05 0.02 0.02 0.04 0.01 0.12 1508 341.9 9.4 2.3
623 1.000 0.000 0.04 0.10 0.01 0.22 0.20 0.07 0.03 0.03 0.02 0.05 0.03 0.02 0.02 0.02 0.13 527 137.2 3.8 0.8
---
679 0.433 0.071 0.02 0.10 0.01 0.23 0.16 0.07 0.01 0.08 0.01 0.07 0.04 0.02 0.01 0.01 0.16 163 79.4 1.9 0.3
619 1.000 0.000 0.02 0.07 0.03 0.27 0.18 0.07 0.01 0.04 0.01 0.06 0.03 0.02 0.00 0.02 0.16 456 110.2 2.9 0.8

---

686 0.631 0.079 0.08 0.04 0.03 0.17 0.20 0.09 0.03 0.03 0.03 0.07 0.02 0.01 0.07 0.00 0.14 656 198.7 5.5 1.0

561 1.000 0.000 0.05 0.03 0.03 0.15 0.20 0.10 0.05 0.03 0.02 0.07 0.05 0.03 0.02 0.02 0.15 1071 538.9 16.5 3.6

---

688 0.655 0.043 0.03 0.03 0.03 0.19 0.31 0.10 0.06 0.03 0.01 0.05 0.03 0.03 0.03 0.02 0.04 915 395.1 12.0 2.5

578 1.000 0.000 0.03 0.02 0.04 0.18 0.30 0.12 0.05 0.04 0.02 0.06 0.04 0.02 0.02 0.02 0.04 740 714.6 20.6 2.9

---

690 0.657 0.172 0.06 0.04 0.01 0.12 0.52 0.07 0.03 0.02 0.02 0.04 0.02 0.01 0.01 0.01 0.02 252 106.0 3.0 0.8

534 1.000 0.000 0.03 0.04 0.01 0.17 0.38 0.10 0.04 0.02 0.02 0.07 0.07 0.02 0.02 0.01 0.02 438 183.8 4.8 1.6

---

691 0.419 0.054 0.06 0.06 0.02 0.18 0.27 0.10 0.03 0.02 0.04 0.06 0.02 0.02 0.02 0.02 0.09 1246 587.1 18.4 5.2

637 1.000 0.000 0.02 0.07 0.03 0.20 0.27 0.08 0.03 0.03 0.03 0.06 0.03 0.02 0.01 0.02 0.09 790 229.4 6.2 1.5

---

693 0.567 0.060 0.05 0.10 0.04 0.17 0.29 0.08 0.03 0.04 0.03 0.06 0.03 0.02 0.02 0.01 0.03 626 227.0 6.0 1.1

540 1.000 0.000 0.04 0.09 0.04 0.17 0.28 0.10 0.03 0.04 0.01 0.08 0.02 0.01 0.01 0.01 0.07 732 109.2 3.0 0.8

---

695 0.526 0.070 0.05 0.05 0.01 0.18 0.29 0.12 0.04 0.03 0.01 0.03 0.03 0.03 0.01 0.02 0.08 797 349.1 9.7 1.4

665 1.000 0.000 0.04 0.07 0.01 0.20 0.25 0.12 0.04 0.04 0.04 0.05 0.04 0.03 0.01 0.02 0.05 569 358.8 10.0 2.1

Appendix C
Educational Model Data and Results

Hospital Code	Workload Produced	Outpatient Visits	Staff FTE	Teaching FTE	Research FTE	Resident FTE	Resident Equivalent	Estimated Workload	Relative Error
402	414768	9516	41.1	0.0	0.0	5.00	*	568362	0.37031
405	307204	8207	25.4	7.3	4.2	42.00	10.0006	378790	0.23302
436	229943	2807	15.5	0.0	0.0	0.00	*	263543	0.14613
437	330770	6286	17.8	4.8	1.4	28.50	11.6781	314604	-0.04887
438	336571	7030	18.5	4.6	0.3	24.00	10.8225	326121	-0.03105
442	174170	4575	10.0	0.0	0.0	0.00	*	141498	-0.18759
452	245330	9636	15.9	6.1	1.4	16.00	13.2803	210630	-0.14144
455	900844	23086	101.4	27.0	6.0	103.50	7.2906	1483207	0.64646
460	275782	9700	33.5	7.5	0.6	29.00	-1.8088	520764	0.88832
500	571247	19691	60.5	15.3	8.3	77.50	15.2252	763670	0.33685
501	575395	16849	44.7	14.4	7.1	77.00	26.1455	567696	-0.01338
502	436188	5513	20.1	0.0	0.0	7.50	8.7329	352339	-0.19223
503	164410	4697	12.1	0.0	0.0	0.00	*	174051	0.05864
504	227259	10203	18.8	1.9	0.2	7.00	4.4914	240653	0.05894
505	338613	8919	27.6	0.0	1.2	0.00	*	335960	-0.00783
506	609044	17086	53.9	19.5	16.4	73.50	33.6344	560626	-0.07950
508	781762	21452	57.1	15.3	7.4	95.00	32.3421	727292	-0.06968
509	915722	18186	64.1	19.1	8.6	79.00	34.9656	847778	-0.07420
512	482615	8060	37.3	12.2	8.6	66.00	17.8585	547557	0.13456
513	148002	12961	21.0	0.0	0.0	0.00	*	175494	0.18575
514	134568	3645	14.4	0.0	0.0	0.00	*	230598	0.71362
515	402728	12842	39.7	0.0	0.0	0.00	*	486614	0.20829
516	714665	32361	72.2	0.0	0.0	0.00	*	679712	-0.04891
517	249992	4419	14.9	0.0	0.0	0.00	*	225221	-0.09909
518	375867	18959	40.0	9.9	0.6	16.00	10.0215	453327	0.20608
519	203175	4482	14.1	0.0	0.0	5.00	*	210890	0.03797
520	659081	12111	45.6	0.0	0.0	0.00	*	596995	-0.09420
521	784727	14825	30.9	12.9	6.8	103.00	48.6545	433761	-0.44725
523	841711	24564	86.9	18.3	15.2	163.00	20.2884	1151078	0.36755
525	874949	29214	60.8	3.9	8.1	76.00	31.8584	600703	-0.31344
526	593856	22859	86.4	28.4	27.0	137.00	25.8717	913333	0.53797
527	899900	44483	128.5	20.3	14.5	117.00	4.7511	1418806	0.57663
528	879896	29763	77.3	11.3	5.5	85.00	21.0433	954688	0.08500
529	196912	5828	15.3	0.0	0.0	0.00	*	207001	0.05124

531	259892	10479	20.6	4.4	4.6	16.00	11.8604	211855	-0.18484
532	360862	6885	27.3	0.0	0.0	0.00	*	386677	0.07154
533	227146	4479	19.1	0.0	1.1	4.00	*	275392	0.21240
534	433951	10344	27.5	14.0	3.7	71.00	24.0493	435834	0.00434
535	587759	19764	53.4	12.1	9.3	97.00	21.2022	656762	0.11740
537	678585	34582	63.1	23.4	6.4	116.00	41.2003	650142	-0.04192
538	449541	10442	30.8	0.0	0.0	0.00	*	381833	-0.15062
539	554309	24928	46.5	18.9	7.0	84.00	36.0849	462213	-0.16614
540	345106	4981	16.9	0.0	0.0	5.00	*	248368	-0.28031
541	1041471	34274	108.6	14.9	8.1	99.00	10.5312	1342677	0.28921
542	587965	4482	42.2	5.2	3.2	12.00	3.1180	692621	0.17800
543	607752	10405	30.1	12.5	4.8	85.00	31.6317	498402	-0.17993
544	635266	19154	44.4	10.1	3.0	52.00	24.1265	548384	-0.13676
546	922962	55823	106.8	54.5	19.8	153.00	79.4396	821933	-0.10946
549	1076938	28887	57.9	25.2	14.3	127.00	74.1328	535263	-0.50298
550	475352	15385	43.8	0.0	0.2	2.50	*	506248	0.06500
552	494501	11281	45.6	16.1	1.8	41.50	10.8126	695008	0.05475
553	597707	24825	65.3	17.9	10.0	73.00	21.8012	717558	0.20052
554	625991	14743	53.8	22.3	27.3	101.00	45.9614	451766	-0.27832
555	446318	14114	28.9	15.1	0.0	38.00	24.8180	400667	-0.10228
556	724419	13229	64.0	13.4	3.0	49.00	6.9030	972923	0.34304
557	317973	4309	24.4	0.0	0.0	0.00	*	384150	0.20812
558	753493	18041	40.9	24.3	11.5	111.00	56.2939	475788	-0.36856
561	826508	28075	96.0	16.2	8.6	109.00	5.3125	1238819	0.49886
562	208456	6500	16.0	0.0	0.0	1.00	*	206726	-0.00830
564	308410	6202	18.9	0.0	0.0	0.00	*	259901	-0.15729
565	399117	8605	26.4	0.0	0.0	0.00	*	341494	-0.14438
566	117566	3663	16.9	0.0	0.0	1.00	*	271594	1.31013
567	256740	4199	13.0	0.0	0.0	0.00	*	197700	-0.22996
568	224955	7726	18.5	0.0	0.0	0.00	*	226434	0.00658
569	256977	3539	15.5	0.0	0.0	0.00	*	250644	-0.02465
570	348558	16533	30.4	10.0	2.5	39.50	17.3819	342680	-0.01687
573	763384	25033	55.3	12.6	11.2	100.00	37.9487	588685	-0.22885
574	193368	4091	12.0	0.0	0.0	0.00	*	183078	-0.05322
575	178983	4388	9.6	0.0	0.0	1.00	*	138183	-0.22796
578	1326188	28388	114.2	49.1	8.3	180.00	50.2836	1687396	0.27237
579	228608	3503	18.0	0.0	0.0	0.00	*	292591	0.27988
580	1253511	47909	98.0	23.8	14.5	131.00	63.8027	892457	-0.28803
581	331344	9322	25.0	5.2	2.7	30.00	9.4504	361564	0.09120
583	715098	17526	50.3	10.1	8.2	84.25	26.5213	645825	-0.09687
584	564207	13563	30.0	5.9	5.2	78.50	26.2643	445904	-0.20968
585	299413	4428	15.3	0.0	0.0	0.00	*	231672	-0.22625
586	857103	17125	43.5	18.0	5.5	67.00	46.6869	561752	-0.34459

589	597928	18727	45.6	11.4	7.9	75.00	26.4117	526798	-0.11896
590	404050	18251	45.5	12.0	3.9	42.00	10.8719	555109	0.37386
591	326712	6101	15.8	0.0	0.0	0.00	*	210452	-0.35585
592	285647	4538	20.8	0.0	0.0	0.00	*	320623	0.12244
594	507593	5487	19.6	0.0	0.4	5.00	*	277459	-0.45338
595	448563	9075	32.4	0.0	0.0	0.00	*	432363	-0.03612
596	834636	14978	54.7	18.7	14.7	82.00	41.7378	651490	-0.21943
597	230192	7248	14.0	2.2	0.0	7.00	6.4177	220706	-0.04121
598	1430035	30524	85.0	7.9	6.9	99.00	45.4455	1047796	-0.26729
599	193830	6408	20.8	0.0	0.0	2.00	*	287669	0.48413
600	1203509	59705	115.5	57.6	7.1	203.00	82.2562	1209443	0.00493
603	533099	14366	34.8	8.7	6.9	79.00	24.9381	448988	-0.15778
604	573686	5291	51.8	0.0	0.8	5.00	*	806417	0.40568
605	594815	21939	64.0	15.0	1.0	77.00	7.9486	898863	0.51116
607	595745	9308	31.2	14.6	7.7	76.00	33.6352	466309	-0.21727
608	262818	9397	23.7	0.9	0.0	10.00	-0.3164	352466	0.34111
609	312426	8057	17.6	0.0	0.0	2.00	*	205728	-0.34151
610	257145	4704	25.7	0.0	0.0	2.00	*	398672	0.55037
612	554622	30949	67.2	22.9	7.3	91.00	26.1246	708545	0.27753
613	467924	13359	41.1	0.0	0.1	0.00	*	498986	0.06638
614	1104786	20709	61.6	16.0	3.4	108.00	43.2969	908066	-0.17806
617	139938	2419	5.0	0.0	0.0	0.00	*	96865	-0.30780
618	1235830	25256	98.2	50.5	32.5	161.00	83.0757	1027044	-0.16894
619	214342	5186	13.6	0.0	0.0	0.00	*	190221	-0.11253
620	657724	11106	56.6	0.0	0.1	2.00	*	794831	0.20846
621	488513	9579	31.8	2.4	0.0	45.00	6.9353	539610	0.10460
622	244313	5134	25.3	1.5	0.0	21.00	-6.9822	474709	0.94303
623	294250	14308	19.9	2.7	0.2	19.00	12.6227	206285	-0.29895
626	841871	25330	35.3	12.2	7.9	96.00	59.3149	283720	-0.66299
627	262556	11080	20.7	11.0	6.1	42.00	20.6626	221607	-0.15596
629	686119	42798	60.9	23.0	4.6	95.00	50.4177	456598	-0.33452
630	846841	39783	119.8	45.6	4.4	159.00	20.4283	1596135	0.88481
631	286204	13550	27.0	0.4	0.0	42.00	1.7276	384744	0.34430
632	704688	32104	74.7	24.0	3.0	79.00	25.7373	876951	0.24445
635	724233	11917	56.5	27.7	11.5	92.00	35.7927	791620	0.09305
636	552420	14065	31.2	17.6	4.4	69.00	35.7863	430040	-0.22153
637	671854	12926	36.3	4.3	1.2	10.00	20.1991	475972	-0.29155
640	868852	26798	87.4	19.3	18.8	95.50	28.4131	942702	0.08500
641	437519	3766	26.3	0.0	0.2	0.00	*	421812	-0.03590
642	547467	26160	73.8	21.5	11.7	109.00	16.9847	857797	0.56685
644	760263	24025	59.0	13.7	1.1	49.00	23.9849	717393	-0.05639
645	355074	6636	23.1	0.0	0.1	0.00	*	320007	-0.09876
646	622540	22233	49.4	9.2	9.0	77.00	26.7398	512939	-0.17605

647	291397	5111	12.0	0.0	0.0	0.00	*	165103	-0.43341
648	973940	22427	63.3	27.3	8.7	100.00	52.1111	790441	-0.18841
649	246773	6539	16.6	0.0	0.0	0.00	*	215954	-0.12489
650	356070	27211	45.4	0.0	4.2	58.00	5.9234	401119	0.12652
652	783020	22534	63.5	29.5	13.4	106.00	47.3720	727343	-0.07111
653	314449	6237	19.8	0.0	0.0	0.00	*	274157	-0.12813
654	293699	12862	23.6	6.0	0.5	25.00	10.9474	303214	0.03240
655	264064	7324	21.0	0.0	0.0	0.00	*	274832	0.04078
656	303400	9529	21.7	0.0	0.0	0.00	*	247542	-0.18411
657	1042623	29701	89.9	11.3	12.9	87.00	25.6243	1020018	-0.02168
658	561918	23845	49.4	7.2	0.0	31.50	13.7904	560066	-0.00330
659	545316	13537	44.2	0.0	0.0	0.00	*	548730	0.00626
660	628710	17848	47.7	6.3	0.0	87.50	12.2371	739844	0.17677
662	588137	18057	75.0	14.1	32.5	112.00	23.0047	696580	0.18439
663	520685	22499	54.7	19.9	15.6	85.00	32.8599	507580	-0.02517
664	766966	35698	57.2	27.9	17.6	135.00	69.3386	373268	-0.51332
665	553434	32893	77.8	31.5	23.0	100.00	41.8258	609488	0.10128
666	187201	3038	12.0	0.0	0.0	0.00	*	201634	0.07710
667	695817	15413	28.8	15.1	3.8	45.50	45.2013	327375	-0.52951
668	293756	7366	17.0	0.0	0.0	0.00	*	207990	-0.29196
670	436386	18018	29.8	19.7	6.3	71.50	38.3802	320807	-0.26486
671	1084495	32532	52.0	30.0	12.9	127.00	87.7771	401333	-0.62994
673	998782	41858	79.8	27.6	7.2	119.50	56.6355	784883	-0.21416
674	798119	15174	55.2	10.1	0.6	29.50	16.5370	805370	0.00909
676	331489	5710	19.0	0.0	0.0	0.00	*	270224	-0.18482
677	617364	19537	38.4	1.8	1.8	18.00	19.9517	396092	-0.35841
678	565543	21606	47.7	17.1	7.6	69.00	30.8221	514871	-0.08960
679	369022	6190	18.5	0.0	0.0	3.00	*	253502	-0.31304
680	559046	1058	41.3	1.6	0.0	7.00	-8.1833	784431	0.40316
685	506711	12556	46.6	0.0	0.0	0.00	*	605678	0.19531
686	355534	3261	28.5	0.0	0.2	1.00	*	467067	0.31370
687	184983	3403	11.0	0.0	0.0	0.00	*	178677	-0.03409
688	718188	29717	94.9	17.0	11.9	141.00	5.7088	1196674	0.66624
689	517005	14011	60.7	36.2	8.6	109.00	26.8857	916021	0.77178
690	*	*	*	0.0	*	0.00	*	*	*
691	1173567	65753	135.4	52.9	32.3	191.00	87.4938	1023491	-0.12788
693	464600	25665	46.5	5.3	0.0	25.00	10.8422	478020	0.02889
695	811304	35700	91.6	39.5	20.8	114.00	52.4237	869027	0.07115

Appendix D
Chain YYY Budgets Using Different Algorithms

Column Definitions

Previous Budget : Total Direct Patient-Care Budget in Previous Year.
Budget Std.Dev. : Standard Deviation of Previous Budget.
10%. Prop. Incr. : Budget Allocated with a 10% Increase over Previous Year.
Minimum_Risk Budget : Budget Allocated Using the Minimum-Risk Algorithm.
Minimum_Risk %Inc. : Proportion of Increase from Previous Year.
Eq._Probability Budget : Budget Allocated Using the Equal-Probability Algorithm.
Eq._Probability %Inc. : Proportion of Increase from Previous Year.
Eff.Adjusted Budget : Budget Allocated MOO Efficiency to Adjust a Minimum Risk Budget.
Eff.Adjusted %Inc. : Proportion of Increase from Previous Year.

Hosp.	Previous	Budget	10% Prop.	Minimum_Risk		Eq._Probability		Eff.Adjusted	
Code	Budget	Std.Dev.	Incr.	Budget	%Inc.	Budget	%Inc.	Budget	%Inc.
402	43940	2220.1	48334	46665	0.062	46817	0.065	45303	0.03102
405	12269	1265.2	13496	13783	0.123	13934	0.136	13026	0.06170
436	20045	1067.2	22050	21408	0.068	21408	0.068	20727	0.03400
437	58821	3667.2	64703	63363	0.077	63363	0.077	61092	0.03861
438	30058	1108.2	33064	31421	0.045	31572	0.050	30739	0.02266
442	28049	1108.7	30854	29411	0.049	29563	0.054	28730	0.02428
452	32783	1617.3	36061	34751	0.060	34903	0.065	40270	0.22837
455	32611	1254.1	35873	34125	0.046	34277	0.051	33368	0.02320
460	13418	2256.3	14760	16295	0.214	16295	0.214	14857	0.10722
500	47943	2674.4	52737	51274	0.069	51274	0.069	49608	0.03473
501	27482	1936.2	30230	29905	0.088	29905	0.088	28693	0.04406
502	49052	7476.5	53958	58439	0.191	58288	0.188	82884	0.68971
503	38694	1802.1	42564	40965	0.059	40965	0.059	47082	0.21678
504	20800	837.8	22879	21859	0.051	21859	0.051	24713	0.18815
505	26796	2215.3	29475	29521	0.102	29672	0.107	28158	0.05084
506	38240	2608.3	42064	41571	0.087	41571	0.087	39905	0.04354

508	52674	2183.3	57942	55399	0.052	55399	0.052	54037	0.02587
509	46337	1419.7	50971	48154	0.039	48154	0.039	47246	0.01961
512	25161	1672.7	27677	27280	0.084	27280	0.084	26220	0.04211
513	31954	1949.3	35150	34377	0.076	34377	0.076	33166	0.03792
514	51605	7533.6	56765	60991	0.182	60991	0.182	85678	0.66028
515	24624	7442.1	27087	34011	0.381	33860	0.375	57888	1.35085
516	110123	5868.8	121135	117390	0.066	117390	0.066	137309	0.24687
517	30741	1206.8	33815	32255	0.049	32255	0.049	31498	0.02462
518	46001	15397.8	50601	65380	0.421	65077	0.415	55690	0.21063
519	14333	583.2	15767	15090	0.053	15090	0.053	17066	0.19067
520	59631	5056.4	65594	65990	0.107	65990	0.107	62810	0.05331
521	42753	1617.1	47028	44721	0.046	44873	0.050	43737	0.02302
522	15682	958.5	17250	16893	0.077	16893	0.077	20125	0.28337
523	63125	3503.1	69438	67516	0.070	67516	0.070	65320	0.03477
525	121177	30977.4	133295	160088	0.321	159483	0.316	140633	0.16056
526	60166	2780.9	66182	63648	0.058	63648	0.058	61907	0.02894
527	124109	8878.5	136520	135162	0.089	135162	0.089	129636	0.04453
528	86953	4115.1	95648	92101	0.059	92101	0.059	89527	0.02960
529	68450	5829.0	75295	75717	0.106	75717	0.106	72084	0.05309
531	20775	1010.6	22852	21986	0.058	22138	0.066	21381	0.02917
532	25184	4341.7	27702	30634	0.216	30634	0.216	27909	0.10822
533	25674	1447.1	28241	27491	0.071	27491	0.071	26582	0.03538
534	31256	3131.4	34381	35192	0.126	35192	0.126	33224	0.06298
535	50691	1633.4	55760	52659	0.039	52811	0.042	51675	0.01941
537	75581	2371.7	83139	78609	0.040	78609	0.040	77020	0.01904
538	69988	5600.8	76987	76953	0.100	76953	0.100	73471	0.04976
539	32978	1519.7	36275	34946	0.060	34946	0.060	33962	0.02985
540	57519	5408.7	63271	64332	0.118	64332	0.118	82282	0.43051
541	43004	5011.8	47305	49212	0.144	49212	0.144	46108	0.07217
542	12477	2171.7	13725	15202	0.218	15202	0.218	13840	0.10924
543	49137	3473.5	54051	53528	0.089	53528	0.089	51333	0.04469
544	65255	12688.7	71781	81152	0.244	81001	0.241	73204	0.12181
546	59743	3295.2	65718	63831	0.068	63831	0.068	75005	0.25545
549	61560	1639.4	67716	63528	0.032	63679	0.034	62544	0.01599
550	38212	3595.7	42033	42754	0.119	42754	0.119	40483	0.05943
552	43304	2510.1	47635	46484	0.073	46484	0.073	44894	0.03671
553	36219	1076.1	39841	37581	0.038	37581	0.038	36900	0.01881
554	35167	1283.9	38683	36832	0.047	36832	0.047	35999	0.02367
555	47304	1525.3	52035	49272	0.042	49272	0.042	48288	0.02080
556	57587	7976.5	63346	67580	0.174	67428	0.171	62583	0.08675
557	47239	2755.4	51963	50721	0.074	50721	0.074	48980	0.03686
558	48268	1364.1	53095	49933	0.035	50085	0.038	49101	0.01726
561	83716	5871.3	92087	91134	0.089	90983	0.087	87425	0.04431

562	29020	1134.1	31922	30383	0.047	30534	0.052	29701	0.02347
564	43483	1435.0	47831	45300	0.042	45300	0.042	50197	0.15442
565	57011	2219.3	62712	59736	0.048	59888	0.050	58374	0.02391
566	40368	5280.7	44405	47030	0.165	46878	0.161	43699	0.08251
567	26314	5488.2	28945	33127	0.259	33127	0.259	29720	0.12945
568	11947	573.0	13142	12704	0.063	12704	0.063	12326	0.03169
569	43956	2772.1	48352	47438	0.079	47438	0.079	56772	0.29157
570	23931	1049.3	26325	25294	0.057	25294	0.057	24613	0.02848
573	45479	1399.1	50027	47296	0.040	47296	0.040	46312	0.01831
574	29838	1674.8	32822	31957	0.071	31957	0.071	30898	0.03553
575	16542	796.9	18196	17601	0.064	17601	0.064	20281	0.22605
578	78885	4328.6	86773	84335	0.069	84335	0.069	81610	0.03455
579	32013	1719.0	35215	34133	0.066	34133	0.066	39977	0.24877
580	126732	5866.6	139405	133999	0.057	133999	0.057	130365	0.02867
581	27116	1212.4	29828	28630	0.056	28630	0.056	27873	0.02791
583	60018	2896.8	66020	63652	0.061	63652	0.061	61835	0.03027
584	26399	1001.7	29038	27610	0.046	27761	0.052	27004	0.02293
585	37569	1440.9	41326	39386	0.048	39386	0.048	44300	0.17914
586	68822	1677.7	75705	70942	0.031	70942	0.031	69882	0.01540
589	29031	1105.7	31934	30393	0.047	30545	0.052	29712	0.02347
590	34769	1930.6	38246	37192	0.070	37192	0.070	35980	0.03482
591	63877	4702.6	70264	69781	0.092	69781	0.092	66829	0.04622
592	17438	4181.7	19181	22737	0.304	22737	0.304	20087	0.15194
594	101261	4943.7	111387	107468	0.061	107468	0.061	124251	0.22704
595	29542	2544.3	32497	32722	0.108	32722	0.108	31132	0.05380
596	61592	3454.6	67751	65983	0.071	65983	0.071	63787	0.03564
597	18366	989.6	20203	19578	0.066	19729	0.074	18972	0.03297
598	42809	1292.5	47090	44475	0.039	44475	0.039	43642	0.01945
599	28855	2675.9	31740	32185	0.115	32185	0.115	30520	0.05772
600	103537	3340.9	113891	107625	0.039	107776	0.041	105581	0.01974
603	45307	1548.7	49837	47275	0.043	47275	0.043	46291	0.02173
604	92859	44811.1	102145	149029	0.605	148120	0.595	121020	0.30327
605	50607	2578.0	55667	53786	0.063	53786	0.063	52196	0.03141
607	39732	1310.4	43705	41398	0.042	41398	0.042	40565	0.02096
608	34801	1695.5	38281	36921	0.061	36921	0.061	42682	0.22646
609	45899	1230.0	50488	47413	0.033	47564	0.036	46656	0.01650
610	28808	5992.1	31688	36377	0.263	36226	0.258	32592	0.13137
611	31054	2241.9	34159	33931	0.093	33931	0.093	32492	0.04631
612	53787	3377.8	59166	58026	0.079	58026	0.079	55906	0.03940
613	102811	6499.9	113092	110986	0.080	110835	0.078	106899	0.03976
614	97088	2033.5	106797	99662	0.027	99662	0.027	106612	0.09809
617	20869	1459.1	22956	22686	0.087	22686	0.087	27600	0.32251
618	92529	3402.1	101782	96768	0.046	96768	0.046	94649	0.02291

619	28298	2810.6	31127	31780	0.123	31780	0.123	30039	0.06153
620	115256	23586.6	126782	144780	0.256	144325	0.252	130018	0.12808
621	56343	1817.4	61977	58614	0.040	58614	0.040	57478	0.02015
622	5434	1302.7	5978	7100	0.306	7100	0.306	6267	0.15326
623	30009	1492.7	33010	31826	0.061	31978	0.066	30918	0.03027
626	70415	3131.6	77457	74352	0.056	74352	0.056	72383	0.02795
627	26519	2681.9	29171	29850	0.126	29850	0.126	28184	0.06279
629	69801	3167.1	76782	73738	0.056	73738	0.056	71770	0.02820
630	121943	14998.7	134137	140716	0.154	140565	0.153	131330	0.07698
631	15781	1145.5	17359	17143	0.086	17295	0.096	16462	0.04318
632	89412	9571.7	98354	101373	0.134	101221	0.132	95393	0.06689
635	42645	1595.3	46909	44613	0.046	44613	0.046	43629	0.02308
636	59515	4350.2	65467	64966	0.092	64966	0.092	62240	0.04578
637	60436	2712.4	66480	63767	0.055	63918	0.058	62101	0.02755
640	25346	2357.8	27880	28374	0.119	28374	0.119	26860	0.05975
641	62994	10159.9	69293	75711	0.202	75560	0.199	69353	0.10095
642	38621	1853.2	42483	40892	0.059	41044	0.063	39757	0.02941
644	72893	3150.5	80183	76830	0.054	76830	0.054	74862	0.02701
645	17195	8612.8	18914	27944	0.625	27944	0.625	22569	0.31255
646	55538	4258.0	61091	60837	0.095	60837	0.095	58187	0.04771
647	45545	1283.9	50100	47211	0.037	47211	0.037	51586	0.13264
648	88545	2299.2	97400	91422	0.032	91422	0.032	89984	0.01625
649	32500	2878.5	35750	36133	0.112	36133	0.112	34316	0.05589
650	34173	1540.2	37590	36141	0.058	36141	0.058	41365	0.21045
652	26694	787.5	29363	27602	0.034	27753	0.040	27148	0.01702
653	26988	1131.2	29687	28350	0.050	28502	0.056	27669	0.02524
654	22856	1573.7	25142	24825	0.086	24825	0.086	23840	0.04304
655	50435	3830.0	55478	55280	0.096	55280	0.096	68096	0.35018
656	17019	4344.2	18721	22469	0.320	22469	0.320	19744	0.16012
657	66918	4116.9	73610	72065	0.077	72065	0.077	69492	0.03847
658	30797	2477.1	33877	33976	0.103	33976	0.103	32387	0.05163
659	52853	7293.5	58138	61937	0.172	61937	0.172	85890	0.62507
660	32299	1149.4	35529	33662	0.042	33813	0.047	32980	0.02109
662	31697	1287.4	34867	33363	0.053	33363	0.053	32530	0.02627
663	29908	1143.4	32898	31270	0.046	31422	0.051	30589	0.02278
664	48700	2269.1	53570	51576	0.059	51576	0.059	50138	0.02953
665	45193	4688.3	49713	51098	0.131	51098	0.131	48145	0.06532
666	7994	2072.7	8793	10568	0.322	10568	0.322	17268	1.16009
667	51893	2013.0	57082	54467	0.050	54467	0.050	53180	0.02480
668	38486	1448.3	42335	40303	0.047	40303	0.047	39394	0.02359
670	40564	2327.6	44621	43441	0.071	43441	0.071	42003	0.03546
671	113079	5606.1	124386	120043	0.062	120043	0.062	139082	0.22996
673	86457	5883.5	95102	93875	0.086	93724	0.084	113619	0.31417

674	111118	11176.7	122230	125047	0.125	124895	0.124	118158	0.06336
676	22189	4079.3	24408	27337	0.232	27337	0.232	24763	0.11599
677	36898	4271.4	40588	42197	0.144	42197	0.144	39548	0.07182
678	32218	1295.8	35439	33883	0.052	33883	0.052	33050	0.02584
679	26098	7496.0	28708	35485	0.360	35485	0.360	30791	0.17982
680	35807	2708.3	39388	39138	0.093	39289	0.097	37473	0.04652
685	26876	2130.3	29563	29601	0.101	29601	0.101	28238	0.05069
686	40092	2185.3	44102	42818	0.068	42818	0.068	50221	0.25264
687	26108	1285.1	28718	27773	0.064	27773	0.064	26940	0.03188
688	81970	3028.5	90167	85755	0.046	85755	0.046	83863	0.02309
689	45484	4688.5	50032	51389	0.130	51389	0.130	66930	0.47151
690	23581	1879.2	25939	26003	0.103	26003	0.103	24792	0.05136
691	57002	3421.9	62702	61241	0.074	61241	0.074	59121	0.03718
693	64354	4723.7	70790	70259	0.092	70259	0.092	67307	0.04588
695	47115	1763.4	51827	49386	0.048	49386	0.048	48251	0.02410

References

[1] Aiken, Linda H. and Bays, Karl D.
The Medicare Debate - Round One.
New England Journal of Medicine 311:1196-1200, November, 1984.

[2] Aitchison J, and Brown J.
The Lognormal Distribution.
Monographs Cambridge University Press, Cambridge, England., 1957.

[3] Alonso Olea, Manuel.
Cien años de Seguridad Social.
Papeles de Economía Española 12:197-118, 1980.

[4] American Hospital Association.
Managerial Cost Accounting for Hospitals.
American Hospital Association, Chicago, Illinois, 1980.

[5] Anderson Gerald F. and Steinberg, Earl, P.
Hospital Readmissions in the Medicare Population.
New England Journal of Medicine 311:1349-1352, November, 1984.

[6] Anthony, Robert N. and Herzlinger, Regina E.
Management Control in Nonprofit Organizations.
Richard D. Irving, Chicago, Illinois , 1975.

[7] Anthony, Robert N. and Young, David W.
Management Control in Nonprofit Organizations.
Richard D. Irving, Chicago, Illinois , 1984.

[8] Ashcraft, Marie L.F.
Severity of Illness in VA Medical Centers: An Analysis of the Relationship between Hospital Characteristics and Patients' Disease Stage.
Great lakes HSR&D Field Program, 1984.

[9] Bauer, Katharine G.
Hospital Rate Setting - This Way to Salvation?
Milbank Memorial Fund Quarterly, John B. McKinlay ed. 9:223-264, 1982.

[10] Blue Cross and Blue Shield.
Medical Necessity Guidelines on Respiratory Care (Inpatient).
Technical Report, Blue Cross and Blue Shield Association, Chicago, Illinois, October, 1982.

[11] Blue Cross and Blue Shield.
Medical Necessity Guidelines on Diagnostic Imaging.
Technical Report, Blue Cross and Blue Shield Association, Chicago, Illinois, July, 1984.

[12] Becker E. and Sloan F.
Utilization of Hospital Services: The Roles of Teaching, Case Mix and Reimbursement.
Inquire 20(3):248-264, 1983.

[13] Bessent A., Bessent W., Kennington J. and Reagan B.
An Application of Mathematical Pogramming to Assess Productivity in the Houston Independent School District.
Management Science 28-12:1355-1367, December, 1982.

[14] Bitran, Gabriel R.
Theory and Algorithms for Liner Multiple Objective Programs with Zero-One Variables.
Mathematical Programming 17:362-390, 1979.

[15] Bitran, Gabriel R. and Hax, Arnoldo C.
Disaggregation and Resource Allocation Using Convex Knapsak Problems with Bounded Variables.
Management Science 27(4), April, 1981.

[16] Brewster, Alan C. et al.
Medical Illness Severity Grouping System (MEDISGRPS): A Clinically-Based Approach to Classifying Hospital Patients at Admission.
MediQual Systems Inc., Chicago, Ill, 1984.

[17] Broyles, Robert W.
Hospital Accounting Practice. Volume II. (Managerial Accountting).
Aspen Publications, Rockville, Maryland., 1982.

[18] Charnes A., Cooper W.W. and Rhodes, E.
Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through.
Management Science 27(6), June, 1981.

[19] Conn, Rex B., Aller, Raymond D., and Lundberg, George D.
Identifying Costs of Medical Care. An Essential Step in Allocating Resources.
JAMA 253:1586-1589, March, 1985.

[20] Daniels, M, and Schroeder, S.A.
Variation Among Physicians in Use of Laboratory Tests.
Medical Care 15:482-487, 1977.

[21] Davis, Carolyne K.
The Impact of Prospective Payment on Clinical Resarch.
JAMA 253(5):686-687, February 1, 1985.

[22] Dearden, John.
Interdivisional Pricing.
Harvard Business Review 38(1):117-125, January/February, 1960.

[23] DeGroot, Morris H.
Probability and Statistics.
Addison-Wesley, Reading, MA., 1975.

[24] Demlo, Linda K. and Campbell P.M.
Improving Hospital Discharge Data: Lessons from the National Hospital Discharge Survey.
Medical Care 19(10):1030-1040, October, 1981.

[25] Detsky, Allan S., Stagey, Sidney R. and Bombardier, Claire.
The Effectiveness of a Regulatory Strategy in Containing Hospital Costs. The Ontario Experience.
New England Journal of Medicine 309:151-159, July, 1983.

[26] Department of Health, Education and Welfare. Health Care Financing Administration.
System for Uniform Hospital Reporting.
HCFA, Washington D.C., 1978.

[27] Health Care Financing Administration.
International Classification of Diseases, 9th Revision. Clinical Modification. 2nd edition.
Technical Report, Department of Health and Human Services. Health Care Financing Administration, 1980.

[28] Dowling, William L.
Prospective Rate Setting.
Aspen Publications, Rockville, Maryland, 1977.

[29] Eisenberg, J.
The Use of Ancillary Services: A Role for Utilization Review?
Medical Care 20:849-861, 1982.

[30] Eisenberg, J.
An Educational Program to Modify Laboratory Utilization of Housestaff.
Medical Education 52:578-581, 1977.

[31] Great Britain's Department of Health and Social Security.
Sharing Resources for Health in England. Report of the Resource Allocation Working Party.
Her Majesty's Stationery Office, London, England., 1976.

[32] Feldstein, Martin S.
Econommic Analysis for Health Service Efficiency.
Markham Publishing Company, Chicago Ill., 1968.

[33] Fetter, R.B.
Multiple Uses of a Patient Classification Scheme.
Center for the Study of Health Sciences. Yale University, New Haven, CT, 1976.

[34] Fetter R.B., et al.
The Application of Diagnostic Specific Cost Profiles to Cost and Reimbursement Control in Hospitals.
Journal of Medical Systems 1(2):137-149, 1977.

[35] Fetter, R.B., Shin, Y., Freeman, J.L. and Averil, R.F.
Case Mix Definition by Diagnosis-Related Groups.
Medical Care 18(2), 1980.
Supplement.

[36] Garber, Alan M., Fuchs, Victor R, and Silverman, James F.
Case Mix, Costs, and Outcomes: Differences between Faculty and Community Services in a University Hospital.
New England Journal of Medicine 310:1231-1236, May, 1984.

[37] Ginsburg, Paul B. and Sloan, Frank A.
Hospital Cost Shifting.
New England Journal of Medicine 310:893-898, April, 1984.

[38] Gonnella, Joseph S., editor.
Clinical Criteria for Disease Staging.
SysteMetrics, Inc., Santa Barbara, CA, 1983.

[39] Gonnella, Joseph S. et al.
Staging of Disease. A case-Mix Measurement.
Journal of the American Medical Association 251(5):637-646, February, 1984.

[40] Heyssel, Robert M, et al.
Decentralized Management in a Teaching Hospital.
New England Journal of Medicine 310:1477-1480, May, 1984.

[41] Horn Susan D. and Sharkey Phoebe D.
Measuring Severity of Illness to Predict Patient Resource Use Within DRGs.
Inquiry , Winter, 1983.

[42] Horn S.D. et al.
Measuring Severity of Illness: Homogeneous Case Mix Groups.
Medical Care , January, 1983.

[43] Hughes, Robert A. et al.
The Ancillary Services Review Program in Massachusetts. Experience of the 1982 Pilot Project.
JAMA 252:1727-1732, October, 1984.

[44] Hunt, Karen.
DRG-What It Is, How It Works, and Why It Will Hurt.
Medical Economics , September 5, 1983.

[45] Iglehart, John K.
Medicare Begins Prospective Payment of Hospitals.
New England Journal of Medicine 308:1428-1432, June, 1983.

[46] Kenney, Ralph L. and Raiffa, Howard.
Decision with Multiple Objectives: Preferences and Value Tradeoffs.
John Wiley and Sons, New York, 1976.

[47] Lave, Judith R.
The Medicare Adjustment for the Indirect Costs of Medical Education: Historical Development and Current Status.
University of Pittsburg, Pittsburg, PA, January 1985.

[48] Martz, E.W. and Ptakowski, R.
Educational Costs to Hospitalizad Patients.
Journal of Medical Education 53:383-386, May, 1978.

[49] McGraw-Hill Newsletter.
Perspecrives/Washington Report on Medicine and Health.
McGraw-Hill Newsletter , March 11, 1985.

[50] Meyer, Jack A.
Passing the Health Care Buck: Who Pays the Hidden Cost?
American Enterprise Institute for Public Research, Whasington D.C., 1983.

[51] Miller, Rober B. and Wichern, Dean W.
Intermediate Business Statistics: Analysis of Variance, Regression and Time Series.
Holt, Rinehart and Winston, New York, NY, 1977.

[52] New England Medical Center.
NEMC Management Control System.
1985.

[53] Omenn, Gilbert S. and Conrad, Douglas A.
Implications of DRGs for Clinicians.
New England Journal of Medicine 311(20):1314-1317, November, 1984.

[54] Platt, Roger.
Cost Containment - Another View.
New England Journal of Medicine 309(12), September 5, 1983.

[55] Ryan, Thomas A.,Jr. and Joiner, Brian L.
Normal Probability Plots and Tests for Normality.
Technical Report, Statistics Department. Pennsylvania State University, Undated.

[56] Ryan, Thomas A.,Jr, Joiner, Brian L. and Ryan, Barbara F.
MINITAB Reference Manual.
Technical Report, Statistics Department. Pennsylvania State University, 1981.

[57] Schroeder S.A. and O'Leary D.S.
Differences in Laboratory Use and Length of Stay between University and Comunity Hospitals.
Journal of Medical Education 52:418-420, May, 1977.

[58] Sherman H. David.
Improving the Productivity of Service Businesses.
Sloan Management Review (25-3), 1984.

[59] Smits, Helen L. and Watson, Rita E.
DRGs and the Future of Surgical Practice.
New England Journal of Medicine 311(25), December 20, 1984.

[60] Stern, Robert S. and Epstein, Arnold M.
Institutional Responses to Prospective Payment Based on Diagnosis-Related Groups: Implications for Cost, Quality, and Access.
New England Journal of Medicine 312:621-627, March, 1985.

[61] Tukey John W.
Exploratory Data Analysis.
Addison Wesley, Reading, Massachusetts., 1977.

[62] Administrator of Veterans Affairs.
Annual Report 1982.
Technical Report, Veterans Administration, June, 1983.

[63] Valor Sabatier, Josep.
High Variance within some DRGs at the New England Medical Center. Reduction by Using the Severity of Index Illness.
Personal Communication to the New England Medical Center Staff , 1985.

[64] Wennberg, John E. and Gittelsohn, A.
Small Area Variations in Health Care Delivery.
Science :1102-1108, December, 1973.

[65] Wennberg, John E., McPherson, Klim and Caper, Philip.
Will Payement Based on Diagnosis-Related Groups Control Hospital Costs?
New England Journal of Medicine 311:295-299, August, 1984.

[66] Wood, Charles T.
Relate Hospital Charges to Use of Services.
Harvard Business Review , March-April, 1982.

[67] Yarbro, John W. and Mortenson, Lee E.
The Need for Diagnosis-Related Group 471. Protection for Clinical Research.
JAMA 253(5):684-685, February 1, 1985.

[68] Young, Wanda W.
Incorporating Severity of Illness and Co-Morbidity in Case-Mix Measurement.
Health Care Financing Review , December, 1984.

[69] Young, David W. and Saltman, Richard B.
Preventive Medicine for Hospital Costs.
Harvard Business Review :126-133, January-February, 1983.

[70] Zieve, L.
Misinterpretation and Abuse of Laboratory Test by Clinicians.
Annuals of the New York Acadamy of Sciences 134:563-572, 1966.

[71] Zook, Christopher J. et al.
Repeated Hospitaliation for the Same Disease: A Multiplier of the National Health Costs.
Milbank Memorial Fund Quarterly/Health and Society 58-3:87-104, 1980.