
Retrospective Theses and Dissertations

1984

Using Simulation to Predict the Financial Effect of Hospital Management Policies Under a Prospective Reimbursement

Timothy G. Atkins
University of Central Florida

 Part of the [Engineering Commons](#)

Find similar works at: <https://stars.library.ucf.edu/rtd>

University of Central Florida Libraries <http://library.ucf.edu>

This Masters Thesis (Open Access) is brought to you for free and open access by STARS. It has been accepted for inclusion in Retrospective Theses and Dissertations by an authorized administrator of STARS. For more information, please contact STARS@ucf.edu.

STARS Citation

Atkins, Timothy G., "Using Simulation to Predict the Financial Effect of Hospital Management Policies Under a Prospective Reimbursement" (1984). *Retrospective Theses and Dissertations*. 4688.

<https://stars.library.ucf.edu/rtd/4688>

USING SIMULATION TO PREDICT THE FINANCIAL
EFFECT OF HOSPITAL MANAGEMENT POLICIES
UNDER A PROSPECTIVE REIMBURSEMENT SYSTEM

BY

TIMOTHY G. ATKINS
B.S.E., University of Central Florida, 1982

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Graduate Studies Program of the College of Engineering
University of Central Florida
Orlando, Florida

Fall Term
1984

ABSTRACT

Recent legislation by Medicare restricts its reimbursement per patient according to the patient's particular type of disease. The reimbursement is based on a set of Diagnosis Related Groups (DRG's), which categorizes patients into disease classifications. As a result, hospitals must make efficiency gains and managers must look for new ways to provide quality care while containing costs.

A simulation technique was developed by which the financial results of particular administrative policies can be predicted. Patient billing data were collected over a three-month period and analyzed for the purpose of simulating length of stay and resource consumption per cost center. Regression analyses were used to approximate departmental costs as a function of length of stay and to estimate total cost as a function of certain departmental costs. Distribution-fitting techniques were used to determine the method of random generation for independent variables. The simulation model was run with two embellishments to illustrate how policies are interjected and results are interpreted.

TABLE OF CONTENTS

LIST OF TABLES	v
LIST OF FIGURES	vii
LIST OF VARIABLES AND ACRONYMS	viii
Chapter	
I. INTRODUCTION	1
The Cost of Health Care	1
The Nature of Health Care Delivery	2
TEFRA and the DRG Classification System	5
II. THE RESPONSE OF HOSPITALS TOWARD PROSPECTIVE REIMBURSEMENT	8
The Effects of DRG Reimbursement on Health Care Delivery	8
Cost-Control Strategies in Hospitals	11
III. MODEL DEVELOPMENT	16
Overview of Simulation	16
Problem Formulation	17
Model Building	23
IV. ANALYSIS OF DATA	25
Selection of DRG's and Data Collection	25
Length of Stay Analysis	31
Resource Consumption Analysis	41
Application to Simulation	51
V. SIMULATION DESIGN AND APPLICATION	54
Selection of Simulation Language	54
The Network Portion of the Model	55
The Discrete-Event Portion of the Model	61
Verification and Initial Validation of the Model	71
Interjection of Policies and Forecasts	76
VI. CONCLUSIONS AND RECOMMENDATIONS	80

TABLE OF CONTENTS

Appendices

1A.	SPSS ANALYSIS OF LOSTOT.	84
1B.	SPSS ANALYSIS OF LOGLOS.	89
2.	SPSS ANALYSIS OF PCTICU.	94
3.	EXAMPLE OF SPSS REGRESSION ANALYSIS OF TCOST = $C_0 + C_1 \times \text{LAB} + C_2 \times \text{PHARM} + C_3 \times \text{SUPP} + C_4 \times$ $\text{RETHE} + C_5 \times \text{XRAY}$	98
4.	EXAMPLES OF BREAKDOWN OF CHARGES PER DAY ACCORDING TO LENGTH OF STAY.	102
5.	EXAMPLE OF SPSS REGRESSION ANALYSIS OF CHARGES = $C_0 + C_1 \times \text{LOSTOT} + C_2 \times \text{LOSREG} + C_3 \times \text{LOSI} +$ $C_4 \times \text{LOSTOT}^2 + C_5 \times \text{LOSREG}^2 + C_6 \times \text{LOSI}^2$	104
6A.	EXAMPLE OF SPSS ANALYSIS OF DEPARTMENTAL CHARGES . . .	110
6B.	EXAMPLES OF SPSS ANALYSIS OF THE NATURAL LOGARITHM OF DEPARTMENTAL CHARGES.	112
7.	FORTRAN SUBROUTINE EVENT	118
	REFERENCES.	122

LIST OF TABLES

1.	Ranking of DRG's by Total Charges.	26
2.	Number of Patient Cases Collected for Analysis	28
3.	Chi-Square Calculation for LOGLOS, DRG 127	37
4.	Chi-Square Test Results and LOSTOT Distributions for each DRG	39
5.	PCTICU Variable Generation Parameters.	41
6.	Coefficients of Regression Equation, $TCOST = C_0 + C_1 \times$ $LAB + C_2 \times PHARM + C_3 \times SUPP + C_4 \times RETHER + C_4^0 \times XRAY$.	43
7.	Coefficients of Regression Equation, $HCOST = K_0 +$ $K_1 \times [CC_1 \times LAB] + K_2 \times [CC_2 \times PHARM] + K_3 \times [CC_1^0$ $\times SUPP] + K_4 \times [CC_4 \times RETHER] + K_5 \times [CC_5 \times XRAY]$	44
8.	Regression Coefficients and R^2 Values for: Cost Center Charge = $C_0 + C_{11} \times LOSTOT + C_{12} \times LOSTOT^2 + C_{21} \times$ $LOSREG + C_{22}^0 \times LOSREG^2 + C_{31} \times LOSICU + C_{32} \times LOSICU^2$. .	48
9.	Chi-Square Test Results and Department Charge Distribution by DRG for Charges Not Generated from Regression Equations.	52
10.	ATRIB Array Positions for Patient Attributes	59
11.	Medicare Patients per DRG, 1983.	64
12.	Observed Cost-to-Charge Ratios for Cost Centers Included in the Model (January-March, 1984)	64
13.	1983-84 Medicare Payment Rates and Outlier Parameters for Florida Urban Hospitals.	65
14.	Array Values for the Special Linear Department Charge Approximation: $CHARGE (JDEP) = LOSTOT \times CHGMAX(ID, JDEP) /$ $LOSMAX(ID)$	68
15.	Case-Mix and Proportion of Medicare Patients from Simulation with No Policies Introduced	71

LIST OF TABLES (Continued)

16.	Comparison of Simulated Average Departmental Costs and Actual Costs	73
17.	Comparison of the Average Cost per Patient by DRG.	75

LIST OF FIGURES

1.	Annual percentage increase in total hospital expenditures.	1
2.	Example of a patient billing abstract.	18
3.	Example of a resource consumption report	19
4.	A-B-C analysis of DRG's.	21
5.	SPSS code used for analysis of patient billing data. . . .	29
6.	A portion of the file "PATIENT DATA" which illustrates the structure of the records	30
7.	Frequency histogram and statistics of LOSTOT for DRG 127 .	33
8.	Frequency histogram and statistics of LOGLOS for DRG 127, A normal distribution is superimposed.	34
9.	SLAM network for patient cost simulation	56
10.	SLAM program listing for patient simulation.	60
11.	SLAM initialization subroutine INTLC	69
12.	Functional flowchart for subroutine EVENT.	70
13.	Summarized results of simulation with no policies introduced	73
14.	Summary report of simulation with radiology efficiency increase	77
15.	Summary report of simulation with a length of stay extension policy	79

LIST OF VARIABLES AND ACRONYMS

ANCDEF:	Unspecified charges for ancillary services
ANES:	Charges for anesthetic supplies and services
ATRIB:	Attribute array for SLAM simulation
AVGLOS:	Medicare's average length of stay, used for outlier payment calculation
BLOOD:	Total charges for blood
CARD:	Total charges from the EEG-EKG-Cardiology department
CC(X), CRATIO(X):	Cost-to-charge ratio for department X
CLMTOL:	Medicare's cost outlier threshold
CPXRAY:	Average unit cost per x-ray
DELIV:	Delivery room charges
DRG:	Diagnosis related group
ER:	Emergency room fees
ERPHYS:	Emergency room physician fees
HCOST:	Total estimated cost to the hospital = LAB x CC(LAB) + PHARM x CC(PHARM) + ... + ANCDEC x CC (ANCDEF)
LAB:	The patient's total charges from the laboratory department
LOGLOS:	The natural logarithm of the length of stay
LOSA:	The patient's length of stay in a semi-private room
LOSB:	The patient's length of stay in a private room
LOSICU:	The patient's length of stay in an intensive care unit

LIST OF VARIABLES AND ACRONYMS (Continued)

LOSREG:	The patient's length of stay in a private or semi-private room = LOSA + LOSB
LOSTOT:	The total length of stay = LOSREG + LOSICU
LTRIMP:	Medicare outlier length of stay limit
NUCMED:	Charges from the nuclear medicine center
OROOM:	Charges for operating room facilities
OTLPAY:	Expected ratio of outlier reimbursement to outlier costs
OUTLIR:	Expected proportion of Medicare outliers
PARATE:	Medicare reimbursement amount
PAYEXP:	Expected proportion of payment received from non-Medicare patients
PCRATE:	Percentage of the DRG reimbursement rate in effect
PCTICU:	The percentage of days spent in an intensive care unit = LOSICU/LOSTOT
PHARM:	Total charges from the pharmacy department
PHTHER:	Total charges for physical therapy
PMEDCR:	Expected proportion of Medicare patients
REHAB:	Rehabilitation charges
RESCON:	Resource consumption parameter array
RETHER:	Total charges for respiratory therapy
ROOMDF:	Unspecified room charges
SCAN:	Charges for scans

LIST OF VARIABLES AND ACRONYMS (Continued)

SLAM:	Simulation Language for Alternative Modeling
SPSS:	Statistical package for the social sciences
SUPP:	Total charges for medical supplies
TEFRA:	Tax Equity and Fiscal Responsibility Act of 1982
TCOST:	Total cost to the patient = LAB + PHARM + SUPP + CARD + PHTHER + RETHER + BLOOD + ER + ERPHYS + OROOM + ANES + XRAY + NUCMED + SCAN + DELIV + REHAB + ANCDEF
χ^2 :	Chi-square test statistic for distribution fitting
XLOS:	Array which contains length of stay parameters
XRAY:	Charges for x-rays

CHAPTER I

INTRODUCTION

The Cost of Health Care

The present costs of medical care in America are generally perceived to be extremely high. In addition, the rate of increase of these costs exceeds the inflation rate in most areas of the country. Hofmann (1983) reports that thirty years ago Americans spent less than five percent of their total income for health care; since then, that percentage has doubled. Figure 1 shows the annual percentage increase in cost during recent years from the perspective of hospitals.

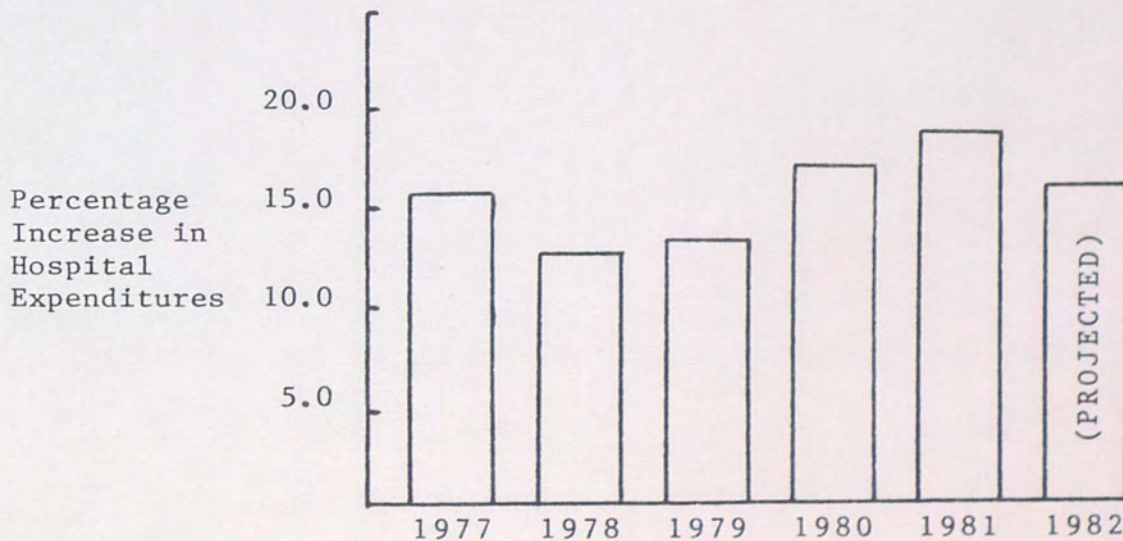


Fig. 1. Annual percentage increase in total hospital expenditures (Hofmann 1983).

The runaway nature of health care costs can be attributed primarily to the fact that there has been little incentive for health care providers to contain costs. The health care system has unique characteristics which tend to hinder any incentive to contain costs.

The Nature of Health Care Delivery

Unlike a normal industry, providers of medical care have not been subject to the traditional laws of supply and demand. The demand for health care has not been affected by the amount of increase in its cost. Thus, this cost has been free to increase dramatically with no adverse affect to the providers; on the contrary, the providers have benefitted from this increase. Some of the main characteristics which allow the health care system to behave in such a way are as follows:

1. The consumer (or patient) usually has very limited input with respect to the type or quantity of the services rendered. With the exception of the initial selection of a physician, patients take little part in any of the decision-making processes having to do with the consumption of resources. In general, they do not have any urgent concern to save cost, since most of the cost is normally paid by insurance carriers. In 1950, individuals paid for two-thirds of total health bills; in 1980, that proportion had been reduced to one-third. Currently, less than ten percent of physician fees are borne directly by the patient. Furthermore,

a large portion of the patient's expenditures are tax deductible. It is plain to see how little incentive a patient has to check the actual cost of care which he receives.

2. Insurance companies do not check the actual cost of care either. Like the patient, they have little or nothing to say on the selection of treatment and procedures. The full payment is usually unchallenged, not only as to the necessity of each service rendered, but also to any increase in previous prices, because higher medical bills imply higher insurance premiums, hence greater profit for insurance companies.

3. Physicians make up the main element in health care delivery which could exercise a great measure of control over the cost of medical care. However, they practice what is known as "defensive medicine" in their desire to assure the best possible treatment for their patients as well as to avoid possible malpractice lawsuits. Defensive medicine involves routinely performing many tests and procedures, some of which may not contribute to the quality of care. It is normal for a patient to expect an excessive number of examinations upon admission, and equate this treatment to quality service. Although many of the routine procedures may be justified for a given set of symptoms, there are also many which are not; and only a qualified medical practitioner can differentiate between the two.

4. Hospitals are, of course, the most common facility in which health care is provided. Hospitals do compete for physicians

but do not practice competition with respect to price. They have had little incentive to do so since its customers have not been in a position to "shop" for the best prices. In relation to physicians, hospitals have not been pressured to monitor their consumption of resources since it is feared that such an action would decrease the quality of care and put the hospitals in greater danger of malpractice lawsuits. Furthermore, more expenditures simply means more reimbursement from payors.

All of these peculiarities of the health care system illustrate why a free market competition has been unable to control the increase of medical costs. Recognizing these facts, the government has increased the degree of its intervention in the medical care business, with the purpose of guaranteeing quality and affordable care to all segments of the public. Its actions have included the Hill-Burton Act of 1946, the Community Health Services and Facilities Act of 1961, the Comprehensive Health Planning Act of 1966 and the National Health Planning and Resource Act of 1974. As a result of such legislation, Florida and other states have instituted programs such as the Certificate of Need, Peer Standard Review Organizations, and Comprehensive Health Planning, all of which represent regulatory efforts designed to restrain the great increases in health care costs.

TEFRA and the DRG Classification System

The federal government's most recent regulatory effort to curb health care costs was the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982, which became effective in October, 1983. A \$7 billion Medicare deficit predicted for 1988 was expected to grow to \$63 billion in 1995; over these seven years, the accumulated deficit would have exceeded \$310 billion (Grimaldi 1983a). TEFRA allows Medicare to be a more prudent buyer of medical services by imposing limits on hospital and physician reimbursement. This rate setting through "prospective reimbursement" attempts to restrain increases in health care expenditures by establishing, prior to a hospital's fiscal year, limits on the reimbursement that a hospital will receive for its services.

As indicated previously, traditional reimbursement methods have allowed many inefficiencies to be built into health care systems. Retrospective payment by insurance groups has enabled hospitals and physicians to cover the cost of inefficiencies by simply increasing charges. Under this policy, the providers are neither penalized for wastefulness nor rewarded for cost containment. In response to this, Medicare's prospective reimbursement has been designed to encourage cost containment. The reimbursement is based on a set of diagnosis related groups (DRG's), which is defined by Moore to be "a classification scheme which categorizes patients who are medically related with respect to diagnosis and treatment, and are statistically similar in their lengths of stay" (1983).

Under TEFRA, a hospital will receive a fixed payment for each patient according to the patient's DRG, regardless of the hospital's expense (there are exceptions to this rule when the patient has an extremely long length of stay for a certain DRG). Grimaldi (1983b) reports that this legislation will reduce Medicare and Medicaid expenditures by more than \$14 billion between 1983 and 1985.

It should be noted that prospective reimbursement has been tried in several states since 1971. New Jersey, Maryland and Massachusetts have had mandatory rate setting programs for all payors: Washington, Connecticut, New York and Rhode Island have had rate setting for some types of payors. A number of states have voluntary rate review programs, and others have mandatory disclosure of financial information by hospitals without rate setting. Medicare's prospective reimbursement system is similar to the New Jersey DRG system, which has 467 DRG's. Since some of these DRG's are segregated according to the patient's age, only 356 of them are applicable to Medicare patients.

DRG's were introduced by Thompson et al. (1975), of Yale University, and were intended as a means of grouping patients by discharge diagnosis to measure a hospital's resource utilization, performance and cost. There has been much praise given to the system as a cost-control method. As Drummer (1982) points out, the DRG system is a valuable management tool; resource consumption can be broken down into its cost components, such as radiology, so that

wasteful cost centers can be identified. Reports can also be generated to compare the performance of individual physicians.

However, there has been much criticism of the system. Many administrators consider the number of DRG's to be excessive and that the information needed to support such a system would be very cumbersome. On the other hand, Horn (1983) advocates that the DRG's do not adequately segregate patients into medically similar categories, and that a "severity of illness" index should be incorporated for each DRG. This would theoretically make the reimbursement for each patient more representative of the hospital's actual cost.

The theories that exist among practitioners will be tested as prospective reimbursement by DRG's take effect. The changes in procedures involved in health care delivery may or may not be drastic; only time will determine this.

CHAPTER II

THE RESPONSE OF HOSPITALS TOWARD PROSPECTIVE REIMBURSEMENT

The Effects of DRG Reimbursement on Health Care Delivery

Prospective reimbursement will change the management of health care because hospitals and physicians will no longer be able to increase their revenue by increasing their billing charges. The services spent on a Medicare patient in a given DRG will only be reimbursed to a pre-determined limit; therefore, a hospital will lose money if its cost of service for a given patient exceeds this limit and will profit if the cost is contained below the limit. Calder (1983) reports that a recent poll shows "most hospital administrators expect that their Medicare revenue will be about the same or even higher under a prospective payment system". However, their expectations may not be justified; the California Hospital Association says that eighty percent of America's private hospitals will be penalized under DRG reimbursement (Robinson 1983). So the question remains: will a rate setting policy put enough financial pressure on hospitals to slow the rate of health care cost inflation?

Data from the initial 26 DRG hospitals (in New Jersey) shows that their operating expenses rose 13.8% in 1980 as compared with a national average of 17% (Drummer 1982). Hospitals from other

rate-setting states have had consistently lower expenses per admission than non-rate-setting states (Biles et al. 1980). This seems to indicate that prospective pay can have a cost-containing effect. However, these hospitals have prospective reimbursement for all payors.

There will be various reactions from hospital administrators toward Medicare's new reimbursement policy. The most obvious options are: to offset potential revenue losses through efficiency gains, shift the losses to non-Medicare patients, obtain greater revenue from non-patient care activities, or reduce the quality and accessibility of services (Grimaldi 1983c). Of course, the most desirable alternative would be to function more efficiently. Increasing charges to non-Medicare patients will be only a temporary solution since all insurance carriers are expected to adopt some type of prospective pay scheme. Reducing the quality of care is apparently the most undesirable alternative.

The medical records departments in hospitals will play an increasingly important role in the reporting of information to management and insurance companies. Presently, many hospital information systems are designed to collect and aggregate data, but it cannot be readily integrated into a meaningful tool for cost control. With DRG's, these systems will become more sophisticated in order to properly summarize and format patient data for management decision support (Kukla and Bachofer 1983). Efficient

information systems are also needed to maintain a good cash flow through hospitals by producing timely, complete and accurate reports to insurance carriers.

In relation to the reporting of information, much emphasis has been placed on the development of diagnosis reporting techniques which will increase reimbursement. In some cases, the principal and secondary diagnoses of a patient can be legitimately interchanged and result in the patient being classified into a higher paying DRG. However, these techniques will not produce long-term gains for hospitals since the patients' lengths of stay from one year will be used to determine the next year's DRG payments: the payment for a DRG will be lowered if the average length of stay has been reduced. Therefore, purposely classifying less severely ill patients into a DRG which was designed to represent more severely ill patients will eventually reduce the payment for one of the DRG's. Furthermore, in most multi-diagnosis cases, interchanging the diagnoses would be "blatantly unethical", according to Simborg (1981).

Other unethical practices may appear as some hospitals attempt to gain revenue by manipulation of admission procedures. Some potential outpatients may be treated as inpatients (the DRG rate does not apply to outpatients). Patients with multiple problems may be readmitted, to receive a multiple DRG payment (Grimaldi 1983b). However, these policies will also reduce a hospital's future reimbursement since the average length of stay for a DRG will be reduced.

Although prospective reimbursement may indirectly cause unethical practices among some hospitals, it will accomplish its primary purpose by encouraging cost containment in health care delivery procedures. Hospital managers will introduce many cost-control policies in an effort to provide quality care to patients for less expense.

Cost-Control Strategies in Hospitals

For many people, the thought of reducing hospital expenses implies a reduction in the quality of services. However, Grimaldi says that eliminating inefficiencies in tests or procedures does not imply that the quality of care is impaired. On the contrary, the savings can be used to supply more and better services (Grimaldi 1983b).

Five variables play a major role in the cost of hospital care. As defined by Doremus (1983), they are:

1. physician practices (quantity and type of services given)
2. quality of inputs (facilities, ancillary services)
3. the patient (response to treatment, general physical condition, etc.)
4. the illness (over 14,000 diagnostic and surgical procedure codes, and thousands of combinations of them)
5. the patient's "degree of being healed"

As mentioned previously, the hospital should not take actions which would reduce the quality of inputs: patients should be the

beneficiaries of cost-control strategies, not its victims. A hospital does have control over the costs which its employees generate, and should make every effort to keep these costs from rising while maintaining or increasing the quality of services. DRG's will enable hospitals to do this more effectively by providing a meaningful measure of output. There will be incentive for hospitals to concentrate more on productivity. Many engineering techniques will be introduced into this productivity management which have not been previously applied to the hospital industry. McLarney and Davis (1983) report that the hospital engineering community has recently accounted for more than \$2 billion in savings to American hospitals. The incentives from prospective reimbursement can only increase the role of engineering techniques.

Two of the variables, namely the patient and his degree of being healed, cannot be controlled by the hospital. The remaining two variables over which a hospital can and should exercise some measure of control are the illnesses of their patients and the practices of physicians. These two variables will be the main ones considered in this paper.

In larger cities, hospitals can be somewhat selective in the types of illnesses which they treat. They can decide to specialize in some categories of medicine while drawing back from other areas which could be served by neighboring institutions (Korkok 1982). This specialization could produce significant gains in cost savings; but the greatest component of a hospital's cost is determined by physician practices.

As early as ten years ago, the American Hospital Association reported that 80 to 85 percent of costs in a hospital's budget were generated by physicians (Gosfield 1983). Therefore, if major savings in cost are to be realized, there must be cooperation from physicians. Using DRG's, individual physicians' practice patterns can be observed and compared with the normal range of practice. Those physicians who show a consistently excessive use of a hospital's resources can then be encouraged to practice more cost-effective medicine. For example, if most physicians order between three and seven x-rays for patients in a certain DRG, and one physician orders a consistently greater number without any difference in the patients' overall health, the wasteful physician should be encouraged to practice more cost-effective medicine. Also, resource monitoring systems can be used for each case by establishing a length of stay review date and a dollar quota for ancillary service use. When the review data or dollar quota is reached, physicians can be contacted to examine the need for the extra resources (Kovener and Palmer 1983).

Requesting physicians to cooperate in cost-control efforts should not be equated with restricting their practices. Although some physicians may take offense at resource monitoring systems, Kovener and Palmer report that many of them are accustomed to the concept of a "normal range" of test results and know that their practice patterns can be analyzed in a similar way. Those who have worked with their medical staffs have been gratified with the

results; only those who have not yet tried remain skeptical. Also, it is interesting to note that only fifteen percent of the physicians account for about eighty percent of the extravagance in resource consumption (Kovener and Palmer 1983).

Much of the excessive costs are incurred by ancillary services, particularly in radiology. X-rays account for six to ten percent of the nation's total health expenditures. Many x-rays are unnecessary, according to a World Health Organization report. The following types of x-rays do not appear to produce results that justify the cost or exposure: many "routine" chest x-rays, chest x-rays during pregnancy, pre-operative chest x-rays, and back x-rays for patients with lumbrosacral pain ("Many X-Rays" 1983). These are just a few examples of how a greater number of resources does not necessarily contribute to the quality of service. With prospective payment, this wastefulness will need to be minimized along with excessive resource consumption in every other cost center.

Hospitals will introduce many new types of cost control strategies in response to DRG reimbursement. It is believed that simulation can be a valuable tool in the planning of administrative policies. The objective of this research is to develop a simulation to project the financial effects of such policies on a hospital's total reimbursement.

Simulation is a technique for developing a representation of an actual system in order to replicate or project the effects of certain changes to the system. Many times, direct experimentation

with a system is either infeasible or involves great risk; simulation provides a numerical representation of the system which can be manipulated without great risk. The results of modifications to the simulated system can be measured, and provide an indication of the actual effects of the modifications.

In relation to case-mix management, a simulation can generate a certain mix of patients based on historical data, along with the expected amount of resources which they would consume. Then, different management policies can be interjected to limit the number of resources in a specific DRG, or to limit the number of admissions of patients with certain illnesses, and the net gain or loss in reimbursement can be calculated. This will give administrators an indication of which policies would be most worthwhile to introduce and provide them with a more defined basis of cooperation with physicians with respect to resource consumption.

CHAPTER III

MODEL DEVELOPMENT

Overview of Simulation

The basic objective of this simulation is to generate cost per patient based on the expected cost per DRG for a hospital and interject modifications, or policies, to the healthcare delivery process in order to simulate the total financial effects of these policies. For a useful and accurate model, the expected costs should be generated by separate cost components; then, separate policies can be applied to each component. For example, radiology expense is one component of a hospital's total expense. The administrators may desire to predict the effect of reducing the number of X-rays given to patients in certain DRG's by a proposed percentage. Policies to reduce certain patients' lengths of stay could also be considered. The hospital may want to introduce a maximum length of stay for some DRG's, which could be enforced in a certain percentage of cases. Selective admissions policies could also be considered, i.e., if the hospital desires to refer certain patients to other institutions. Similarly, forecasted changes in patient case mix or total patient volume could be interjected. This simulation will project the net savings or losses which would result from the introduction of such policies and forecasts.

Problem Formulation

Several costs are generated in the treatment of a patient. The hospital which contributed data to perform this research has segregated its costs into the following cost centers:

- | | |
|-----------------------|-----------------------------------|
| 1. Laboratory | 11. X-ray |
| 2. Pharmacy | 12. Nuclear Medicine |
| 3. Medical Supplies | 13. Respiratory Therapy |
| 4. EEG-EKG-Cardiology | 14. Scan |
| 5. Physical Therapy | 15. Delivery Room |
| 6. Blood | 16. Rehab |
| 7. Emergency Room | 17. Miscellaneous ancillary costs |
| 8. Operating Room | 18. Semi-private |
| 9. Recovery Room | 19. Miscellaneous room costs |
| 10. Anesthesia | 20. Intensive Care Unit (ICU) |

For each DRG, the expected value of the expense from each of these cost categories can be derived from historical data, which is available through a hospital's management information system. Individual patient billing data specifies the length of stay and the amount charged for patient care within each cost center. With this information, the average charge and variance of charges can be derived. Figure 2 shows a typical billing abstract.

Resource consumption reports are generally available through a hospital's DRG information system. The format of such a report is shown in Figure 3. Although it does give the average length

DATE OF SERVICE	DESCRIPTION OF HOSPITAL SERVICES	SERVICE CODE	TOTAL CHARGES	EST COVERAGE #1	EST COVERAGE #2	EST COVERAGE #3	EST COVERAGE #4
COMMAND BILLING ABSTRACT							
DIAGNOSIS AND PROCEDURES: DISCHARGE/FINAL DIAGNOSIS: 436 *CVA 413.9 *ANGINA PECTORIS NEC/NOS 342.9 HEMIPLEGIA NOS 401.9 HYPERTENSION NOS 414.0 CORONARY ATHEROSCLEROSIS SURGICAL PROCEDURES: 87.03 C.A.T. SCAN OF HEAD							
				02/16/84	26		
PHYSICIAN: OPERATING: 000026 ALTERNATE CARE: TRANSFER DESTINATION: GROUPER USED: MC83 DRG #: 014 DRG RATE PER CASE: 3747.70 OUTLIER VALUE:							
DATE OF SERVICE	DESCRIPTION OF HOSPITAL SERVICES	SERVICE CODE	TOTAL CHARGES	EST COVERAGE #1	EST COVERAGE #2	EST COVERAGE #3	EST COVERAGE #4
SUMMARY OF CHARGES							
	R&C INTENSIVE 50DAYS	350.00DAY	1750.00	1750.00			
	R&C SEMI-PR 12DAYS	155.00DAY	1860.00	1860.00			
	LABORATORY	06	355.00	355.00			
	PHARMACY	10	367.25	367.25			
	MED SUPPLIES	13	69.35	69.35			
	INHALATION THER	15	204.60	204.60			
	EKG	16	188.00	148.00	40.00		
	PHYSICAL THER	19	324.00	324.00			
	EMERGENCY ROOM	23	100.00	100.00			
	ER PHYS FEE	51	33.00	1.32	31.68		
	EMI & SCANS	29	325.00	325.00			
SUB-TOTAL OF CHARGES			5596.20	5524.52	71.68		
POLICY DEDUCTIBLE				356.00CR	71.68CR	427.68	
			5596.20	5168.52	71.68	427.68	
							PAY THIS AMOUNT:

Fig. 2. Example of a patient billing abstract.

of stay and charges from each cost center by DRG, there is no measure of variance presented, which is required to build an accurate simulation model. Therefore, a special report should be generated, or the variance should be manually calculated from the patient billing abstracts.

04/27/84
HRQRCPRF

RESOURCE CONSUMPTION PROFILE
BY DRG

		DISCHARGES FOR DEC - FEB 1984						PATIENTS INCLUDED: ALL					
MC83 DRG FINAL NO: 323		PTS		TOTAL	PCT	RATIO	AVG/PT	MAX/PT	MIN/PT	AVG/PD			
URINARY STONES AGE >69 AND/OR C.C.		PT DAYS		4	0.29		6.3	12	4				
PR FLD 93003-93006:999999,D,1A OAO,1A OAO		CHARGES		11,155	0.32		2,789	5,951	1,042	446			
SCHED OPT: 01 FINY A I111		EST REIMB		8,114	0.26	0.7273	2,028	2,318	1,844	325			
DEFAULT:N		EST COST		8,658	0.33	0.7762	2,165	4,443	936	346			
		EST PROFIT		-545	-6.71		-136	1,040	-2,467	-22			
COST CENTER		<--PTS-->		<-----CHARGES----->			<-----COST----->			<--VOL-->		<--DAYS-->	
-----		NDR	PCT	TOTAL	PCT	AVG/PT	TOTAL	PCT	AVG/PT	TOTAL	AVG	TOTAL	AVG
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
ANCILLARY	1 LABORATORY	4	100.00%	1,198	10.74%	299	855	9.87%	214	49	12		
	2 PHARMACY	4	100.00%	1,759	15.77%	440	688	7.94%	172	440	110		
	3 CSR	4	100.00%	993	8.90%	248	515	5.95%	129	114	29		
	4 EEG-EKG-CARDIA	3	75.00%	491	4.40%	164	144	1.67%	48	4	1		
	8 ER	1	25.00%	35	0.31%	35	26	0.29%	26	1	1		
	10 OR	3	75.00%	1,255	11.25%	418	1,260	14.55%	420	11	4		
	11 RECOVERY RM	2	50.00%	255	2.29%	128	158	1.83%	79	9	5		
	12 ANES	2	50.00%	443	3.97%	221	278	3.21%	139	6	3		
	13 XRAY	3	75.00%	702	6.29%	234	458	5.29%	153	15	5		
	14 NJC MED	1	25.00%	150	1.34%	150	89	1.02%	89	2	2		
ROUTINE	63 SEMI	4	100.00%	3,875	34.74%	969	4,190	48.39%	1,047			25	6.3

Fig. 3. Example of a resource consumption report.

For the purpose of establishing this simulation, three month's worth of data were analyzed. It is recommended, however, that data from a complete year be used. This will provide for a more stable model, and produce results that more accurately describe the health care system.

The hospital under consideration discharged 6,098 patients in 1983 (1,375 of which were Medicare patients). These patients

incurred \$13.5 million in charges, and represent 403 DRG's. Since the analysis of all 403 DRG's would be burdensome, the ones which contributed most to the hospital's total charges (or similarly, the total costs) should be considered. This is analogous to the process involved with industry's A-B-C inventory analysis (Lovener and Palmer 1983). By this process, managers focus attention to the few items which account for a great portion of the total inventory value. By exercising tight control over these "class A" items, a great portion of the total volume can be controlled with relatively little effort.

When ranked in order of charges, the twenty highest DRG's accounted for 38.5% of the total charges. For Medicare patients, the twenty highest DRG's accounted for 46.2% of the total Medicare charges. Hospital managers should initially bring attention to the "class A" DRG's, which is recommended to be the top twenty or twenty-five. Figure 4 illustrates the relationship of the DRG's to total charges (or costs).

The variables which will be used in the analysis of the data are defined as follows:

ANCDEF:	unspecified charges for ancillary services
ANES:	charges for anesthetic supplies and services
BLOOD:	total charges for blood
CARD:	total charges from the EEG-EKG-Cardiology department
CC(X):	cost-to-charge ratio for department X

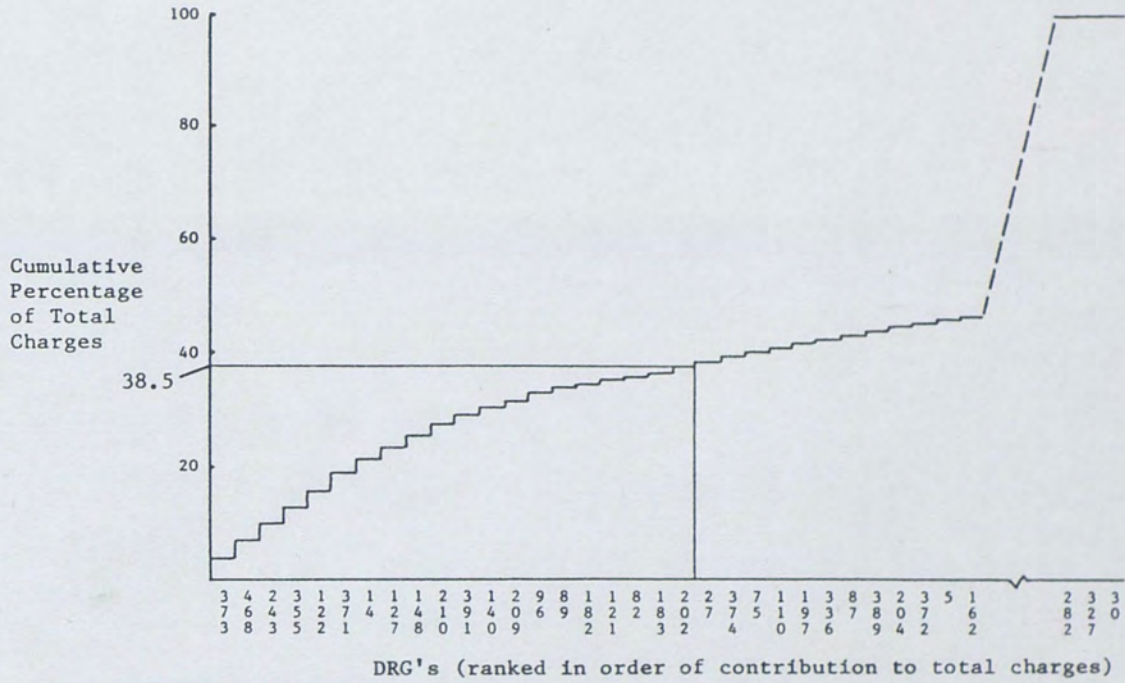


Fig. 4. A-B-C analysis of DRG's

- DELIV: delivery room charges
- DRG: the numerical DRG assignment for a patient
- ER: emergency room fees
- ERPHYS: emergency room physician fees
- LAB: the patient's total charges from the laboratory department
- LOSA: the patient's length of stay in a semi-private room
- LOSB: the patient's length of stay in a private room
- LOSICU: the patient's length of stay in an intensive care unit

LOSREG: the patient's length of stay in a private or semi-private room = LOSA + LOSB
 LOSTOT: the total length of stay = LOSREG + LOSICU
 NUCMED: charges from the nuclear medicine center
 OROOM: charges for operating room facilities
 PCTICU: the percentage of days spent in an intensive care unit = LOSICU/LOSTOT
 PHARM: total charges from the pharmacy department
 PHTHER: total charges for physical therapy
 REHAB: rehabilitation charges
 RETHER: total charges for respiratory therapy
 ROOMDF: unspecified room charges
 SCAN: charges for scans
 SUPP: total charges for medical supplies
 TCOST: total cost to the patient
 = LAB + PHARM + SUPP + CARD + PHTHER + RETHER +
 BLOOD + ER + ERPHYS + OROOM + ANES + XRAY +
 NUCMED + SCAN + DELIV + REHAB + ANCDEF
 HCOST: total estimated cost to the hospital
 = LAB x CC(LAB) + PHARM + CC(PHARM) + ... +
 ANCDEF x CC(ANCDEF)
 XRAY: charges for x-rays

The objective of this simulation is to generate patients, assign each one a DRG based on the actual historical case mix of the hospital, and then to assign LOS values and resource consumption data according to the DRG. After the validity of this model is tested against the actual hospital summary reports, the simulated policies can be introduced and the net change in cost can be projected.

Model Building

The flow of patients through the hospital will be simulated. Patient will "arrive" and be assigned certain attributes (DRG, LOS, and resource consumption) which are representative of the actual data. Some of these attributes will be generated by random variables with distributions that fit the frequency distribution of the actual data. For example, a hospital's cost per case is generally "skewed rightward" which implies a lognormally or exponentially shaped distribution (Grimaldi and Micheletti 1983). The average value and variance of the cost for such a distribution can, therefore, be used to generate costs in the simulation. The attributes which cannot be fitted to a theoretical distribution will be generated empirically from triangular distributions, which have three parameters: a minimum, a maximum and a mode (Law and Kelton 1982).

In this model, cost will be generated by first generating the charge from each department (since the charge data is available) and multiplying the charge by the cost-to-charge ratio of that department. These products will then be accumulated to obtain a total cost for the patient. After the model has been verified, the hospital policies to be simulated can be logically introduced within the code of the simulation.

There are some relationships among the variables which may prove helpful in the construction of the model. First, the number of cost centers included in the simulation can be reduced

by selecting a few of the cost centers from which most of the charges are incurred. An approximation of total cost per patient can be derived as a function of these centers, and as a result, much manipulation of data and computer code can be avoided with little detriment to the performance of the model. For example, in this research, a regression analysis was performed for the equation:

$$\text{TCHARGE} = A \times \text{LAB} + B \times \text{PHARM} + C \times \text{SUPP} + D \times \text{RETHET} + E \\ \times \text{XRAY}$$

where A, B, C, D and E are the corresponding regression coefficients. This resulted in a very high multiple regression coefficient within each DRG. The data from these five cost centers can, therefore, be used to approximate total charges or costs with this equation.

Secondly, since the cost of treating a patient is directly related to the LOS, the model should reflect this by using some relationships between charges and lengths of stay. These relationships will be discussed in the following chapter.

CHAPTER IV

ANALYSIS OF DATA

Selection of DRG's and Data Collection

As mentioned previously, the inclusion of all DRG's for analysis would be very cumbersome; therefore, only some of the top cost-generating DRG's should be included. Table 1 lists the top twenty-five DRG's for the contributing hospital in order of total charges, along with the number of patients (total and Medicare) which were assigned to each DRG.

Depending on the amount of available data and the nature of the illness, hospital managers may not want to analyze all of the top DRG's. Other questions should be considered such as:

1. Are there enough cases within each DRG to build a statistically sound model?
2. Since Medicare patients are the only patients which provide a restricted reimbursement, does the hospital want to concentrate only on DRG's which have had a considerable number of Medicare patients?
3. Can hospital managers practically enforce cost containment policies within a certain DRG? For example, a DRG which involves major surgery would be generally not a good target for cost containment policies.
4. Can admissions policies be enforced for a particular DRG? Only hospitals in or near major cities would be able to effectively refer patients to other institutions.

TABLE 1

RANKING OF DRG'S BY TOTAL CHARGES
 January - December, 1983
 Total Charges = \$13,507,221

Ranking	DRG Number	% of Total Charges	Cumulative Percent	Number of Patients	Number of Medicare Patients
1	373	3.80	3.80	589	0
2	468	3.35	7.15	67	25
3	243	3.08	10.23	143	44
4	355	3.07	13.30	170	5
5	122	2.61	15.91	77	35
6	371	2.59	18.50	177	0
7	14	2.30	20.80	60	52
8	127	2.16	22.96	85	63
9	148	2.07	25.03	27	19
10	210	1.76	26.79	26	22
11	391	1.67	28.46	677	0
12	140	1.46	29.92	96	49
13	209	1.30	31.22	19	16
14	96	1.20	32.42	45	31
15	89	1.15	33.57	35	22
16	182	1.12	34.69	75	44
17	121	1.05	35.74	29	14
18	82	1.00	36.74	37	21
19	183	.86	37.60	83	11
20	202	.86	38.46	21	3
21	27	.80	39.26	4	1
22	374	.79	40.05	86	0
23	75	.78	40.83	11	4
24	110	.74	41.57	6	4
25	197	.72	42.29	16	10

Considering these questions, managers may desire to exclude some of the "class A" DRG's and include some others which did not appear in the top twenty-five.

For the purposes of illustrating the proposed approach, the following six DRG's were selected for analysis:

1. 141: specific cerebrovascular disorders except transient ischemic attacks
2. 127: heart failure and shock
3. 148: major small and large bowel procedures age > 69 and/or complications or comorbidity
4. 210: hip and femur procedures except major joint age > 69 and/or complications or comorbidity
5. 243: medical back problems
6. 468: unrelated operation procedure

These are a subset of the class A DRG's after performing an A-B-C analysis of the DRG's to which Medicare patients were assigned. The data for each of these DRG's were collected over a three-month period.

These DRG's represent a wide range of statistical situations to be considered for this simulation. Although this research does not involve a complete analysis of all class A DRG's, a methodology will be established by which a simulation of patients in any set of DRG's can be performed.

In order to effectively evaluate the total flow of patients and their costs, a seventh category of patients should be introduced which incorporates all other DRG's which are not specified. To provide this, a random sample was taken of every tenth patient which was assigned a DRG other than the ones which were chosen for

in-depth analysis. The billing data for this sample were categorized into DRG 999 for the purpose of this analysis. The data for this sample were collected over the same three-month period. The number of cases collected for each selected DRG is given in Table 2.

TABLE 2
NUMBER OF PATIENT CASES COLLECTED FOR ANALYSIS

DRG	Number of Cases
14	16
127	34
148	8
210	15
243	26
468	7
999 (other)	52

For each case, the following billing variables will be used in the analysis:

- | | | |
|--|------------|------------|
| 1. DRG (coded 999 if DRG is other than 14, 127, 148, 210, 243 and 468) | 8. PHTHER | 15. X-RAY |
| 2. LOSREG | 9. RETHER | 16. NUCMED |
| 3. LOSICU | 10. BLOOD | 17. SCAN |
| 4. LAB | 11. ER | 18. DELIV |
| 5. PHARM | 12. ERPHYS | 19. REHAB |
| 6. SUPP | 13. OROOM | 20. ANCDEF |
| 7. CARD | 14. ANES | 21. ROOMDF |

From this data, the simulation of patient cost by department can be built per DRG. Analysis of length of stay data will determine the method by which the simulated patients' lengths of stay are generated. Likewise, departmental charge data will be analyzed to determine the method of generating resource consumption.

For this analysis, the Statistical Package for the Social Sciences (SPSS) was used to provide histograms, regression equations and other tools for building the simulation model. The SPSS code which sets up the data for analysis is listed in Figure 5.

```

TITLE 'STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS'
FILE HANDLE PAT /NAME="PATIENT DATA"
DATA LIST FILE=PAT
      /1 DRG 1-3 LOSA 4-6 LOSB 7-9 LOSICU 10-12
      LAB 13-19 (2) PHARM 20-26 (2)
      SUPP 27-33 (2) CARD 34-40 (2) PHTHER 41-47 (2) RETHER 48-54 (2)
      BLOOD 55-61 (2) ER 62-68 (2) ERPHYS 69-75 (2) ORROOM 76-82 (2)
      ANES 83-89 (2) XRAY 90-96 (2) NUCMED 97-103 (2) SCAN 104-110(2)
      DELIV 111-117 (2) REHAB 118-124 (2) ANCDEF 125-131 (2)
      ROOMDF 132-138 (2)
COMPUTE TCOST=LAB+PHARM+SUPP+CARD+PHTHER+RETHERR+BLOOD+ER+ERPHYS
      +ORROOM+ANES+XRAY+NUCMED+SCAN+DELIV+REHAB+ANCDEF+ROOMDF
COMPUTE LOSREG=LOSA+LOSB
COMPUTE PCTICU=LOSICU/(LOSICU+LOSREG)
COMPUTE LOSTOT=LOSREG+LOSICU
COMPUTE LOGLOS=LN(LOSTOT)
COMPUTE L=LAB
COMPUTE P=PHARM
COMPUTE S=SUPP
COMPUTE R=RETHERR
COMPUTE X=XRAY
IF LAB GT 0 LLAB=LN(LAB)
IF PHARM GT 0 LPHARM=LN(PHARM)
IF SUPP GT 0 LSUPP=LN(SUPP)
IF RETHER GT 0 LRESP=LN(RETHERR)
IF XRAY GT 0 LXRAY=LN(XRAY)
COMPUTE LOS2=LOSTOT**2
COMPUTE REG2=LOSREG**2
COMPUTE ICU2=LOSICU**2
COMPUTE LPD=LAB/LOSTOT
COMPUTE PPD=PHARM/LOSTOT
COMPUTE SPD=SUPP/LOSTOT
COMPUTE RPD=RETHERR/LOSTOT
COMPUTE XPD=XRAY/LOSTOT
MISSING VALUES PCTICU (0,1)/L TO X (0)
VARIABLE LABELS LOSA"LOS (SEMI-PRIVATE)"LOS B"LOS (PRIVATE)"
      LOSREG"LOS (REGULAR)"
      LOSICU"LOS (I. C. U.)"PHARM"PHARMACY"
      SUPP"MEDICAL SUPPLIES"CARD"EEG-EKG-CARDIA"
      PHTHER"PHYSICAL THERAPY"RETHERR"RESPIRATORY THER. "
      ER"EMERGENCY ROOM"ERPHYS"E. R. PHYSICIAN"
      ORROOM"OPERATING & RECEIVING"ANES"ANESTHESIA"
      NUCMED"NUCLEAR MEDICINE"DELIV"LABOR AND DELIV"
      ANCDEF"ANC DEF"ROOMDF"ROOM DEF"
SPLIT FILE BY DRG

```

Fig. 5. SPSS code used for analysis of patient billing data.

The data were set up in a file named "PATIENT DATA" and read from there by the SPSS program by the commands in lines two and three. Line three specifies the structure of the data into field widths. For example, the DRG variable is the first variable in the record, and its value occupies the first three spaces of the record; and XRAY is the fifteenth variable, which occupies seven spaces (90 through 96), two of which are decimal places (the decimal point takes up one of the seven spaces). Figure 6 lists some of the records from this data file. Each record is 138 characters long.

```

999 7 0 0 383.00 106.00 0.00 282.00 0.00 0.00 0.00 0.00 0.00 0.00 115.00 0.00 0.00 0.00 0.00
999 3 0 2 297.00 98.00 24.00 738.00 0.00 129.00 0.00 43.00 43.00 0.00 0.00 64.00 0.00 0.00 0.00 0.00
999 0 14 0 629.001167.00 391.00 141.00 0.00 198.00 0.00 35.00 33.00 0.00 0.00 210.00 0.00 0.00 0.00 0.00
999 8 0 2 646.00 513.00 294.00 141.00 0.001233.00 0.00 100.00 95.00 0.00 0.00 109.00 324.00 0.00 0.00 0.00
999 5 0 0 401.00 191.00 162.00 188.00 0.00 72.00 0.00 43.00 43.00 0.00 0.00 64.00 0.00 0.00 0.00 0.00
999 2 0 3 294.00 438.00 139.00 141.00 0.00 271.00 0.00 25.00 23.00 0.00 0.00 45.00 0.00 0.00 0.00 0.00
999 20 0 0 265.00 884.001509.00 47.00 0.00 0.00 0.00 25.00 23.00 950.00 368.00 65.00 0.00 400.00 0.00 0.00
999 13 0 0 564.001045.00 535.00 47.00 0.00 313.00 0.00 0.00 0.00 645.00 261.00 192.00 0.00 0.00 0.00 0.00 0.00
999 16 0 0 679.00 507.00 378.00 47.00 64.00 45.00 0.00 35.00 23.00 0.00 0.00 145.00 181.00 0.00 0.00 0.00
999 12 0 0 243.00 319.00 473.00 0.00 0.00 10.00 0.00 0.00 0.00 500.00 203.00 129.00 0.00 0.00 0.00 0.00
999 1 0 0 109.00 43.00 49.00 47.00 0.00 0.00 0.00 0.00 0.00 448.00 0.00 0.00 0.00 0.00 0.00 0.00
999 10 0 5 585.001105.00 867.00 0.00 66.00 386.00 312.00 25.00 23.00 0.00 0.00 294.00 0.00 0.00 0.00 0.00 0.00
999 4 0 0 136.00 247.00 157.00 0.00 0.00 0.00 0.00 43.00 0.00 0.00 0.00 45.00 0.00 0.00 0.00 0.00
999 7 0 0 262.00 413.00 273.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 70.00 0.00 0.00 0.00 0.00
999 4 0 0 299.00 129.00 142.00 47.00 0.00 0.00 104.00 43.00 43.00 0.00 0.00 110.00 0.00 0.00 0.00 0.00
999 7 0 2 394.00 813.00 161.00 0.00 0.00 0.00 208.00 25.00 23.00 0.00 0.00 307.00 0.00 0.00 0.00 0.00
999 4 0 0 141.00 154.00 452.00 0.00 0.00 45.00 0.00 0.00 0.00 0.00 0.00 192.00 0.00 325.00 0.00 0.00
999 8 0 0 149.00 102.00 26.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 224.00 181.00 0.00 0.00 0.00
999 4 0 0 100.00 36.00 0.00 94.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 179.00 0.00 400.00 0.00 0.00
999 6 0 0 177.00 106.00 83.00 47.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 180.00 0.00 0.00 0.00 0.00

```

Fig. 6. A portion of the file "PATIENT DATA" which illustrates the structure of the records.

The section of code which follows the file statements introduces new variables as functions of the file variables. The use of these new variables will be explained later.

The "SPLIT FILE BY DRG" statement segregates the data analysis according to DRG. Since DRG's were derived as a grouping of diseases with patients which have statistically similar lengths of stay and resource consumption, it is plainly advantageous to categorize the data analysis and model construction by DRG.

The analysis of length of stay will be independent of other variables; however, for the resource consumption analysis, it will be determined if definite relationships exist between the expected amount of resources used by a patient and the length of stay of the patient. These relationships will be used in the simulation to generate resource consumption according to length of stay.

Length of Stay Analysis

The length of stay is the primary controlling variable that determines the amount of resources which are consumed by a patient. Of course, there are those patients which have a shorter length of stay than others, yet a greater amount of resource consumption. However, by examining patients within each DRG, the number and extent of these variations can be greatly reduced. Also, by considering intensive care stay and regular room stay separately, certain variations can be expected, since the rate at which

intensive care patients use resources is generally greater than that of patients under regular care. Furthermore, by examining each component of cost, an account for certain variations can be made. For example, emergency room costs are obviously independent from a patient's length of stay, since these costs are generally fixed and are incurred before the patient begins rooming in the hospital.

For the simulation, the total length of stay (LOSTOT) and the percentage of stay which was intensive care (PCTICU) will be generated for each patient. The analysis of both of these variables follows.

A frequency histogram for LOSTOT, with complete statistics and frequency table, is produced by the following SPSS code:

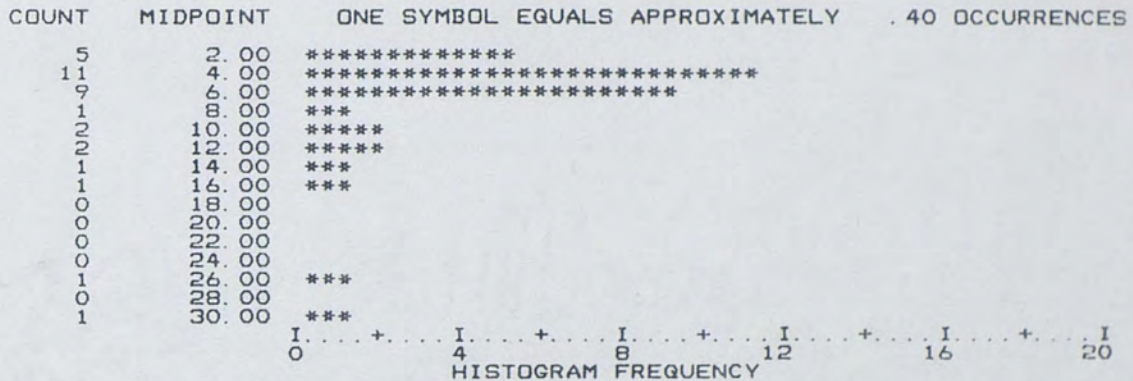
```
FREQUENCIES VARIABLES = LOSTOT/  
HISTOGRAM = INCREMENT (2)/  
STATISTICS = ALL
```

The results (Appendix 1A) show a lognormally-shaped frequency distribution for most DRG's. The LOSTOT histogram for DRG 127 is shown in Figure 7.

The next step is to test theoretical distributions to be used to generate LOSTOT in the simulation. The chi-square goodness of fit test was chosen to evaluate the theoretical distribution against the actual distribution of values. Since most DRG's had LOSTOT histograms that were lognormally-shaped, the lognormal distribution was chosen for evaluation, using the parameters of the sample from

DRG: 127
 LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	1.00	2	5.9	5.9	5.9
	2.00	3	8.8	8.8	14.7
	3.00	5	14.7	14.7	29.4
	4.00	6	17.6	17.6	47.1
	5.00	6	17.6	17.6	64.7
	6.00	3	8.8	8.8	73.5
	7.00	1	2.9	2.9	76.5
	8.00	1	2.9	2.9	79.4
	9.00	1	2.9	2.9	82.4
	10.00	1	2.9	2.9	85.3
	11.00	1	2.9	2.9	88.2
	12.00	1	2.9	2.9	91.2
	13.00	1	2.9	2.9	94.1
	14.00	1	2.9	2.9	97.1
	15.00	1	2.9	2.9	100.0
	16.00	1	2.9	2.9	
	17.00	1	2.9	2.9	
	18.00	1	2.9	2.9	
	19.00	1	2.9	2.9	
	20.00	1	2.9	2.9	
	21.00	1	2.9	2.9	
	22.00	1	2.9	2.9	
	23.00	1	2.9	2.9	
	24.00	1	2.9	2.9	
	25.00	1	2.9	2.9	
	26.00	1	2.9	2.9	
	27.00	1	2.9	2.9	
	28.00	1	2.9	2.9	
	29.00	1	2.9	2.9	
	30.00	1	2.9	2.9	
	TOTAL	34	100.0	100.0	



MEAN	6.706	STD ERR	1.088	MEDIAN	5.000
MODE	4.000	STD DEV	6.346	VARIANCE	40.275
KURTOSIS	6.156	S E KURT	1.955	SKEWNESS	2.394
S E SKEW	.403	RANGE	29.000	MINIMUM	1.000
MAXIMUM	30.000	SUM	228.000		
VALID CASES	34	MISSING CASES	0		

Fig. 7. Frequency histogram and statistics of LOSTOT for DRG 127.

the observed data. For example, for DRG 127, it is hypothesized that LOSTOT is lognormally distributed with a mean of 6.71 days and a standard deviation of 6.35 days. In order to test this hypothesis, it is necessary to examine the distribution of the natural log of

LOSTOT, labeled LOGLOS by the SPSS code. The following code produces statistics and frequency histograms for LOGLOS:

```
FREQUENCIES VARIABLES = LOGLOS/
HISTOGRAM = NORMAL INCREMENT (0.2)/
STATISTICS = ALL
```

The NORMAL command superimposes a normal distribution over each histogram. The results for each DRG are presented in Appendix 1B. Figure 8 shows the results for DRG 127.

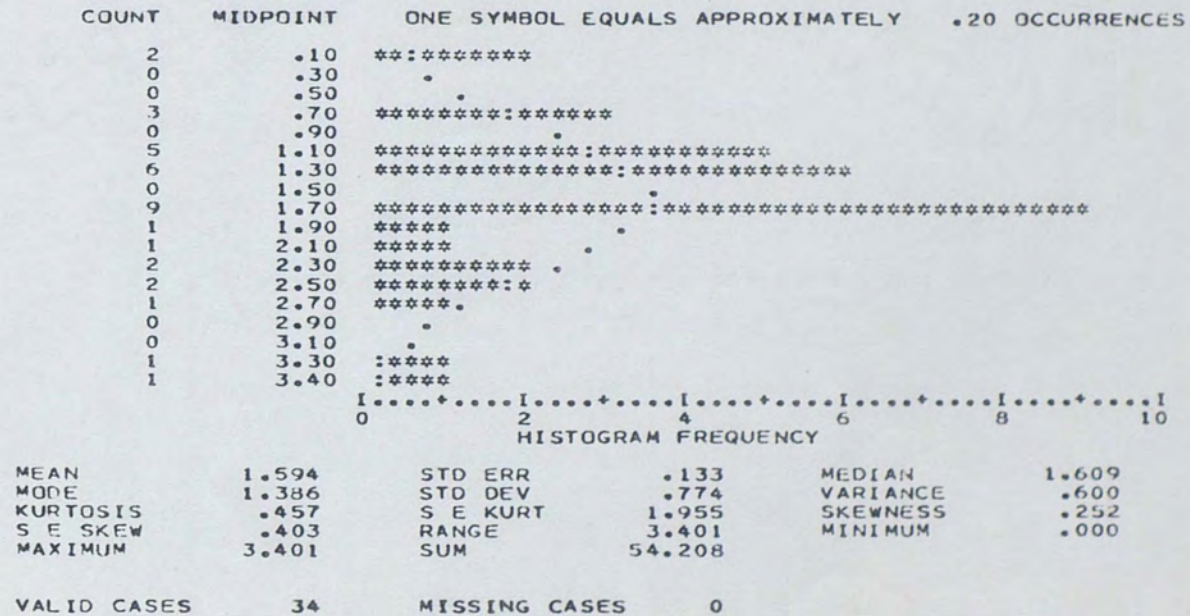


Fig. 8. Frequency histogram and statistics of LOGLOS for DRG 127. A normal distribution is superimposed.

A hypothesis which is equivalent to the one previously stated is that LOGLOS is normally distributed. This is the hypothesis that will be tested for each DRG. Note that if

$$X \sim \text{lognormal} (\mu_x, \sigma_x^2),$$

then

$$Y \sim \text{normal} (\mu_y, \sigma_y^2)$$

with

$$E(X) = \mu_x = e^{\mu_y + (\sigma_y^2/2)} \quad (1)$$

and

$$\text{Var}(X) = \sigma_x^2 = e^{2\mu_y + \sigma_y^2} (e^{\sigma_y^2} - 1) \quad (2)$$

(Hines and Montgomery 1980). The theoretical mean and standard deviation of LOSTOT will be derived by using these relationships with the sample mean and standard deviation of LOGLOS.

Using a sample of size N , the values for LOGLOS are arranged into K class intervals. The chi-square test statistic is defined as

$$X_o^2 = \sum_{i=1}^K \frac{(O_i - E_i)^2}{E_i}$$

where:

O_i = the observed frequency in interval number i

E_i = the theoretical normal distribution frequency for interval number i

X_0^2 approximately follows the chi-square distribution with $K-p-1$ degrees of freedom, where p is the number of parameters in the theoretical distribution (for a normal distribution, $p = 2$). The hypothesis that LOGLOS conforms to a normal distribution with the same mean and variance of the sample would be rejected if $X_0^2 > X_{\alpha, K-p-1}^2$. $X_{\alpha, K-p-1}^2$ is the percentage point of the chi-square random variable with $K-p-1$ degrees of freedom such that the probability that X_0^2 exceeds this value is α . For this research, α is chosen to be 0.05. Also, as a rule, the minimum value for the expected frequency for each interval is set to three. If an expected frequency is less than three, the corresponding interval can be combined with an adjacent interval (the class intervals are not required to be of equal width). Although there is no agreement as to the minimum value of expected frequencies, values of three, four and five are widely accepted (Hines and Montgomery 1980).

As an example, the chi-square goodness of fit test will be performed on LOGLOS for DRG 127. Table 3 lists the intervals chosen with their corresponding cumulative standard normal distribution values, theoretical frequencies and observed frequencies. Recall that N for this sample is 34, and the mean and standard deviation are $\bar{Y} = 1.59$ and $S_{\bar{Y}} = 0.77$, respectively.

From a statistical table, $X_{0.05, 2}^2$ is found to be 5.99 (Hines and Montgomery 1980). Since X_0^2 is less than this value, the

TABLE 3
 CHI-SQUARE CALCULATION FOR LOGLOS, DRG 127
 (N = 34, $\bar{Y} = 1.59$, $S_{\bar{Y}} = 0.77$)

Interval i	Lower Limit A	Upper Limit B	Standard Normal Value for B $= \frac{B - \bar{Y}}{S_{\bar{Y}}}$	Cumulative Frequency Values		Theoretical Frequency E_i $= [F(B) - F(A)] \times N$	Observed Frequency O_i	$\frac{(O_i - E_i)^2}{E_i}$
				F(A)	F(B)			
1	$-\infty$	0.80	-1.03	0.000	0.152	5.17	5	0.006
2	0.80	1.50	-0.12	0.152	0.452	10.20	11	0.063
3	1.50	1.90	0.40	0.452	0.655	6.90	9	0.639
4	1.90	2.60	1.31	0.655	0.905	8.50	6	0.735
5	2.60	∞	∞	0.905	1.000	3.23	3	0.016

$$\chi^2_o = 1.459$$

hypothesis that LOGLOS follows a normal distribution with a mean of 1.59 and a standard deviation of 0.77 cannot be rejected; equivalently, the hypothesis that LOSTOT follows a lognormal distribution with a mean of 6.60 days (equation 1) and a standard deviation of 5.93 days (from equation 2) cannot be rejected. (Note that the mean and standard deviation derived from the LOGLOS parameters approximate the actual LOSTOT parameters.)

A chi-square test was performed for LOGLOS within each DRG. There was one DRG for which the variable did not pass the chi-square test, and two for which there was insufficient data to perform the test. For these DRG's, it was determined that a triangular distribution be used for the generation of LOSTOT. There are three parameters required for a triangular distribution: the minimum, the mode, and the maximum. These parameters were taken empirically from each sample. If there was no single mode, the mid-point of the most frequent interval in the SPSS histogram was used. Table 4 presents the chi-square test results and distributions to be used to generate LOSTOT for each DRG.

It is worthwhile to note that the DRG's for which the lognormal distribution could not be assigned were also the ones with the smallest sample size. Perhaps a larger sample would indicate that LOSTOT was also lognormally distributed for these DRG's.

Furthermore, in the absence of data, an experienced practitioner will be able to estimate the minimum, maximum and most

TABLE 4
CHI-SQUARE TEST RESULTS AND LOSTOT DISTRIBUTIONS FOR EACH DRG

DRG	No. Patients in Sample	χ^2_0	$\chi^2_{0.05, K-3}$	Hypothetical Distribution Type: T-Triangular L-Lognormal	For Lognormal Distribution: μ_x, σ_x (Computed From Y, SY)	For Triangular Distribution Min, Mode, Max
14	16	0.56	3.84	L	13.82, 13.53	--
127	34	1.46	5.99	L	6.60, 5.93	--
148	8	--	--	T	--	9, 12, 29
210	15	4.06	3.84	T	--	5, 21, 32
243	26	0.25	5.99	L	9.89, 7.17	--
468	7	--	--	T	--	2, 8, 24
999	52	0.84	5.99	L	8.45, 7.73	--

likely length of stay for any specific disease. It may even be advantageous to use these parameters as opposed to ones derived from only a few pieces of data.

The second variable to be generated with respect to length of stay is PCTICU. The following SPSS code was used to produce frequency histograms for PCTICU by DRG:

```
FREQUENCIES VARIABLES = PCTICU/  
HISTOGRAM = INCREMENT (0.1)
```

The results of this analysis are given in Appendix 2. Since the PCTICU variables did not consistently exhibit a frequency pattern which corresponded to a classical theoretical distribution, the triangular distribution was chosen for the simulation. Table 5 summarizes the triangular distribution parameters for PCTICU by DRG. For greater accuracy in the generation of this variable, the expected probability that PCTICU equals zero ($P[0]$) and the expected probability that PCTICU equals one ($P[1]$) have been introduced. The observed ratios will be used to estimate the expected probabilities. The triangular distribution parameters are derived only with values of PCTICU other than zero and one. Again, in practice, in the absence of data, an experienced practitioner will be able to estimate the minimum, most likely and maximum percentage of the time a patient spends in intensive care without much difficulty.

TABLE 5

PCTICU VARIABLE GENERATION PARAMETERS

DRG	P(0)	P(1)	No. of Cases For Which $0 < \text{PCTICU} < 1$	Triangular Distribution		
				Min	Mode	Max
14	0.44	0.13	7	0.18	0.23	0.59
127	0.44	0.09	16	0.10	0.50	0.67
148	0.63	0.00	3	0.20	0.24	0.46
210	0.80	0.00	3	0.05	0.06	0.09
243	0.96	0.00	1	0.04	0.04	0.04
468	0.86	0.00	1	0.06	0.06	0.06
999	0.75	0.06	10	0.08	0.40	0.60

With this portion of the analysis, the total length of stay for patients can be randomly generated along with the number of days spent in intensive care and regular care. The following analysis will be that of resource consumption by department, which will determine the way by which resource consumption will be simulated.

Resource Consumption Analysis

The first step in this analysis is to focus attention on certain cost centers with which the total cost can be approximated. This is due to the fact that, for many cases, costs were incurred in only a few cost centers. By analyzing data and generating costs

for only a few centers, and using these costs to estimate total costs, much cumbersome manipulation of data can be avoided. In this research, a regression analysis was performed to approximate the total cost to the patient (TCOST) as a linear function of five cost centers: lab, pharmacy, supplies, respiratory therapy and radiology. These centers were chosen because they appeared to be the more frequently used centers and had the greater contribution to total cost. In equation form, the model to be analyzed is:

$$\begin{aligned} \text{TCOST} = & C_0 + C_1 \times \text{LAB} + C_2 \times \text{PHARM} + C_3 \times \text{SUPP} \\ & + C_4 \times \text{RETHET} + C_5 \times \text{XRAY} \end{aligned}$$

where C_i is the corresponding regression coefficient for each variable. The SPSS code which performs such an analysis is:

```
REGRESSION VARIABLES = TCOST LAB PHARM SUPP RETHER XRAY/
DEPENDENT = TCOST/STEPWISE = LAB PHARM SUPP RETHER XRAY
```

The STEPWISE command enters the independent variables into the equation in order of their significance to the dependent variable; if a variable to be entered has negligible significance, the analysis of the equation is terminated. The results (example in Appendix 3 show a very high multiple regression coefficient for this model within each DRG. A summary of the results is shown in Table 6.

TABLE 6

COEFFICIENTS OF REGRESSION EQUATION

$$\text{TCOST} = C_0 + C_1 \times \text{LAB} + C_2 \times \text{PHARM} + C_3 \times \text{SUPP} + C_4 \times \text{RETHER} + C_5 \times \text{XRAY}$$

Coefficients of Determination (R^2) are also given.

DRG	C_0	C_1	C_2	C_3	C_4	C_5	R^2
14	-134.12	10.89	2.94	0.00	0.00	0.00	0.97
127	600.00	2.41	3.08	0.00	2.23	0.00	0.99
148	3238.49	7.98	0.00	1.82	0.00	0.00	0.98
210	2941.31	5.14	0.00	2.52	3.81	0.00	0.94
243	507.90	0.00	2.38	0.00	0.67	0.00	0.97
468	368.69	8.44	3.69	0.00	0.00	0.00	0.99
999	274.67	1.06	0.69	2.06	1.15	1.38	0.89

This regression analysis has dealt with the cost to the patients. However, the hospital's costs also need to be generated. Therefore, a similar regression model was tested which has the form:

$$\begin{aligned} \text{HCOST} = & K_0 + K_1 \times [\text{CC}_1 \times \text{LAB}] + K_2 \times [\text{CC}_2 \times \text{PHARM}] \\ & + K_3 \times [\text{CC}_3 \times \text{SUPP}] + K_4 \times [\text{CC}_4 \times \text{RETHER}] \\ & + K_5 \times [\text{CC}_5 \times \text{XRAY}] \end{aligned}$$

where CC_i is the observed cost-to-charge ratio for department i , and K_j is the corresponding regression coefficient for each variable. This set of regression equations also produced excellent results (Table 7).

TABLE 7

COEFFICIENTS OF REGRESSION EQUATION

$$\text{HCOST} = K_0 + K_1 \times [\text{CC}_1 \times \text{LAB}] + K_2 \times [\text{CC}_2 \times \text{PHARM}]$$

$$+ K_3 \times [\text{CC}_3 \times \text{SUPP}] + K_4 \times [\text{CC}_4 \times \text{RETHET}] + K_5 \times [\text{CC}_5 \times \text{XRAY}]$$
 Coefficients of Determination (R^2) are also given.

DRG	K_0	K_1	K_2	K_3	K_4	K_5	R^2
14	122.38	1.75	0.00	2.43	0.88	0.00	0.98
127	157.52	1.03	1.92	0.00	1.07	0.00	0.99
148	-356.50	3.48	2.47	0.79	0.00	0.00	~1.00
210	607.25	1.57	0.00	1.36	1.60	2.33	0.95
243	177.06	1.25	2.71	0.00	0.54	0.00	0.96
468	580.02	0.00	3.62	0.00	0.00	0.00	0.92
999	226.15	1.33	0.00	3.26	1.10	0.00	0.77

The next step in resource consumption analysis is to determine what relationship, if any, exists between the costs incurred in each center and the length of stay. If costs can be generated in the simulation as a function of length of stay, then simulated policies which result in the reduction of length of stay would be reflected accordingly in the cost of care. Initially, a linear model was tested which took the form

$$\text{COST}(I) = C_0 + C_1 \times \text{LOSREG} + C_2 \times \text{LOSICU}$$

where $\text{COST}(I)$ is the cost to the patient for services from cost center I. This model resulted in very poor correlation. Therefore, the rate of resource consumption was examined, i.e., the

cost incurred in each cost center per day. Although the actual cost for each day of stay is not singularly available, the average cost per day for a patient can be simply calculated by dividing the departmental cost by the length of stay. The average costs per day can be analyzed to determine how the rate of resource consumption varies with length of stay. If this rate were to remain relatively constant for each increment of length of stay, it could be hypothesized that the resource consumption rate is an independently distributed random variable. To perform this analysis, new variables were introduced into the SPSS program:

```

COMPUTE LPD = LAB/LOSTOT
COMPUTE PPD = PHARM/LOSTOT
COMPUTE SPD = SUPP/LOSTOT
COMPUTE RPD = RETHER/LOSTOT
COMPUTE XPD = XRAY/LOSTOT
COMPUTE AUX = LOSTOT
RECODE AUX (1 THRU 3=1) (4 THRU 6=2) (7 THRU 9=3)
          (10 THRU 12=4) (13 THRU 15=5) (16 THRU 18=6)
          (19 THRU HI=7)

```

The first set of variables (LPD for lab charge per day, PPD for pharmacy charge per day, etc.) defines the average rate of resource consumption from each department. The auxiliary variable AUX groups the LOSTOT variables into class intervals of width three. The SPSS statement

```
BREAKDOWN LPD TO XPD BY AUX
```


presents a brief statistical analysis of LPD, PPD, SPD, RPD and XPD for each value of AUX. Appendix 4 contains some examples of the results of this breakdown by DRG.

The results indicate that the rate of resource consumption does not remain constant as LOSTOT changes; instead, as LOSTOT increases, the consumption per day tends to decrease over an interval of values, then it tends to increase. For example, for DRG 14, the mean supply charge per day (SPD) is \$260.85 for AUX=1 (LOSTOT = 1, 2 and 3); this variable reaches a minimum value of \$24.42 for AUX=4 (LOSTOT = 10, 11 and 12), and increases to \$89.72 for AUX=7 (LOSTOT = 19, 20, 21, ...). This is the general pattern in each department for all of the DRG's. A mathematical model which approximates this behavior is of the form

$$Y = A - B \times X + C \times X^2$$

where Y is the consumption (charges or costs) per day, X is the length of stay, and A, B and C are positive constants.

As a consequence of this finding, a regression model was tested which incorporates the quadratic model. Intensive care stay (LOSICU) and regular care stay (LOSREG) were included in this analysis along with their sum (LOSTOT), since each one of these variables might have a different relationship to the amount of resources consumed. In equation form, the model is

$$\begin{aligned}
 Y = & A - B_1 \times \text{LOSTOT} + C_1 \times \text{LOSTOT}^2 \\
 & - B_2 \times \text{LOSREG} + C_2 \times \text{LOSREG}^2 \\
 & - B_3 \times \text{LOSICU} + C_3 \times \text{LOSICU}^2
 \end{aligned}$$

The SPSS programming required for such an analysis is

```

REGRESSION VARIABLES = LOSTOT LOSREG LOSICU LOS2 REG2
ICU2 LAB PHARM SUPP RETHER XRAY/
STATISTICS = ALL/
DEPENDENT = LAB PHARM SUPP RETHER XRAY/
STEPWISE = LOSTOT LOS2 LOSREG REG2 LOSICU ICU2

```

Recall that LOS2, REG2 and ICU2 were computed as the squares of LOSTOT, LOSREG and LOSICU, respectively.

An example of the results of the regression analyses are given in Appendix 5. Table 8 presents the coefficients of the equations along with their respective coefficients of determination (R^2).

The models to be used in the simulation are those with R^2 values which are greater than or equal to 0.55 (or correlation coefficients greater than or equal to 0.74). Some models cannot be accepted because the equation may produce negative resource consumption values. These criteria for model selection resulted in seventeen regression equations which can be used to generate departmental charges as a function of length of stay. The remaining

TABLE 8

REGRESSION COEFFICIENTS AND R^2 VALUES FOR: COST CENTER CHARGE

$$= C_0 + C_{11} \times \text{LOSTOT} + C_{12} \times \text{LOSTOT}^2 + C_{21} \times \text{LOSREG} + C_{22} \times \text{LOSREG}^2 + C_{31} \times \text{LOSICU} + C_{32} \times \text{LOSICU}^2$$

Cost Center	DRG	Coefficients of Cost Center Charge = F(LOS) Regression Model										Coefficient Determination (R^2)
		C_0	C_{11}	C_{12}	C_{21}	C_{22}	C_{31}	C_{32}				
LAB	14	229.12	0	0	0	0	32.34	0	0.44			
	127	182.85	25.50	0	0	0	0	15.03	0.67			
	148	182.07	0	0	0	2.63	0	0	0.55			
	210	117.04	18.01	0	0	0	0	0	0.28			
	243	172.12	0	0	0	0	283.73	0	0.35			
	468	133.25	0	0.92	0	0	0	0	0.91			
999	108.40	26.05	0	0	0	49.63	0	0.44				
PHARM	14	490.80	0	5.95	-94.99	0	0	0	0.88			
	127	133.65	0	-8.68	0	10.66	0	61.73	0.60			
	148	-409.71	0	0	0	12.11	0	0	0.66*			
	210	58.26	28.99	0	0	0	348.80	0	0.70			
	243	-10.60	24.63	0	0	0	1971.55	0	0.96			
	468	156.81	0	3.22	0	0	0	0	0.87			
999	33.32	45.58	0	0	0	79.61	0	0.37				
SUPP	14	181.75	0	0	0	0	157.15	0	0.77			
	127	186.91	-34.83	-3.83	0	6.10	0	30.71	0.64			
	148	-10.22	0	5.49	0	0	0	0	0.95			
	210	214.21	52.99	0	0	0	0	0	0.40			
	243	14.07	11.11	0	0	0	526.37	0	0.73			
	468	186.17	0	0.90	0	0	758.58	0	0.99			
999	235.28	0	4.41	0	-41.29	0	0	0.56				

TABLE 8 (Continued)

Cost Center	DRG	Coefficients of Cost Center Charge = F(LOS) Regression Model							Coefficient Determination (R^2)
		C ₀	C ₁₁	C ₁₂	C ₂₁	C ₂₂	C ₃₁	C ₃₂	
RETHR	14	119.99	0	0	0	0	0	24.58	0.93
	127	164.82	0	0	31.18	0	0	49.63	0.47
	148	-2969.16	0	0	0	20.46	0	0	0.68*
	210	64.24	0	0	0	0	721.60	-302.46	0.54
	243	53.10	0	0	0	0	2181.20	0	0.73
	468	125.78	-62.38	0	0	5.97	-594.00	0	~1.00
	999	127.79	0	0	0	0	178.91	0	0.28
XRAY	14	71.31	0	0	0	0	0	1.65	0.52
	127	**	0	0	0	0	0	0	--
	148	- 121.85	0	0	0	1.49	0	0	0.63*
	210	**	0	0	0	0	0	0	--
	243	110.35	0	0.29	0	0	0	0	0.17
	468	**	10.13	0	0	0	0	0	--
	999	66.98	10.13	0	0	0	0	0	0.16

* Model rejected due to possible negative value as a result.

** No model generated: All variables insignificant.

eighteen departmental charges will be generated as independently distributed random variables. They will be generated from distributions derived from observed frequencies, in a procedure similar to the one by which length of stay (LOSTOT) distributions were determined. The SPSS histograms for departmental charges were produced by the following code:

```
FREQUENCIES VARIABLES = L to R/
      HISTOGRAM = INCREMENT (200)/
      STATISTICS = ALL
FREQUENCIES VARIABLES = X/
      HISTOGRAM = INCREMENT (100)/
      STATISTICS = ALL
```

The variables L, P, S, R and X are equivalent to LAB, PHARM, SUPP, RETHER, and XRAY with the exception that zero values are treated as missing (see Figure 5). The simulation will generate values accordingly. The histograms, as was the case for length of stay analysis, indicate a lognormal distribution. This is consistent with the statement by Grimaldi and Micheletti that resource consumption distributions are generally "skewed rightward" (1983). Therefore, the histograms for the log of the department charges were generated by the SPSS code:

```
FREQUENCIES VARIABLES = LLAB LPHARM LSUPP LRESP LXRAY/
      HISTOGRAM = NORMAL INCREMENT (0.5)/
      STATISTICS = ALL
```

Appendix 6A and 6B contain the first and second set of histograms.

It was hypothesized that the departmental charges were log-normally distributed. A chi-square goodness of fit test was performed on each of the variables. As was performed for LOSTOT, the variables which did not pass the chi-square test were assigned triangular distributions. A summary of the distribution type and parameters for department charges is in Table 9. Again, for generation by the distributions, the probability that the departmental charges equal zero ($P[\emptyset]$) was introduced.

Application to Simulation

The results of this analysis will be incorporated into the simulation by using a random number generator to produce logical branching along with lognormal and triangular distribution values for length of stay and resource consumption. One set of regression equations will relate the charges from five cost centers (lab, pharmacy, supplies, respiratory therapy and radiology) to the length of stay. The regression equations for total cost approximation will be used to estimate the total costs for a patient as a function of these cost centers, in conjunction with their cost-to-charge ratios.

It is important to note that this simulation will reflect the data from only a three-month period. More data may be required to build a simulation which is more representative of the patient case mix that a hospital encounters throughout the year (due to seasonality of case mix). However, the purpose of this research

TABLE 9

CHI-SQUARE TEST RESULTS AND DEPARTMENT CHARGE DISTRIBUTION
BY DRG FOR CHARGES NOT GENERATED FROM REGRESSION EQUATIONS

Department	DRG	P[Ø]	No. Patients in Sample	χ^2_o	$\chi^2_{o,K-3}$	Hypothetical Distribution Type: T-Triangular L-Lognormal	For Lognormal Distribution: μ, σ (Calculated From Y, SY)	For Triangular Distribution: Min, Mode, Max
LAB	14	0	16	2.81	3.84	L	375.2, 423.9	-
	210	0	15	0.36	3.84	L	452.7, 230.4	-
	243	0	26	0.27	5.99	L	188.7, 124.2	-
	999	0	52	0.87	7.81	L	347.7, 252.1	-
PHARM	148	0	8	--	--	T	-	1055.2, 1755.2, 6909.6
	999	0	52	6.56	7.81	L	480.1, 725.1	-
SUPP	210	0	15	1.37	3.84	L	1284.4, 1003.0	-
	127	0.21	27	0.18	5.99	L	685.4, 884.4	-
RETHR	148	0.25	6	--	--	T	-	21.8, 321.8, 9335.1
	210	0.47	8	--	--	T	-	29.0, 129.0, 763.2
	999	0.46	28	2.03	5.99	L	577.4, 1358.1	-
	14	0.19	13	--	--	T	-	41.0, 41.0, 536.0
XRAY	127	0.03	33	--	5.99	L	131.6, 71.8	-
	148	0	8	--	--	T	-	45.0, 45.0, 773.0
	210	0	15	--	--	T	-	241.0, 391.0, 589.0
	243	0.12	23	0.10	5.99	L	169.8, 127.8	-
	468	0.29	5	--	--	T	-	64.0, 114.0, 220.0
	999	0.08	48	2.95	7.81	L	160.0, 127.2	-

is to establish a methodology by which the model can be constructed with the analysis of any set of data. The following chapter discusses this method in detail.

CHAPTER V

SIMULATION DESIGN AND APPLICATION

Selection of Simulation Language

Patient flow through a hospital can be simulated with any of several languages which are presently available on the market. The General Purpose Simulation System (GPSS), SIMSCRIPT and Simulation Language for Alternative Modeling (SLAM) software packages are a few of the ones which provide for the maintenance of stochastic processes, generation of random variables and statistic collection. SLAM II was the language chosen for the simulation in this research (Pritsker and Pegden, 1979). Although the flow of simulation logic is unique to this software, the modeling principles which will be illustrated can be applied with any language.

SLAM II is a FORTRAN-based language which incorporates network modeling with optional discrete-event modeling, which is coded directly with FORTRAN. The network portion displays certain events encountered by an entity, represented by nodes, and activities through which an entity passes, represented by arrows. Events include the creation or arrival of an entity to the system, its entrance into or exit from a queue, and its departure from the system. Typical activities include services performed for the

entity and other time-dependent processes, as well as conditional branching to different events. The discrete-event portion provides for computation of detailed or complicated routines within special events for which the network's generalized event routines are insufficient.

For this simulation, the initial network portion will model the arrival of patients to the hospital and the assignment of DRG's. The discrete-event section will then generate the length of stay and resource consumption data for each patient. This section is where the simulated policies are to be introduced, along with the routine to calculate the reimbursement to the hospital. Following this, the second network portion will collect statistics for cost and profit analysis.

The Network Portion of the Model

In this simulation, the SLAM network portion will be used to assign a DRG number to an arriving patient and to collect statistics for each patient after the length of stay and resource consumption variables have been generated in the FORTRAN subroutine. The network is presented in Figure 9 and depicts the probabilistic branching required for assigning DRG's and collecting various statistics. The shapes and functions of the nodes are particularly designed for the SLAM software (Pritsker and Pegden, 1979).

The first node on the left side of the network is the CREATE node. Patients are generated according to the parameters specified

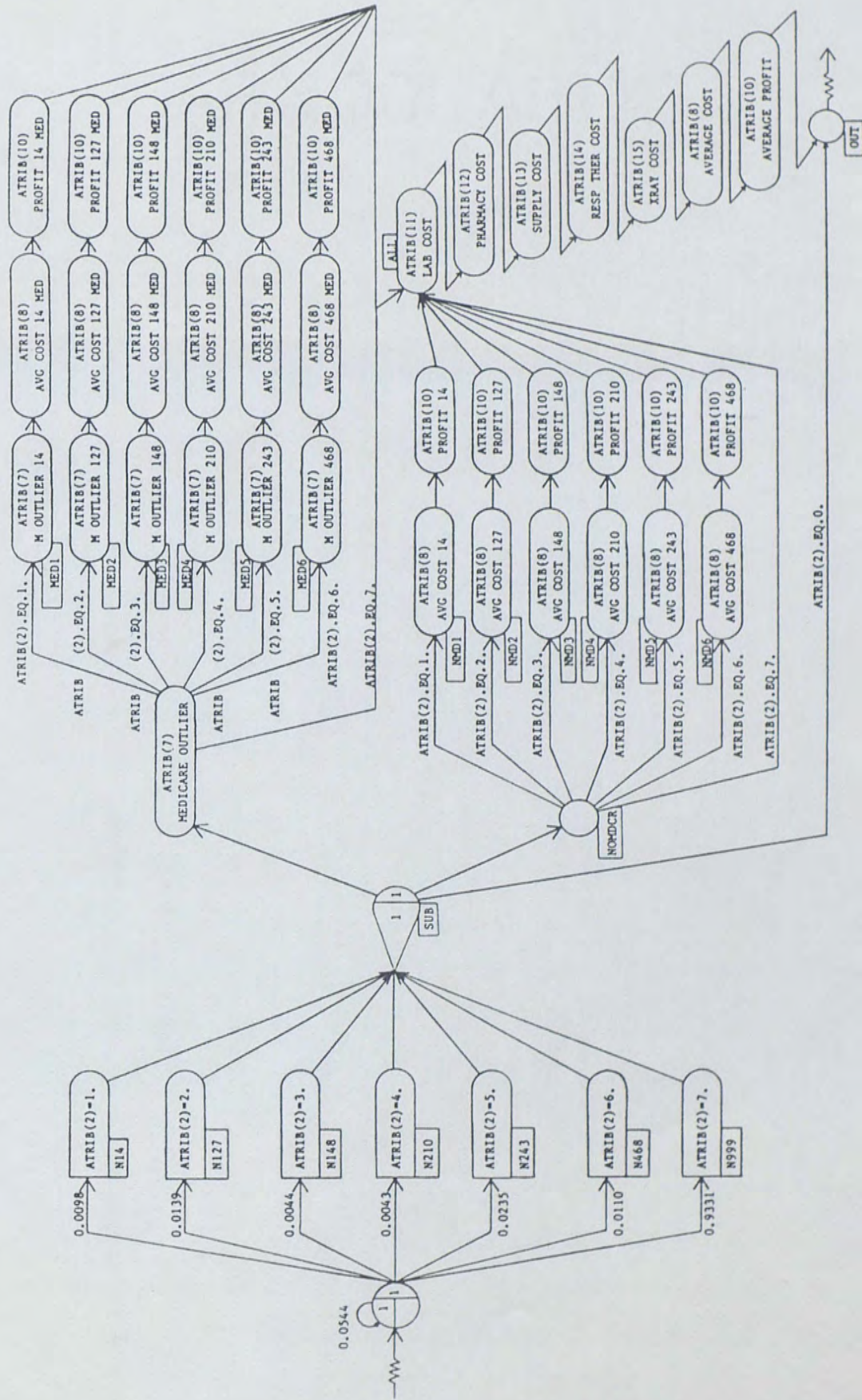


Fig. 9. SLAM network for patient cost simulation.

by this node. The parameters involved in this simulation are the interarrival time, the attribute mark number, and the maximum number of branches which can be taken upon completion of the CREATE routine. The attribute mark number designates the array position to be used to store the time of arrival. The SLAM array is named ATRIB, and can store up to 100 attributes for each entity which passes through the system. In this network, ATRIB(1) will be used to store the patient's time of arrival. The use of other array positions will be explained later.

For the purposes of this research, the interarrival time was chosen to be fixed. Stochastic processes are not a factor in this simulation; however, they may be introduced after further development. The interarrival time can then be randomly generated from one of SLAM's random variable functions. There were 6,098 patients which passed through the hospital in 1983. If the hospital forecasts their case load to increase by ten percent in 1984 (to 6,708 patients), this corresponds to an average interarrival time of 0.0544 days. (This value appears above the CREATE node in the network.)

Upon completion of the CREATE event, each patient is assigned a DRG code based on the actual 1983 case mix. The branches emanating from the CREATE node have associated probabilities which are equal to the observed proportions of the occurrence of each DRG in 1983. This is where forecasts of case-mix changes can be introduced. For example, if the hospital expects a great influx of elderly

population into their community, the increased proportion of patients in particular DRG's can be reflected.

After assignment of a DRG number, the EVENT node calls the FORTRAN discrete-event subroutine. This subroutine generates all of the length of stay and resource consumption values for each patient based on the results of the analysis of data. The ATRIB array position used for each variable in this subroutine is defined in Table 10.

After returning from the discrete-event portion, statistics are collected separately for Medicare and non-Medicare patients. For Medicare patients, the outlier flag is collected for all patients and per DRG (the averaged value will be the percentage of outliers). Cost and profit statistics will also be collected. For non-Medicare patients, only cost and profit will be collected. (These sets of statistics will not be collected for DRG 999.) For all patients, departmental costs will be collected along with total cost and profit.

The SLAM program code for the simulation is presented in Figure 10. The first three lines provide general information about the simulation, set limits on the number of entities attributes in the system and define the time interval for the simulation (0-365 days). The statements for the nodes and arrows in the network follow.

TABLE 10

ATTRIB ARRAY POSITIONS FOR PATIENT ATTRIBUTES

ATTRIB Array Positions	Description of Attribute (Variable Name in Parenthesis)
1	Time of Arrival
2	DRG code (1 through 7) (ID)
3	Total Length of Stay (LOSTOT)
4	Length of Stay in Regular Room (LOSREG)
5	Length of Stay in ICU (LOSICU)
6	Medicare Flag (0 = non-Medicare, 1 = Medicare)
7	Outlier Flag (0 = non-outlier, 1 = outlier)
8	Hospital's Total Cost (TCOST)
9	Reimbursement to Hospital (PAY)
10	Profit [ATTRIB(9) - ATTRIB(8)]
11	Laboratory Cost
12	Pharmacy Cost
13	Supply Cost
14	Respiratory Therapy Cost
15	Radiology Cost

The function of the SLAM network is to "create" patients, assign a DRG to each one, and collect statistics for performance evaluation. The actual cost generation and application of management policies is performed in the discrete-event subroutine.

```

1 GEN,T. ATKINS,PATIENTS,7/29/84;
2 LIM,1,15,50;
3 INIT,0.,365.;
4 NETWORK;
5 CREATE,,0544,,1,,1;
6 ACTIVITY,,0.0098,N14;
7 ACTIVITY,,0.0139,N127;
8 ACTIVITY,,0.0044,N148;
9 ACTIVITY,,0.0043,N210;
10 ACTIVITY,,0.0235,N243;
11 ACTIVITY,,0.0110,N468;
12 ACTIVITY,,0.9331,N999;
13 N14 ASSIGN,ATTRIB(2)=1.;
14 ACT,,SUB;
15 N127 ASSIGN,ATTRIB(2)=2.;
16 ACT,,SUB;
17 N148 ASSIGN,ATTRIB(2)=3.;
18 ACT,,SUB;
19 N210 ASSIGN,ATTRIB(2)=4.;
20 ACT,,SUB;
21 N243 ASSIGN,ATTRIB(2)=5.;
22 ACT,,SUB;
23 N468 ASSIGN,ATTRIB(2)=6.;
24 ACT,,SUB;
25 N999 ASSIGN,ATTRIB(2)=7.;
26 SUB EVENT,1,1;
27 ACT,,ATTRIB(2).EQ.0.,OUT;
28 ACT,,ATTRIB(6).EQ.0.,NOMDCR;
29 ACT,,ATTRIB(6).EQ.1.;
30 COLCT,ATTRIB(7),MEDICARE OUTLIER;
31 ACT,,ATTRIB(2).EQ.1.,MED1;
32 ACT,,ATTRIB(2).EQ.2.,MED2;
33 ACT,,ATTRIB(2).EQ.3.,MED3;
34 ACT,,ATTRIB(2).EQ.4.,MED4;
35 ACT,,ATTRIB(2).EQ.5.,MED5;
36 ACT,,ATTRIB(2).EQ.6.,MED6;
37 ACT,,ATTRIB(2).EQ.7.,ALL;
38 MED1 COLCT,ATTRIB(7),M OUTLIER 14;
39 COLCT,ATTRIB(8),AVG COST 14 MED;
40 COLCT,ATTRIB(10),PROFIT 14 MED;
41 ACT,,ALL;
42 MED2 COLCT,ATTRIB(7),M OUTLIER 127;
43 COLCT,ATTRIB(8),AVG COST 127 MED;
44 COLCT,ATTRIB(10),PROFIT 127 MED;
45 ACT,,ALL;
46 MED3 COLCT,ATTRIB(7),M OUTLIER 148;
47 COLCT,ATTRIB(8),AVG COST 148 MED;
48 COLCT,ATTRIB(10),PROFIT 148 MED;
49 ACT,,ALL;
50 MFD4 COLCT,ATTRIB(7),M OUTLIER 210;
51 COLCT,ATTRIB(8),AVG COST 210 MED;
52 COLCT,ATTRIB(10),PROFIT 210 MED;
53 ACT,,ALL;
54 MED5 COLCT,ATTRIB(7),M OUTLIER 243;
55 COLCT,ATTRIB(8),AVG COST 243 MED;
56 COLCT,ATTRIB(10),PROFIT 243 MED;
57 ACT,,ALL;
58 MED6 COLCT,ATTRIB(7),M OUTLIER 468;
59 COLCT,ATTRIB(8),AVG COST 468 MED;
60 COLCT,ATTRIB(10),PROFIT 468 MED;
61 ACT,,ALL;
62 NOMDCR GOON;
63 ACT,,ATTRIB(2).EQ.1.,NMD1;
64 ACT,,ATTRIB(2).EQ.2.,NMD2;
65 ACT,,ATTRIB(2).EQ.3.,NMD3;
66 ACT,,ATTRIB(2).EQ.4.,NMD4;
67 ACT,,ATTRIB(2).EQ.5.,NMD5;
68 ACT,,ATTRIB(2).EQ.6.,NMD6;
69 ACT,,ATTRIB(2).EQ.7.,ALL;
70 NMD1 COLCT,ATTRIB(8),AVG COST 14;
71 COLCT,ATTRIB(10),PROFIT 14;
72 ACT,,ALL;
73 NMD2 COLCT,ATTRIB(8),AVG COST 127;
74 COLCT,ATTRIB(10),PROFIT 127;
75 ACT,,ALL;
76 NMD3 COLCT,ATTRIB(8),AVG COST 148;
77 COLCT,ATTRIB(10),PROFIT 148;
78 ACT,,ALL;
79 NMD4 COLCT,ATTRIB(8),AVG COST 210;
80 COLCT,ATTRIB(10),PROFIT 210;
81 ACT,,ALL;
82 NMD5 COLCT,ATTRIB(8),AVG COST 243;
83 COLCT,ATTRIB(10),PROFIT 243;
84 ACT,,ALL;
85 NMD6 COLCT,ATTRIB(8),AVG COST 468;
86 COLCT,ATTRIB(10),PROFIT 468;
87 ALL COLCT,ATTRIB(11),LAB COST;
88 COLCT,ATTRIB(12),PHARMACY COST;
89 COLCT,ATTRIB(13),SUPPLY COST;
90 COLCT,ATTRIB(14),RESP THER COST;
91 COLCT,ATTRIB(15),XRAY COST;
92 COLCT,ATTRIB(8),AVERAGE COST;
93 COLCT,ATTRIB(10),PROFIT;
94 OUT TERMINATE;
95 END;
96 FIN;

```

Fig. 10. SLAM program listing for patient simulation.

The Discrete-Event Portion of the Model

This FORTRAN subroutine is the heart of the patient flow model. All of the results of the data analysis are incorporated with this routine to generate length of stay, resource consumption and total cost for each patient. The results of the data analysis are assigned to the following array variables:

XLOS(7,8)	Length of stay parameters for each DRG
RESCON(7,5,6)	Resource consumption parameters for each DRG by department. Includes regression coefficients and lognormal and triangular distribution parameters.
TCHARG(7,6)	Total charge regression equation coefficients (from Table 6)
TCOST(7,6)	Total cost regression equation coefficients (from Table 7)

The positions within XLOS(ID,J) are defined as follows (ID is the DRG slot and ranges from 1 to 7):

<u>Cell Number (J)</u>	<u>Description of Contents</u>
1	If this value equals zero, it indicates that a lognormal distribution will be used to generate LOSTOT. Otherwise, a triangular distribution will be used and the cell contains the maximum value parameter for the triangular distribution.
2	For a lognormal distribution, the theoretical mean of LOSTOT; for a triangular distribution, the mode parameter.
3	For a lognormal distribution, the standard deviation of LOSTOT; for a triangular distribution, the minimum value parameter.
4	The expected probability that PCTICU equals zero.
5	The expected probability that PCTICU equals one.

- 6 The minimum value parameter of the triangular distribution for PCTICU.
- 7 The node parameter of the PCTICU triangular distribution.
- 8 The maximum value parameter of the PCTICU triangular distribution.

The coefficients of LOSTOT in the departmental charge regression equations derived in Chapter IV (see Table 7) were combined with those of LOSREG and LOSICU, since $LOSTOT = LOSREG + LOSICU$. The results are equations with five independent variables, which take the form:

$$\begin{aligned} \text{CHARGE} = & C_0 + C_1 \times \text{LOSREG} + C_2 \times \text{LOSIKU} \\ & + C_3 \times \text{LOSREG}^2 + C_4 \times \text{LOSIKU}^2 + C_5 \times \text{LOSTOT}^2 \end{aligned}$$

where the C_i 's are the regression coefficients. These equations will be included in the array RESCON (ID,JDEP,K). The positions within RESCON (ID,JDEP,K) are defined as follows (JDEP is the department number, and ranges from 1 to 6).

<u>Cell Number (K)</u>	<u>Description of Contents</u>
1	If this value is zero, it indicates that a distribution (lognormal or triangular) will be used to generate charges from the designated department. Otherwise, a regression equation will be used and the cell contains the constant (C_0) of the equation.
2	Coefficient C_1 if regression equation is being used; for distribution generation, the expected probability that the departmental charges equal zero.
3	For regression, coefficient C_2 ; for generation by distribution, this cell contains the distribution type flag (\emptyset for lognormal, 1 for triangular).

- 4 Coefficient C_3 of regression equation; theoretical mean for lognormal distribution; or minimum value parameter for triangular distribution.
- 5 Coefficient C_4 of regression equation; standard deviation for lognormal distribution; or mode parameter for triangular distribution.
- 6 Coefficient C_5 of regression equation; or maximum parameter for triangular distribution; (not applicable for lognormal distribution).

The TCOST array contains the coefficients of the total cost regression equations (Table 7). The coefficients are arranged sequentially (i.e., C_0 is assigned to cell 1, C_1 assigned to cell 2, etc.). Likewise, the TCHARG array contains the total charge regression coefficients from Table 6.

Several other variables are required for a complete model of patient resource consumption. These are defined as follows:

- PMEDCR(ID): The expected proportion of Medicare patients for each DRG. The proportions observed from 1983 data will be used as estimates. Table 11 presents these proportions.
- CRATIO(JDEP): The cost-to-charge ratio for each department. These actual ratios from a three-month period are presented in Table 12.
- CPXRAY: The unit charge of one x-ray in dollars (the radiology charge generated in the model will be rounded to the nearest unit charge).

Variables pertinent to the computation of reimbursement to the hospital are:

- PARATE(ID): The pre-determined Medicare reimbursement amount for each DRG, in dollars (not applicable for DRG 999). These amounts are given in Table 13.

TABLE 11
 MEDICARE PATIENTS PER DRG, 1983

DRG	Number of Patients, 1983	Number of Medicare Patients	Proportion of Medicare Patients
14	60	52	0.87
127	85	63	0.74
148	27	19	0.70
210	26	22	0.85
243	143	44	0.31
468	67	25	0.37
999	5690	1150	0.20
Total	6098	1375	0.23

TABLE 12
 OBSERVED COST-TO-CHARGE RATIOS FOR COST CENTERS
 INCLUDED IN THE MODEL (JANUARY-MARCH, 1984)

Cost Center	Cost-To-Charge Ratio
Laboratory	0.713
Pharmacy	0.391
Supplies	0.518
Respiratory Therapy	0.447
Radiology	0.653

TABLE 13

1983-84 MEDICARE PAYMENT RATES AND OUTLIER
PARAMETERS FOR FLORIDA URBAN HOSPITALS

DRG	Payment Rate (\$)	Trim Point (Days)	National Average Length of Stay (Days)
14	3558.95	30	9.9
127	2738.34	28	7.8
148	6707.21	37	17.0
210	5481.16	38	17.8
243	1986.67	28	7.5
468	5534.83	31	11.2
999	2887.26*	N.A.	N.A.

* Estimated average rate for all DRG's other than 14, 127, 148, 243 and 468.

- AVGLOS(ID): Medicare's average length of stay for each DRG, used for outlier payment calculation. Table 12 presents these values.
- LTRIMP(ID): Medicare's "trim point", or outlier threshold limit for each DRG. Patients whose length of stay exceeds this value are considered outliers. These limits are presented in Table 12.
- PAYEXP: Expected proportion of payment received from non-Medicare patients. The proportion observed from the data for this research was 90%.
- OUTLIR: Expected proportion of outliers, all Medicare patients. Johnson and Appel report that this value is approximately 4.5% (1983). This proportion will be used to generate outliers for DRG 999.

- OTLPAY: Expected ratio of Medicare reimbursement received to the cost of treatment for outliers. Johnson and Appel (1983) state that Medicare "will pay no more than 30%-40% of total outlier cost". Therefore, this ratio was chosen to be equal to 40%. This will be used to compute an estimated reimbursement for all Medicare outliers in DRG 999.
- CLMTOL: Medicare's cost outlier threshold. Any patient whose accumulated charges exceed this amount is also considered an outlier. For Florida urban hospitals, this amount is \$11,900.
- PCRATE: Percentage of the DRG reimbursement rate in effect. For 1983-84, Medicare will reimburse hospitals 25% of the DRG rate plus 75% of the traditional charge-based reimbursement.

For the following fiscal years, this weighted payment will change until 100% DRG reimbursement is in effect. For this simulation, PCRATE = 25%.

Initial test runs of the simulation revealed that the departmental charge regression equations were valid for only a certain range of length of stay values. Specifically, when a patient's length of stay exceeded the maximum length of stay from the three-month data base, or fell below the minimum observed value, extremely large or even negative charges were frequently generated. Therefore, an algorithm was developed to produce realistic results. In cases where the generated charges fell outside the observed range of charges, the following linear approximation was substituted for the regression model:

$$\text{CHARGE}(\text{JDEP}) = \text{LOSTOT} \times (\text{CHGMAX}(\text{ID}, \text{JDEP}) / \text{LOSMAX}(\text{ID}))$$

where:

$\text{CHGMAX}(\text{ID}, \text{JDEP})$ = the maximum observed charge from department JDEP for DRG ID

$\text{LOSMAX}(\text{ID})$ = the maximum observed length of stay for DRG ID. (Note that this does not necessarily correspond to the maximum charges from each department.)

Also, $\text{CHGMIN}(\text{ID}, \text{JDEP})$ is defined as the minimum observed charge from department JDEP for DRG ID. Although the effectiveness of this algorithm has not been measured, it will provide a viable approximation for department charges. In theory, the maximum length of stay from several patient samples correlates reasonably well with maximum departmental charges from those samples. In any case, the proportional relationship of charges to length of stay will be incorporated in this algorithm. Furthermore, the number of cases for which this algorithm will be used should be relatively small. The values for the arrays used in the algorithm are given in Table 14.

All of the variables defined to this point are read into the simulation by the SLAM subroutine named INTLC. The listing of this routine is given in Figure 11. The data is read in free format from records which are appended to the SLAM network statements. The common block labeled UCOM1 will also be used by the discrete-event subroutine (EVENT) to receive the values read in INTLC.

TABLE 14

ARRAY VALUES FOR THE SPECIAL LINEAR DEPARTMENT CHARGE APPROXIMATION:
 $\text{CHARGE}(\text{JDEP}) = \text{LOSTOT} \times \text{CHGMAX}(\text{ID}, \text{JDEP}) / \text{LOSMAX}(\text{ID})$

ID	DRG No.	LOSMAX (ID) (Days)	CHGMIN(ID, JDEP), CHGMAX(ID, JDEP), (\$)				
			JDEP = 1 (Lab)	JDEP = 2 (Pharmacy)	JDEP = 3 (Supplies)	JDEP = 4 (Resp. Ther.)	JDEP = 5 (X-ray)
1	14	27	27., 712.	142., 3651.	0., 2943.	0., 6503.	0., 536.
2	127	30	88., 1092.	9., 2634.	0., 1136.	0., 2788.	0., 376.
3	148	29	343., 1767.	1055., 6910.	457., 4743.	0., 9335.	41., 773.
4	210	32	211., 928.	99., 1391.	143., 1946.	0., 763.	241., 589.
5	243	24	62., 456.	61., 2577.	0., 818.	0., 2234.	0., 427.
6	468	25	39., 661.	9., 2037.	6., 1205.	0., 2069.	0., 220.
7	999	20	41., 1126.	36., 1672.	0., 1509.	0., 1552.	0., 601.


```

SUBROUTINE INTLC
COMMON/SCOM1/ ATRIB(100),DD(100),DDL(100),DTNOW,II,MFA,MSTOP,NCLNRR
1,NCRDR,NPRNT,NNRUN,NNSET,NTAPE,SS(100),SSL(100),TNEXT,TNOW,XX(100)
COMMON/UCOM1/ PMEDCR(7),PARATE(7),AVGLOS(7),LTRIMP(7),XLOS(7,8),RE
2SCON(7,5,6),CRATIO(5),TCOST(7,6),TCHARG(7,6),NDRG,NDEPT,CPXRAY,PAY
3EXP,OUTLIR,OTLPAY,CLMTOL,PCRATE,LOSMAX(7),CHGMIN(7,5),CHGMAX(7,5)
NDEPT=5
NDRG=7
CPXRAY=49.00
OUTLIR=0.045
OTLPAY=0.40
CLMTOL=11900.00
PAYEXP=0.90
PCRATE=0.25
NDP1=NDEPT+1
NDP7=NDEPT+7
DO 10 I=1,NDRG
READ(5,*) PMEDCR(I)
READ(5,*) PARATE(I)
READ(5,*) AVGLOS(I)
READ(5,*) LTRIMP(I)
READ(5,*) LOSMAX(I)
10 READ(5,*) (XLOS(I,J),J=1,8)
CONTINUE
DO 20 J=1,NDEPT
READ(5,*) CRATIO(J)
DO 20 I=1,NDRG
20 READ(5,*) (RESCON(I,J,K),K=1,6)
CONTINUE
DO 30 I=1,NDRG
30 READ(5,*) (TCOST(I,J),J=1,NDP1)
CONTINUE
DO 35 I=1,NDRG
35 READ(5,*) (TCHARG(I,J),J=1,NDP1)
CONTINUE
DO 40 I=1,NDRG
40 READ(5,*) (CHGMIN(I,J),J=1,NDEPT)
READ(5,*) (CHGMAX(I,J),J=1,NDEPT)
CONTINUE
RETURN
END

```

Fig. 11. SLAM initialization subroutine INTLC.

A functional flowchart of subroutine EVENT is presented in Figure 12. The flowchart illustrates the logical process of length of stay and resource consumption generation, as well as the reimbursement scheme. Also, it indicates the placement of certain management policies at particular stages of the program. The program listing of subroutine EVENT is shown in Appendix 7. Note that the

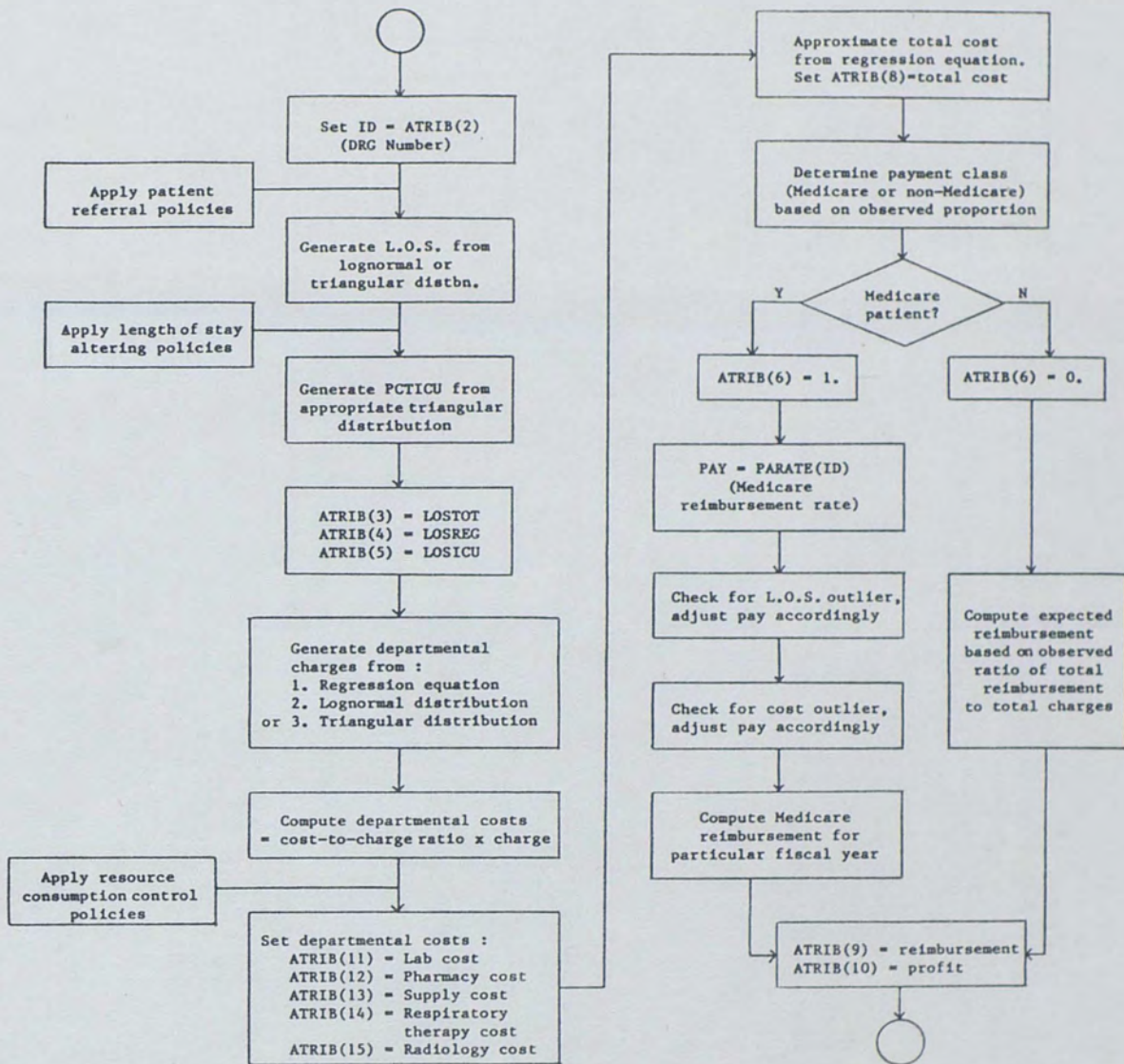


Fig. 12. Functional flowchart for subroutine EVENT.

maximum reasonable length of stay for any patient was set equal to 60 days. Any generated L.O.S. value which exceeds this is discarded.

Verification and Initial Validation of the Model

The results of the simulation with no policies interjected are presented in Figure 13. For initial verification, the percentage of patients and proportion of Medicare patients in each DRG was calculated, and the results are given in Table 15. Over the 365-day interval, 6718 patients passed through the system (6708 were expected) and 1536, or 22.8%, of them were Medicare patients (the expected value was 23.0%). 5.6% of the Medicare patients were outliers (4.5% was expected). The average, minimum and maximum department costs are within reason. These results indicate that the model is mathematically and logically sound.

TABLE 15

CASE-MIX AND PROPORTION OF MEDICARE PATIENTS
FROM SIMULATION WITH NO POLICIES INTRODUCED
(Actual 1983 Values in Parenthesis, Where Applicable)

DRG	Number of Non-Medicare Patients	Number of Medicare Patients	Percentage of Outliers (Medicare Patients Only)
14	10 (8)	65 (52)	15.4
127	23 (22)	77 (63)	0.0
148	11 (8)	21 (19)	42.9
210	4 (4)	31 (22)	1.0
243	109 (99)	53 (44)	0.4
468	55 (42)	21 (25)	0.0
999	4970 (4540)	1268 (1150)	-
Total	5723 (5182)	1536 (1375)	5.6

SLAM SUMMARY REPORT

SIMULATION PROJECT PATIENTS

BY T. ATKINS

DATE 7/29/1984

RUN NUMBER 1 OF 1

CURRENT TIME 0.3650E+03

STATISTICAL ARRAYS CLEARED AT TIME 0.0000E+00

STATISTICS FOR VARIABLES BASED ON OBSERVATION

	MEAN VALUE	STANDARD DEVIATION	COEFF. OF VARIATION	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBSERVATIONS
MEDICARE OUTLIER	0.5664E-01	0.2312E+00	0.4082E+01	0.0000E+00	0.1000E+01	1536
M OUTLIER 14	0.1538E+00	0.3636E+00	0.2363E+01	0.0000E+00	0.1000E+01	65
AVG COST 14 MED	0.1766E+04	0.1418E+04	0.8032E+00	0.4277E+03	0.7825E+04	65
PROFIT 14 MED	0.4485E+04	0.4204E+04	0.9371E+00	0.3872E+03	0.2755E+05	65
M OUTLIER 127	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	77
AVG COST 127 MED	0.9819E+03	0.4827E+03	0.4916E+00	0.4217E+03	0.2666E+04	77
PROFIT 127 MED	0.2597E+04	0.9903E+03	0.3813E+00	0.1436E+04	0.5967E+04	77
M OUTLIER 148	0.4288E+00	0.5071E+00	0.1183E+01	0.0000E+00	0.1000E+01	21
AVG COST 148 MED	0.5688E+04	0.1732E+04	0.3046E+00	0.3195E+04	0.8840E+04	21
PROFIT 148 MED	0.6029E+04	0.2670E+04	0.4429E+00	0.1493E+04	0.1131E+05	21
M OUTLIER 210	0.9677E-01	0.3005E+00	0.3106E+01	0.0000E+00	0.1000E+01	31
AVG COST 210 MED	0.2735E+04	0.5753E+03	0.2103E+00	0.1834E+04	0.4018E+04	31
PROFIT 210 MED	0.5425E+04	0.1178E+04	0.2172E+00	0.3680E+04	0.7696E+04	31
M OUTLIER 243	0.3774E-01	0.1924E+00	0.5098E+01	0.0000E+00	0.1000E+01	53
AVG COST 243 MED	0.7478E+03	0.4436E+03	0.5932E+00	0.3811E+03	0.3071E+04	53
PROFIT 243 MED	0.8576E+03	0.5549E+03	0.6471E+00	-0.3587E+03	0.4240E+04	53
M OUTLIER 468	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	21
AVG COST 468 MED	0.1481E+04	0.6477E+03	0.4374E+00	0.8427E+03	0.2799E+04	21
PROFIT 468 MED	0.3638E+04	0.1433E+04	0.3940E+00	0.2226E+04	0.6556E+04	21
AVG COST 14	0.1260E+04	0.9886E+03	0.7844E+00	0.4610E+03	0.3577E+04	10
PROFIT 14	0.3992E+04	0.2543E+04	0.6369E+00	0.1072E+04	0.8660E+04	10
AVG COST 127	0.9346E+03	0.4794E+03	0.5129E+00	0.4357E+03	0.2389E+04	23
PROFIT 127	0.2391E+04	0.1269E+04	0.5307E+00	0.1004E+04	0.6302E+04	23
AVG COST 148	0.5685E+04	0.1830E+04	0.3218E+00	0.3060E+04	0.9383E+04	11
PROFIT 148	0.5685E+04	0.2877E+04	0.5061E+00	0.1690E+04	0.1124E+05	11
AVG COST 210	0.2478E+04	0.4340E+03	0.1752E+00	0.2075E+04	0.3015E+04	4
PROFIT 210	0.5098E+04	0.1091E+04	0.2140E+00	0.3716E+04	0.6220E+04	4
AVG COST 243	0.7594E+03	0.4536E+03	0.5973E+00	0.4177E+03	0.3235E+04	109
PROFIT 243	0.5689E+03	0.5132E+03	0.9020E+00	0.1585E+03	0.3017E+04	109
AVG COST 468	0.1405E+04	0.4524E+03	0.3219E+00	0.8427E+03	0.2614E+04	55
PROFIT 468	0.2786E+04	0.1292E+04	0.4638E+00	0.1179E+04	0.6236E+04	55
LAR COST	0.2452E+03	0.1765E+03	0.7199E+00	0.1534E+02	0.2476E+04	6718
PHARMACY COST	0.1924E+03	0.2857E+03	0.1485E+01	0.2245E+01	0.4549E+04	6718
SUPPLY COST	0.2098E+03	0.2784E+03	0.1327E+01	0.1269E+02	0.2391E+04	6718
RESP THER COST	0.1485E+03	0.4534E+03	0.3052E+01	0.0000E+00	0.1262E+05	6718
XRAY COST	0.9859E+02	0.8677E+02	0.8802E+00	0.0000E+00	0.1120E+04	6718
AVERAGE COST	0.1389E+04	0.1075E+04	0.7743E+00	0.3811E+03	0.1624E+05	6718
PROFIT	0.9441E+03	0.1083E+04	0.1147E+01	-0.3587E+03	0.2755E+05	6718

Fig. 13. Summarized results of simulation with no policies introduced.

Thorough validation of the model is not possible at this stage of research. This is due to the fact that there is little information available from the hospital which would be useful for model

validation. However, some validation can be accomplished with the information that is at hand.

The departmental costs can also be validated to a certain degree. To accomplish this, the new charge data were converted to costs by the cost-to-charge ratios and compared with the simulated costs. Table 16 shows this comparison.

TABLE 16
COMPARISON OF SIMULATED AVERAGE DEPARTMENTAL
COSTS AND ACTUAL COSTS

Department	Actual Average Cost (\$)	Simulated Average Cost (\$)	Error (%)
Lab	247.0	245.2	0.7
Pharmacy	184.6	192.4	4.2
Supplies	178.4	209.8	17.6
Respiratory Therapy	123.7	148.5	20.0
Radiology	98.9	98.6	0.3

The reason for the large over-approximation in the supply and respiratory therapy departments is that the distributions used in this generation are not representative of actual data. First, the triangular distributions which were used were based on a small amount of data, which in a few cases contained an extremely high maximum. The mean of the distribution, then, was much larger than that of the data. For example, for DRG 148, the actual mean

non-zero respiratory therapy cost was \$841.30, and the maximum value was \$4173.00. The costs generated from the particular triangular distribution in this department and DRG resulted in a mean value of \$1307.

Second, the mean values for the log-normal distributions were transformed from the parameters of the logged data; and in some cases, this mean was quite different from the actual mean. For example, for DRG 999, the actual mean non-zero respiratory therapy cost was \$194.60. The mean which was transformed from the logged data was \$258.10. The latter value was used to generate costs in the simulation, since it was the result of the positive chi-square test.

It is believed that a larger data base would decrease the magnitude of errors in the simulated costs, for two reasons: the use of more data could possibly eliminate the need for triangular distributions, since there would be enough data points to attempt to fit a log normal distribution to the data; and more data would result in a more stable transformation between the parameters of the actual data and their logged values in cases for which a log-normal distribution would be used.

To further validate the model, the costs per DRG were compared. Table 17 presents the comparison, which indicates a very accurate model for most DRG's. The large errors can be attributed primarily to the following facts: DRG's number 148 and 468 were analyzed

with only eight and seven data points, respectively. The value of regression equations derived from this quantity of data is questionable and the average cost generated for DRG 148 tends to support this.

Second, the data for the miscellaneous category 999 is evidently not as statistically similar as data which is segregated by DRG. However, the inclusion of more DRG's for particular analysis will result in fewer DRG's incorporated into the miscellaneous category. It is believed that this will tend to cause the category to have more statistically similar data. The inaccuracy which appears in the simulation results strengthens the need for a larger data base.

TABLE 17
COMPARISON OF THE AVERAGE
COST PER PATIENT BY DRG

DRG	Actual Average Cost (\$)	Simulated Average Cost (\$)	Error (%)
14	1698.6	1699.	0.0
127	996.0	971.0	2.5
148	4336.8	5687.	31.1
210	2673.5	2706.	1.2
243	693.3	755.6	8.5
468	1489.6	1426.	4.3
999	1180.7	1379.	16.7

Interjection of Policies and Forecasts

This simulation is capable of predicting the effects of many types of alterations to the system. One alteration has already been introduced, namely, the forecasted increase in patient load. For the purposes of illustration, two management policies will be introduced. The first policy is that of decreasing the costs incurred in the radiology department by ten percent. The FORTRAN code that is inserted immediately following the department cost calculation is:

```
IF (J.NE.5) GO TO 100
  ATRIB(K)=.90*ATRIB(K)
100 CONTINUE
```

The summary report from the simulation is given in Figure 14. The total profit is \$6.344 million ($\944.40×6718). With no policy, the profit was \$6.342 million. The simulation indicates that a ten percent increase in efficiency for the radiology department would result in a net gain on the order of \$2000.

The second policy is that of extending the length of stay of patients whose stay approaches the outlier trim point. This policy would be attempted under the assumption that outliers (Medicare and non-Medicare combined) are profitable to hospitals. The patient's length of stay will be extended by two days if the length of stay is within two days of the trim point. This policy

is simulated by the following code in subroutine EVENT (the code is inserted immediately after length of stay is generated):

```

LOSDIF=LOS-LTRIMP(ID)

IF(LOSDIF.GT.-2) LOS=LOS+2

```

SLAM SUMMARY REPORT

SIMULATION PROJECT PATIENTS BY T. ATKINS
DATE 7/29/1984 RUN NUMBER 1 OF 1

CURRENT TIME 0.3650E+03
STATISTICAL ARRAYS CLEARED AT TIME 0.0000E+00

STATISTICS FOR VARIABLES BASED ON OBSERVATIONS

	MEAN VALUE	STANDARD DEVIATION	COEFF. OF VARIATION	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBSERVATIONS
MEDICARE OUTLIER	0.5666E-01	0.2312E+00	0.4082E+01	0.0000E+00	0.1000E+01	1536
M OUTLIER 14	0.1538E+00	0.3636E+00	0.2363E+01	0.0000E+00	0.1000E+01	65
AVG COST 14 MED	0.1766E+04	0.1418E+04	0.8032E+00	0.4277E+03	0.7825E+04	65
PROFIT 14 MED	0.4486E+04	0.4204E+04	0.9371E+00	0.3872E+03	0.2755E+05	65
W OUTLIER 127	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	77
AVG COST 127 MED	0.9819E+03	0.4827E+03	0.4916E+00	0.4217E+03	0.2666E+04	77
PROFIT 127 MED	0.2597E+04	0.9703E+03	0.3813E+00	0.1436E+04	0.5967E+04	77
M OUTLIER 148	0.4286E+00	0.5071E+00	0.1183E+01	0.0000E+00	0.1000E+01	21
AVG COST 148 MED	0.5688E+04	0.1732E+04	0.3046E+00	0.3195E+04	0.8840E+04	21
PROFIT 148 MED	0.6029E+04	0.2670E+04	0.4429E+00	0.1493E+04	0.1131E+05	21
M OUTLIER 210	0.9677E-01	0.3005E+00	0.3106E+01	0.0000E+00	0.1000E+01	31
AVG COST 210 MED	0.2674E+04	0.5764E+03	0.2156E+00	0.1775E+04	0.3944E+04	31
PROFIT 210 MED	0.5488E+04	0.1174E+04	0.2138E+00	0.3739E+04	0.7770E+04	31
W OUTLIER 243	0.3774E-01	0.1924E+00	0.5098E+01	0.0000E+00	0.1000E+01	53
AVG COST 243 MED	0.7478E+03	0.4436E+03	0.5932E+00	0.3811E+03	0.3071E+04	53
PROFIT 243 MED	0.8576E+03	0.5549E+03	0.6471E+00	-0.3587E+03	0.4240E+04	53
M OUTLIER 468	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	21
AVG COST 468 MED	0.1481E+04	0.6477E+03	0.4374E+00	0.8427E+03	0.2799E+04	21
PROFIT 468 MED	0.3638E+04	0.1433E+04	0.3940E+00	0.2226E+04	0.6556E+04	21
AVG COST 14	0.1260E+04	0.9886E+03	0.7844E+00	0.4610E+03	0.3577E+04	10
PROFIT 14	0.3992E+04	0.2543E+04	0.6369E+00	0.1072E+04	0.8660E+04	10
AVG COST 127	0.9346E+03	0.4794E+03	0.5129E+00	0.4357E+03	0.2389E+04	23
PROFIT 127	0.2391E+04	0.1269E+04	0.5307E+00	0.1004E+04	0.6302E+04	23
AVG COST 148	0.5685E+04	0.1830E+04	0.3218E+00	0.3060E+04	0.9383E+04	11
PROFIT 148	0.5685E+04	0.2877E+04	0.5061E+00	0.1690E+04	0.1124E+05	11
AVG COST 210	0.2425E+04	0.4347E+03	0.1792E+00	0.2015E+04	0.2963E+04	4
PROFIT 210	0.5150E+04	0.1088E+04	0.2113E+00	0.3775E+04	0.6272E+04	4
AVG COST 243	0.7594E+03	0.4536E+03	0.5973E+00	0.4177E+03	0.3235E+04	109
PROFIT 243	0.5689E+03	0.5132E+03	0.9020E+00	0.1585E+03	0.3017E+04	109
AVG COST 468	0.1405E+04	0.4524E+03	0.3219E+00	0.8427E+03	0.2614E+04	55
PROFIT 468	0.2786E+04	0.1292E+04	0.4638E+00	0.1179E+04	0.6236E+04	55
LAB COST	0.2452E+03	0.1765E+03	0.7199E+00	0.1534E+02	0.2476E+04	6718
PHARMACY COST	0.1924E+03	0.2857E+03	0.1485E+01	0.2245E+01	0.4549E+04	6718
SUPPLY COST	0.2098E+03	0.2784E+03	0.1327E+01	0.1269E+02	0.2391E+04	6718
RESP THER COST	0.1485E+03	0.4534E+03	0.3052E+01	0.0000E+00	0.1262E+05	6718
XRAY COST	0.8874E+02	0.7809E+02	0.8800E+00	0.0000E+00	0.1009E+04	6718
AVERAGE COST	0.1388E+04	0.1075E+04	0.7742E+00	0.3811E+03	0.1624E+05	6718
PROFIT	0.9444E+03	0.1084E+04	0.1148E+01	-0.3587E+03	0.2755E+05	6718

Fig. 14. Summary report of simulation with radiology efficiency increase.

The summary report of this simulation is in Figure 15. The total profit is \$6.395 million. Compared to the profit with no policy, indications are that this policy would be desirable if it could be practically enforced.

These two examples illustrate how simulation can be a viable tool in the selection and enforcement of certain hospital management strategies, as well as predicting results of forecasts for planning purposes. Although this research is not comprehensive in its scope, it is believed that further investigation in this area will produce a lasting contribution which could help to support hospital administrators' planning and decision making.

S L A M S U M M A R Y R E P O R T

SIMULATION PROJECT PATIENTS

BY T. ATKINS

DATE 7/29/1984

RUN NUMBER 1 OF 1

CURRENT TIME 0.3650E+03

STATISTICAL ARRAYS CLEARED AT TIME 0.0000E+00

STATISTICS FOR VARIABLES BASED ON OBSERVATION

	MEAN VALUE	STANDARD DEVIATION	COEFF. OF VARIATION	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBSERVATIONS
MEDICARE OUTLIER	0.5729E-01	0.2325E+00	0.4058E+01	0.0000E+00	0.1000E+01	1536
M OUTLIER 14	0.1538E+00	0.3636E+00	0.2363E+01	0.0000E+00	0.1000E+01	65
AVG COST 14 MED	0.1778E+04	0.1454E+04	0.8180E+00	0.4277E+03	0.8289E+04	65
PROFIT 14 MED	0.4528E+04	0.4279E+04	0.9450E+00	0.3872E+03	0.2755E+05	65
M OUTLIER 127	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	77
AVG COST 127 MED	0.9819E+03	0.4827E+03	0.4916E+00	0.4217E+03	0.2666E+04	77
PROFIT 127 MED	0.2597E+04	0.9903E+03	0.3813E+00	0.1436E+04	0.5967E+04	77
M OUTLIER 148	0.4286E+00	0.5071E+00	0.1183E+01	0.0000E+00	0.1000E+01	21
AVG COST 148 MED	0.5688E+04	0.1732E+04	0.3046E+00	0.3195E+04	0.8840E+04	21
PROFIT 148 MED	0.6029E+04	0.2670E+04	0.4429E+00	0.1493E+04	0.1131E+05	21
M OUTLIER 210	0.9677E-01	0.3005E+00	0.3106E+01	0.0000E+00	0.1000E+01	31
AVG COST 210 MED	0.2735E+04	0.5753E+03	0.2103E+00	0.1834E+04	0.4018E+04	31
PROFIT 210 MED	0.5426E+04	0.1178E+04	0.2172E+00	0.3680E+04	0.7696E+04	31
M OUTLIER 243	0.5660E-01	0.2333E+00	0.4122E+01	0.0000E+00	0.1000E+01	53
AVG COST 243 MED	0.7533E+03	0.4625E+03	0.6139E+00	0.3811E+03	0.3168E+04	53
PROFIT 243 MED	0.8661E+03	0.5838E+03	0.6740E+00	-0.3587E+03	0.4403E+04	53
M OUTLIER 468	0.0000E+00	0.0000E+00	0.9999E+04	0.0000E+00	0.0000E+00	21
AVG COST 468 MED	0.1481E+04	0.6477E+03	0.4374E+00	0.8427E+03	0.2799E+04	21
PROFIT 468 MED	0.3638E+04	0.1433E+04	0.3940E+00	0.2226E+04	0.6556E+04	21
AVG COST 14	0.1260E+04	0.9886E+03	0.7844E+00	0.4610E+03	0.3577E+04	10
PROFIT 14	0.3992E+04	0.2543E+04	0.6369E+00	0.1072E+04	0.8660E+04	10
AVG COST 127	0.9346E+03	0.4794E+03	0.5129E+00	0.4357E+03	0.2389E+04	23
PROFIT 127	0.2391E+04	0.1269E+04	0.5307E+00	0.1004E+04	0.6302E+04	23
AVG COST 148	0.5685E+04	0.1830E+04	0.3218E+00	0.3060E+04	0.9383E+04	11
PROFIT 148	0.5685E+04	0.2877E+04	0.5061E+00	0.1690E+04	0.1124E+05	11
AVG COST 210	0.2478E+04	0.4340E+03	0.1752E+00	0.2075E+04	0.3015E+04	4
PROFIT 210	0.5098E+04	0.1091E+04	0.2140E+00	0.3716E+04	0.6220E+04	4
AVG COST 243	0.7648E+03	0.4654E+03	0.6085E+00	0.4177E+03	0.3235E+04	109
PROFIT 243	0.5756E+03	0.5309E+03	0.9224E+00	0.1585E+03	0.3017E+04	109
AVG COST 468	0.1405E+04	0.4524E+03	0.3219E+00	0.8427E+03	0.2614E+04	55
PROFIT 468	0.2786E+04	0.1292E+04	0.4638E+00	0.1179E+04	0.6236E+04	55
LAB COST	0.2452E+03	0.1765E+03	0.7199E+00	0.1534E+02	0.2476E+04	6718
PHARMACY COST	0.1925E+03	0.2861E+03	0.1486E+01	0.2245E+01	0.4549E+04	6718
SUPPLY COST	0.2458E+03	0.3037E+03	0.1236E+01	0.1269E+02	0.2391E+04	6718
RESP THER COST	0.1487E+03	0.4540E+03	0.3053E+01	0.0000E+00	0.1262E+05	6718
XRAY COST	0.9859E+02	0.8677E+02	0.8802E+00	0.0000E+00	0.1120E+04	6718
AVERAGE COST	0.1506E+04	0.1145E+04	0.7603E+00	0.3811E+03	0.1673E+05	6718
PROFIT	0.9519E+03	0.1085E+04	0.1140E+01	-0.3587E+03	0.2755E+05	6718

Fig. 15. Summary report of simulation with a length of stay extension policy.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATIONS

This research has demonstrated a method by which simulation can be used to assist hospital managers in decision making and financial planning. The DRG grouping system segregates patients into meaningful categories for statistical analysis. Historical records of length of stay and resource consumption were used to construct mathematical models and distributions to simulate the financial process of health care delivery. Linear regression models were particularly useful to estimate a patient's resource consumption per cost center as a function of length of stay, and to estimate total resource consumption as a function of the usage from only a few cost centers. Length of stay data, as well as resource consumption data which could not be modeled with regression, were fitted to lognormal and triangular distributions. An accurate and easily embellished simulation was built with the results of this data analysis.

It is concluded that the three types of mathematical models implemented in this simulation (the lognormal distribution, the triangular distribution and regression equations) are sufficient for a complete and accurate generation of patient attributes. The SLAM simulation language provides lognormal and triangular random

variable generators, along with built-in routines for simulating patient arrival and statistics collection for performance evaluation. The SLAM language is primarily recommended, however, for its flexibility with respect to the interjection of simulated policies within the FORTRAN subroutine EVENT. The logic of a policy can be simply represented with FORTRAN, which is a common programming language.

For further research, it is recommended that a larger data base be used for the determination of regression equations and distribution types. At least one year's worth of data (preferably two) should be collected for a statistically sound analysis. Most large hospitals presently have direct access to the data from data centers. Also, a greater number of DRG's should be selected for in-depth analysis. If more DRG's are included, there will be a fewer number incorporated into the miscellaneous "other" category (DRG 999). This miscellaneous category will then tend to exhibit a greater degree of statistical stability. For even more stability, it is recommended that a separate statistical analysis be performed for Medicare and non-Medicare patients.

Many policies and forecasts other than the ones mentioned in this research can be simulated. A list of suggested forecasts and policies follows:

Forecasts:

1. Total patient population
2. Case-mix changes (population by DRG)
3. Changes in departmental cost-to-charge ratios due to efficiency gains or losses

Policies:

1. Length of stay alternatives
2. Resource consumption constraints per department
3. Patient referral policies
4. Increased charges per department

It is believed that the application of the simulation technique developed in this research would benefit hospitals as administrators begin to exercise control under the dispensation of prospective payment. This technique provides a way to predict the financial results of several projected changes to a particular hospital's health care delivery process. Managers can use this in medium and long-range planning and to test the effectiveness of hypothetical strategies. With a fixed reimbursement mechanism, tools such as this will become increasingly desirable in an effort to contain the cost of health care.

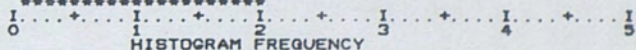
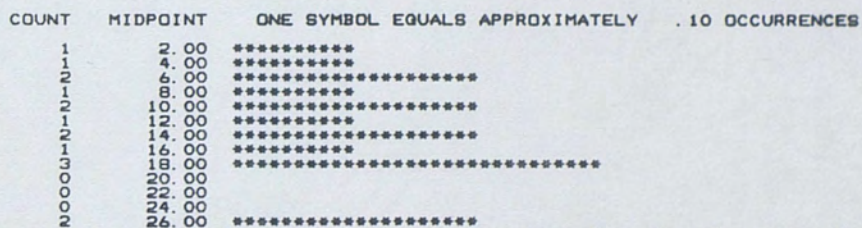
APPENDICES

APPENDIX 1A

SPSS ANALYSIS OF LOSTOT

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DROS
 11:15:38 University of Central Florida IBM 4341-12 VM/SP3 CMS
 DRG: 14
 LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	1.00	1	6.3	6.3	6.3
	4.00	1	6.3	6.3	12.6
	5.00	1	6.3	6.3	18.9
	6.00	1	6.3	6.3	25.0
	7.00	1	6.3	6.3	31.3
	9.00	1	6.3	6.3	37.5
	10.00	1	6.3	6.3	43.8
	11.00	1	6.3	6.3	50.0
	14.00	2	12.6	12.6	62.6
	15.00	1	6.3	6.3	68.9
	17.00	2	12.6	12.6	81.5
	18.00	1	6.3	6.3	87.8
	23.00	1	6.3	6.3	93.8
	27.00	1	6.3	6.3	100.0
TOTAL		16	100.0	100.0	

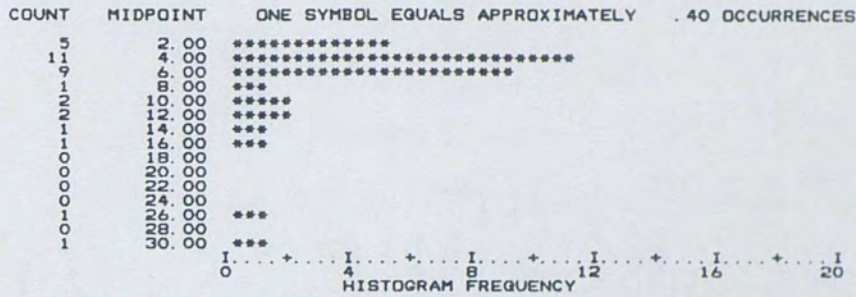


MEAN	12.500	STD ERR	1.828	MEDIAN	12.500
MODE	14.000	STD DEV	7.312	VARIANCE	53.467
KURTOSIS	-.232	S E KURT	1.933	SKEWNESS	.451
S E SKEW	.564	RANGE	26.000	MINIMUM	1.000
MAXIMUM	27.000	SUM	200.000		

VALID CASES 16 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:39 University of Central Florida IBM 4341-12 VM/SP3 CMS
 DRG: 127
 LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	1.00	2	5.9	5.9	5.9
	2.00	3	8.8	8.8	14.7
	3.00	9	14.7	14.7	29.4
	4.00	6	17.6	17.6	47.1
	5.00	3	17.6	17.6	64.7
	6.00	3	8.8	8.8	73.5
	7.00	1	2.9	2.9	76.5
	9.00	1	2.9	2.9	79.4
	10.00	1	2.9	2.9	82.4
	11.00	1	2.9	2.9	85.3
	12.00	1	2.9	2.9	88.2
	13.00	1	2.9	2.9	91.2
	16.00	1	2.9	2.9	94.1
	23.00	1	2.9	2.9	97.1
	30.00	1	2.9	2.9	100.0
TOTAL		34	100.0	100.0	

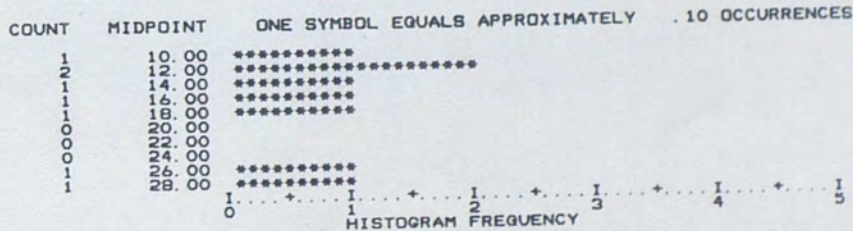


MEAN	6.706	STD ERR	1.088	MEDIAN	5.000
MODE	4.000	STD DEV	6.346	VARIANCE	40.275
KURTOSIS	6.156	S E KURT	1.953	SKEWNESS	2.394
S E SKEW	.403	RANGE	29.000	MINIMUM	1.000
MAXIMUM	30.000	SUM	228.000		

VALID CASES 34 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:39 University of Central Florida IBM 4341-12 VM/SP3 CMS
 DRG: 148
 LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	9.00	1	12.5	12.5	12.5
	12.00	2	25.0	25.0	37.5
	14.00	1	12.5	12.5	50.0
	15.00	1	12.5	12.5	62.5
	18.00	1	12.5	12.5	75.0
	26.00	1	12.5	12.5	87.5
	29.00	1	12.5	12.5	100.0
TOTAL		8	100.0	100.0	



MEAN	16.875	STD ERR	2.510	MEDIAN	14.500
MODE	12.000	STD DEV	7.100	VARIANCE	50.411
KURTOSIS	-.366	S E KURT	1.969	SKEWNESS	.954
S E SKEW	.752	RANGE	20.000	MINIMUM	9.000
MAXIMUM	29.000	SUM	135.000		

VALID CASES 8 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:39 University of Central Florida IBM 4341-12 VM/SP3 CMS

DRG: 210

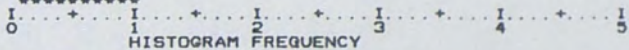
LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	5.00	1	6.7	6.7	6.7
	12.00	1	6.7	6.7	13.3
	13.00	1	6.7	6.7	20.0
	14.00	1	6.7	6.7	26.7
	15.00	1	6.7	6.7	33.3
	16.00	1	6.7	6.7	40.0
	18.00	1	6.7	6.7	46.7
	19.00	2	13.3	13.3	60.0
	20.00	1	6.7	6.7	66.7
	21.00	1	6.7	6.7	73.3
	22.00	2	13.3	13.3	86.7
	28.00	1	6.7	6.7	93.3
	32.00	1	6.7	6.7	100.0
TOTAL		15	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

```

1 6.00 *****
0 8.00 *****
0 10.00 *****
1 12.00 *****
2 14.00 *****
2 16.00 *****
1 18.00 *****
3 20.00 *****
0 22.00 *****
0 24.00 *****
0 26.00 *****
1 28.00 *****
0 30.00 *****
1 32.00 *****
    
```



MEAN	18.400	STD ERR	1.690	MEDIAN	19.000
MODE	19.000	STD DEV	6.344	VARIANCE	42.829
KURTOSIS	.928	S E KURT	1.932	SKEWNESS	.162
S E SKEW	.580	RANGE	27.000	MINIMUM	5.000
MAXIMUM	32.000	SUM	276.000		

VALID CASES 15 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:40 University of Central Florida IBM 4341-12 VM/SP3 CMS

DRG: 243

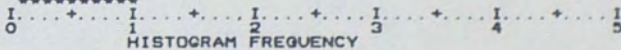
LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	2.00	1	3.8	3.8	3.8
	3.00	2	7.7	7.7	11.5
	4.00	2	7.7	7.7	19.2
	5.00	2	7.7	7.7	26.9
	6.00	3	11.5	11.5	38.5
	7.00	1	3.8	3.8	42.3
	8.00	3	11.5	11.5	53.8
	9.00	2	7.7	7.7	61.5
	10.00	2	7.7	7.7	69.2
	12.00	1	3.8	3.8	73.1
	13.00	1	3.8	3.8	76.9
	14.00	1	3.8	3.8	80.8
	15.00	1	3.8	3.8	84.6
	16.00	1	3.8	3.8	88.5
	21.00	1	3.8	3.8	92.3
	23.00	1	3.8	3.8	96.2
	25.00	1	3.8	3.8	100.0
TOTAL		26	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

```

3 3.00 *****
4 5.00 *****
4 7.00 *****
3 9.00 *****
2 11.00 *****
2 13.00 *****
2 15.00 *****
1 17.00 *****
0 19.00 *****
1 21.00 *****
1 23.00 *****
1 25.00 *****
    
```



MEAN	9.692	STD ERR	1.214	MEDIAN	8.000
MODE	6.000	STD DEV	6.189	VARIANCE	38.302
KURTOSIS	.650	S E KURT	1.946	SKEWNESS	1.116
S E SKEW	.456	RANGE	23.000	MINIMUM	2.000
MAXIMUM	25.000	SUM	252.000		

VALID CASES 26 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:39 University of Central Florida IBM 4341-12 VM/SP3 CMS

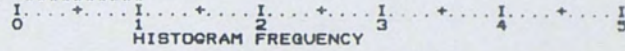
DRG: 468

LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	2.00	1	14.3	14.3	14.3
	3.00	1	14.3	14.3	28.6
	7.00	1	14.3	14.3	42.9
	8.00	2	28.6	28.6	71.4
	17.00	1	14.3	14.3	85.7
	24.00	1	14.3	14.3	100.0
	TOTAL	7	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

2	3.00	*****
0	5.00	
1	7.00	*****
2	9.00	*****
0	11.00	
0	13.00	
1	15.00	
0	17.00	*****
0	19.00	
0	21.00	
1	23.00	*****



MEAN	9.857	STD ERR	2.988	MEDIAN	8.000
MODE	8.000	STD DEV	7.904	VARIANCE	62.476
KURTOSIS	.425	S E KURT	2.000	SKEWNESS	1.110
S E SKEW	.794	RANGE	22.000	MINIMUM	2.000
MAXIMUM	24.000	SUM	69.000		

VALID CASES 7 MISSING CASES 0

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:40 University of Central Florida IBM 4341-12 VM/SP3 CMS

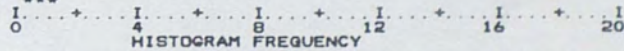
DRG: 999

LOSTOT

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	1.00	5	9.6	9.6	9.6
	2.00	1	1.9	1.9	11.5
	4.00	7	13.5	13.5	25.0
	5.00	7	13.5	13.5	38.5
	6.00	7	13.5	13.5	51.9
	7.00	3	5.8	5.8	57.7
	8.00	4	7.7	7.7	65.4
	9.00	2	3.8	3.8	69.2
	10.00	1	1.9	1.9	71.2
	12.00	1	1.9	1.9	73.1
	13.00	5	9.6	9.6	82.7
	14.00	4	7.7	7.7	90.4
	15.00	2	3.8	3.8	94.2
	16.00	2	3.8	3.8	98.1
	20.00	1	1.9	1.9	100.0
	TOTAL	52	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .40 OCCURRENCES

6	2.00	*****
7	4.00	*****
14	6.00	*****
7	8.00	*****
3	10.00	*****
1	12.00	***
1	14.00	*****
4	16.00	*****
0	18.00	
1	20.00	***



MEAN	7.846	STD ERR	.658	MEDIAN	6.000
MODE	4.000	STD DEV	4.742	VARIANCE	22.486
KURTOSIS	-.580	S E KURT	1.968	SKEWNESS	.555
S E SKEW	.330	RANGE	19.000	MINIMUM	1.000
MAXIMUM	20.000	SUM	408.000		

VALID CASES 52 MISSING CASES 0

APPENDIX 1B

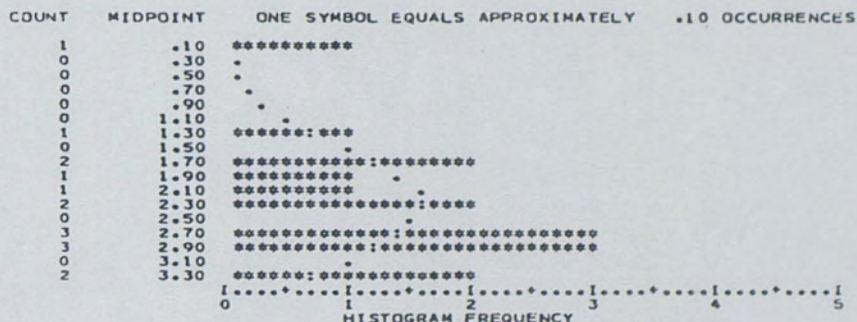
SPSS ANALYSIS OF LOGLOS

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:45 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SPJ CMS

DRG: 14

LOGLOS

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.00	1	6.3	6.3	6.3
	1.39	1	6.3	6.3	12.5
	1.61	1	6.3	6.3	18.8
	1.79	1	6.3	6.3	25.0
	1.95	1	6.3	6.3	31.3
	2.20	1	6.3	6.3	37.5
	2.30	1	6.3	6.3	43.8
	2.40	1	6.3	6.3	50.0
	2.64	2	12.5	12.5	62.5
	2.71	1	6.3	6.3	68.8
	2.83	2	12.5	12.5	81.3
	2.89	1	6.3	6.3	87.5
	3.22	1	6.3	6.3	93.8
	3.30	1	6.3	6.3	100.0
	TOTAL	16	100.0	100.0	

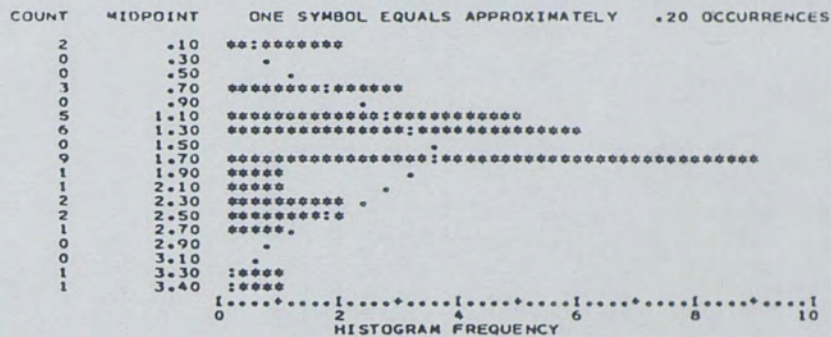


MEAN	2.293	STD ERR	.206	MEDIAN	2.518
MODE	2.639	STD DEV	.823	VARIANCE	.677
KURTOSIS	2.970	S E KURT	1.933	SKEWNESS	-1.478
S F SKEW	.564	RANGE	3.296	MINIMUM	.000
MAXIMUM	3.296	SUM	36.689		

VALID CASES 16 MISSING CASES 0

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:45 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VH/SP3 CMS
 DRG: 127
 LOGLOS

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.00	2	5.9	5.9	5.9
	.69	3	8.8	8.8	14.7
	1.10	5	14.7	14.7	29.4
	1.39	6	17.6	17.6	47.1
	1.61	6	17.6	17.6	64.7
	1.79	3	8.8	8.8	73.5
	1.95	1	2.9	2.9	76.5
	2.20	1	2.9	2.9	79.4
	2.30	1	2.9	2.9	82.4
	2.40	1	2.9	2.9	85.3
	2.48	1	2.9	2.9	88.2
	2.56	1	2.9	2.9	91.2
	2.77	1	2.9	2.9	94.1
	3.22	1	2.9	2.9	97.1
	3.40	1	2.9	2.9	100.0
TOTAL		34	100.0	100.0	

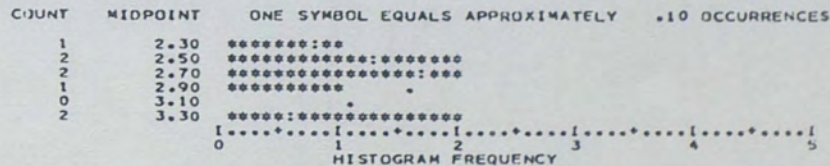


MEAN	1.594	STD ERR	.133	MEDIAN	1.609
MODE	1.386	STD DEV	.774	VARIANCE	.600
KURTOSIS	.457	S E KURT	1.955	SKEWNESS	.252
S E SKEW	.403	RANGE	3.401	MINIMUM	.000
MAXIMUM	3.401	SUM	54.208		

VALID CASES 34 MISSING CASES 0

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:45 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VH/SP3 CMS
 DRG: 148
 LOGLOS

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	2.20	1	12.5	12.5	12.5
	2.48	2	25.0	25.0	37.5
	2.64	1	12.5	12.5	50.0
	2.71	1	12.5	12.5	62.5
	2.89	1	12.5	12.5	75.0
	3.26	1	12.5	12.5	87.5
	3.37	1	12.5	12.5	100.0
TOTAL		8	100.0	100.0	

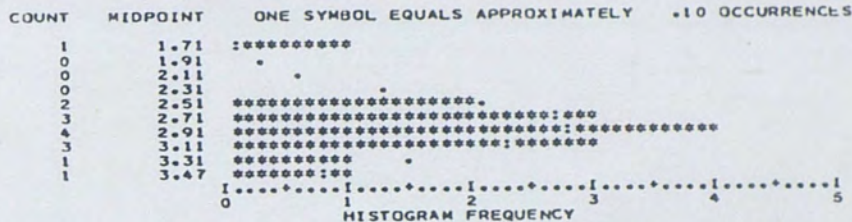


MEAN	2.754	STD ERR	.141	MEDIAN	2.674
MODE	2.485	STD DEV	.400	VARIANCE	.160
KURTOSIS	-.696	S E KURT	1.969	SKEWNESS	.444
S E SKEW	.752	RANGE	1.170	MINIMUM	2.197
MAXIMUM	3.367	SUM	22.030		

VALID CASES 8 MISSING CASES 0

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:46 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS
 DRG: 210
 LOGLOS

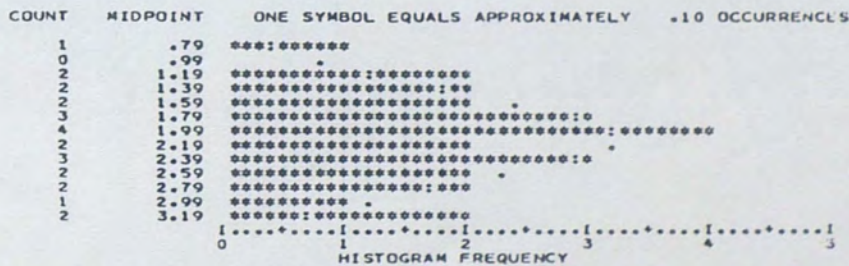
VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	1.61	1	6.7	6.7	6.7
	2.48	1	6.7	6.7	13.3
	2.56	1	6.7	6.7	20.0
	2.64	1	6.7	6.7	26.7
	2.71	1	6.7	6.7	33.3
	2.77	1	6.7	6.7	40.0
	2.89	1	6.7	6.7	46.7
	2.94	2	13.3	13.3	60.0
	3.00	1	6.7	6.7	66.7
	3.04	1	6.7	6.7	73.3
	3.09	2	13.3	13.3	86.7
	3.33	1	6.7	6.7	93.3
	3.47	1	6.7	6.7	100.0
TOTAL		15	100.0	100.0	



MEAN	2.839	STD ERR	.112	MEDIAN	2.944
MODE	2.944	STD DEV	.433	VARIANCE	.188
KURTOSIS	4.119	S E KURT	1.932	SKEWNESS	-1.538
S E SKEW	.580	RANGE	1.856	MINIMUM	1.609
MAXIMUM	3.466	SUM	42.579		
VALID CASES	15	MISSING CASES	0		

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:46 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS
 DRG: 243
 LOGLOS

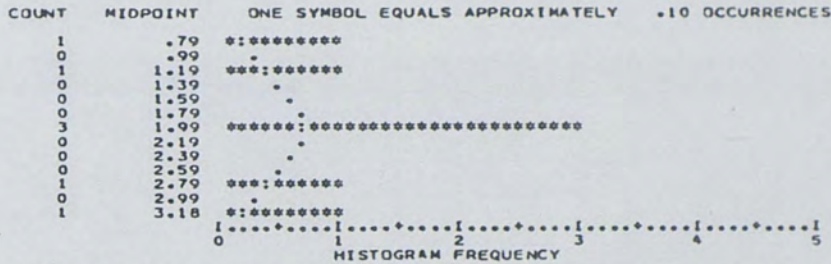
VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.69	1	3.8	3.8	3.8
	1.10	2	7.7	7.7	11.5
	1.39	2	7.7	7.7	19.2
	1.61	2	7.7	7.7	26.9
	1.79	3	11.5	11.5	38.5
	1.95	1	3.8	3.8	42.3
	2.08	3	11.5	11.5	53.8
	2.20	2	7.7	7.7	61.5
	2.30	2	7.7	7.7	69.2
	2.48	1	3.8	3.8	73.1
	2.56	1	3.8	3.8	76.9
	2.64	1	3.8	3.8	80.8
	2.71	1	3.8	3.8	84.6
	2.77	1	3.8	3.8	88.5
	3.04	1	3.8	3.8	92.3
	3.14	1	3.8	3.8	96.2
	3.22	1	3.8	3.8	100.0
TOTAL		26	100.0	100.0	



MEAN	2.077	STD ERR	.128	MEDIAN	2.079
MODE	1.792	STD DEV	.650	VARIANCE	.423
KURTOSIS	-.416	S E KURT	1.946	SKEWNESS	-1.144
S E SKEW	.456	RANGE	2.526	MINIMUM	.643
MAXIMUM	3.219	SUM	54.009		
VALID CASES	26	MISSING CASES	0		

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:46 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS
 DRG: 468
 LOGLOS

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.69	1	14.3	14.3	14.3
	1.10	1	14.3	14.3	28.6
	1.95	1	14.3	14.3	42.9
	2.08	2	28.6	28.6	71.4
	2.83	1	14.3	14.3	85.7
	3.18	1	14.3	14.3	100.0
TOTAL		7	100.0	100.0	

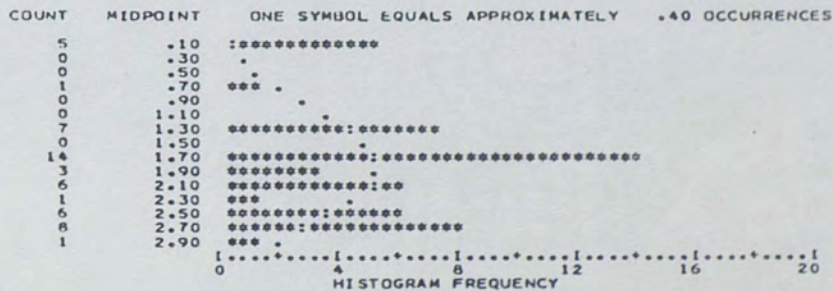


MEAN	1.987	STD ERR	.332	MEDIAN	2.079
MODE	2.079	STD DEV	.877	VARIANCE	.769
KURTOSIS	-.710	S E KURT	2.000	SKENNESS	-.196
S E SKEW	.794	RANGE	2.485	MINIMUM	.693
MAXIMUM	3.178	SUM	13.008		

VALID CASES 7 MISSING CASES 0

27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:47 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS
 DRG: 999
 LOGLOS

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.00	5	9.6	9.6	9.6
	.69	1	1.9	1.9	11.5
	1.39	7	13.5	13.5	25.0
	1.61	7	13.5	13.5	38.5
	1.79	7	13.5	13.5	51.9
	1.95	3	5.8	5.8	57.7
	2.08	4	7.7	7.7	65.4
	2.20	2	3.8	3.8	69.2
	2.30	1	1.9	1.9	71.2
	2.48	1	1.9	1.9	73.1
	2.56	5	9.6	9.6	82.7
	2.64	4	7.7	7.7	90.4
	2.71	2	3.8	3.8	94.2
	2.77	2	3.8	3.8	98.1
	3.00	1	1.9	1.9	100.0
TOTAL		52	100.0	100.0	



MEAN	1.825	STD ERR	.108	MEDIAN	1.792
MODE	1.386	STD DEV	.779	VARIANCE	.607
KURTOSIS	.739	S E KURT	1.968	SKENNESS	-.992
S F SKEW	.330	RANGE	2.996	MINIMUM	.000
MAXIMUM	2.996	SUM	94.881		

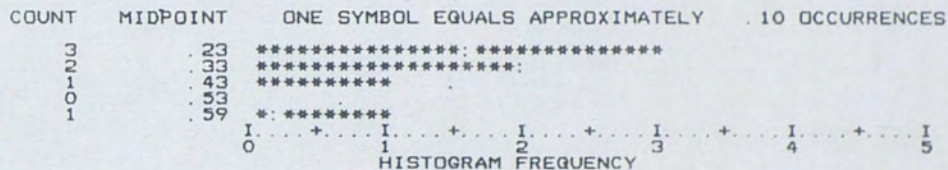
VALID CASES 52 MISSING CASES 0

APPENDIX 2

SPSS ANALYSIS OF PCTICU

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:41 University of Central Florida IBM 4341-12 VM/SP3 CMS
 DRG: 14
 PCTICU

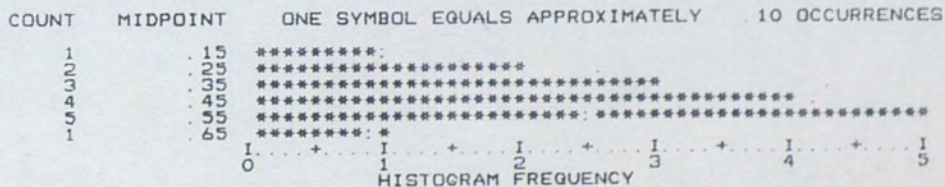
VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.18	1	6.3	14.3	14.3
	.1	1	6.3	14.3	28.6
	.4	1	6.3	14.3	42.9
	.9	1	6.3	14.3	57.1
	.43	1	6.3	14.3	71.4
	.59	1	6.3	14.3	85.7
	.00	7	43.8	MISSING	100.0
	1.00	2	12.5	MISSING	
	TOTAL	16	100.0	100.0	



VALID CASES 7 MISSING CASES 9

DRG: 127
 PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.10	1	2.9	6.3	6.3
	.20	2	5.9	12.5	18.8
	.33	3	8.8	18.8	37.5
	.40	2	5.9	12.5	50.0
	.42	1	2.9	6.3	56.3
	.45	1	2.9	6.3	62.5
	.50	5	14.7	31.3	73.8
	.67	1	2.9	6.3	100.0
	.00	15	44.1	MISSING	
	1.00	3	8.8	MISSING	
	TOTAL	34	100.0	100.0	

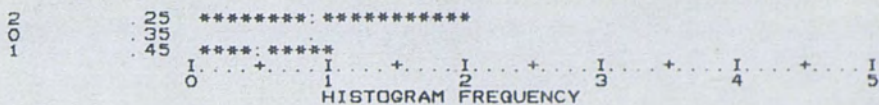


VALID CASES 16 MISSING CASES 18

DRG: 148
PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.20	1	12.5	33.3	33.3
	.24	1	12.5	33.3	66.7
	.46	1	12.5	33.3	100.0
	.00	5	62.5	MISSING	
	TOTAL	8	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

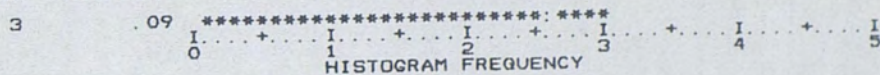


VALID CASES 3 MISSING CASES 5

DRG: 210
PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.05	1	6.7	33.3	33.3
	.06	1	6.7	33.3	66.7
	.09	1	6.7	33.3	100.0
	.00	12	80.0	MISSING	
	TOTAL	15	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

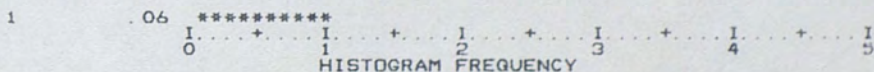


VALID CASES 3 MISSING CASES 12

DRG: 468
PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.06	1	14.3	100.0	100.0
	.00	6	85.7	MISSING	
	TOTAL	7	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES



VALID CASES 1 MISSING CASES 6

DRG: 243
PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.04	1	3.8	100.0	100.0
	.00	25	96.2	MISSING	
	TOTAL	26	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES
 1 .04 *****
 I.....+.....I.....+.....I.....+.....I.....+.....I
 0 1 2 3 4 5
 HISTOGRAM FREQUENCY
 VALID CASES 1 MISSING CASES 25

DRG: 999
PCTICU

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	.08	1	1.9	10.0	10.0
	.13	1	1.9	10.0	20.0
	.20	1	1.9	10.0	30.0
	.21	1	1.9	10.0	40.0
	.22	1	1.9	10.0	50.0
	.33	1	1.9	10.0	60.0
	.40	2	3.8	20.0	80.0
	.50	1	1.9	10.0	90.0
	.60	1	1.9	10.0	100.0
	.00	39	75.0	MISSING	
	1.00	3	5.8	MISSING	
	TOTAL	52	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES
 2 .13 *****:*****
 3 .23 *****:*****
 1 .33 *****
 2 .43 *****:
 1 .53 *****
 1 .60 ***:*****
 I.....+.....I.....+.....I.....+.....I.....+.....I
 0 1 2 3 4 5
 HISTOGRAM FREQUENCY
 VALID CASES 10 MISSING CASES 42

APPENDIX 3

EXAMPLE OF SPSS REGRESSION ANALYSIS OF
TCOST = C₀ + C₁ x LAB + C₂ x PHARM
+ C₃ x SUPP + C₄ x RETHER + C₅ x XRAY

22 SEP 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 21:49:00 University of Central Florida IOM 4341-12 VM/SP3 CMS

DRG: 14

*** MULTIPLE REGRESSION ***

VARIABLE LIST NUMBER 1 LISTWISE DELETION OF MISSING DATA

EQUATION NUMBER 1 DEPENDENT VARIABLE.. TCOST

BEGINNING BLOCK NUMBER 1. METHOD: STEPMSE LAB PHARM SUPP RETHER XRAY

VARIABLE(S) ENTERED ON STEP NUMBER 1.. PHARM PHARMACY

MULTIPLE R .91439
 R SQUARE .83611
 ADJUSTED R SQUARE .82440
 STANDARD ERROR 2096.59984

ANALYSIS OF VARIANCE
 REGRESSION 1 313951638.09419 313951638.09419 MEAN SQUARE
 RESIDUAL 14 61540232.19916 4395730.87137

F = 71.42194 SIGNIF F = .0000

VARIABLES IN THE EQUATION				VARIABLES NOT IN THE EQUATION						
VARIABLE	B	SE B	BETA	T	SIG T	VARIABLE	BETA IN PARTIAL	MIN TOLER	T	SIG T
PHARM	4.24822	.50269	.91439	8.451	.0000	LAB	.46265	.90496	7.669	.0000
(CONSTANT)	2378.61272	669.15401		3.555	.0032	SUPP	.42017	.18783	1.669	.1189
						RETH	.07812	.39025	.438	.6687
						XRAY	.21790	.46201	1.878	.0830

*** MULTIPLE REGRESSION ***

VARIABLE(S) ENTERED ON STEP NUMBER 2.. LAB

MULTIPLE R .98505
 R SQUARE .97033
 ADJUSTED R SQUARE .96339
 STANDARD ERROR 925.75339

ANALYSIS OF VARIANCE
 REGRESSION 12 38435028.34517 18217310.17138 MEAN SQUARE
 RESIDUAL 13 1114124.95018 857019.22694

F = 212.56852 SIGNIF F = .0000

VARIABLES IN THE EQUATION				VARIABLES NOT IN THE EQUATION						
VARIABLE	B	SE B	BETA	T	SIG T	VARIABLE	BETA IN PARTIAL	MIN TOLER	T	SIG T
PHARM	2.93562	.28029	.63186	10.473	.0000	SUPP	-.04196	-.09133	-.318	.7562
(CONSTANT)	10.89844	1.42131	.46265	7.669	.0000	RETH	-.07355	-.25957	-.931	.3702
						XRAY	-.02550	.43649	-.362	.7236

FOR BLOCK NUMBER 1 PIN = 0.050 LIMITS REACHED.

ORC: 147

***** MULTIPLE REGRESSION *****
 EQUATION NUMBER 1 DEPENDENT VARIABLE.. TCOST

 BEGINNING BLOCK NUMBER 1. METHOD: STEPWISE LAB PHARM SUPP RETHER XRAY

VARIABLE(S) ENTERED ON STEP NUMBER 1.. RETHER RESPIRATORY THER.

MULTIPLE R .95096
 R SQUARE .90432
 ADJUSTED R SQUARE .89133
 STANDARD ERROR 1083.85672
 ANALYSIS OF VARIANCE
 REGRESSION 32 3531072.95198 MEAN SQUARE
 RESIDUAL 32 37591852.79523 1174743.39983
 F = 302.45726 SIGNIF F = .0000

VARIABLES IN THE EQUATION				VARIABLES NOT IN THE EQUATION					
VARIABLE	B	SE B	BETA	T	SIG T	VARIABLE	BETA IN PARTIAL MIN TOLER	T	SIG T
RETH	5.04250	.28994	.95096	17.391	.0000	LAB	.21755	3.346	.0022
(CONSTANT)	1274.86005	240.71751		5.296	.0000	PHARM	.49373	8.193	.0000
						SUPP	.36613	5.790	.0000
						XRAY	-.01247	-.173	.8640

 VARIABLE(S) ENTERED ON STEP NUMBER 2.. PHARM PHARMACY

MULTIPLE R .98477
 R SQUARE .96977
 ADJUSTED R SQUARE .96782
 STANDARD ERROR 619.93746
 ANALYSIS OF VARIANCE
 REGRESSION 2 381026534.79122 MEAN SQUARE
 RESIDUAL 31 11875590.85599 383083.57600
 F = 497.31515 SIGNIF F = .0000

VARIABLES IN THE EQUATION				VARIABLES NOT IN THE EQUATION					
VARIABLE	B	SE B	BETA	T	SIG T	VARIABLE	BETA IN PARTIAL MIN TOLER	T	SIG T
RETH	2.90139	.31953	.52869	8.773	.0000	LAB	-.16816	7.046	.0000
PHARM	3.22907	.51941	.49373	8.193	.0000	SUPP	-.03328	-.297	.7684
(CONSTANT)	1233.31253	137.55547		8.966	.0000	XRAY	-.01437	-.348	.7304

ORG: 127

*** MULTIPLE REGRESSION ***

EQUATION NUMBER 1 DEPENDENT VARIABLE.. TCOST

VARIABLE(S) ENTERED ON STEP NUMBER 3.. LAB

MULTIPLE R .99429
 R SQUARE .98861
 ADJUSTED R SQUARE .98748
 STANDARD ERROR 386.14631

ANALYSIS OF VARIANCE
 REGRESSION 3
 RESIDUAL 30

SUM OF SQUARES 388428856.57483
 MEAN SQUARE 129476285.52493
 4473269.07236
 149108.56908

F = 868.33332 SIGNIF F = .0000

VARIABLES IN THE EQUATION			VARIABLES NOT IN THE EQUATION		
VARIABLE	B	SE B	BETA	T	SIG T
RETHR	2.23049	.21530	.42065	10.360	.0000
PHARM	3.07546	.24685	.47024	12.459	.0000
LAB	2.41322	.34250	.18816	7.046	.0000
(CONSTANT)	600.00783	124.27370		4.828	.0000

VARIABLE	BETA IN	PARTIAL	MIN TOLER	T	SIG T
SUPP	.01101	-.02873	.05576	.155	.8780
XRAY	-6.959E-04	-.00498	.19381	-.027	.9788

FOR BLOCK NUMBER 1 PIN = 0.050 LIMITS REACHED.

APPENDIX 4

EXAMPLES OF BREAKDOWN OF CHARGES
PER DAY ACCORDING TO LENGTH OF STAY

07 JUN 84 REGRESSION ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:25:43 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS

DRG: 14

----- DESCRIPTION OF SUBPOPULATIONS -----

CRITERION VARIABLE LPD
 BROKEN DOWN BY AUX

VARIABLE	VALUE	LABEL	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION			40.2265	49.2359	16
AUX	1.00		181.5000	.0000	1
AUX	2.00		63.6319	69.4279	3
AUX	3.00		14.5097	10.7907	2
AUX	4.00		20.8391	5.0616	2
AUX	5.00		27.5431	20.7342	3
AUX	6.00		24.3587	9.2425	3
AUX	7.00		22.4136	.7744	2

07 JUN 84 REGRESSION ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:26:43 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS

DRG: 14

----- DESCRIPTION OF SUBPOPULATIONS -----

CRITERION VARIABLE PPD
 BROKEN DOWN BY AUX

VARIABLE	VALUE	LABEL	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION			77.8485	92.3770	16
AUX	1.00		345.7500	.0000	1
AUX	2.00		94.2259	115.6491	3
AUX	3.00		24.8075	.4450	2
AUX	4.00		35.6836	23.0607	2
AUX	5.00		33.2576	20.8934	3
AUX	6.00		43.4879	34.1166	3
AUX	7.00		132.9634	13.3990	2

TOTAL CASES = 16

07 JUN 84 REGRESSION ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:26:43 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS

DRG: 14

----- DESCRIPTION OF SUBPOPULATIONS -----

CRITERION VARIABLE SPD
 BROKEN DOWN BY AUX

VARIABLE	VALUE	LABEL	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION			62.4423	68.0437	16
AUX	1.00		260.8500	.0000	1
AUX	2.00		66.2333	85.7195	3
AUX	3.00		30.8456	17.6917	2
AUX	4.00		24.4193	17.8413	2
AUX	5.00		41.7665	33.1752	3
AUX	6.00		41.4535	37.3398	3
AUX	7.00		89.7241	27.2549	2

TOTAL CASES = 16

APPENDIX 5

EXAMPLE OF SPSS REGRESSION ANALYSIS OF CHARGES =
 $C_0 + C_1 \times \text{LOSTOT} + C_2 \times \text{LOSREG} + C_3$
 $\times \text{LOSICU} + C_4 \times \text{LOSTOT}^2 + C_5 \times$
 $\text{LOSREG}^2 + C_6 \times \text{LOSICU}^2$

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 22:45:33 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 V4/SPJ CMS

ORG: 14

***** MULTIPLE REGRESSION *****

VARIABLE LIST NUMBER 1 LISTWISE DELETION OF MISSING DATA

EQUATION NUMBER 1 DEPENDENT VARIABLE.. LAB

BEGINNING BLOCK NUMBER 1. METHOD: STEPWISE LOSTOT LOS2 LOSREG REG2 LOSICU ICUZ

VARIABLE(S) ENTERED ON STEP NUMBER 1.. LOSICU LOS (I.C.U.)

MULTIPLE R .66703
 R SQUARE .44494
 ADJUSTED R SQUARE .40529
 STANDARD ERROR 163.77690

R SQUARE CHANGE .44494
 F CHANGE 11.22228
 SIGNIF F CHANGE .0048

CONDITION NUMBER BOUNDS: 1.000, 1.000

VAR-COVAR MATRIX OF REGRESSION COEFFICIENTS (B)
 BELOW DIAGONAL: COVARIANCE ABOVE: CORRELATION

LOSIKU 93.21589

XTX MATRIX

	LOSIKU	LAB	LOSTOT	LOSREG	LOS2	REG2	ICUZ
LOSIKU	1.00000	-.66703	-.72857	-.18588	-.83483	-.15267	-.93110
LAB	.66703	.55506	.07909	.11346	.02901	.17075	.12529
LOSTOT	.72857	.07909	.46918	.67303	.35230	.63790	.00391
LOSREG	.18588	.11346	.67303	.96545	.50536	.91505	.00560
LOS2	.83483	.02901	.35230	.50536	.30306	.51629	.03663
REG2	.15267	.17075	.63790	.91505	.51629	.97669	-.00982
ICUZ	.93110	-.12529	.00391	.00560	.03663	-.00982	.13306

ANALYSIS OF VARIANCE
 REGRESSION 1
 RESIDUAL 14
 F = 11.22228 SIGNIF F = .0048

SUM OF SQUARES
 301013.93192
 375520.23245

MEAN SQUARE
 301013.93192
 26822.87375

ORC: 14

***** MULTIPLE REGRESSION *****

EQUATION NUMBER 1 DEPENDENT VARIABLE.. LAB

----- VARIABLES IN THE EQUATION -----										
VARIABLE	B	SE B	95% CONFIDENCE	INTRVL B	BETA	SE BETA	CORREL PART	COR	PARTIAL TOLERANCE	T
LOSICU (CONSTANT)	32.34340 229.12063	9.65484 50.06001	11.63585 120.03684	53.05095 336.20443	.66703	.19912	.66703	.66703	.66703	3.350 4.505

----- VARIABLES NOT IN THE EQUATION -----									
VARIABLE	SIG T	BETA IN	PARTIAL TOLERANCE	MIN TOLER	T	SIG T			
LOSICU (CONSTANT)	.0048 .0005	.16858 .11752	.15499 .15499	.46918 .96545	.566 .566	.5813 .5813			
LOSREG		.09573	.07074	.30306	.255	.0022			
LOS2		.17482	.23190	.97669	.860	.4C56			
REG2		-.94167	-.46104	.13306	-1.873	.0837			
ICU2									

FOR BLOCK NUMBER 1 PIN = 0.050 LIMITS REACHED.

***** SUMMARY TABLE *****

----- SUMMARY TABLE -----

STEP	MULTR	RSQ	ADJRSQ	FIEQUJ	SIGF	RSQCH	FCH	SIGCH	IN:	VARIABLE	DETAIN	CORREL	LABEL
1	.6670	.4449	.4053	11.222	.005	.4449	11.222	.005	IN:	LOSICU	.6670	.6670	LOS (I.C.U.)

ORC: 127

***** MULTIPLE REGRESSION ****

EQUATION NUMBER 1 DEPENDENT VARIABLE.. LAB
 BEGINNING BLOCK NUMBER 1. METHOD: STEPWISE

VARIABLE(S) ENTERED ON STEP NUMBER 1.. LOSTOT

MULTIPLE R .68538
 P SQUARE .46975
 ADJUSTED R SQUARE .45317
 STANDARD ERROR 198.95195

SUM OF SQUARES
 1122081.42220
 1266620.16640

ANALYSIS OF VARIANCE
 REGRESSION 1
 RESIDUAL 32

MEAN SQUARE
 1122081.42220
 39581.90020

F = 28.34836 SIGNIF F = .0000

CONDITION NUMBER BOUNDS: 1.000, 1.000

VAR-COVAR MATRIX OF REGRESSION COEFFICIENTS (B)
 BELOW DIAGONAL: COVARIANCE ABOVE: CORRELATION

LOSTOT 29.78189

XTX MATRIX

	LOSTOT	LAB	LOSREG	LOSICU	LOS2	REG2	ICU2
LOSTOT	1.00000	-.68538	-.96924	-.13382	-.95517	-.94418	-.18220
LAB	.68538	.53025	-.10891	.43858	-.08016	-.13781	.44530
LOSREG	.96924	-.10891	.06057	-.24389	.00107	.03475	-.22567
LOSICU	.02582	.43858	-.24389	.78599	-.01730	-.03492	-.00342
LOS2	.94418	-.13781	.03475	-.11092	.08443	.08653	-.17658
REG2	.18220	.44530	-.22567	.90871	-.06342	-.17658	.96688
ICU2							

DRG: 127

***** MULTIPLE REGRESSION *****
 EQUATION NUMBER 1 DEPENDENT VARIABLE.. LAN

----- VARIABLES IN THE EQUATION -----

VARIABLE	B	SE B	95% CONFIDENCE	INTRVL B	BETA	SE BETA	CORREL PART COR	PARTIAL TOLERANCE	T
LOSTOT (CONSTANT)	29.05628 216.91815	5.45728 50.03429	17.94019 115.00175	40.17238 316.83455	.68538	.12873	.68538	.68538	1.00000 4.335

----- VARIABLES NOT IN THE EQUATION -----

VARIABLE	SIG T	BETA IN	PARTIAL TOLERANCE	MIN TOLER	T	SIG T
LOSREG	.0000	-1.79827	-.60775	.06057	-4.261	.0002
LOSICU	.0001	.44657	-.60775	.98209	4.261	.0002
LOS2		-.91453	-.37182	.08765	-2.230	.0331
REG2		-1.26978	-.57446	.10853	-3.908	.0005
ICU2		.46059	.62193	.96680	4.422	.0001

VARIABLE(S) ENTERED ON STEP NUMBER 2.. ICU2

MULTIPLE R	R SQUARE CHANGE	ANALYSIS OF VARIANCE	MEAN SQUARE
.82149	.20510	REGRESSION	40.03295945
.67485	19.55433	RESIDUAL	25054.63448
.65387	.0001	F =	
STANDARD ERROR	SIGNIF F CHANGE	SIGNIF F =	
158.28656		.0000	

CONDITION NUMBER BOUNDS: 1.034, 4.137

VAR-COVAR MATRIX OF REGRESSION COEFFICIENTS (B)
 BELOW DIAGONAL: COVARIANCE ABOVE: CORRELATION

	LOSTOT	ICU2
LOSTOT	19.49870	-.18220
ICU2	-2.73514	11.55747

DNH: 127

***** MULTIPLE REGRESSION *****
 EQUATION NUMBER 1 DEPENDENT VARIABLE.. LAB

XTX MATRIX

	LOSTOT	ICU2	LAB	LOSREG	LOSICU	LOS2	REG2
LOSTOT	1.03434	-.18845	-.60146	-1.01177	-.03743	-.96712	-.97745
ICU2	-.18845	1.03434	-.46059	.23341	-.93992	-.06560	.18264
LAB	.60146	.46059	.32515	-.00497	.02003	-.05095	-.05648
LOSREG	1.01177	-.23341	-.00497	.00789	-.03178	-.01173	-.00647
LOSICU	-.03743	.93992	.02003	-.03178	.12798	.04723	.02605
LOS2	.96712	-.06560	-.05095	-.01173	.04723	.09349	.07325
REG2	.97745	-.18264	-.05648	-.00647	.02605	.07325	.07628

----- VARIABLES IN THE EQUATION -----

VARIABLE	B	SE B	95% CONFIDENCE	INTRVL D	BETA	SE BETA	CORREL	PART COR	PARTIAL	TOLERANCE	T
LOSTOT	25.49858	4.41573	16.49264	34.50451	.60146	.10416	.59139	.59139	.71987	.26680	5.774
ICU2	15.03328	3.38593	8.09687	21.96937	.46059	.10416	.58538	.45288	.62193	.96680	4.422
(CONSTANT)	182.05347	40.54590	100.15967	265.54727							4.510

----- VARIABLES NOT IN THE EQUATION -----

VARIABLE	SIG T	BETA IN	PARTIAL	TOLERANCE	MIN TOLER	T	SIG T
LOSTOT	.0000	-.63028	-.09820	7.892E-03	7.649E-03	-.540	.5929
ICU2	.0001	.15652	.09820	.12798	.12599	.540	.5929
(CONSTANT)	.0001	-.61023	-.30922	.08349	.08172	-1.781	.0051
		-.74043	-.35963	.07628	.07375	-2.104	.0438

APPENDIX 6A

EXAMPLES OF SPSS ANALYSIS OF
DEPARTMENTAL CHARGES

25 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 11:15:44 University of Central Florida IBM 4341-12 VM/SP3 CMS

DRG: 14

L

COUNT	MIDPOINT	ONE SYMBOL EQUALS APPROXIMATELY	.20 OCCURRENCES
6	126.45	*****	
5	326.45	*****	
4	526.45	*****	
1	711.65	*****	

I + I + I + I + I + I
 0 2 4 6 8 10
 HISTOGRAM FREQUENCY

MEAN	330.194	STD ERR	53.093	MEDIAN	279.250
MODE	26.450	STD DEV	212.373	VARIANCE	45102.278
KURTOSIS	-1.015	S E KURT	1.933	SKEWNESS	.434
S E SKEW	.564	RANGE	685.200	MINIMUM	26.450
MAXIMUM	711.650	SUM	5283.100		

VALID CASES 16 MISSING CASES 0

P

COUNT	MIDPOINT	ONE SYMBOL EQUALS APPROXIMATELY	.20 OCCURRENCES
6	242.05	*****	
5	442.05	*****	
0	642.05		
2	842.05	*****	
0	1042.05		
0	1242.05		
1	1442.05	*****	
0	1642.05		
0	1842.05		
0	2042.05		
0	2242.05		
0	2442.05		
0	2642.05		
0	2842.05		
0	3042.05		
1	3242.05	*****	
0	3442.05		
1	3560.95	*****	

I + I + I + I + I + I
 0 2 4 6 8 10
 HISTOGRAM FREQUENCY

MEAN	827.512	STD ERR	269.227	MEDIAN	375.000
MODE	142.050	STD DEV	1076.909	VARIANCE	1159732.27
KURTOSIS	3.445	S E KURT	1.933	SKEWNESS	2.102
S E SKEW	.564	RANGE	3418.900	MINIMUM	142.050
MAXIMUM	3560.950	SUM	13240.200		

VALID CASES 16 MISSING CASES 0

APPENDIX 6B

EXAMPLES OF SPSS ANALYSIS OF THE NATURAL
LOGARITHM OF DEPARTMENTAL CHARGES

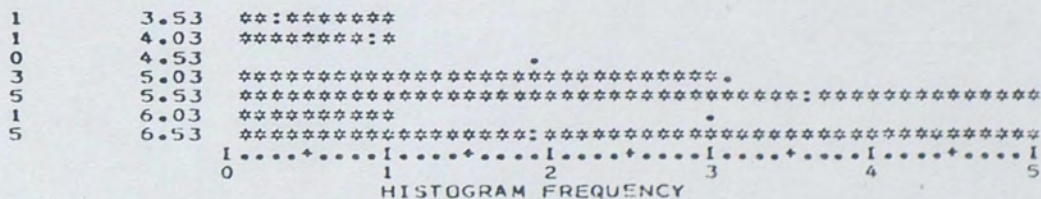
27 AUG 84 STATISTICAL ANALYSIS OF BILLING DATA FOR SELECTED DRGS
 20:41:48 UNIVERSITY OF CENTRAL FLORIDA IBM 4341-12 VM/SP3 CMS

DRG: 14

LLAB

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	3.28	1	6.3	6.3	6.3
	3.87	1	6.3	6.3	12.5
	5.11	1	6.3	6.3	18.8
	5.15	1	6.3	6.3	25.0
	5.20	1	6.3	6.3	31.3
	5.29	1	6.3	6.3	37.5
	5.45	1	6.3	6.3	43.8
	5.59	1	6.3	6.3	50.0
	5.67	1	6.3	6.3	56.3
	5.74	1	6.3	6.3	62.5
	5.87	1	6.3	6.3	68.8
	6.30	1	6.3	6.3	75.0
	6.33	1	6.3	6.3	81.3
	6.38	1	6.3	6.3	87.5
	6.43	1	6.3	6.3	93.8
	6.57	1	6.3	6.3	100.0
TOTAL		16	100.0	100.0	

COUNT MIDPOINT ONE SYMBOL EQUALS APPROXIMATELY .10 OCCURRENCES

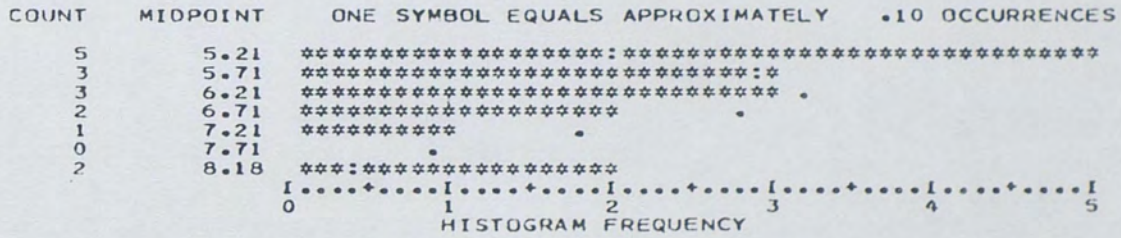


MEAN	5.516	STD ERR	.227	MEDIAN	5.631
MODE	3.275	STD DEV	.907	VARIANCE	.823
KURTOSIS	1.562	S E KURT	1.933	SKEWNESS	-1.240
S E SKEW	.564	RANGE	3.292	MINIMUM	3.275
MAXIMUM	6.568	SUM	88.251		

VALID CASES 16 MISSING CASES 0

DRG: 14
LPHARM

VALUE LABEL	VALUE	FREQUENCY	PERCENT	VALID PERCENT	CUM PERCENT
	4.96	1	6.3	6.3	6.3
	5.07	1	6.3	6.3	12.5
	5.14	1	6.3	6.3	18.8
	5.36	1	6.3	6.3	25.0
	5.42	1	6.3	6.3	31.3
	5.54	1	6.3	6.3	37.5
	5.85	1	6.3	6.3	43.8
	5.89	1	6.3	6.3	50.0
	5.96	1	6.3	6.3	56.3
	6.10	1	6.3	6.3	62.5
	6.25	1	6.3	6.3	68.8
	6.68	1	6.3	6.3	75.0
	6.81	1	6.3	6.3	81.3
	7.25	1	6.3	6.3	87.5
	8.11	1	6.3	6.3	93.8
	8.18	1	6.3	6.3	100.0
TOTAL		16	100.0	100.0	



MEAN	6.161	STD ERR	.252	MEDIAN	5.926
MODE	4.956	STD DEV	1.007	VARIANCE	1.015
KURTOSIS	-.020	S E KURT	1.933	SKEWNESS	.895
S F SKEW	.564	RANGE	3.222	MINIMUM	4.956
MAXIMUM	8.178	SUM	98.584		

VALID CASES 16 MISSING CASES 0

APPENDIX 7

FORTRAN SUBROUTINE EVENT


```

SUBROUTINE EVENT(I)
COMMON/SCOM1/ ATRIB(100),DD(100),DDL(100),DTNOW,II,MFA,MSTOP,NCLNR
I,NCRDR,NPRNT,NNRUN,NNSET,NTAPE,SS(100),SSL(100),TNEXT,TNOW,XX(100)
COMMON/UCOM1/ PMEDCR(7),PARATE(7),AVGLOS(7),LTRIMP(7),XLOS(7,8),RE
2SCON(7,5,6),CRATIO(5),TCOST(7,5),TCHARG(7,6),NDRG,NOEPT,CPXHAY,PAY
3EXP,OUTLIR,OTLPAY,CLMTOL,PCRATE,LOSMAX(7),CHGMIN(7,5),CHGMAX(7,5)
C          ID = DRG NUMBER
C          ID=IFIX(ATRIB(2))
C
C          GENERATING LOSTOT
C          TRIANGULAR OR LOGNORMAL ?
1          IF (XLOS(ID,1).EQ.0.) LOS=IFIX(RLOGN(XLOS(ID,2),XLOS(ID,3),1)+.5)
          IF (XLOS(ID,1).GT.0.) LOS=IFIX(TRIAG(XLOS(ID,3),XLOS(ID,2),XLOS(ID
*          ,1),2)+.5)
          IF (LOS.LT.1) LOS=1
          IF (LOS.GT.60) GO TO 1
C          ** APPLY L.O.S. POLICIES **
C
C          GENERATING PCTICU
C          RN=DRAND(3)
          IF (RN.LT.XLOS(ID,4)) GO TO 10
          X=1-XLOS(ID,5)
          IF (RN.GT.X) GO TO 20
          PCTICU=TRIAG(XLOS(ID,6),XLOS(ID,7),XLOS(ID,8),3)
          LOSI=IFIX(LOS*PCTICU+.5)
          GO TO 30
10         LOSI = 0
          GO TO 30
20         LOSI = LOS
30         ATRIB(3)=FLOAT(LOS)
          ATRIB(5)=FLOAT(LOSI)
          LOSR=LOS-LOSI
          ATRIB(4)=FLOAT(LOSR)
C
C          GENERATING RESOURCE CONSUMPTION (CHARGES) BY DEPARTMENT
C          AND APPROXIMATING TOTAL CHARGES FROM REGRESSION
C
          CHARGE=TCHARG(ID,1)
          DO 100 J=1,NOEPT
          K=J+10
          L=J+1
C          DETERMINING METHOD OF GENERATING CHARGES
C          (IF RESCON(ID,J,1)=0, GENERATE FROM DISTRIBUTION)
          IF (RESCON(ID,J,1).EQ.0.) GO TO 50
C          (ELSE FROM REGRESSION: CHARGE = F LOSREG, LOSICU )
          CH=RESCON(ID,J,1)
          CH=CH + RESCON(ID,J,2)*LOSR + RESCON(ID,J,3)*LOSI
          CH=CH + RESCON(ID,J,4) * LOS**2

```



```

CH=CH + RESCON(ID,J,5)*LOS#**2 + RESCON(ID,J,6)*LOS#**2
IF (CH.LT.CHGMIN(ID,J).OR.CH.GT.CHGMAX(ID,J)) CH=LOS*CHGMAX(ID,J)/
*LOSMAX(ID)
C      ROUNDING XRAY COST TO THE NEAREST UNIT COST
IF (J.NE.5) GO TO 90
CH = FIX(CH/CPXRAY+.5)
GO TO 90
C      CHARGE>0 ?
50  RN=DRAND(4)
IF (RN.GT.RESCON(ID,J,2)) GO TO 60
CH=0.
GO TO 90
C      LOGNORMAL OR TRIANGULAR ?
60  IF (RESCON(ID,J,3).EQ.1.) GO TO 70
C      LOGNORMAL
CH = RLOGN(RESCON(ID,J,4),RESCON(ID,J,5),5)
GO TO 90
C      TRIANGULAR
70  CH = TRIAG(RESCON(ID,J,4),RESCON(ID,J,5),RESCON(ID,J,6),6)
C      ROUNDING XRAY COST TO THE NEAREST UNIT COST
80  IF (J.LT.5) GO TO 90
CH=FIX(CH/CPXRAY+.5)*CPXRAY
IF (CH.EQ.0.) CH=CPXRAY
C      TOTAL CHARGE APPROXIMATION FROM TCHARG REGRESSION
90  CHARGE=CHARGE+CH*TCHARG(ID,L)
C      USE COST-TO-CHARGE RATIO TO ESTIMATE DEPARTMENTAL COST
ATTRIB(K)=CH*CRATIO(J)
100 CONTINUE
C
C      APPLYING ADMISSIONS POLICIES (PATIENT DEFERRED => ATTRIB(2)=0.)
C
C      APPLYING RESOURCE CONSUMPTION POLICIES
C
C      TOTAL COST APPROXIMATION FROM TCOST REGRESSION
COST=TCOST(ID,1)
DO 200 J=1,NDEPT
K=J+10
L=J+1
COST=COST+ATTRIB(K)*TCOST(ID,L)
200 CONTINUE
ATTRIB(8)=COST
C
C      ** PAYMENT SCHEME **
C
C      MEDICARE PATIENT ?
ATTRIB(6)=0.
ATTRIB(7)=0.
RN=DRAND(7)

```



```

C      IF (RN.LT.PMEDCR(ID)) GO TO 210
C      NON-MEDICARE PATIENT EXPECTED REIMBURSEMENT
C      PAY=CHARGE*PAYEXP
C      GO TO 300
C
C      ** MEDICARE **
C 210  PAY=PARATE(ID)
C      ATRIB(6)=1.
C
C      CHECKING FOR OUTLIERS: DRG 999 ('OTHER' CATEGORY)
C      IF (ID.NE.NDRG) GO TO 220
C      LOS OUTLIER FOR DRG 999 ?
C      RN=DRAND(8)
C      IF (RN.GT.OUTLIR) GO TO 250
C      PAY=CHARGE*OTLPAY
C      GO TO 240
C
C      CHECKING FOR OUTLIERS: DRGS 14, 127, 148, 210, 243, 468
C 220  IF (LOS.LE.LTRIMP(ID)) GO TO 230
C      LOS OUTLIER ADDITIONAL PAY CALCULATION
C      PYPDAY=0.60*PAY/AVGLOS(ID)
C      XDAYS=LOS-LTRIMP(ID)
C      PAY=PAY+XDAYS*PYPDAY
C      GO TO 240
C
C      CHECKING FOR COST OUTLIERS
C 230  CLIMIT=1.5*PARATE(ID)
C      IF (CLIMIT.LT.CLMTOL) CLIMIT=CLMTOL
C      IF (CHARGE.LE.CLMTOL) GO TO 250
C      COST OUTLIER ADDITIONAL PAY CALCULATION
C      ADDPAY=0.60*(0.72*CHARGE-CLIMIT)
C      IF (ADDPAY.LT.0) ADDPAY=0.
C      PAY=PAY+ADDPAY
C 240  ATRIB(7)=1.
C      FINAL PAYMENT CALCULATION
C      BASED ON PARTICULAR FISCAL YEAR (25%,50%,75% OR 100% MEDICARE PMT)
C 250  PAY = PCRATE * PAY + (1-PCRATE) * CHARGE
C
C 300  ATRIB(9)=PAY
C      PROFIT OR LOSS
C 320  ATRIB(10)=PAY-COST
C 1000 RETURN
C      END

```


REFERENCES

- Barnard, C. "Preparing for Case Mix: The Role of Data Processing." Healthcare Financial Management 37 (June 1983): 57-70.
- Biles, B.; Schramm, C.; and Atkinson, J. "Hospital Cost Inflation Under State Rate-Setting Programs." New England Journal of Medicine 303 (September 18, 1980): 664-667.
- Calder, B. "Poll Says Most Administrators Don't Fear Losses From Prospective Pay." Modern Healthcare 13 (February 1983): 28-30.
- Doremus, H. "A Reimbursement System that Limits the Costs of Hospital Care." Healthcare Financial Management 37 (April 1983): 86-91.
- Drummer, K. "Letter from the Editor." Agenda 2 (Summer 1982): 1-8.
- Gosfield, A. "Pitfalls in Medicare Part B: Old System with New Significance to Hospitals." Healthcare Financial Management 37 (May 1983): 54-72.
- Grimaldi, P., and Micheletti, J. Diagnosis Related Groups: A Practitioner's Guide. Chicago: Pluribus Press, 1983.
- Grimaldi, P. "Prospective Payment Scheme Overhauls Hospital's Financial Incentives." Hospital Progress 64 (August 1983): 46-52.
- Grimaldi, P. "Public Law 97-248: The Implication of Prospective Payment Schedules." Nursing Management 14 (February 1983): 25-27.
- Hines, W., and Montgomery, D. Probability and Statistics in Engineering and Management Science, 2nd ed. New York: John Wiley and Sons, 1980.
- Hofmann, P. "Physician-Administrator Collaboration Slows Hospital Cost Increases." Hospital Progress 64 (July 1983): 60-72.

- Horn, S. "Does Severity of Illness Make a Difference in Prospective Payment?" Healthcare Financial Management 37 (May 1983): 49-52.
- Johnson, A., and Appel, G. "Hospitals Will Fight Biased DRG System." Modern Healthcare 13 (July 1983): 192-194.
- Korcok, M. "DRG Plan Not Enough to Curb Health Costs: Speaker." Hospitals 56 (December 16, 1982): 17-20.
- Kovener, R., and Palmer, M. "Implementing the Medicare Prospective Pricing System." Healthcare Financial Management 37 (August 1983): 44-46.
- Kukla, S., and Bachofer, H. "Building Up Reporting Systems." Hospitals 57 (July 16, 1983): 77-80.
- Law, A.M., and Kelton, W.D. Simulation Modeling and Analysis. New York: McGraw-Hill Book Company, 1982.
- "Many X-rays Are Unnecessary, WHO Report Says." Hospital Peer Review 8 (May 1983): 63-64.
- McLarney, V., and Davis, J. "Efficient Engineering." Hospitals 57 (August 1, 1983): 67-69.
- Moore, B. "Implementing and Improving Your Case Mix Management System." DRG's and Case Mix Management: A Contemporary Challenge. Presented by the American Medical Record Association, April 7-8, 1983, Orlando, Florida.
- Nathanson, M. "Medical Records' New Financial Role Dramatically Shifts Hospital Priorities." Modern Healthcare 13 (April 1983): 50-52.
- Norvsis, M. SPSSX Introductory Statistics Guide. New York: McGraw-Hill Book Company, 1983.
- Orefice, J., and Jennings, M. "Productivity - A Key to Managing Cost-per-Case." Healthcare Financial Management 37 (August 1983): 18-24.
- Pritsker, A., and Pegden, C. Introduction to Simulation and SLAM. New York: John Wiley and Sons, 1979.
- Robinson, J. "80% of All Hospitals Will Be Hit by \$2 Billion Medicare Penalty." Modern Healthcare 13 (January 1983): 20.

Simborg, D. "DRG Creep: A New Hospital-Acquired Disease."
New England Journal of Medicine 304 (June 25, 1981): 1602-
1604.

"The Medicare Prospective Payment System: Implementing Regulations -
Their Implications for Hospitals." Ernst and Whinney Publica-
tion J58475, 1983.

Thompson, J.; Fester, R.; and Mross, C. "Case Mix and Resource
Use." Inquiry 12 (December 1975): 300-312.