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Using Data Envelopment Analysis and Translog methods to investigate blood center operations: Efficiency, economies of scale, and economies of scope

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USING DATA ENVELOPMENT ANALYSIS AND TRANSLOG METHODS TO INVESTIGATE BLOOD CENTER OPERATIONS: EFFICIENCY, ECONOMIES OF SCALE, AND ECONOMIES OF SCOPE

by

Steven Horng-Shuh Hao

A dissertation submitted to the
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To

Su-Er,

Janice and Julie

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This work is dedicated to Su, my daughters, Janice and Julie, and my parents for their constant encouragement and support.

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USING DATA ENVELOPMENT ANALYSIS AND TRANSLOG METHODS TO INVESTIGATE BLOOD CENTER OPERATIONS: EFFICIENCY, ECONOMIES OF SCALE, AND ECONOMIES OF SCOPE

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The purpose of this dissertation is to illustrate how Data Envelopment Analysis (DEA) and Translog (transcendental logarithmic) methods can be applied to measure blood center efficiency and to estimate scale and scope economies. The dissertation develops two production process models of blood center operations: Model A employs blood components distributed (BCD) as the proxy of output and labor, capital, and material as inputs; Model B employs BCD, specialized laboratory services (SLS), and specialized clinical services (SCS) as outputs and labor, capital, and material as inputs.

The first stage of this study empirically measures individual blood center efficiency by using the DEA methodology for both Models A and B. It also uses regression analysis to identify factors which may have an impact on blood center efficiency. The second stage of this research applies Translog methodology to investigate scale economies for Model A as well as scale and scope economies for Model B. Finally, the study estimates best practice returns to scale and scope by eliminating the most inefficient blood centers based on the DEA study results.

The major contributions of this study are: (1) it is the first study to use DEA in measuring blood center efficiency; (2) it is the first study to use the Translog method

to estimate scale and scope economies base on actual blood center data; (3) the development of two production process models that employ multiple inputs and multiple outputs to represent blood center operations; (4) minimizing inefficiency effects on scale and scope economies estimation by eliminating the less efficient blood centers from such analysis; (5) using regression analysis to identify the relationship between eight potentially causal factors and center inefficiency ratings; (6) illustration of how DEA results could lead to highly specific managerial strategies for improving the efficiency of an inefficient blood center by indicating which inputs are being overutilized, which outputs are being underproduced, and in each case by how much. Results from the scale and scope analyses can be used as a decision-making and planning tool for blood center expansion and pricing of various blood products and services.

CHAPTER I

INTRODUCTION

The measurement and comparison of productivity and operating costs among similar organizations, widely practiced in private industry, is of particular importance today in health care organizations. Sheltered in the past from the competitive forces that impel productivity increases and cost reduction as well as lacking the incentive to enhanced efficiency provided by the profit motive, the managers of nonprofit organizations (NPOs) and public establishments frequently have failed to achieve a standard of operating efficiency comparable to that of private industry. This outcome is exacerbated if the NPO or public enterprise is wholly or partly financed by government or its products are not sold in competition with privately produced substitutes.

The primary difficulty to measure the relative productive efficiency, or productivity for NPOs is that each member of a set of comparable producing units called decision making units (DMUs) often produce several products in ways that preclude establishing a unique cost for each. Thus, it is not surprising that research in cost and productivity measurement, as well as in the study of economies of scale, has concentrated on industries that seem to produce a single output, such as electricity or transport. Measurement difficulties in multiple output productive efficiency analysis, have been commonly circumvented by the use of fixed weights to aggregate the multiple outputs into a single output (see, e.g., Lovell and Schmidt;

1988). Thompson el. al. (1991) applied the Data Envelopment Analysis (DEA) method to show how this practice distorts the measures of productive efficiency in the U.S. oil and gas extraction industry.

The study employs the DEA methodology for comparing costs and efficiency as well as the Translog methodology for measuring returns to scale and scope among regional and community blood centers. These methodologies are illustrated by their application to the measurement of relative performance among a set of 48 blood centers from 1987 to 1989. The study also employs two models to represent blood center operations. Model A is a three input and one output model. Material, labor and capital are the inputs and blood components distributed (BCD) the output. Model B employs the same three inputs; however, it uses three outputs: BCD, specialized laboratory services (SLS) and specialized clinical services (SCS).

Section 1 of this chapter is the prologue. Section 2 presents background information on the historical and present development of the blood services industry in terms of growth in demand, revenue, supply, and other important factors. Section 3 describes research objectives and methodologies. Outline of the dissertation is presented in Section 4.

1. PROLOGUE

Efficiency analysis is important in health care. The health care sector absorbed more than twelve percent of U.S. gross domestic product in 1990, health care expenditures are growing more rapidly than other forms of personal

consumption, and much of the sector lacks the market forces to promote efficiency.

In January 1984, the Health Care Financing Administration published final regulations which revised the conditions and procedures for making Medicare payments to hospitals for inpatient services, thereby changing the payment method from a cost-based, retrospective reimbursement system to the present diagnosis-specific prospective payment system (PPS). The new system's primary purpose is to control federal payments for health-care by providing incentives to hospitals to manage their operations in a more efficient and cost-effective manner.

The basic idea underlying PPS is relatively simple. For each Medicare discharge the hospital is paid a preestablished amount based on its classification into one of 468 diagnosis-related groups (DRGs). While the original intent of DRGs was to control medicare reimbursement, but they may also be used by hospital management for its internal planning and control. If a hospital has operating costs less than the DRG payment rate, the hospital keeps the surplus; if not, it absorbs the loss. Thus, the PPS method of reimbursement places the hospital at risk. In order to survive it must keep its costs in line with the DRG payment rates or find other revenue sources to compensate for the short fall. The PPS form of reimbursement represented a change in the external environment faced by not only the hospitals but also by other health care organizations, such as blood centers, that sell their services to hospitals. Hospitals exerted pressure on blood centers to hold down price increases in order to contain hospital costs. As a consequence, under the present environment, blood centers have recently experienced substantial reductions

in the rate of growth of their traditional revenues and increased costs of testing and testing losses. At the same time, they remain exposed to the rapidly rising costs of health-care related supplies. If there exists a single universal goal for blood centers, it would be organizational survival. Under present conditions a practical way of surviving is for blood centers to improve their operating efficiency and productivity.

Through the use of a relatively new technique known as DEA, this study presents a new and in many ways a more effective means of measuring relative efficiency among blood centers and of identifying its determinant factors. The study also employs Translog (transcendental logarithmic) cost functions to measure blood center returns to scale and scope. Results from the study should assist blood centers in improving their efficiency and help center management to more effectively plan and control its operations.

2. A NEW ERA IN BLOOD SERVICES INDUSTRY

Widespread concern about the safety of the national blood supply, particularly with respect to the human immunodeficiency virus (HIV), has affected the use of blood products to support patients. Surgenor, Wallace, Hao and Chapman conducted national surveys of blood collection and transfusion in the United States in 1982, 1984, 1986, and 1987 and found an unprecedented decline in 1986 and 1987 in the transfusion of whole blood and red cells as well as decline in the collection of

homologous blood.[1] They attributed these changes in blood collection and blood transfusion to the effects upon physician behavior of the HIV epidemic.

2.1 CHANGES IN DEMAND OF BLOOD PRODUCTS

Growth rates in unit demand for blood products from 1971 to 1989 are presented in Table I-1. The data are drawn from the national blood censuses of 1971 and 1980. Also included are American Red Cross (ARC) and Council of Community Blood Centers (CCBC) data through 1987 and ARC data for 1988 and 1989. Growth in unit demand for products is expressed in compound annual growth rates. Throughout the period from 1971 to 1983, the data depict a rapidly growing industry with an approximate annual growth between 8 and 10 percent. From 1983 to 1986, however, the annual rate of growth dropped sharply to 3.3 percent. From 1986 to 1989, the annual rate of growth dropped even further to 0.5 percent. The major reason for this decline in blood products demand was the perception by physicians, surgeons, and the general public of increased transfusion risks associated with AIDS. Table I-1 shows the only real growth in blood product demand from 1986 to 1989 was in cryoprecipitate, a less risky source of factor VIII for hemophiliacs. Demand growth for red cells and plasmas were negative 0.3 and negative 0.1 percent respectively during the 1986-1989 period.

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[1]Surgenor, D. M., E. L. Wallace, S. H. S. Hao, and R. H. Chapman, "Collection and Transfusion of Blood in the United States, 1982-1988". *New England Journal of Medicine*, 1990; 322: 1646-51.

2.2 CHANGES IN REVENUES

Implications of the changes in demand of blood products from a revenue point of view are shown in Table I-2. Growth in unit demand during the 1980-1983 period was compounded by appreciable price increases. The two factors together produced the exceptional average annual rate of growth in revenues of 23.1 percent. In 1983-1986 period this average annual rate of revenue growth was replaced by the much lower rate of 5.9 percent. The rate dropped even further to 4.5 percent during the 1986-1989 period.

Red cells are the most important product of blood center. Revenue from red cells accounted for at least 70 percent of total blood center revenue throughout the period 1970 to 1989. As a result the revenue growth rates for all products and red cells were approximately the same. Table I-3 shows that the 5.9 percent rate of growth for all blood services revenues during 1983-1986 and the 4.5 percent rate of growth for the same in 1986-1989 came from three sources: increased yield (number of products produced per unit of whole blood collected), increased volume of blood collection, and increased prices. During 1983-1986, the increase in revenue resulting from yield increases (products produced and sold) accounted for about 71 percent of total revenue growth, where as price increases accounted for 35 percent and collection decreases accounted for negative 6 percent of such growth. During 1983-1986, the annual increase in revenue of 5.9 percent is attributed to increased yield of 4.1 percent and increased prices of 1.8 percent.

During 1986-1989, increased prices accounted for 90 percent of increases in total revenue, whereas yield increases accounted for only 7 percent and collection increases for 3 percent. Growth in prices amounted to 4.5 percent during 1986-1989 and 1.8 percent during 1983-1986, evidencing increased limitation on the growth in prices because of pressure from hospitals for cost containment. Growth in increased yield and collection combined was a mere 0.5 percent during 1986-1989 (see, Table I-1), suggesting that potential growth in volume is also limited by a leveled demand for blood components.

2.3 CHANGES IN SUPPLY

When an industry moves from a period of fast growth to one of virtual stability, what happens depends on the way the industry is organized and the motivations of the people running it. One factor becomes extremely important, the state of industry supply, particularly when users look upon the industry's products as interchangeable commodities. If demand levels and supply continues to grow, an excess supply develops, producing intensive price competition, particularly in mature industries with homogeneous products.

As shown in Table I-4, during the 1971-1980 period, the supply of whole blood units collected grew at a compound rate of 2.4 percent per year. During 1980-1983, the growth rate of whole blood collection was 4.6 percent per year and the growth in increased product yield was 3.7 percent per year. Growth in collection and yield together produced a supply growth rate of 8.5 percent per year from 1980 to 1983.

During 1983-1986, however, the growth rate of whole blood collections was a negative 0.2 percent per year, whereas the growth in product yield was 2.3 percent. Together the two produced a total growth in supply of 2.1 percent per year. During 1986-1989, the growth in whole blood collections was 0.4 percent per year, the growth in product yield was 1.1 percent per year. Together the two produced a total growth of 0.5 percent per year. What happened is that with the loss in the growth in demand for blood products there occurred a compensating loss of growth in blood supply, so that industry competitive pressures that would otherwise have developed were blunted.

2.4 ALTERNATIVES FOR PRODUCTIVITY IMPROVEMENT

The blood services industry has entered a period of relatively mature development in which growth in unit demand and in prices are both relatively low. What can blood centers managers do to maintain financial viable when income cannot be enhanced through expansion in the volume of products produced and sold, price increases are limited, and costs increases continue? Productivity improvement and/or cost reduction is virtually the only way. Under such conditions private industry, where concern is "return on investment", cost reduction becomes the principal concern. It has to be the principal concern of the blood services industry as well.

2.4.1 Product Yield Increases

There are three ways a blood center can achieve cost reduction through productivity increases. The first is to increase product yield, i.e., to obtain more products from each unit of whole blood collected. Theoretically, it is possible to obtain four units of product from a unit of whole blood (i.e., red cells, plasma, platelets, and cryoprecipitate). However, the market is unable to absorb all of these units. At present, since market growth in demand for blood products is virtually zero, increases in product yields are unlikely to be a major source of future improvements in productivity and revenue enhancement.

2.4.2 Wastage Reduction

A second source of productivity improvement is waste reduction. In this respect, the blood services have done an exceptional job in recent years. In 1970, the wastage rate for red blood cells was 16 percent. By 1980, the rate had declined to 7.4 percent. The rate dropped to 4.1 percent in 1983 and to 3.4 percent in both 1986 and 1989.

A rate below 3.4 percent would be extremely difficult. Thus, wastage reduction, as a major source of improvement in blood services productivity, is virtually exhausted. The only remaining means by which blood centers can increase productivity is to improve operating efficiency; i.e., by reducing labor, material, and/or capital input per unit of output.

2.4.3 Labor, Material, and Capital Input Reduction

Since the blood services industry is labor-intensive (Table I-6 shows that labor cost accounted for 51 to 52 percent of total cost during 1980-1989) one potential major source of productivity improvement is reduction in the quantity of labor per unit of output. The data in Table I-6 are drawn from a large set of regional and community blood centers. In 1980, a full time equivalent employee (FTE) averaged 775 units of whole blood collection and 1120 units of product produced. In 1989, a FTE averaged 600 units of whole blood collection and 1545 units of product produced. The slight decline in collection per FTE from 643 in 1983 to 600 in 1989 is probably due to the joint effects of increased testing, product yield, and new blood services introduced during the intervening years. Total product produced per FTE increased from 1480 in 1983 to 1545 in 1988, indicating a small average productivity increase among the blood centers over this period.

Figure 1 illustrates the variation in productivity differentials among the large set of regional and community blood centers in terms net blood component units distributed per FTE in 1988. Average units distributed per FTE were 1468. However, individual centers productivity ranged from 1000 to 2200 units of FTE; i.e., from 68 percent of average on the less productive side to 150 percent on the more productive side. Obviously there is a wide range of productivity differentials among present blood centers, implying that there is ample overall opportunity for labor productivity improvement in blood services. There also exists a similar wide range of material and capital cost differences in routine laboratory testing among blood

centers,[2] indicating an equal opportunity for material and capital productivity improvement as well.

2.5 ECONOMIES OF SCALE AND SCOPE

If blood services operations are to be improved through increases in productivity, consideration must be given to capturing some of the potential benefits from economies of scale and scope. In order to obtain accurate estimates of economies of scale and scope, productivity differentials or efficiency variations first must be measured and then appropriate actions taken to obtain better estimates of existing returns to scale and scope.

This study investigates returns to scale and scope in blood banking. Results from the study of scale economies should assist individual blood center management to determine whether the level of present operations is providing increasing or decreasing returns to scale. Results from the study of scope economies should help blood center management to determine benefits from bundling or unbundling different products and services as well as acting as a guide in price setting.

3. RESEARCH OBJECTIVES AND METHODOLOGY

The study employs two models to represent blood center operations. Model A is a three input and one output model. Material, labor and capital are the inputs

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[2]Kline, L. M., L. I. Friedman, and M. L. Severns, "Cost Analysis of Routine Laboratory Testing in Blood Centers". *Transfusion* 1986; 26: 227-230.

and blood components distributed the output. Model B employs the same three inputs; however, it uses three outputs: BCD, specialized laboratory services and specialized clinical services. It achieves a more complete presentation of blood center operations. The study employs the DEA methodology to measure each blood center's relative efficiency. Results from the DEA study provide center managers with specific information about center efficiency and direction in order to improve center efficiency, information that is not available from ratio or regression analyses.

Through chi-square and exploratory regression analysis, the study investigates the relationships between eight potentially causal variables and center efficiency ratings. Future extensions of the study may accommodate the differences among these variables in order to generate even better measures of relative efficiency.

Through application of Translog cost function, the study simultaneously estimates the returns to scale and scope properties of blood center operations. By using the center efficiency ratings generated from the DEA study, the less efficient blood centers are excluded from the analysis of "best management practice" returns to scale and returns to scope. Estimates of these returns to scale and returns to scope based on operations of the better managed blood centers are more interesting and accurate estimates of the potential level of productivity obtainable by all blood centers than are the estimates generated by use of the complete sample set which includes both efficient and inefficient centers. Finally, this study illustrated how DEA results can be used as a decision-making and management planning tool for blood services.

4. ORGANIZATION OF THE DISSERTATION

Chapter 2 describes how the relative efficiency of 48 regional or community blood centers in the period from 1987 to 1989 is measured by using DEA. Section 1 provides a general introduction. Section 2 describes conventional approaches to measuring efficiency. Section 3 describes DEA method as well as two related statistical frontier approaches and explains why the DEA method was selected for this study. Section 4 describes the two models of blood center operations and the data used in the study. Section 5 presents results from the DEA, chi-square, and regression analyses of blood center operations and Section 6 provides the conclusions and suggestions for future research using the DEA methodology.

Chapter 3 employs the Translog methodology to estimate economies of scale and scope in the blood services industry. Section 1 describes the concepts of economies of scale and scope in general as well as related issues in the blood services industry. Section 2 provides a brief review of the methodologies employed in previous research studies in estimating returns to scale and scope. Section 3 describes the Translog cost function methodology as well as the research design of the study. Section 4 presents the study results. Section 5 contains study conclusions together with a discussion of contributions and limitations of the methodology.

In Chapter 4 Section 1 summarizes the research findings. Section 2 describes the managerial implications of the study. Section 3 describes its major contributions. Section 4 addresses study limitations and Section 5 concludes with possible future extensions of the research.

TABLE I-1 GROWTH RATES IN UNIT DEMAND OF BLOOD PRODUCTS

	Percent Growth Per Year				
	71-80	80-83	83-86	86-89	80-89
All Products	8.1	10.2	3.3	0.5	4.6
Red Cells	5.2	10.9	3.3	(0.3)	4.6
Platelets	23.9	8.2	5.6	0.9	4.8
Plasmas	26.7	9.0	(2.3)	(0.1)	2.1
Cryoprecipitate	0.2	15.3	4.5	6.0	8.5

Source: National censuses of 1971 and 1980; American Red Cross (ARC) and Council of Community Blood Centers (CCBC) data for 1981-1987; and ARC data for 1988-1989.

TABLE I-2 GROWTH RATES IN REVENUES OF BLOOD PRODUCTS

	Percent Growth Per Year			
	80-83	83-86	86-89	80-89
All Products	23.1	5.9	4.5	10.9
Red Cells	23.9	5.1	4.5	10.8
Platelets	20.2	10.4	4.1	11.4
Plasmas	22.2	0.5	3.9	8.5
Cryoprecipitate	33.8	11.9	11.6	18.7

Source: ARC records using mean prices from 15 randomly selected regional and community blood centers.

TABLE I-3 PRINCIPAL SOURCES OF GROWTH IN TOTAL REVENUES OF REGIONAL AND COMMUNITY BLOOD CENTERS

	Percent Growth Per Year		
	80-83	83-86	86-89
Average rate of growth of revenue	23.1	5.9	4.5
Average rate of growth in prices	11.7	1.8	4.5
Percent of growth from increased yield	21	71	7
Percent of growth from increased collection	26	(6)	3
Percent of growth from increased prices	53	35	90

Source: ARC records using mean prices from 15 randomly selected regional and community blood centers.

TABLE I-4 GROWTH RATES FOR WHOLE BLOOD COLLECTION AND YIELD

	Percent Growth Per Year				
	71-80	80-83	83-86	86-89	80-89
Whole Blood Collection	2.4	4.6	(0.2)	0.4	1.6
Yield	---	3.7	2.3	1.1	2.3

Source: National censuses of 1971 and 1980; ARC & CCBC data for 1981-1987; and ARC data for 1988-1989.

TABLE I-5 PERCENT WASTE ON RED BLOOD CELLS

	70	80	83	86	89
Waste Rate on Red Blood Cells	16	7.4	4.1	3.4	3.4

Source: National censuses of 1971 and 1980; ARC & CCBC data for 1981-1987; and ARC data for 1988-1989.

TABLE I-6 PRODUCTIVITY PER FULL TIME EQUIVALENT STAFF MEMBER

	80	83	86	89
Collection per FTE	775	643	612	600
Total Product Produced per FTE	1120	1480	1520	1545*
Labor Cost/Total Cost	51	51	52	52

Source: ARC and CCBC records
* 1988 data

Net Component Unit Distributed per FTE*
1987–88

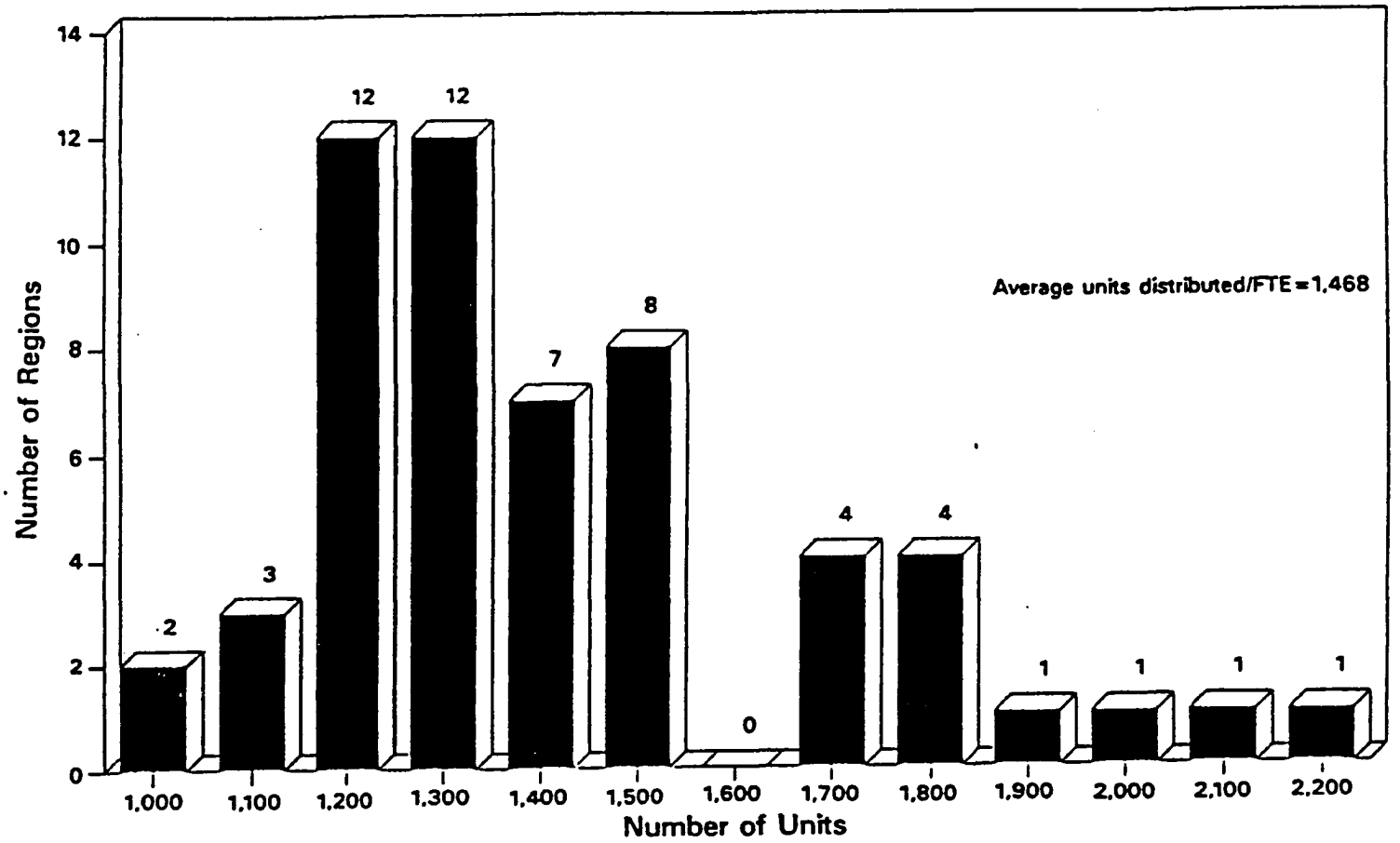

FIGURE 1. PRODUCTIVITY DIFFERENTIALS

* Full Time Equivalent Staff

CHAPTER II

Measuring Blood Center Efficiency

Through Data Envelopment Analysis

1. INTRODUCTION

Regional and community blood centers have recently experienced substantial reductions in the rate of growth of their traditional revenues. Wallace observed that "demand for most blood components has leveled, competition has limited price increases, component yields have ceased to grow, savings from outdating reductions are exhausted, and the prospective payments system for hospital reimbursement constrains increases in prices to hospitals. At the same time, blood centers continue to be faced with increased costs of testing and testing losses and rapidly rising costs of health-care related supplies. Because of lags in distribution volumes and price increases, together with low growth (2%) in component yields and the cessation of savings from reduced outdating, blood center managers are left with few alternatives for enhancing the fiscal position of their centers. Of these, cost reduction (or at least cost containment) through efficiency increases or service reductions offers the greatest potential benefit".[1]

In the 1980s, the threat of human immunodeficiency virus, hepatitis C virus, and other blood-borne diseases has made improvement in the quality of testing and component handling the principal goal of blood services. Improved quality, however,

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[1]Wallace, E. L., "Costing Blood Products and Services". An Editorial in Transfusion 1991; 31: 293-295.

comes with increased costs, which, when coupled with recent constraints on revenue and reimbursement growth, require a shift to efficiency improvement as the principal goal of blood services in the 1990s.

This chapter examines efficiency measurement of the blood center production process using data from 48 blood centers in the period from 1987 to 1989. There are three goals to this part of the study. The first is to measure efficiency. The second is to investigate eight factors that might affect blood center efficiency ratings through multiple regression analysis. The third is to demonstrate how Data Envelopment Analysis (DEA) results can be used as a decision-making tool to help management in planning and control of blood center operations.

The DEA technique has been employed to estimate the relationship between inputs and outputs in the blood center production process. The choice of DEA was motivated by the need to simultaneously consider multiple inputs and outputs and not to impose an arbitrary parametric form for the underlying production correspondence. This chapter not only describes the methodology of DEA and its application in measuring blood center efficiency but also briefly reviews other conventional and leading edge methodologies often used for productive efficiency measurement. The following sections will explain the reasons why DEA was selected for this study and show how DEA methodology is superior to other methods.

The DEA method avoids several methodological problems using ordinary least square (OLS) regression methods. First, cost functions derived from statistical data for nonprofit health care organizations do not conform to theoretical conditions

required to define a cost function. The noncompetitive nature of the market for blood means that it cannot be assumed that inefficient blood centers have been driven out of the market. Therefore, relationships produced by the mean squared-error criterion will not approximate minimum cost of production. This point underlies the theoretical rationale for DEA. In contrast to other statistical frontier methods, DEA allows a frontier comparison without prior specification of a parametric production function.

Second, regression-based cost functions average input/output relationships across individual blood centers. Thus, the economic relationship depicted by a cost function for a group of blood centers may not accurately represent that relationship for any particular blood center in the group. By orienting its estimates to each individual blood center, DEA is applicable even when cost or production functions differ across institutions.

Third, previous cost function studies do not simultaneously deal with the multiple-input, multiple-output nature of blood center production. To the extent that blood centers produce different ancillary services relative to whole blood collection and the production of blood components, an overall picture of production based on whole blood collections alone distorts reality.

In developing DEA, Charnes, Cooper, and Rhodes (1978) built upon the seminal work of Farrell (1957) on the estimation of production functions and the measurement of efficiency . The technique has emerged from economics and operation research in an attempt to bridge the gap between the theoretical notion

of a production function and its empirical estimation. DEA provides not only an intuitively attractive approach to the measurement of performance, but also valuable information for management planning and control. However, in spite of the large number and variety of applications (see Seiford, 1990), DEA remains a technique whose results need reinterpretation before they can be readily grasped and used by decision makers and managers.

In DEA, the entities responsible for converting inputs into outputs are referred to as Decision Making Units (DMUs). This usage is generic and comprehends the activity of many different kinds of organizations and their subdivisions. The DEA technique has been used extensively to measure efficiency in nonprofit organizations and in government units, as well as in the service industries (see Seiford, 1990). However, it is not as well known to health services researchers. Most health related articles reporting the use of DEA involve either general hospitals or nursing homes (Nunamaker 1983; Sherman 1984; Banker, Conrad, and Strauss 1986; Borden 1988; Nyman and Bricker 1989; Bedard and Wen 1990). The challenge for this study is to examine whether DEA yields useful information when applied to blood center production.

The remainder of the chapter has the following structure. Conventional approaches for measuring efficiency are described in Section 2. Section 3 describes and compares DEA with two statistical frontier approaches. Section 4 describes the models and the data. Section 5 presents the results of the analysis and Section 6 provides some conclusions and suggestions for future research.

2. CONVENTIONAL APPROACHES FOR MEASURING EFFICIENCY

Two procedures are commonly used to measure efficiency: ratio analysis and multiple regression. Each suffers in important ways from problems that prohibit it from being used effectively in certain situations.

2.1 RATIO ANALYSIS

Ratio analysis involves the use of various ratios for a group of comparable DMUs to locate relationships that are abnormally high or low. Examples of this type of analysis are the regional operations review information system (RORIS) and regional productivity measures of the American Red Cross (ARC).

Ratio analysis involves the calculation of and attempt to understand the management implications of the relationship between two variables. Each ratio is limited to one output and one input and cannot easily be applied to situations where multiple outputs are produced using multiple inputs. To compensate for the unidimensional aspects of a single ratio, large sets of ratios are calculated as in RORIS and the ARC's regional productivity reports. A blood center may appear relatively efficient on one set of ratios and inefficient on another. While a second blood center may have opposite results for the same ratios. There is no objective means of assigning relative weights to the ratios. Consequently using ratio analysis, it is difficult to conclude overall which blood centers are relatively efficient or inefficient. Ratio analysis is, however, very useful in identifying specific aspects of a blood center's operation that are out of line with norms.

2.2 MULTIPLE REGRESSION

Multiple regression techniques have been used to estimate cost and productivity relationships in blood services. Wallace and Wallace (1982), Pierskalla (1987) and Hao (1988) employed multiple regression together with the Cobb-Douglas production function to test economies of scale in blood center operations.

Regression analysis is more comprehensive than ratio analysis in that it can accommodate multiple outputs and inputs; however, other significant problems are encountered with the technique. The use of least-square regression results in estimates of "average" relationships, which are not necessarily efficient. While econometric-regression types of studies have been used extensively to identify economies of scale and rates of substitution among outputs and inputs, results of such analysis say nothing about efficient rates of substitution, efficient scale size, and efficient rates of transformation because they reflect the combined behavior of efficient and inefficient organizations. Use of regression techniques can provide insights into efficient blood center operations only if the blood centers involved in the study are known to be relatively efficient.

3. LEADING EDGE APPROACHES FOR MEASURING EFFICIENCY

In this section three methods for measuring (or estimating) production efficiency are discussed and compared. The methods avoid many of the problems associated with ratio and regression analysis. They do, however, have unique problems of their own.

3.1 DATA ENVELOPMENT ANALYSIS

Data envelopment explicitly considers multiple outputs and inputs thus avoiding a serious limitation of ratio and regression analysis. DEA is a linear programming technique that when applied to blood services operations compares a center's inputs used to produce its outputs with those of other centers during a common time period. In applying DEA, outputs and inputs need only be measured in natural physical units. DEA identifies those centers that are relatively less efficient and measures their overall inefficiency compared with those of the more efficient centers. Inefficient centers are assigned an efficiency ratio of less than 1 ($E < 1$). Centers with an efficiency ratio of 1 ($E = 1$), however, are not necessarily efficient in an absolute sense. Rather they represent "best practice" among the group of centers in the analysis, meaning that they are not clearly inefficient when compared with other blood centers in the set. This result obtains because the input-output relationship of an absolutely efficient blood center are unknown. Hence a blood center found to be relatively efficient by DEA may be able to improve its operating efficiency. A blood center found by DEA to be inefficient, however, will have identifiable inefficiencies at least as large as those measured by DEA. An inefficient blood center, identified by DEA, will have the apparent ability to produce the same level of outputs with fewer inputs based on the linear combination of output-input activities of those blood centers DEA has identified as efficient.

The advantages of DEA are that it simultaneously considers multiple outputs and inputs of a blood center without depending on any a priori arbitrary fixed

weights scheme and it provides a single summary measure of the relative efficiency of each center compared with the most efficient blood centers in the set. DEA conservatively measures existing inefficiency and the types and amounts of input reductions needed to make inefficient centers as efficient as the most efficient centers in the set. Thus results from a DEA study can help blood center managers identify the means for improving their center's efficiency.

LIMITATIONS OF DEA

DEA has limitations. It requires all inputs and outputs to be specified and measured. This is also a requirement of ratio and multiple regression analysis when used as efficiency measuring procedures. Failure to include a valid input or output in the DEA biases results against efficient users or producers of the input or output. Inclusion of an invalid input or output causes DEA to rate some blood centers more efficient than they really are. Thus, like other types of analysis, DEA must be properly structured.

DEA also assumes that each unit of a given input or output is identical to all other units of the same type. For example, when applied to blood center operations, DEA assumes that the labor input provided by each employee is the same. In fact, one employee may be more experienced or better trained than another and therefore take less time to perform a given task. Constraints on employee flexibility and productivity because of union or other restraining factors may also produce major variations in labor input per FTE among centers. On the output side, DEA assumes that each product or service produced by a blood center is identical to the same

product or service by all other centers. If the quality of the outputs differ, then DEA results will be biased in favor of the blood center in which quality is lowest provided, it requires fewer resources to produce a given output or is able to increase output per unit of input through quality reduction. Fortunately, all blood center outputs have to meet the quality standards established and regulated by Food and Drug Administration, so quality differentials among comparable blood centers ought not be large.

Another weakness of DEA is that its efficiency measurement is very sensitive to outliers and biased toward corner points; i.e., centers with one or more extremely large or small inputs or outputs. Corner points tend to be erroneously classified as efficient by DEA because there are insufficient number of referent points in the analysis which they can be compared in order to establish the appropriate inefficiency score. This is a fundamental weakness of DEA, especially when used in a non-cooperative management environment. Since blood centers or DMUs are evaluated by DEA along their best dimensions (variables), opportunities exist for management of less efficient DMUs to increase their efficiency score through manipulation of reported data. Using a game theory formulation of DEA, Banker (1980) conjectured that rational behavior--i.e., the rationality assumed in the theory of games--would cause DMUs managements to develop "new" outputs or inputs so that by using this strategy they could escape the full pressures of the comparative evaluations of DEA. By moving into input or output dimensions not employed by other DMUs, a blood center's management could appear to be relatively efficient even though some uses

of its inputs might be excessive.

Finally, DEA results are based on sample data enveloped by a deterministic frontier. Consequently the deviation of an observation from the frontier is nonstochastic. No accommodation is made for environmental heterogeneity, random external shocks, noise in the data, measurement error, omitted variables, and the like. All sorts of influences, favorable and unfavorable, beyond the control of the management unit are lumped together by DEA and called inefficiency.

3.2 THE DETERMINISTIC STATISTICAL FRONTIER APPROACH

In contrast to DEA, the deterministic statistical frontier approach uses a statistical techniques to estimate a transformation production or cost frontier and to estimate each DMU's efficiency relative to the estimated frontier. The technique was first proposed by Afriat (1972) and has been extended by Richmond (1974) and Greene (1980) among others.

The deterministic statistical frontier approach is parametric, unlike the DEA approach which is nonparametric, so the frontier is estimated rather than computed. The easiest way to estimate the required parameters is by use of the corrected ordinary least squares technique (COLS) which uses ordinary least squares (OLS) to obtain the best linear unbiased and consistent estimates, and then corrects the constant term so that no observations lie above the estimated frontier. Another way of estimating the required parameters is by maximum likelihood estimation (MLE). The advantage of MLE is that it allows direct estimation of the constant term.

This approach assumes a deterministic frontier, and all deviations from the frontier are attributed to inefficiency. No allowance is made for noise, measurement error, and the like. Extension of the approach to multiple outputs is difficult unless the dual cost frontier is estimated directly and the Kopp-Diewert-Zieschang (1983) decomposition algorithm is used. The most important way in which the deterministic statistical frontier approach differs from DEA is that the frontier and related efficiencies are estimated by statistical techniques rather than computed by programming techniques. For statistical reasons, a large sample size is required, which is clearly a disadvantage. Furthermore, estimates of the parameters and the magnitude of efficiency are not invariant with respect to the specification of a distribution for the efficiency term. On the other hand, the advantage of the statistical approach is the possibility of statistical inference based on the results, although such inference will be valid only if the specified distribution is the true distribution.

3.3 THE STOCHASTIC STATISTICAL FRONTIER APPROACH

The stochastic statistical frontier approach is another alternative to DEA. It uses statistical techniques to estimate efficiency relative to the estimated frontier. In contrast to the deterministic statistical frontier approach, this approach allows the frontier itself to be stochastic. The technique was first proposed by Aigner, Lovell, and Schmidt (1977), and Meeusen and van den Broeck (1977), and has been extended by Schmidt and Lovell (1979,1980) and Huang (1984), among others.

In this approach, in contrast to previous approaches, the data are bounded by a stochastic frontier. Consequently the deviation of an observation from the stochastic frontier may be due either to inefficiency (e_1) or random variation (e_2). The stochastic frontier approach, however, also has drawbacks. Estimation requires a large sample size. As in the deterministic statistical frontier approach, considerable structure is usually imposed on production technology. Moreover, additional structure is imposed on the distribution of inefficiency (e_1). Finally, as in the deterministic statistical frontier approach, the stochastic statistical frontier approach has difficulty dealing with multiple outputs.

The greatest advantage of the stochastic frontier approach is that, unlike other approaches, it introduces into the analysis a disturbance term representing noise, measurement error, and exogenous shocks beyond the control of the production unit. Neither of the other two approaches accommodates for such phenomena which affect every economic relationship. Without such an accommodation statistical noise is counted as inefficiency or spurious efficiency.

3.4 WHY DEA

The major advantages of DEA compared to the deterministic and stochastic statistical frontier approaches is that DEA easily handles multiple outputs and multiple inputs in measuring the relative efficiency of individual blood centers. The lack of need for prescribing the underlying functional form or weights in an a priori manner, means that DEA is empirically based in contrast to the other approaches

which require frontier statistical regressions, productivity indexes, and a great deal of analytical theorizing prior to choosing the forms to be used. DEA is oriented toward observations associated with the individual DMUs, in contrast with customary statistical estimates which are oriented toward all observations. Thus, DEA introduces a new principle for effecting estimates from empirical data which is oriented toward each observation. A least squares regression of the usual statistical approach, on the other hand, uses a single optimization to obtain a single estimating relation from n observations. DEA, however, uses n optimizations for the same n observations in order to obtain efficiency evaluations for each DMU.

4. DEA MODELS APPLIED TO BLOOD CENTER STUDY

The approach of this research is represented by the simple diagram shown in Figure 1. The three inputs for blood center operations are : (1) labor, (2) material and supplies, and (3) capital. On average the labor input constitutes 53 percent of blood center costs; material and supplies account for 25 percent; and capital accounts for the remaining 22 percent. Labor input is measured by the number of full time equivalent employees (FTE). Material and supplies is calculated as the sum of all material and supplies costs. Capital is calculated as the sum of depreciation and interest charges.

4.1 DEA CENTER MODELS

Identification of consistent, quantifiable products from blood center operations is probably the single biggest challenge in blood center productivity measurement. The traditional measure of output has been a simple count of the number of whole blood units collected (WBC). While WBC has the advantage of being easily countable, its major problem is that it does not take account of production and distribution of blood components. WBC is the product of only one phase of blood center operations, donor recruitment and collection and is therefore an inadequate measure of blood center output.

This study employs different measures of blood center outputs. The most important single output of a blood center is the number of blood components it distribute (BCD). However, there are two other important center activities : (1) specialized laboratory services (SLS) and (2) specialized clinical services (SCS). SLS and SCS are procedures performed by blood centers to meet medical and community needs beyond the regular processes of whole blood collection and component production. For study purposes SLS is computed as the sum of the number of reference and processing laboratory tests and procedures performed, plus the number of tissue typing activities performed, plus the number of irradiated blood products produced. SCS is calculated as the sum of the number of autologous units collected plus the number of hemapheresis procedures performed.

The study employs two models of blood center operations. The first model employs BCD as the single output and labor, material, and capital as multiple inputs.

It is called Model A. The second employs all three functions of blood center operations (BCD, SLS, and SCS) as distinct outputs and labor, material, and capital as inputs. It is called Model B. The DEA model form of 142 center observations used to obtain the efficiency score for blood center k (DMU_k) in the analysis set has the following form of the additive DEA model (see Charnes, Cooper, Golany, Seiford, and Stutz 1985):

Objective:

$$\text{Max } h_k = (u_1 * y_{1k} + u_2 * y_{2k} + u_3 * y_{3k})$$

Subject to:

$$v_1 * x_{1k} + v_2 * x_{2k} + v_3 * x_{3k} = 1$$

$$u_1 * y_{1j} + u_2 * y_{2j} + u_3 * y_{3j} - (v_1 * x_{1j} + v_2 * x_{2j} + v_3 * x_{3j}) \leq 0$$

for each $j = 1,2,..., 142$

$0 < u_1, u_2, u_3$, and

$0 < v_1, v_2, v_3$

where:

h_k = the efficiency ratio for DMU k;

$k = 1,2,..., 142$;

u's and v's = artificial weights generated from the model;

y_1 = blood components distributed;

y_2 = specialized laboratory services;

y_3 = specialized clinical services;

x_1 = number of FTE's;

x_2 = material and supplies costs; and

x_3 = capital costs.

When SLS and SCS are zero, Model B becomes Model A. [Technical details of the DEA additive model can be found in Banker, Charnes, Cooper, Swarts, and Thomas (1989).]

4.2 DETERMINANTS OF BLOOD CENTER EFFICIENCY

The study not only measures blood center efficiency using DEA analysis, but also identifies factors which may have an impact on efficiency through the application of chi-square and regression analysis. Eight related factors are included in the exploratory chi-square and regression studies. These eight factors are (1) hospital density, (2) population density, input prices of (3) labor, (4) material, and (5) capital, (6) the ratio of mobile collection to total collections, (7) the growth rate of blood components made (BCM), and (8) the level of output.

The chi-square test helps determine whether these eight factors and the DEA efficiency ratings are related. If two variables are related, knowing the value of one variable helps to predict the value of the other. However, the existence of a relationship between two variables does not mean one causes the other. Variables included in the chi-square analysis which follows are divided into three approximately equal-size groups categorized as low, medium (Med), and high. The chi-square results do not directly measure of the extent to which each factor contributes to the relative efficiency or inefficiency of the set of DEA results. Rather they measure the

statistically significance of the relationship of the individual variables to the measures of blood center efficiency.

Among the factors selected for the chi-square analysis, hospital and population densities are believed to be critical in affecting blood center efficiency measures. High hospital density, measured as the number of hospitals per million population, is normally associated with centers located in rural areas because of the low value of the denominator, per million population. Urban blood centers have constantly maintained that it requires more resources to recruit their donors and the hospitals they serve have higher demands for specialized clinical services than those of rural blood centers. Therefore, the hypothesis is that blood centers with high hospital density tend to be located in rural areas and are more likely to have higher efficiency ratings. As with hospital density, high population density measured as the number of people per square mile in the region served, is hypothesized to be associated with higher inefficiency scores.

In microeconomic theory, input prices are normally treated as exogenous variables because in a competitive environment management is presumed to have little or no control over input prices. This may not be the case in blood banking, since cost minimization is probably not the major goal of nonprofit blood centers. Centers oftentimes use surpluses to purchase more labor, equipment or supplies. So there may be room for blood centers to reduce their input prices. For study purposes labor input price was calculated as the average hourly wage rate of blood center employees. Its mean value was $11.50 per hour with minimum value of $7.00 and

maximum value of $16.80. Material input price was calculated as total material and supplies costs divided by the number of BCDs. Its mean value was $6.90 per BCD with minimum value of $4.70 and maximum value of $11.70. The capital input price was calculated as total capital costs divided by the number of BCDs. Its mean value was $6.30 per BCD with minimum value of $4.00 and maximum value of $9.80. The spreads between minimum and maximum values for all three input prices are over 100 percent, suggesting further investigation of each is needed since centers with higher input prices are hypothesized to have higher inefficiency scores.

The sixth factor is the ratio of mobile collection to total collections. It is unclear whether there exists a relationship between blood center efficiency and the extent of mobile collections. There could be a subtle relationship between blood center efficiency and mobile collections contingent on the scale of blood center operations as well as whether the blood center location was urban, suburban, or rural.

The seventh determinant is growth in blood components made (BCM). This factor ought to accommodate any anomalous cost behavior caused by short term disequilibrium. The hypothesis is that blood centers with stable growth of BCM (0 to 5 percent annual rate) are more likely to be efficient than centers with higher positive (above 5 percent annual rate) or negative growth because the latter involve adjustments in the mix of inputs and factor learning in order to accommodate the changes so that the centers have not yet achieved their potential efficiency at the new production level.

The final determinant is the level of output measured by blood components distributed (BCD). Assuming economies of scale are present, the hypothesis is that blood centers that produce more outputs have higher efficiency ratings.

Since input prices, the growth rate of BCM, and output measure are all based on BCD, the exploratory study of the relationship of the eight factors to blood center efficiency uses only Model A.

5. STUDY RESULTS AND MANAGEMENT INFERENCES

Data from 48 blood centers for the years 1987, 1988, 1989 were used in the DEA study. Since all 48 blood centers have specialized laboratory services and clinical services programs, the sample is relatively homogeneous. Table II-1 gives the minimum, maximum, and mean values for each of the variables in the sample.

5.1 EFFICIENCY RATINGS

Table II-2 summarizes the DEA efficiency ratings from Model A. Two centers were found to be relatively efficient for all three years (mean values = 100.0). Fourteen were from 1 to 10 percent less efficient (mean values = 91.3 - 98.7); another 21 centers were from 11 to 20 percent less efficient (mean values = 80.0 - 88.7); and 11 centers were from 21 to 30 percent less efficient (mean values = 70.0 - 79.7). These differences may have been, in part, the result of differences in the quantity of labor inputs or in the prices of materials and capital, or in outputs of specialized laboratory services (SLS) or clinical services (SCS). Model A did not specify these

as outputs. Eighteen of the centers had an average deviations of 5 percent or above indicating that the DEA efficiency ratings of these centers based on Model A varied from year to year not only because of increased cost incurred but may also because of changes in management practice and control.

Table II-3 summaries the DEA efficiency ratings from Model B. Seven centers were found to be relatively efficient all three years (mean values=100.0); ten centers were from 1 to 10 percent less efficient (mean values=90.0 - 98.0); another 6 centers were from 11 to 20 percent less efficient (mean values=80.3 - 89.3); 12 centers were from 21 to 30 percent less efficient (mean values=70.3 - 79.0); and 13 centers were 31 to 40 percent less efficient (mean values=64.3 - 69.3). While some of these variations in overall efficiency may have been the results of differences in input prices and other regional characteristics, the 25 centers whose efficiency measured less than 20 percent of the relatively efficient set obviously need management attention. It may be that these centers provide uneconomic services; or they use disproportionately larger numbers of people to accomplish tasks than the more efficient centers; or they employ proportionately more equipment or other forms of capital. Whatever the reasons, DEA indicates the existence of potential efficiency problems requiring management investigation.

Table II-4 shows differences of average overall efficiency among centers as measured by Model A between 1987 and 1988 and between 1988 and 1989. These differences are partly due to the fact that blood centers were faced with increased costs of testing and resultant testing losses during the intervals as well as rapidly

rising costs of health care resources required for operation. The result was a 3 percent drop in efficiency from 1987 to 1988 and another 4 percent drop from 1988 to 1989. Assuming the annual cost increase in blood centers is 5 percent or more, then, the adjusted average overall efficiency for 1988 and 1989 would probably be equal to or slightly higher than the average overall efficiency for 1987.

Table II-5 shows there were no differences in overall efficiency as measured by Model B from year to year. These results are probably the combined effects of an increase in SCS which could have generate higher average overall efficiency ratings in 1988 and 1989; however, it was offset by the effect of rising costs of inputs.

Models A and B indicate that the pooling of 1987, 1988 and 1989 data for this study without adjustment created no major unfavorable efficiency ratings in the latter years.

5.2 EFFICIENCY EVALUATION AND REGRESSION RESULTS

Table II-6 to Table II-12 show results of the chi-square analysis. The tables provide information regarding the relatedness of each variable to the DEA results and its level of statistical significance. However, one must look at the actual numbers in each table to determined whether the observed differences are of practical importance.

5.2.1 Chi-Square Analysis

Table II-6 provides a comparative tabulation of the efficiency ratings of the two DEA models, categorized into 3 approximately equal-size groups. The Chi-

Square (χ^2) statistic of 52.86, significant at the 0.1 percent level, indicates that efficiency ratings obtained from the two models are in broad agreement.

Comparisons of efficiency estimates from Model A with the various determinant factors are also categorized into three approximately equal-size groups. Table II-7 compares the DEA efficiency ratings with the factor blood components distributed. The χ^2 statistic of 15.75, significant at the 1 percent level, indicates that the factor blood components distributed is closely related to the DEA measure of efficiency. Table II-8 compares the DEA efficiency ratings with population density. The χ^2 statistic of 18.92, significant at the 0.1 percent level, suggests there exists an inverse relationship between the DEA efficiency ratings and population density.

Table II-9 compares the DEA efficiency ratings with hospital density. The χ^2 statistic of 8.40, significant at 10 percent level, suggests there is a marginal positive relationship between the DEA efficiency ratings and hospital density.

Tables II-10, II-11, and II-12 report the relationship between input prices of labor, material, and capital with the DEA efficiency ratings. In Table II-10 the χ^2 statistic of 15.01, significant at the 1 percent level, suggests centers with a low price of labor are more likely to have low efficiency ratings. This is surprising. One would expect a low labor price to equal to a low total labor cost which, in turn, might be associated with higher efficiency ratings. In Table II-11 the χ^2 statistic of 65.03, significant at the 0.1 percent level, indicates lower input prices of material are related to higher efficiency ratings. This is somewhat surprising since in blood center operations the input prices of material and supplies should be fairly stable across

centers. Obviously this is not the case as the mean value of $6.90, the minimum value of $4.70 and the maximum value of $11.70 attest. One possible interpretation of the outcome is that profitable centers tends to spend money buying more expensive supplies and capital equipment. It may be, however, that since accounting procedures and systems among centers are not standardized, these results are an artifact of accounting. For study purposes, however, this solution to better estimating of input prices of material and supplies is simply not available now. In Table II-12 the χ^2 statistic of 17.52, significant at 1 percent level, suggests that a low price of capital is likely to be associated with high efficiency ratings.

The χ^2 statistic for both BCM growth rate and the mobile collection ratio were not significant at the 10 percent level implying that efficiency is independent of both the rate of BCM growth and the ratio of mobile collections.

5.2.2 Regression Analysis

The DEA inefficiency score from Model A computed as 100 minus the efficiency rating in percentage for each center was regressed on the eight factors described above in a multivariate regression model. Pearson correlations coefficients between the eight determinants were all below .42 (see Table II-13), indicating no serious multicollinearity. A summary of results of this analysis appear in Table II-14. Since the dependent variable is the DEA inefficiency score, interpretation of the signs of the coefficients is that positive (+) signs indicate reduced efficiency or increased inefficiency, while negative (-) signs indicate increased efficiency or reduced inefficiency. The R-square statistic for the entire eight factor model is .65

(F-value of 31.08 significant at the 0.1 percent level).

Of the eight factors, six were significant. Blood centers with higher input prices of material were associated with higher inefficiency (lower efficiency) scores as were centers with higher input prices of capital. These results may be explained by the practice of, when a blood center's operations create a financial surplus, the surplus tends to be used to purchase supplies and capital equipment not strictly essential for routine operations. Surprisingly, higher input prices of labor were also associated with lower inefficiency (higher efficiency) scores. One possible explanation is that employees with higher salaries are more productive than employees with lower salaries after wage rate adjustment. This speculation is supported by evidence that the correlation between the input price of labor and blood components distributed per full time employee was .56, significant at the 1 percent level.

Centers with high hospital density had lower inefficiency (higher efficiency) scores. Centers located in less populated areas had higher hospital density and were associated with higher efficiency ratings. One possible reason is that centers located in rural areas had higher whole blood collection ratios per hundred thousand population. Another is that centers located in rural areas offered fewer specialized clinical services which require more resources per unit of output. Centers with high population density had slightly higher efficiency scores. This appears to be a complex phenomenon. Centers located in urban areas may have low productivity in terms of donor recruitment and collection, but they may also have compensating higher

component yields compared to centers in less populated areas.

Centers with high numbers of blood component distributed had lower inefficiency (higher efficiency) scores, suggesting some economies of scale in blood center operations. Neither the growth rate of blood components made nor the mobile collection ratio proved to be significant.

Stepwise regression results were identical to these complete set of independent variables included in the above reported regression results.

Since the histogram of the dependent variable did not conform to the normal distribution, probably because of the large number of blood centers in the reference set, these observations were excluded from the data set and the regressions performed again. Results of more restricted analysis are reported in Table II-14, Equation 2. The results are generally consistent with that of the full-sample. Population density, no longer significant at the 10 percent level, was the only exception.

5.3 DEA AS A PLANNING TOOL

DEA provides insights into the sources of inefficiency in individual blood centers as well as ways to improve center efficiency. Three examples are cited; one for an large inefficient center, another for a medium size inefficient center, and the last for a small inefficient center.

Table II-15 provides an example of the kinds of reports obtainable from DEA for the blood center identified as DMU 5 using 1987 data on inputs and outputs.

The overall center relative efficiency rating of .897 (100%)= 89.7% was obtained from DEA Model A in the following manner. DMU 5 is a member of the set of 48 centers. From this set DEA selects an efficient set of DMUs to evaluate DMU 5. The selected DMUs are explicitly identified as facet members, consisting of DMUs 12 and 7. The Lambda values associated each of the efficient DMUs are applied by DEA to the inputs and outputs of the facet members to obtain efficient performance values which are shown in the column labelled Value if Efficient. The Lambda values add up to 1 to ensure that all solutions and their associated efficiencies will be evaluated only by reference to original data points and their convex combinations, i.e., by percentage combinations which add to 100 percent. These combinations can then be used to generate comparison points on efficient frontiers. In order for DMU 5 to become efficient, it will have to cut its workforce by 78 employees and reduce its material costs by $680,000 plus eliminating another $50,000 savings from capital costs. Total savings from all inputs reduction amounts to $2.633 million.

DMU's 5 efficiency rating of .845 obtained from Model B consists of DMUs 12, 7, and 1 as facet members. In this multiple output model, DMU 5 is shown to have to reduce its workforce by 73 employees, reduce material costs by $740,000, and at the same time increase SLS output by 34.3 thousand services and SCS by one hundred services to become efficient. Savings from input reduction would be over $2.5 million. If the average charge for a unit of SLS is $15, then the increase in SLS would result in another $514,500. Thus total potential savings are over $3 million. This information provided by the two DEA models gives managers some direction

and possible ways of improving center efficiency. Eliminating 78 employees may not be possible and an increase in SLS may not be appropriate if there exists no demand for the services. Still the center is likely to have some alternatives for reducing its combination of inputs and increasing certain outputs provided there exists demand.

Table II-16 illustrates how a medium-sized blood center identified as DMU 23 can be analyzed using DEA. According to Model A its efficiency rating is .857, with DMU 44, and 19 as facet members. Total potential savings from input reduction required for DMU 23 to become efficient are estimated at $1.339 million. Model B efficiency ratings of .704, derived from DMU 12, 1, and 7 as the facet members, a set completely different from Model A facet members indicates potential savings from input reduction of $252,000. Assuming the average charge for each unit of SLS and SCS is $15, the required increase in output expansion to achieve efficiency would produce another $750,000 in revenue. Thus, increase in revenue together with savings from cost reduction amount to more than $1 million according to Model B. For a medium size blood center with average total costs of $8 million, savings of $1.339 million from input reduction amounts to 17 percent of its total costs.

Table II-17 illustrates estimated savings for a small blood center DMU 40. Its efficiency is .860 according to Model A and .721 according to Model B. Even a small blood center such as DMU 40 potentially can save $660,000 by reducing its inputs according to Model A. The savings from input reduction per Model B amount to $151,000 and a revenue increase from output expansion of 23.7 thousand units of

SLS could generate another $355,000. Thus, total potential savings for DMU 40 amount to $507,000.

6. CONCLUSIONS AND SUGGESTIONS

In this chapter the relatively efficiency of 48 blood centers over a period of three years was measured by both single and multiple output DEA models. Efficiency ratings from the two models proved to be in general agreement (χ^2 statistic significant at 0.1 percent). The study of factors affecting blood center efficiency identified five determinants significant at the 1 percent level: high input prices of material and capital were associated with low efficiency ratings; high hospital density was associated with high efficiency ratings, blood centers with large numbers of blood components distributed had higher efficiency ratings, suggesting economies of scale in blood center operations; and high input prices of labor were associated with high efficiency ratings.

Finally, three examples indicating the dollar amount of savings available to individual center by becoming efficient were provided to show how results of a DEA analysis can be used for managerial planning and control.

LIMITATIONS AND FUTURE EXTENSIONS

Because blood centers have their own cost accounting systems to measure material and capital costs and procedures in each system vary, inferences from this study must be considered with this limitation in mind.

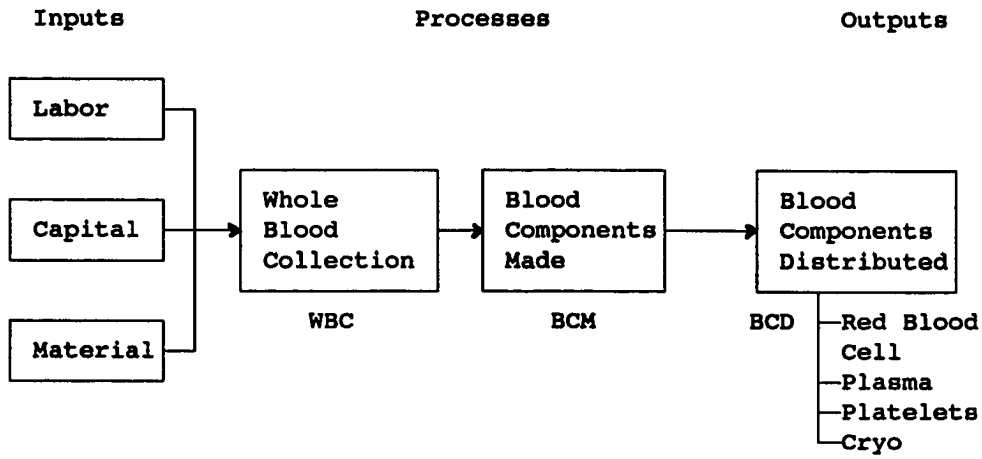
In applying DEA analysis to a set of centers, potential variable selection and data variation problems must be recognized and, where possible, their impact upon the DEA efficiency scores reduced. For instance, DEA's reliability could be improved through implementation of standardized accounting and reporting requirements coupled with an extensive audit function. Such procedures would help reduce any manipulative efforts of the managements of DMUs. In addition, standardization of data accumulation systems would aid in reducing variations across DMUs caused by different measurement methods.

A possible extension of this study would be to focus on disaggregated labor input by functional areas such as recruitment, collection, testing and labeling, component production, distribution, specialized services, and administration. Given such a breakdown, DEA results would show how many employees in each functional area would have to be eliminated for an inefficient center to become efficient. Since, the number of DMUs for which there are observations should be greater than the number of constraints, for DEA efficiency evaluations it is generally advisable that the number of DMUs should be greater than three times the sum of number of inputs and outputs (Banker, Charnes, Cooper, Swarts, Thomas, 1989). With 48 DMUs involved in this study over the period 1987 to 1989, this study of blood center efficiency could be expanded to include total of 15 input and output variables.

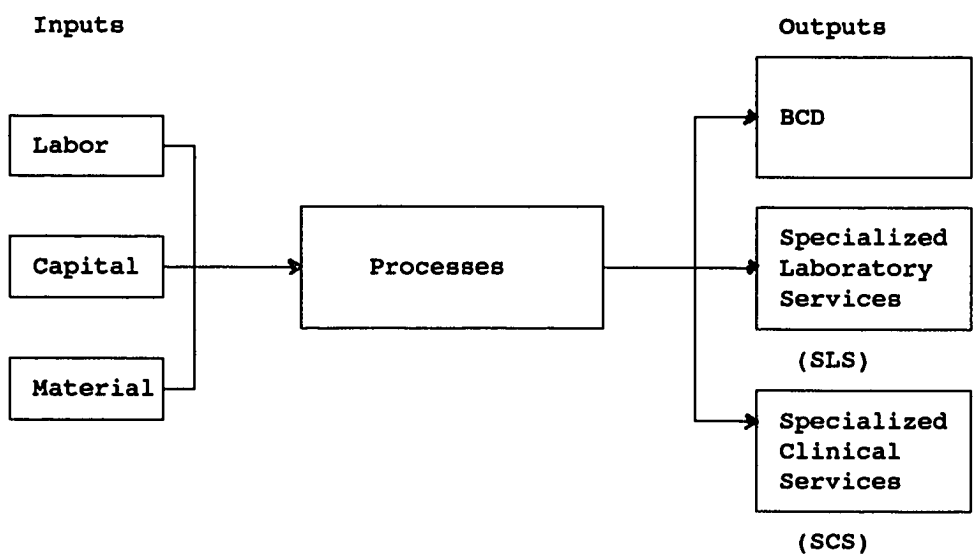
The DEA method can also be applied to measure functional efficiency, such as collection or component production efficiency. If each and every individual output value can be assumed as its fair market price, then it is possible to extend the

measurement of efficiency to the measurement of maximum surplus or minimum deficit for an individual blood center.

Another extension would be to apply the stochastic statistical frontier approach to the single output model and compare results with DEA Model A findings (eg. see Banker, Datar and Kemerer, 1991). It might also be interesting to develop a decision support system or graphical presentations (eg. see Desai and Walters, 1991) to assist managers to visualize the extent of improvement in DEA efficiency ratings in response to different input reductions and/or output expansion scenarios.



Model A



Model B

FIGURE 2. BLOOD CENTER OPERATIONS MODELS A AND B

Table II-1 DESCRIPTIVE STATISTICS OF DEA STUDY VARIABLES

Variable	Minimum	Mean	Maximum
Outputs in Units			
BCD	48,629	263,926	715,836
SLS	1,239	25,134	145,386
SCS	100	3,179	18,654
Inputs			
Labor (FTE)	31	168	436
Material Cost (x10,000)	$32.17	$181.53	$560.57
Capital Cost (x10,000)	$29.97	$170.69	$590.57
Determinants			
Hospitals/Million Pop.	8.3	34.0	186.7
Population/Sq. Mile	2.0	165.7	1,309.0
Input Price of Labor	$7.0	$11.5	$16.8
Input Price of Material	$4.7	$6.9	$11.7
Input Price of Capital	$4.0	$6.3	$9.8
Mobile Collection Ratio (%)	50.8	77.6	96.3
BCM Growth Rate	-12.9	2.8	42.3
BCD (x1,000)	48.6	263.9	715.8

Note: N=142 blood centers; BCD=Blood Components Distributed; SLS=Specialized Laboratory Services; SCS=Specialized Clinical Services; BCM=Blood Components Made; FTE=Full Time Equivalent Employees.

Table II-2 MODEL A AVERAGE BLOOD CENTER EFFICIENCY OVER 3 YEARS

Blood Center ID	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION	85.9437	8.6678	142
1	92.3333	6.8069	3
2	88.6667	3.2146	3
3	100.0000	.0000	3
4	94.6667	4.7258	3
5	86.6667	2.8868	3
6	87.3333	4.5092	3
7	93.0000	6.0828	3
8	81.3333	3.5119	3
9	76.0000	4.2426	2
10	80.6667	4.7258	3
11	85.0000	.0000	3
12	100.0000	.0000	3
13	84.3333	4.1633	3
14	87.3333	5.5076	3
15	86.6667	5.5076	3
16	70.6667	.5774	3
17	88.6667	1.1547	3
18	77.3333	1.1547	3
19	95.6667	4.0415	3
20	81.3333	7.3711	3
21	91.3333	5.1316	3
22	79.6667	5.5076	3
23	82.0000	4.5826	3
24	81.0000	2.6458	3
25	74.0000	3.6056	3
26	79.6667	5.8595	3
27	75.3333	7.6376	3
28	85.6667	2.5166	3
29	85.6667	4.1633	3
30	74.3333	5.0332	3
31	95.6667	4.0415	3
32	80.0000	4.0000	3
33	91.3333	3.0551	3
34	91.6667	8.0208	3
35	80.6667	1.5275	3
36	70.0000	9.8995	2
37	84.3333	3.0551	3
38	77.6667	6.0277	3
39	73.0000	1.7321	3
40	83.3333	2.5166	3
41	87.0000	5.5678	3
42	96.6667	4.1633	3
43	92.0000	2.0000	3
44	98.6667	2.3094	3
45	83.0000	7.0000	3
46	94.6667	5.0332	3
47	93.6667	5.5076	3
48	97.0000	5.1962	3

Table II-3 MODEL B AVERAGE BLOOD CENTER EFFICIENCY OVER 3 YEARS

Blood Center ID	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION	81.7606	13.4349	142
1	100.0000	.0000	3
2	76.0000	6.2450	3
3	100.0000	.0000	3
4	98.0000	3.4641	3
5	81.6667	3.5119	3
6	68.0000	.0000	3
7	87.3333	11.1505	3
8	78.6667	4.0415	3
9	73.0000	1.4142	2
10	68.0000	1.7321	3
11	67.3333	2.0817	3
12	100.0000	.0000	3
13	75.6667	9.5044	3
14	74.3333	6.6583	3
15	100.0000	.0000	3
16	64.3333	1.5275	3
17	93.6667	6.5064	3
18	70.3333	2.5166	3
19	85.6667	14.5029	3
20	67.3333	3.0551	3
21	80.3333	.5774	3
22	65.6667	2.0817	3
23	72.0000	2.0000	3
24	90.0000	3.0000	3
25	68.3333	2.5166	3
26	69.3333	3.7859	3
27	87.0000	9.5394	3
28	89.3333	11.0151	3
29	79.0000	1.7321	3
30	70.0000	1.0000	3
31	100.0000	.0000	3
32	68.6667	1.5275	3
33	68.6667	2.0817	3
34	91.6667	8.0208	3
35	65.0000	1.0000	3
36	68.5000	2.1213	2
37	68.0000	3.6056	3
38	73.0000	4.3589	3
39	70.0000	3.6056	3
40	76.6667	4.1633	3
41	93.6667	10.9697	3
42	100.0000	.0000	3
43	91.3333	15.0111	3
44	97.3333	4.6188	3
45	94.6667	9.2376	3
46	92.0000	8.0000	3
47	97.6667	4.0415	3
48	100.0000	.0000	3

Table II-4 MODEL A AVERAGE EFFICIENCY BY YEAR FOR ALL CENTERS

Year	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION	85.9437	8.6678	142
87	89.3750	8.3504	48
88	86.1915	7.5286	47
89	82.1915	8.6969	47

Table II-5 MODEL B AVERAGE EFFICIENCY BY YEAR FOR ALL CENTERS

Year	MEAN	STD DEV	CASES
FOR ENTIRE POPULATION	81.7606	13.4349	142
87	81.8125	14.6035	48
88	81.8936	13.0954	47
89	81.5745	12.7990	47

Table II-6 COMPARISON OF MODEL A & B EFFICIENCY RATINGS

		Model B			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	23 13.3	19 16.1	2 14.6	44 31.0%
	Med	18 17.0	24 20.5	14 18.5	56 39.4%
	High	2 14.6	9 15.4	31 13.9	42 29.6%
	Column Total	43 30.3%	52 36.6%	47 33.1%	142 100.0%

Chi-Square = 52.86 with 4 d.f., p < 0.001.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Model B Efficiency: Low (.61-.70), Med (.71-.90), High (.91-1.0)

Table II-7 COMPARISON OF EFFICIENCY AND BCD

		Blood Components Distributed			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	12 14.3	22 14.3	10 15.5	44 31.0%
	Med	14 18.1	18 18.1	24 19.7	56 39.4%
	High	20 13.6	6 13.6	16 14.8	42 29.6%
	Column Total	46 32.4%	46 32.4%	50 35.2%	142 100.0%

Chi-Square =15.75 with 4 d.f., p<0.01.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
BCD: Low (40,000-155,000), Med (155,001-300,000), High (300,001-720,000)

Table II-8 COMPARISON OF EFFICIENCY AND POPULATION DENSITY

		Population Density			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	9 14.9	20 16.1	15 13.0	44 31.7%
	Med	14 18.9	23 20.5	19 16.5	56 40.3%
	High	24 13.2	8 14.3	7 11.5	39 28.1%
	Column Total	47 33.8%	51 36.7%	41 29.5%	139 100.0%

Chi-Square = 18.92 with 4 d.f., $p < 0.001$.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Population Density: Low (1-69), Med (70-139), High (140-750)

Table II-9 COMPARISON OF EFFICIENCY AND HOSPITAL DENSITY

		Hospital Density			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	17 14.8	16 14.8	11 14.5	44 31.4%
	Med	23 18.8	17 18.8	16 18.4	56 40.0%
	High	7 13.4	14 13.4	19 13.1	40 28.6%
	Column Total	47 33.6%	47 33.6%	46 32.9%	140 100.0%

Chi-Square = 8.40 with 4 d.f., $p < 0.10$.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Hospital Density: Low (8-23.9), Med (24-33.9), High (34-100)

Table II-10 COMPARISON OF EFFICIENCY AND PRICE OF LABOR

		Price of Labor			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	23 14.0	10 14.9	10 14.0	43 30.5%
	Med	16 18.3	23 19.5	17 18.3	56 39.7%
	High	7 13.7	16 14.6	19 13.7	42 29.8%
	Column Total	46 32.6%	49 34.8%	46 32.6%	141 100.0%

Chi-Square = 15.01 with 4 d.f., p < 0.01.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Price of Labor: Low ($7.0-$10.74), Med ($10.75-$12.24), High ($12.25-$17.00)

Table II-11 COMPARISON OF EFFICIENCY AND PRICE OF MATERIAL

		Price of Material			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	0 13.9	12 15.2	32 14.9	44 31.0%
	Med	18 17.7	29 19.3	9 18.9	56 39.4%
	High	27 13.3	8 14.5	7 14.2	42 29.6%
	Column Total	45 31.7%	49 34.5%	48 33.8%	142 100.0%

Chi-Square = 65.03 with 4 d.f., p < 0.001.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Price of Material: Low ($4.5-$6.09), Med ($6.10-$7.14), High ($7.15-$11.75)

Table II-12 COMPARISON OF EFFICIENCY AND PRICE OF CAPITAL

		Price of Capital			
	Count Exp Val	Low	Med	High	Row Total
Model A	Low	6 14.3	17 14.9	21 14.9	44 31.0%
	Med	18 18.1	23 18.9	15 18.9	56 39.4%
	High	22 13.6	8 14.2	12 14.2	42 29.6%
	Column Total	46 32.4%	48 33.8%	48 33.8%	142 100.0%

Chi-Square = 17.52 with 4 d.f., p < 0.01.

Model A Efficiency: Low (.61-.81), Med (.82-.90), High (.91-1.0)
Price of Capital: Low ($3.9-$5.79), Med ($5.8-$6.69), High ($6.70-$9.9)

Table II-13 CORRELATION COEFFICIENTS

	DEP	V1	V2	V3	V4	V5	V6	V7	V8
DEP	1.000	-.189*	-.045	-.287**	.670**	.356**	-.024	-.106	-.142
V1	-.189*	1.000	-.393**	.039	-.023	.028	-.167*	-.063	-.375**
V2	-.045	-.393**	1.000	.070	.038	.087	.237**	.003	.390**
V3	-.287**	.039	.070	1.000	-.179*	.325**	.262**	-.080	.419**
V4	.670**	-.023	.038	-.179*	1.000	.243**	.156	-.102	-.037
V5	.356**	.028	.087	.325**	.243**	1.000	.036	-.079	.320**
V6	-.024	-.167*	.237**	.262**	.156	.036	1.000	-.084	.303**
V7	-.106	-.063	.003	-.080	-.102	-.079	-.084	1.000	-.023
V8	-.142	-.375**	.390**	.419**	-.037	.320**	.303**	-.023	1.000

* Significance at .05, ** Significance at .01

Note: n=142; DEP=Inefficiency; V1=Hospitals per Million Population; V2=Population Density; V3=Price of Labor; V4=Price of Material; V5=Price of Capital; V6=Mobile Collection Ratio; V7=Growth Rate of BCM; V8=Blood Components Distributed.

Table II-14 REGRESSION RESULTS OF MODEL A

Equation 1 includes all 142 cases
Dependent Variable = Inefficiency = 100 - Model A Efficiency

Multiple R	.80718	Analysis of Variance	
R Square	.65153		DF
Adjusted R Square	.63057	Regression	8
Standard Error	5.26835	Residual	133

F = 31.08413 SIGNIF F = .0000

Variables in the Equation

VARIABLE	B	SE B	BETA	T	SIG T
PR MATERIAL	3.290154	.354978	.530134	9.269	.0000
PR CAPITAL	3.209720	.508615	.378568	6.311	.0000
PR LABOR	-.965050	.311781	-.195515	-3.095	.0024
HOSP DEN	-.116567	.021788	-.319018	-5.350	.0000
POP DEN	-.004321	.002254	-.112514	-1.918	.0573
BCM GROWTH R	-.008033	.006378	-.065380	-1.259	.2101
MOBILE COLL R	-.002609	.004846	-.030912	-.538	.5912
BCD	-1.16178E-05	3.4312E-06	-.229187	-3.386	.0009
(Constant)	.353794	8.877977		.040	.9683

Equation 2 excludes efficient blood centers
Dependent Variable = Inefficiency = 100 - Model A Efficiency

Multiple R	.77812	Analysis of Variance	
R Square	.60547		DF
Adjusted R Square	.57778	Regression	8
Standard Error	4.65441	Residual	114

F = 21.86852 SIGNIF F = .0000

Variables in the Equation

VARIABLE	B	SE B	BETA	T	SIG T
PR MATERIAL	2.859778	.329133	.556659	8.689	.0000
PR CAPITAL	2.622797	.492675	.359749	5.324	.0000
PR LABOR	-.798997	.287352	-.201083	-2.781	.0064
HOSP DEN	-.086962	.022858	-.258888	-3.804	.0002
POP DEN	-.003732	.002304	-.109911	-1.620	.1081
BCM GROWTH R	-.004297	.005876	-.044002	-.731	.4661
MOBILE COLL R	-.005168	.004621	-.074849	-1.118	.2657
BCD	-7.58611E-06	3.6680E-06	-.161590	-2.068	.0409
(Constant)	2.266695	8.244000		.275	.7839

Table II-15 POTENTIAL SAVINGS PER YEAR FOR DMU 5

Model A Efficiency = .897

Facet:	12	7		
Lambda =	.377	.623		
Outputs	**Value Measured**		**Value if Efficient**	**Slack**
BCD (x10,000)	49.6		49.6	0.
Inputs				
Labor (FTE)	321		243	78
Material (x1,000)	$3770		$3090	$680
Capital (x1,000)	$2660		$2610	$50
Savings from Input Reduction				
Labor (x1,000)				$1,903.2
Material (x1,000)				$680.0
Capital (x1,000)				$50.0
Total Savings (x1,000)				$2,633.2

Model B Efficiency = .845

Facet:	12	1	7		
Lambda =	.432	.081	.488		
Outputs	**Value Measured**			**Value if Efficient**	**Slack**
BCD (x10,000)	49.6			49.6	0.
SLS (x1,000)	56.9			91.2	34.3
SCS (x100)	49.3			50.3	1.0
Inputs					
Labor (FTE)	321			248	73
Material (x1,000)	$3770			$3030	$740
Capital (x1,000)	$2660			$2660	0
Savings from Input Reduction					
Labor (x1,000)					$1,781.2
Material (x1,000)					$740.0
Capital (x1,000)					0.0
Total Savings (x1,000)					$2,521.2

Table II-16 POTENTIAL SAVINGS PER YEAR FOR DMU 23

Model A Efficiency = .857			
Facet:	44	19	
Lambda =	.266	.734	
Outputs	**Value Measured**	**Value if Efficient**	**Slack**
BCD (x10,000)	22.7	22.7	0.
Inputs			
Labor (FTE)	144	101	43
Material (x1,000)	$1410	$1070	$340
Capital (x1,000)	1$230	$1100	$130
Savings from Input Reduction			
Labor (x1,000)			$868.6
Material (x1,000)			$340.0
Capital (x1,000)			$130.0
Total Savings (x1,000)			$1,338.6

Model B Efficiency = .704				
Facet:	12	1	7	
Lambda =	.432	.081	.488	
Outputs	**Value Measured**		**Value if Efficient**	**Slack**
BCD (x10,000)	22.7		22.7	0.
SLS (x1,000)	22.2		69.5	47.3
SCS (x100)	14.7		37.0	22.3
Inputs				
Labor (FTE)	144		133	11
Material (x1,000)	$1410		$1410	0
Capital (x1,000)	$1230		$1200	$30
Savings from Input Reduction				
Labor (x1,000)				$222.2
Material (x1,000)				0.0
Capital (x1,000)				$30.0
Total Savings (x1,000)				$252.2

Table II-17 POTENTIAL SAVINGS PER YEAR FOR DMU 40

Model A Efficiency = .860

Facet:	44	19		
Lambda =	.833	.167		
Outputs	**Value Measured**		**Value if Efficient**	**Slack**
BCD (x10,000)	10.1		10.1	0.
Inputs				
Labor (FTE)	75		48	27
Material (x1,000)	$620		$510	$110
Capital (x1,000)	$550		$510	$40
Savings from Input Reduction				
Labor (x1,000)				$510.3
Material (x1,000)				$110.0
Capital (x1,000)				$40.0
Total Savings (x1,000)				$660.3

Model B Efficiency = .721

Facet:	12	31	65	46	94		
Lambda =	.034	.132	.046	.358	.431		
Outputs	**Value Measured**					**Value if Efficient**	**Slack**
BCD (x10,000)	10.1					10.1	0.
SLS (x1,000)	2.9					26.6	23.7
SCS (x100)	8.1					8.1	0.
Inputs							
Labor (FTE)	75					67	8
Material (x1,000)	$620					$620	0
Capital (x1,000)	$550					$550	0
Savings from Input Reduction							
Labor (x1,000)							$151.2
Material (x1,000)							0.0
Capital (x1,000)							0.0
Total Savings (x1,000)							$151.2

CHAPTER III

ECONOMIES OF SCALE AND ECONOMIES OF SCOPE IN BLOOD BANKING

1. INTRODUCTION

Two types of production economies can be achieved by blood centers: economies of scale , which are associated with blood center size, and economies of scope, which arise from the joint production and distribution of two or more products and services. Blood centers realize economies of scale if increased output causes production costs to rise proportionately less. If economies of scale exist average production costs per unit decline as output rises. Conversely, if average costs rise as output increases, diseconomies of scale are present. Economies of scope arise if two or more products can be jointly produced at a lower total cost than is incurred if they are produced independently. Diseconomies of scope are present if the total cost of joint production is more than the sum of their costs produced independently.

In the previous chapter two statistical frontier approaches for estimating blood center efficiency were reviewed: one was the deterministic frontier approach, the other the stochastic. Such statistical production or cost frontiers represent best management practice, whereas standard non-frontier estimation techniques estimate average management practice. This distinction is important if key aspects of management practice, such as returns to scale and return to scope, are different at the frontier than below it. In practice statistical frontiers models assume shortfalls

from the frontier to be the result of inefficiency which simply shift the entire function down in a parallel fashion. Thus the frontier function is a neutral transformation of the average function. This is unfortunate because estimation of return to scale and return to scope are the same for both the frontier and non-frontier approaches.

This study employs the Translog (transcendental logarithmic) cost function and cost share equations to estimate economies of scale and economies of scope in blood banking. It can be a frontier or non-frontier approach depending whether or not the constant term is corrected. The strategy of the research is to develop two models for estimation purposes. The first model, Model A, is a single output model; the second model, Model B, is a multiple output model. The analysis is performed using both models and the complete data set from 48 blood centers for the period 1987 to 1989. This analysis investigates "average" return to scale and scope in blood banking in general. The same analysis is then performed using the reduced data set of blood centers, those with higher than average efficiency ratings based on the DEA results from the previous chapter. This second analysis produces "best practice" estimates of return to scale and scope in blood banking.

For identification purposes, Model A with the complete data set is called Model A1; Model A with the reduced data set is called Model A2. Similarly, Model B with the complete data set is called Model B1; Model B with the reduced data set is called Model B2.

1.1 ECONOMIES OF SCALE

There exist two kinds of economies of scale: (1) economies that arise from increases in the production of individual products called product-specific economies of scale; and (2) economies associated with increases in all firm outputs called global economies of scale. The two types are synonymous for a single product firm, however, both types may be present for firms producing more than one product. In multiproduct firms, global economies of scale occur if total costs increase proportionately less than total output when there is a proportionate increase in each of the firm's products. With global economies of scale, average costs decline as the firm expands production while maintaining a constant product mix.

1.2 ECONOMIES OF SCOPE

There are two types of economies of scope, global and product-specific. To measure global economies of scope, it is necessary to compare the costs of joint production and separate production, assuming a given proportionate volume for each product. Given a product mix, if the total costs from joint production of all products in the product mix are less than the sum of the costs of producing each product independently, global economies of scope are present. Product-specific economies of scope for a product result from joint production efficiencies with one or a number of products in the mix. To determine which product pairs share scope economies in production, cost complementarities between all pairs of products need to be computed. A cost complementarity exists between two products if the marginal cost of producing one product declines when it is produced jointly with the other.

1.3 SOURCES OF SCALE AND SCOPE ECONOMIES

Scale economies and their implications for competitive advantage are well understood. The primary strategic implication in an industry subject to scale economies is that a firm must expand output in order to achieve scale benefits and remain competitive. The concept of the value-added chain by Porter (1985) adds richness to the analysis of scale economies as a source of competitive advantage. It has been suggested that scale efficiencies are often obtained through increased specialization and through the creation of dedicated assets and systems.

Scope economies can take place due to many reasons- the classic example is the joint production of outputs such as wool and mutton. Teece (1980) concludes that as long as scope economies derive from proprietary information or a specialized indivisible physical asset, a multiproduct enterprise is most efficient. He takes the energy industry as an example of this, where petroleum search and removal techniques can be applied to coal. Ghoshal (1987) categorizes the sources of scope economies as shared physical assets, shared external relations, and shared learning in product diversification and market diversification.

1.4 PRODUCTION ECONOMIES IN BLOOD BANKING

Cost leadership is one of the generic strategies for business firms (Porter, 1980). In contrast to the for-profit firm, there is no reason to believe a priori that profit maximization is a reasonable goal to impute to nonprofit organizations (NPO). Most commonly, NPOs have been assumed to maximize the quality and/or quantity

of the services they produce. The goal of maximizing service quality may seem reasonable for a NPO managed by professionals who derive strong satisfaction from doing craftsman-like work, independent of the monetary needs or desires of their customer. Quantity maximization, in turn, may be imputed as a goal for managers who are empire builders or who are altruists who seek to serve as broad a segment of the public as possible. Optimizing models of these types implicitly assume that NPOs seek to minimize costs consistent with the goals they pursue. However, behavior theory has argued that, whatever objectives NPOs may pursue with respect to quantity or quality of output, they are inherently subject to productive inefficiency (that is, failure to minimize costs) owing to the absence of ownership claims to residual earnings (Hansmann, 1980). This argument and the underlying theory is clearest when applied to entrepreneurial NPOs, which constitute the majority of financially significant NPOs. Those who control such organizations--whether the managers or the boards of trustees who appoint the managers--are unable, by virtue of the nondistribution of earnings constraint, to appropriate for themselves the net earnings obtained by reducing costs. Thus they have little incentive to operate the organization in a manner that minimizes costs.

A study of the hypotheses of economies of scale and economies of scope in the blood banking industry faces the difficulty: that blood centers may not be pursuing the goal of minimizing costs. For this reason early studies (Hao, 1988; Wallace and Wallace, 1982; Jacobs and Rawson, 1978) found no discernible pattern of economies or diseconomies of scale and concluded that blood center size had no

consistent appreciable effect on blood center costs They observed from the spread of data points above and below the regression line that some centers were substantially less productive and others substantially more productive than the average. This dispersion, however, was not related to size. Wide variations in size also suggests vast differences in the organization and management of blood centers. The present study tries to discount some of these inefficiency effects by eliminating the less efficient blood centers in order to get "best practice" estimates of economies of scale and scope.

Making better use of specialized labor and capital in the conduct of blood banking functions and spreading fixed costs over greater levels of output are usually cited as the predominant sources of economies of scale in blood banking. The six major functions in blood banking are: administration, donor recruiting, blood collection, laboratory testing, blood components production, inventory and distribution. Pierskalla (1987) found the potential for economies of scale in most of the functions by applying industrial engineering and simulation techniques. His study concluded that economies of scale can be realized by blood centers which collect between 50,000 to 75,000 units of whole blood annually. Furthermore, he concluded there exists the potential for economies of scale at even higher levels of operations but the rate of improvement decreases with increasing output. Another study concluded that the adoption of expensive automated equipment in blood centers involving large fixed costs cannot be justified for centers that process less than 100,000 units per year (Kline et. al.,1986). Anecdotal evidence also suggests that

economies of scope in blood banking can be achieved by diversifying into blood related specialized laboratory testing and typing. It is not clear, however, whether blood centers providing hemapheresis procedures achieve economies or diseconomies of scope.

1.5 ORGANIZATION OF CHAPTER

This chapter is organized as follows. Section 2 provides a brief literature review of the methodologies previously used in research on estimating economies of scale and scope. Section 3 describes the Translog methodology, the research design, and key assumptions of the empirical study. Section 4 presents study results. Section 5 contains study conclusions together with a discussion of contributions, limitations, and future research extensions.

2. LITERATURE REVIEW

Methods for estimating economies of scale and optimum size may be classified according to the following analytical techniques: (1) synthetic firm approach, (2) the survivorship method, (3) classification analysis, (4) the Farrell or DEA technique, and (5) statistical analysis.

2.1 SYNTHETIC FIRM APPROACH

Techniques used for this approach include budgeting, mathematical programming, industrial engineering and simulation models. All are well adapted to estimating an industry's cost curve under the assumption of a single 'most efficient' technology. Synthetic models can trace out short run cost-output relationships for different size firms. Long run envelope curves can then be sketched beneath the short run curves. In the case of a single productive activity carried out by firms of various sizes, the budgeting method may be best adapted to derive the short run average cost (SRAC) and long run average cost (LRAC) curves. If the firms are involved in several productive activities, linear programming models are often used as well.

There is a major problem common to all these methods. It is first necessary to determine a set of technical coefficients which describe the transformation of inputs into outputs. The underlying assumptions of technical coefficients determine the final shape of the cost curves. In general, it is assumed in such analysis that firms of similar size utilize a common technology and input mix. Because of this, the

synthetic firm approach poorly represents reality and hence its results must be interpreted with caution.

2.2 THE SURVIVORSHIP METHOD

Stigler [1958] referred to the method of analyzing economies of scale as the 'survivorship principle'. According to him, the survivor technique solves the problem of determining the optimum firm size as follows: "Classify the firms in an industry by size, and calculate the shares of the industry output coming from each class over time. If the shares of a given class fall, it is relatively inefficient, and in general is more inefficient the more rapidly the shares fall." Simply stated, the size concentration of firms within an industry is estimated at two discrete points in time. The model assumes that the most efficient firms endure and the more inefficient firms operating at higher costs are eliminated through competition. If the efficient firms increase in size over time, it is concluded that this may be the result of economies of scale.

The advantage of Stigler's method lies in its simplicity and low data requirement. It may be useful in studying industries with few firms or where cost data is difficult to obtain. It is not used, however, in studies where sufficient cost-output data are available because more information can be derived from other approaches.

2.3 CLASSIFICATION ANALYSIS

Classification analysis is a non-statistical means of estimating a few discrete points on the average cost curve. The method divides sample firms into groups of different sizes. Average costs are estimated for each size group and plotted on a graph. Comparison of cost-output points is used as the basis for determining if economies or diseconomies of scale exist in the industry.

Although this method represents reality, it does not allow for rigorous statistical testing of the factors affecting the relationship between cost and output. It provides only a few discrete points assumed to lie on the LRAC curve. The technique cannot estimate the frontier cost function; rather it provides an estimate of the cost curve which might exist for the average firm within each size group.

2.4 THE FARRELL OR DEA TECHNIQUE

This method, described and employed in the previous chapter, makes use of accounting data from individual firms to construct a frontier cost function. It calculates multidimensional efficiency indices from accounting data and applies these indices to derive the frontier function. Economies of scale are addressed by comparing the economic efficiency indices with measures of firm size.

Although the method separates the effects of scale into production costs and technical efficiency, its common fault is that the approach is very sensitive to measurement errors and it cannot estimate returns to scope.

2.5 STATISTICAL ANALYSIS

The application of an econometric function utilizing accounting data from firm records on costs and outputs is the most common method of estimating scale economies. This method makes use of actual cost data from firms that are in production; therefore results of the analysis are truer representations of reality than those obtained by the previously described methods. Statistical analysis can relate information concerning economies and diseconomies of scale associated with firm management. Furthermore, tests of statistical significance can determine the degree of confidence in these estimates. It is for these reasons that the statistical analysis method is chosen here as the analytical tool for studying economies of scale and scope in blood banking. The specified technique used is a multivariate regression model which jointly estimates a translog (transcendental logarithmic) cost function and selected cost share equations by means of a simultaneous equation system. The usual problems of applying statistical analysis to accounting data exist in this analysis. In order to arrive at reliable results, an adequate number of sample observations must be obtained for testing.

3. RESEARCH METHODOLOGY AND RESEARCH DESIGN

In this section the statistical models which identify both their structural and functional forms are specified. Decisions to be made regarding the models include the dependent and independent variables chosen for inclusion in the econometric equations. Explanations of the estimation procedures and their underlying assumptions are also presented. The data source and construction in formulating the models are also discussed. Finally, the variables used in the models are defined in detail.

3.1 STRUCTURAL FORM OF THE TRANSLOG COST MODEL

The production function is specified as:

$$Y = f(L, M, C) \tag{1}$$

where:

Y = output per period of time,

L = labor input,

M = material and supplies input, and

C = capital input.

In economic theory this relationship is referred to as the primal form. Output (Y) is measured in actual physical units of output; inputs (L, M, C) are similarly measured in physical units of inputs. Since raw data for empirical studies are not always collected in physical measurements and it is not possible to handle multiple output without accurate price data for individual product, it is difficult to apply the

primal approach.

An alternative to the primal form is the dual or duality approach involving the relationships between economic observations which are dual to the physical technology. Simply stated this means technology may be equivalently represented by either the physical production function or the cost function.

The theory of the dual approach appeared in the early works of Hotelling (1935) and Hicks (1946). The first comprehensive treatment of the subject and proof of the basic duality of cost and production was done by Shephard (1953). Subsequently, extensions of the formal theory of duality were later made by Shephard (1970) and Diewart (1974).

The major advantages of using the cost function instead of the production function are: (a) cost functions are homogeneous in prices regardless of the homogeneity properties of production functions; (b) factors of production measured in input prices are exogenous decision variables; (c) the error term is not as great in using cost figures; and (d) input prices are not greatly affected by multicollinearity in estimating cost functions. In addition, the principal advantage of using a cost function is that cost data are more readily available. The production function (1), thus, can be alternatively described by the cost function:

$$C = f(P_1, P_2, P_3) \qquad (2)$$

where:

C = total costs per period of time,

P_1 = input price of labor,

P_2 = input price of material and supplies, and

P_3 = input price of capital.

3.2 FUNCTIONAL FORM OF THE TRANSLOG COST MODEL

In this study the analyses of economies of scale and economies of scope in blood banking employ the translog cost function to formulate relationships between multiproduct outputs and multiple inputs. Properties of the translog cost function were developed by Christensen, Jorgenson and Lau (1971). Many applications of the single product translog cost functions had been published (Christensen, Jorgenson and Lau, 1973; Benston et. al., 1982; Goldstein et. al., 1987). Applications of multiproduct translog cost functions to estimate economies of scale and scope in various industries can be found in the literature beginning in the 1980's (Conrad and Strauss, 1983; Murray and White, 1983; Banker, Conrad and Strauss, 1986; Kim, 1986; and Mester, 1987).

The three output Model B Translog cost function to estimate the returns to scale and scope in blood banking is represented by the following logarithmic equation:

$$\begin{aligned}\ln C = {} & \alpha_0 + \alpha_1 \ln Y_1 + \alpha_2 \ln Y_2 + \alpha_3 \ln Y_3 \\ & + \beta_1 \ln P_1 + \beta_2 \ln P_2 + \beta_3 \ln P_3 \\ & + \tfrac{1}{2}\sigma_{11} \ln Y_1 \ln Y_1 + \tfrac{1}{2}\sigma_{22} \ln Y_2 \ln Y_2 + \tfrac{1}{2}\sigma_{33} \ln Y_3 \ln Y_3 \\ & + \sigma_{12} \ln Y_1 \ln Y_2 + \sigma_{13} \ln Y_1 \ln Y_3 + \sigma_{23} \ln Y_2 \ln Y_3 \\ & + \tfrac{1}{2}\gamma_{11} \ln P_1 \ln P_1 + \tfrac{1}{2}\gamma_{22} \ln P_2 \ln P_2 + \tfrac{1}{2}\gamma_{33} \ln P_3 \ln P_3 \\ & + \gamma_{12} \ln P_1 \ln P_2 + \gamma_{13} \ln P_1 \ln P_3 + \gamma_{23} \ln P_2 \ln P_3\end{aligned}$$

$$+\delta_{11}\ln Y_1\ln P_1+\delta_{12}\ln Y_1\ln P_2+\delta_{13}\ln Y_1\ln P_3$$

$$+\delta_{21}\ln Y_2\ln P_1+\delta_{22}\ln Y_2\ln P_2+\delta_{23}\ln Y_2\ln P_3$$

$$+\delta_{31}\ln Y_3\ln P_1+\delta_{32}\ln Y_3\ln P_2+\delta_{33}\ln Y_3\ln P_3 \quad (3)$$

where:

C = Total costs,

Y_1 = Blood Components Distributed,

Y_2 = Specialized Laboratory Services,

Y_3 = Specialized Clinical Services,

P_1 = Input Price of Labor,

P_2 = Input Price of Material and Supplies, AND

P_3 = Input Price of Capital.

The cost function must be homogeneous of degree one in input prices in order to correspond to a well behaved production function. This implies the following relationships among parameters:

$$\beta_1+\beta_2+\beta_3=1$$

$$\gamma_{11}+\gamma_{12}+\gamma_{13}=0$$

$$\gamma_{22}+\gamma_{12}+\gamma_{23}=0$$

$$\gamma_{33}+\gamma_{13}+\gamma_{23}=0$$

$$\delta_{11}+\delta_{12}+\delta_{13}=0$$

$$\delta_{21}+\delta_{22}+\delta_{23}=0$$

$$\delta_{31}+\delta_{32}+\delta_{33}=0$$

Estimates of global returns to scale in the multiproduct model when all outputs are increased by a common factor, λ, are obtained by differentiating (3) with respect to all Y_i,

$$\eta = d\ln C/\lambda = \Sigma_i \, d\ln C/d\ln Y_i \qquad (4)$$

If η is greater than 1, blood centers experience decreasing returns to scale as costs rise proportionately more than output. An η value equal to 1 indicates constant returns to scale, and a value less than 1 indicates increasing returns to scale. In order to enhance the analysis instead of making η a function of a single scale variable, the researcher allows it to respond to differences in output mix as well as differences in factor prices. Translog cost curves therefore assume more realistic shapes and need not be restricted to the smooth monotonically increasing or decreasing paths imposed by the more restricted Cobb-Douglas and constant elasticity of substitution (CES) specifications.

Interproduct complementarities or product-specific paired economies of scope are determined by the relative values of the α_i and σ_{ij} parameters. An approximate test of a multiproduct cost function exhibits product-specific economies of scope if

$$\alpha_i\alpha_j + \sigma_{ij} < 0 \qquad (5)$$

Output combinations satisfying (5) enjoy cost complementarities or jointness in their production. A single firm can therefore provide them at a lower cost than other firms which specialize and attempt to produce and sell the outputs individually.

The derived demand functions for the factors of production can be computed by partially differentiating the cost function with respect to factor prices, such as:

$$dC/dP_i = X_i$$

This result, known as the Shephard's lemma (1967), is expressed in logarithmic form for the translog cost function as:

$$d\ln C/d\ln P_i = S_i$$

where S_i indicates the cost share of the ith factor input. Thus, the translog cost function yields the cost share equations:

$$S_1 = \beta_1 + \gamma_{11}\ln P_1 + \gamma_{12}\ln P_2 + \gamma_{13}\ln P_3 + \delta_{11}\ln Y_1 + \delta_{21}\ln Y_2 + \delta_{31}\ln Y_3 \quad (6)$$

$$S_2 = \beta_2 + \gamma_{22}\ln P_2 + \gamma_{12}\ln P_1 + \gamma_{23}\ln P_3 + \delta_{12}\ln Y_1 + \delta_{22}\ln Y_2 + \delta_{32}\ln Y_3 \quad (7)$$

$$S_3 = \beta_3 + \gamma_{33}\ln P_3 + \gamma_{13}\ln P_1 + \gamma_{23}\ln P_2 + \delta_{13}\ln Y_1 + \delta_{23}\ln Y_2 + \delta_{33}\ln Y_3 \quad (8)$$

In summary, the translog cost function is an approximation of the almost homothetical production function, in that the cost function can be written as a separate function in output and factor prices. The translog cost function does not impose restrictions on the elasticities of substitution between units in the production process and economies of scale and economies of scope can easily be derived, as shown above.

3.3 ESTIMATION PROCEDURE FOR THE TRANSLOG COST MODEL

The estimation procedure used in the translog cost model entails an econometric approach which quantifies the economic process in terms of relationships. The

statistical technique used to explain these relationship is a multivariate regression system which jointly estimates the translog cost function and the cost share equations. Including the cost share equations in the estimation procedure has the beneficial effect of adding many additional degrees of freedom without adding any unrestrictive regression coefficients. This results in more efficient estimates than would be obtained by only applying ordinary least squares to the cost function.

Since the sum of the cost shares must equal one by definition, one of the equations is redundant. Any attempt to estimate the complete system will create problems. Fortunately, maximum likelihood estimates are invariant to the equation we choose to exclude. Equations (6) and (7) selected along with equation (3) comprise the full cost system.

The multivariate regression system which jointly estimates the translog cost function and the cost share equations is estimated by means of a simultaneous equation system. Maximum-likelihood estimates are obtained by estimating the cost equation with labor share and material share equations using the iterative seemingly unrelated regression equations (SURE) technique. Restrictions implying homogeneity of degree one in input prices and symmetry are imposed.

One of the reasons for estimating a flexible function form like the translog is that it does not impose any a priori restrictions on the structural form of the production function which is its dual. By placing additional restrictions on the parameters of the translog, it can be made to correspond to a more restrictive production technology. The restrictive forms can be estimated, and, because

maximum-likelihood estimates are obtained, the likelihood-ratio test can be used to test the restricted vs. unrestricted technology.

Five hypotheses are tested for each model. These are:

(1) homotheticity of the production function,

(2) homogeneity with respect to output of the production function,

(3) unitary elasticity of substitution of the production function between inputs,

(4) generalized Cobb-Douglas production function, and

(5) globally constant returns to scale of the production function.

The production function is homothetic when the marginal rates of substitution in production are independent of scale effects and depend only on relative prices. The cost function corresponding to a homothetic production function is separable in outputs and factor price. Thus, restrictions on the cost function needed to imply a homothetic production technology for Model A are: $\delta_{ij}=0$; $i=1$; $j=1,2,3$ (2 restrictions independent of linear homogeneity in input price restrictions). For Model B they are: $\delta_{ij}=0$; $i,j=1,2,3$ (6 independent restrictions). A homothetic production technology is further restricted to be homogeneous in output if the elasticity of cost with respect to output is constant. Restrictions required on the cost function for Model A are: $\delta_{ij}=0$; $i=1$; $j=1,2,3$; $\sigma_{ik}=0$; $i=1$; $k=1$ (3 independent restrictions). For Model B they are: $\delta_{ij}=0$; $i,j=1,2,3$; $\sigma_{ik}=0$; $i,k=1,2,3$ (12 independent restrictions). The production function has unitary elasticity of substitution among all factor inputs when all second order terms in factor prices in

the translog function are eliminated. The restrictions necessary on both Models A and B are: $\gamma_{ij}=0$; i,j=1,2,3 (3 restrictions independent of symmetry and linear homogeneity in input price restrictions). The production function is Cobb-Douglas if it is homogeneous in output with unitary elasticity of substitution. Thus, the restrictions required on the cost function of Model A are:$\delta_{ij}=0$; i=1; j=1,2,3; $\sigma_{ik}=0$; i,k=1; $\gamma_{ij}=0$; i,j=1,2,3 (6 independent restrictions). For Model B are: $\delta_{ij}=0$; i,j=1,2,3; $\sigma_{ik}=0$; i,k=1,2,3; $\gamma_{ij}=0$; i,j=1,2,3 (15 independent restrictions). Finally the production function has globally constant returns to scale when the degree of returns to scale measures equals 1 for all output and input price values. For Model A,

$$Scale = \frac{1}{\Sigma_i[\alpha_i + \Sigma_k \sigma_{ik} \ln y_k + \Sigma_j \delta_{ij} \ln p_j]}$$

so the necessary restrictions are:$\alpha_1=1$; $\sigma_{11}=0$; $\delta_{11}+\delta_{21}+\delta_{31}=0$; $\delta_{12}+\delta_{22}+\delta_{32}=0$; $\delta_{13}+\delta_{23}+\delta_{33}=0$; (4 independent restrictions). The necessary restrictions for Model B are: $\alpha_1+\alpha_2+\alpha_3=1$; $\Sigma_i\sigma_{ik}=0$ k=1,2,3; $\Sigma_i\delta_{ij}=0$ j=1,2,3 (6 independent restrictions). Since the error terms on the cost and share equations are assumed to be distributed normally, the likelihood ratio (LR), which is the value of the likelihood under the restricted hypothesis divided by the value of the likelihood under no restrictions, simplifies to

$$LR = [\frac{|\Omega_R|}{|\Omega_U|}]^{-m2}$$

where: $|\Omega_R|$ = determinant of the restricted disturbance covariance matrix across equations;

$|\Omega_U|$ = determinant of the unrestricted disturbance covariance matrix across equations; and

T = number of blood centers.

The test statistic, -2ln LR, is distributed asymptotically χ^2 with degree of freedom equal to the number of independent restrictions imposed.

3.4 ASSUMPTIONS OF THE TRANSLOG COST MODEL

The following assumptions apply to the translog cost function estimated by means of the iterative Zellner procedure as discussed above:

1. At the level of an individual blood center, it is assumed that the supply of inputs is perfectly elastic, and therefore input prices can be taken as fixed.
2. At the blood center or industry level, input prices are proper exogenous variables. Managers make decisions on factor use according to exogenous prices, which makes actual factor quantity levels endogenous decision variables.
3. The regressors in the cost share equations are uncorrelated with the disturbance terms.
4. The cost shares of each equation always sum to unity; hence, the sum of disturbances across the equation is zero at each observation. This assumption implies that the disturbance covariance matrix is singular and non diagonal.

3.5 MODELS AND DATA

Two Models A1 and B1 are estimated using all 142 observations. Model A1 is a single output model, which employs blood components distributed as the single output. The purpose is to investigate average return to scale in blood banking. Model B1 employs blood components distributed, specialized laboratory services, and specialized clinical services as the outputs. It is designed to study average returns to scale and to scope in blood banking. Model A2 employs a reduced set of 81 blood centers with efficiency ratings above .85 based on the DEA study. Results from this model estimate best practice returns to scale. Model B2 employs a reduced set of 71 blood centers with efficiency ratings above .80 based on the DEA study. Results from this model estimate best practice returns to scale and to scope. All estimations were derived by seemingly unrelated regressions on the IBM 3084-QX using the SAS SYSLIN procedure.

Data required for estimation of the Translog cost function and share equations include total center costs, individual outputs and resource input prices . These information were obtained from 48 blood centers for the period 1987 to 1989.

Total costs, C, include all labor, material and real capital expenses per year. For the single output models A1 and A2, Y_1 is defined as blood components distributed and is measured as the sum of net whole blood, red blood cells, platelets, cryoprecipitate, and plasma distributed. For the multiproduct models B1 and B2, Y_1 is measured by blood components distributed as in single product model ; Y_2 as the number of specialized laboratory tests and services (the sum of reference or

processing lab tests, tissue typing tests for transfusion and numbers of irradiated blood products); and Y_3 as the number of specialized clinical services (the sum of numbers of apheresis procedures and therapeutic hemapheresis procedures and autologous collections).

Three input categories are identified for both Models A and Models B: labor, material and supplies, and fixed capital. The input price of labor, P_1, is measured by the average hourly rate based on salaries paid to employees, determined by dividing total labor costs by the number of full-time equivalent employees. The input price of material and supplies for Models A, P_2, was obtained by summing all variable materials and supplies costs and dividing by the total number of blood components distributed per year. The input price of material and supplies for Models B, P_2, was calculated as the sum of all material and supplies costs divided by the sum of (a) the number of blood components distributed, (b) specialized laboratory services and (c) specialized clinical services per year. The input price of capital for models A, P_3, was computed as the sum of depreciation and interests and divided by the number of blood components distributed. The input price of capital for models B, P_3, was obtained by dividing total capital cost by the sum of all three outputs. Table III-1 gives the minimum, maximum, and mean values for each of the variables in the samples.

4. RESULTS

Goodness-of-fit measures for the cost equation and the two estimated share equations are presented in Table III-2 for all models. The estimated parameters and their standard errors and t-statistics are presented in Table III-3 for Model A1, in Table III-4 for Model B1, in Table III-5 for Model A2, and in Table III-6 for Model B2. These parameter estimates of costs permits investigation of the production structure of the blood banking industry.

Structural tests of the cost functions obtained from the four models are presented in Table III-7. Models A1 and A2 reject ($p<.05$) the hypothesis that there exists among the centers constant returns to scale. Economies of scale and/or diseconomies of scale exist among the centers in whole blood collection, components production and distribution. The constant returns to scale hypothesis for the centers was rejected for Model B2 at a highly significant level ($p<.01$) but not rejected at a marginal level ($p=.10$) for Model B1 indicating that results of estimations of returns to scale were significantly different between the average and best practice approaches in the three outputs setting. Thus, three out of the four models reject constant returns to scale hypothesis at .05 or .01 level, inferring that economies of scale and/or diseconomies of scale are present in blood banking.

Since homotheticity was rejected at the .10 marginal level only by model A1, it can be concluded that the marginal rates of input substitution in production are independent of scale effects and depend only on relative input prices. Both Models B1 and B2 rejected the homogeneous and Cobb-Douglas functional forms, meaning

that results from previous studies using these restricted forms were biased and not properly structured. Some restricted functional forms were not rejected as expected. These may be due to measurement errors with regard to input prices of material and capital.

Changes in total costs across a function usually differ depending on the level of outputs and differences in input prices. Measures of these effects are evaluated at three sample points: (a) the sample means of outputs and input prices for the average blood center; (b) the minimum values of outputs and mean prices of inputs for the small blood center; and (c) the maximum values of outputs and mean prices of inputs for the large blood center. Most calculated statistics are not linear functions of estimated parameters, so exact standard deviations cannot be calculated. Because of the complexity of obtaining an approximate standard deviation, only the estimates of returns to scale and to scope will be reported.

4.1 GLOBAL ECONOMIES OF SCALE

Both single output Models A1 and A2 indicate that large blood centers enjoy a 5% cost savings compared with medium-size blood centers and small blood centers require 10% more inputs than average blood centers in order to increase output. These results are significant at the 5 percent level as shown by the structural tests in Table III-7 and the results in Table III-8.

Estimates of global economies of scale for Model B1 are similar to those for Models A1 and A2 but were not statistical significant even at the 10 percent level.

This is probably due to large standard deviations in the estimates. Results from Model B2 show that large blood centers could achieve a 22% cost savings compare with medium-size blood centers, and small blood centers would encounter 26% cost increases when compared with the average blood center. These results are significant at the 1% level (see Table III-7 and Table III-8). Return to scale estimates from Models B1 and B2 are quite different. They reveal that efficiency differentials among blood centers could distort the findings of economies of scale using the multiple output approach if this issue is not addressed.

The average blood center in this study distributes 264,000 units of blood components, (see Table III-1) and is operating in the range of constant returns to scale according to both the single and multiple output models. The average blood center produces 2.5 units of blood components per unit of whole blood collected. Thus, the study concludes that the average blood center with annual whole blood collection of 100,000 units or 264,000 units of blood components distributed needs to increase its outputs in order to enjoy scale economies. According to the models small blood centers operate in the range of diseconomies of scale. While largest blood centers with over 700,000 thousand units of BCD annually, if efficient, enjoy a 22% lower cost of output expansion compared with the average blood center.

4.2 PRODUCT-SPECIFIC PAIRED ECONOMIES SCOPE

Table III-9 provides estimates of product-specific paired economies of scope for Models B1 and B2. In both cases negative values indicate that economies of

scope are present in blood banking with joint production of blood components distributed (BCD) and specialized laboratory services (SLS). The value -2.288 from Model B2 is significantly less than zero indicating there exists strong cost complementarities between BCD and SLS. Both Models B1 and B2 show diseconomies of scope present with joint production of BCD and specialized clinical services (SCS). But results from Model B2 for the more efficient blood centers show smaller diseconomies of scope compared with those of the average blood center. Joint production of SLS and SCS evidence slight economies of scope; however, the results may not be significant since the values are close to zero.

4.3 PRODUCT-SPECIFIC ECONOMIES OF SCALE

The level of fixed costs associated with production must be determined in order to analyze product-specific scale economies. In specifying the translog as the functional form of the cost function the cost must equal zero when any output is equal to zero. Estimated values of product-specific scale economies are often unreliable as evidenced by the huge standard errors reported in banking studies (Mester, 1987). In this study 10 percent of the sample mean outputs is chosen as a reference point to estimate fixed cost, which lies within the sample range for SLS and SCS but not for BCD. Accordingly, product-specific scale economies derived from the translog multiple output cost function are written as (Kim, 1986)

$$SL_i = \frac{\exp(\alpha_0) - \exp(\alpha_0 + \alpha_i \ln\epsilon + 1/2\, \sigma_{ii}(\ln\epsilon)^2)}{\alpha_i \exp(\alpha_0)}$$

where $e = 0.1$ is used in place of 0, since ln 0 is not defined.

Table III-10 reports the estimates of product-specific scale economies for the average blood center. Derivation of product-specific scale economies is rather complicated, since it requires evaluation of incremental cost at an output level close to zero. Therefore, no attempt was made to obtain the standard errors of product-specific scale economies. The degree of product-specific scale economies for y_1 is 1.712, suggesting substantial diseconomies of scale associated with the activity of blood components distributed. These results are not in agreement with the finding in Table III-8 and probably are not reliable because the estimate of fixed cost of producing BCD, using 10% of the average value of BCD, is about half the value of minimum BCD which is outside the range for reliable results.

There are highly significant economies of scale with respect to SLS, as indicated by the degree of product-specific scale economies of .286 for y_2. Since the product-specific scale economies for y_3 is higher than 1, this suggests small diseconomies of scale associated with SCS. It may be important to note that the product-specific scale economies for y_2 is smaller than for y_1 and y_3, indicating that blood centers have an incentive to expand their specialized laboratory services.

4.4 GLOBAL PRODUCT-SPECIFIC ECONOMIES OF SCOPE

The degree of overall scope economies for the blood center model B evaluated at the point of approximation can be derived by (Kim, 1986)

$$SC = [\exp(\alpha_0+\alpha_2 \ln e+\alpha_3 \ln e + 1/2\,\sigma_{22}(\ln e)^2 + 1/2\sigma_{33}(\ln e)^2)$$
$$+\exp(\alpha_0+\alpha_1 \ln e+\alpha_3 \ln e+1/2\sigma_{11}(\ln e)^2+1/2\sigma_{33}(\ln e)^2)$$
$$+\exp(\alpha_0+\alpha_1 \ln e+\alpha_2 \ln e+1/2\sigma_{11}(\ln e)^2+1/2\sigma_{22}(\ln e)^2)$$
$$-\exp(\alpha_0)]/\exp(\alpha_0)$$

Product-specific scope economies with respect to y_i at the point of approximation of the translog cost function can be estimated by (Kim, 1986)

$$SC_i=[\exp(\alpha_0+\Sigma_{j\neq i}\sigma_j \ln e+1/2\Sigma_{j\neq i}\Sigma\sigma_{ij}(\ln e)^2)$$
$$+\exp(\alpha_0+\alpha_i \ln e+1/2\sigma_{ii}(\ln e)^2)-\exp(\alpha_0)]$$
$$/\exp(\alpha_0)$$

Table III-11 presents estimates of global as well as product-specific scope economies for various groupings of blood center outputs. Scope economies measure the percentage savings (increases) that are due to joint production. Note that all values of scope economies except $\{Y_3\}$ with $\{Y_1$ & $Y_2\}$ are positive, implying the presence of economies of scope. As indicated by the degree of 0.224 for overall scope economies if a blood center combines the production of Y_1, Y_2, and Y_3, it is estimated to have a cost saving of 22.4 percent compared with three blood centers each producing one output. If the production of Y_1 is combined with Y_2 and Y_3 the blood center should achieve a cost saving of 18 percent. The degree of savings of Y_2 combined with Y_1 and Y_3 is greater than any other means of obtaining scope economies. Thus, a blood center should achieve greater savings from combining Y_2 with other existing outputs. If, however, the production of Y_3 is combined with Y_1 and Y_2 a blood center should incur an 18.6 percent cost increase, indicating that a blood center should perform better without combining Y_3 with other existing outputs.

5. SUMMARY AND CONCLUSIONS

A system of cost equations was employed to identify and estimate economies of scale and scope in blood banking. The Translog cost function was selected in order to avoid imposing unnecessary restrictions on the production/cost relationships. Likelihood ratio tests were then used along with selective parameter restrictions to test for the applicability of five restricted functional forms:(1) homotheticity, (2) homogeneity, (3) unitary elasticities of substitution, (4) Cobb-Douglas, and (5) global constant returns to scale.

The study employed four models. Models A1 and A2 employed blood components distributed as the single output and concluded there exist economies of scale among large blood centers and diseconomies of scale among small blood centers. The average blood centers with 100,000 units of whole blood collection per year appears to have constant return to scale. Models B1 and B2 considered blood components distributed, specialized laboratory services, and specialized clinical services as the outputs of blood centers. Model B2 showed significant scale economies among large blood centers and diseconomies of scale among small blood centers. But results from Model B1 fail to reject the hypothesis of constant returns to scale. Three out of the four models showed economies of scale for large centers, diseconomies of scale for small centers, and constant returns to scale for the average blood centers. Blood centers having whole blood collection of 100,000 units or more per year are estimated as having economies of scale. The more whole blood units the center collects, the more savings could be generated from returns to scale.

Models B1 and B2 showed strong economies of scope with joint production of blood components distributed and specialized laboratory services; diseconomies of scope with joint production of blood components distributed and specialized clinical services; and slight or constant returns to scope with joint production of specialized laboratory and clinical services.

These results of returns to scale and scope in blood banking are in general agreement with blood center manager's speculations. If full impact of competition in blood banking arrives today, the first thing blood center has to do is to improve its efficiency. Blood centers should also actively pursue every opportunity to expand its specialized laboratory services and avoid deeper involvement in specialized clinical services. Blood centers which are heavily involved in specialized clinical services should price these services differently from laboratory services in order to compensate high costs associated with producing them. Small centers should not get involved in clinical services unless its costs can be completely reimbursed. Small centers should increase its blood collection and export surplus units to large hospitals in other areas to withstand price competition or merging with a large center.

In interpreting these finding, it is important to pay close attention to the limitations of the study. There undoubtedly have been measurement errors in determining input prices, especially of capital and material. Blood centers included in Models A2 and B2 do not all have DEA efficiency ratings of 1, so the best practice estimates of returns to scale and returns to scope according to these models are only approximated by this study.

A possible extension to get better best practice estimates of economies of scale and scope would be by adjusting input prices and total costs lower and/or adjusting outputs higher to move the inefficient blood centers to the efficient frontier by using DEA study results. This would involve some calculation to obtain the adjusted total costs, input prices, and outputs required for the inefficient center to become efficient. This approach would have the same number of observations as Models A1 and B1.

Table III-1 TRANSLOG STUDY VARIABLES VALUES

Variable	Minimum	Mean	Maximum
Total Cost (x1,000)	1,348.2	7,839.0	23,118.8
Labor Share	.392	.527	.606
Material Share	.158	.248	.390
Capital Share	.177	.225	.291
Outputs			
BCD	48,629	263,926	715,836
SLS	1,239	25,134	145,386
SCS	100	4,179	18,654
Input Price			
Labor	$7.0	$11.5	$16.8
Material	$4.7	$6.9	$11.7
Capital	$4.0	$6.3	$9.8

BCD : Blood Components Distributed
SLS : Specialized Laboratory Services
SCS : Specialized Clinical Services

Table III-2 TRANSLOG MODELS GOODNESS OF FIT MEASUREMENTS

	Sum of Squared Errors SSE	Degrees of Freedom DF	Mean Square Error MSE=SSE/DF	R Square
Model A1 (142 Cases)				
Cost Equation	1.3110	132	0.0099	0.9842
Labor Cost Share	0.1790	137	0.0013	0.2894
Material Cost Share	0.0508	137	0.0004	0.7613
Model B1 (142 Cases)				
Cost Equation	0.8482	121	0.0070	0.9898
Labor Cost Share	0.1779	135	0.0013	0.2936
Material Cost Share	0.0504	135	0.0004	0.7632
Model A2 (81 Cases with E > .85)				
Cost Equation	0.7074	71	0.0100	0.9893
Labor Cost Share	0.1011	76	0.0013	0.2595
Material Cost Share	0.0265	76	0.0003	0.6387
Model B2 (71 Cases with E > .80)				
Cost Equation	0.3607	50	0.0072	0.9938
Labor Cost Share	0.1083	64	0.0017	0.2615
Material Cost Share	0.0296	64	0.0005	0.6290

Table III-3 MODEL A1 PARAMETER ESTIMATES (142 Cases)

	VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T-Ratio	PROB >|T|
α_0	INTERCEPT	-9.89988109	2.12485617	-4.659	0.0001
α_1	ln y_1	1.70494994	0.35134530	4.853	0.0001
β_1	ln p_1	0.06918137	0.06961936	0.994	0.3223
β_2	ln p_2	0.44191384	0.04885333	9.046	0.0001
β_3	ln p_3	0.48890478	0.05952170	8.214	0.0001
σ_{11}	ln $y_1$ln y_1	-0.05614442	0.02895145	-1.939	0.0547
γ_{11}	ln $p_1$ln p_1	0.10105100	0.01511515	6.685	0.0001
γ_{22}	ln $p_2$ln p_2	0.14824800	0.00437202	33.908	0.0001
γ_{33}	ln $p_3$ln p_3	0.13752425	0.00382953	35.912	0.0001
γ_{12}	ln $p_1$ln p_2	-0.05588738	0.00803031	-6.960	0.0001
γ_{13}	ln $p_1$ln p_3	-0.04516362	0.00724275	-6.236	0.0001
γ_{23}	ln $p_2$ln p_3	-0.09236063	0.00389649	-23.704	0.0001
δ_{11}	ln $y_1$ln p_1	0.00191632	0.00436644	0.439	0.6615
δ_{12}	ln $y_1$ln p_2	-0.00068556	0.00232648	-0.295	0.7687
δ_{13}	ln $y_1$ln p_3	-0.00123076	0.00207901	-0.592	0.5549

Y_1 : Blood Components Distributed
P_1 : Input Price of Labor
P_2 : Input Price of Material
P_3 : Input Price of Capital

Table III-4 MODEL B1 PARAMETER ESTIMATES (142 Cases)

	VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T-Ratio	PROB >|T|
α_0	INTERCEPT	-9.65623186	2.32584225	-4.152	0.0001
α_1	ln y_1	1.65235408	0.55088498	2.999	0.0033
α_2	ln y_2	-0.14414258	0.20262641	-0.711	0.4783
α_3	ln y_3	0.28474449	0.21514069	1.324	0.1883
β_1	ln p_1	0.10116250	0.07421426	1.363	0.1755
β_2	ln p_2	0.39549632	0.04861089	8.136	0.0001
β_3	ln p_3	0.50334118	0.05779529	8.709	0.0001
σ_{11}	ln $y_1$ln y_1	-0.02057767	0.07453893	-0.276	0.7830
σ_{22}	ln $y_2$ln y_2	0.04816543	0.01544704	3.118	0.0023
σ_{33}	ln $y_3$ln y_3	0.11901603	0.02119919	5.614	0.0001
σ_{12}	ln $y_1$ln y_2	-0.00322663	0.02816664	-0.115	0.9090
σ_{13}	ln $y_1$ln y_3	-0.06622993	0.03086208	-2.146	0.0340
σ_{23}	ln $y_2$ln y_3	-0.02936469	0.01427431	-2.057	0.0420
γ_{11}	ln $p_1$ln p_1	0.09975964	0.01474949	6.764	0.0001
γ_{22}	ln $p_2$ln p_2	0.14793058	0.00426234	34.706	0.0001
γ_{33}	ln $p_3$ln p_3	0.13746519	0.00377668	36.398	0.0001
γ_{12}	ln $p_1$ln p_2	-0.05511252	0.00782901	-7.040	0.0001
γ_{13}	ln $p_1$ln p_3	-0.04464713	0.00707735	-6.308	0.0001
γ_{23}	ln $p_2$ln p_3	-0.09281806	0.00381552	-24.326	0.0001
δ_{11}	ln $y_1$ln p_1	0.00484148	0.00791808	0.611	0.5421
δ_{12}	ln $y_1$ln p_2	-0.00191063	0.00421507	-0.453	0.6512
δ_{13}	ln $y_1$ln p_3	-0.00293085	0.00377752	-0.776	0.4394
δ_{21}	ln $y_2$ln p_1	-0.00556847	0.00371640	-1.498	0.1368
δ_{22}	ln $y_2$ln p_2	0.00300309	0.00197725	1.519	0.1316
δ_{23}	ln $y_2$ln p_3	0.00256538	0.00177369	1.446	0.1508
δ_{31}	ln $y_3$ln p_1	0.00238061	0.00457350	0.521	0.6037
δ_{32}	ln $y_3$ln p_2	-0.00157770	0.00243402	-0.648	0.5182
δ_{33}	ln $y_3$ln p_3	-0.00080291	0.00218032	-0.368	0.7134

Y_1 : Blood Components Distributed
Y_2 : Specialized Laboratory Services
Y_3 : Specialized Clinical Services
P_1 : Input Price of Labor
P_2 : Input Price of Material
P_3 : Input Price of Capital

Table III-5 MODEL A2 PARAMETER ESTIMATES (81 Cases)

	VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T-Ratio	PROB >|T|
α_0	INTERCEPT	-10.53404294	2.88399394	-3.653	0.0005
α_1	ln y_1	1.80713342	0.48093046	3.758	0.0004
β_1	ln p_1	0.04156763	0.09999607	0.416	0.6790
β_2	ln p_2	0.51032024	0.07326910	6.965	0.0001
β_3	ln p_3	0.44811213	0.08222869	5.450	0.0001
σ_{11}	ln $y_1$ln y_1	-0.06412976	0.03960735	-1.619	0.1102
γ_{11}	ln $p_1$ln p_1	0.13254222	0.02736094	4.844	0.0001
γ_{22}	ln $p_2$ln p_2	0.14747732	0.00729399	20.219	0.0001
γ_{33}	ln $p_3$ln p_3	0.14445907	0.00683429	21.137	0.0001
γ_{12}	ln $p_1$ln p_2	-0.06778023	0.01399342	-4.844	0.0001
γ_{13}	ln $p_1$ln p_3	-0.06476199	0.01349976	-4.797	0.0001
γ_{23}	ln $p_2$ln p_3	-0.07969709	0.00692888	-11.502	0.0001
δ_{11}	ln $y_1$ln p_1	-0.00095436	0.00483003	-0.198	0.8440
δ_{12}	ln $y_1$ln p_2	0.00076965	0.00247222	0.311	0.7565
δ_{13}	ln $y_1$ln p_3	0.00018471	0.00238217	0.078	0.9384

Y_1 : Blood Components Distributed
P_1 : Input Price of Labor
P_2 : Input Price of Material
P_3 : Input Price of Capital

Table III-6 MODEL B2 PARAMETER ESTIMATES (71 Cases)

	VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T-Ratio	PROB >|T|
α_0	INTERCEPT	-19.61940485	3.95647150	-4.959	0.0001
α_1	ln y_1	3.80910340	1.03998457	3.663	0.0007
α_2	ln y_2	-0.61943243	0.42679047	-1.451	0.1539
α_3	ln y_3	0.08404091	0.37736068	0.223	0.8248
β_1	ln p_1	0.03829290	0.12407411	0.309	0.7591
β_2	ln p_2	0.42242596	0.08492040	4.974	0.0001
β_3	ln p_3	0.53928115	0.09306460	5.795	0.0001
σ_{11}	ln $y_1$ln y_1	-0.26270850	0.15917173	-1.650	0.1061
σ_{22}	ln $y_2$ln y_2	0.01353578	0.04354070	0.311	0.7574
σ_{33}	ln $y_3$ln y_3	0.13588914	0.04014387	3.385	0.0015
σ_{12}	ln $y_1$ln y_2	0.06992329	0.07450061	0.939	0.3532
σ_{13}	ln $y_1$ln y_3	-0.05336010	0.06098569	-0.875	0.3865
σ_{23}	ln $y_2$ln y_3	-0.03957026	0.02271265	-1.742	0.0886
γ_{11}	ln $p_1$ln p_1	0.10404048	0.02777024	3.746	0.0005
γ_{22}	ln $p_2$ln p_2	0.14209248	0.00779136	18.237	0.0001
γ_{33}	ln $p_3$ln p_3	0.13526550	0.00681087	19.860	0.0001
γ_{12}	ln $p_1$ln p_2	-0.05543373	0.01450060	-3.823	0.0004
γ_{13}	ln $p_1$ln p_3	-0.04860675	0.01342990	-3.619	0.0008
γ_{23}	ln $p_2$ln p_3	-0.08665875	0.00712140	-12.169	0.0001
δ_{11}	ln $y_1$ln p_1	-0.00892773	0.01446900	-0.617	0.5405
δ_{12}	ln $y_1$ln p_2	0.00581003	0.00756147	0.768	0.4465
δ_{13}	ln $y_1$ln p_3	0.00311770	0.00699631	0.446	0.6581
δ_{21}	ln $y_2$ln p_1	0.00386911	0.00721847	0.536	0.5947
δ_{22}	ln $y_2$ln p_2	-0.00254016	0.00377155	-0.674	0.5042
δ_{23}	ln $y_2$ln p_3	-0.00132895	0.00348861	-0.381	0.7051
δ_{31}	ln $y_3$ln p_1	0.00164364	0.00742735	0.221	0.8259
δ_{32}	ln $y_3$ln p_2	-0.00089191	0.00388392	-0.230	0.8195
δ_{33}	ln $y_3$ln p_3	-0.00075173	0.00359218	-0.209	0.8352

Y_1 : Blood Components Distributed
Y_2 : Specialized Laboratory Services
Y_3 : Specialized Clinical Services
P_1 : Input Price of Labor
P_2 : Input Price of Material
P_3 : Input Price of Capital

Table III-7 TRANSLOG MODELS STRUCTURAL TESTS

	Test Statistic -2 ln LR	Degrees of Freedom	Chi-Square Value at .1 Significance Level
Model A1 (142 Cases)			
Unrestricted Cost Function			
Homotheticity	4.78 *	2	4.60
Homogeneity in Output	6.75 *	3	6.25
Unitary Elasticity of Substitution	10.43 **	3	6.25
Cobb-Douglas	10.52	6	10.64
Global Constant Returns to Scale	12.27 **	4	7.78
Model B1 (142 Cases)			
Unrestricted Cost Function			
Homotheticity	1.42	6	10.64
Homogeneity in Output	40.96 ***	12	18.55
Unitary Elasticity of Substitution	1.82	3	6.25
Cobb-Douglas	40.70 ***	15	22.31
Global Constant Returns to Scale	7.70	6	10.64
Model A2 (81 Cases)			
Unrestricted Cost Function			
Homotheticity	2.13	2	4.60
Homogeneity in Output	5.29	3	6.25
Unitary Elasticity of Substitution	-.58	3	6.25
Cobb-Douglas	1.30	6	10.64
Global Constant Returns to Scale	9.84 **	4	7.78
Model B2 (71 Cases)			
Unrestricted Cost Function			
Homotheticity	6.42	6	10.64
Homogeneity in Output	39.38 ***	12	18.55
Unitary Elasticity of Substitution	-.55	3	6.25
Cobb-Douglas	33.39 ***	15	22.31
Global Constant Returns to Scale	24.56 ***	6	10.64

* significant at .10, ** significant at .05, *** significant at .01

Table III-8 GLOBAL ECONOMIES OF SCALE ESTIMATIONS

Model A (1 Output)	A1 (142 Cases)	A2 (81 Cases with E > .85)
Large	.95	.95
Medium	1.00	1.00
Small	1.10	1.10
Model B (3 Output)	**B1 (142 Cases)**	**B2 (71 Cases with E > .80)**
Large	.92	.78
Medium	1.00	1.00
Small	1.11	1.26

Table III-9 PRODUCT-SPECIFIC PAIRED ECONOMIES OF SCOPE ESTIMATIONS

Model B (3 Output)	B1 (142 Cases)	B2 (71 Cases with E > .80)
SCOPE (BCD,SLS)	-.241	-2.288
SCOPE (BCD,SCS)	.405	.267
SCOPE (SLS,SCS)	-.070	-.092

BCD : Blood Components Distributed
SLS : Specialized Laboratory Services
SCS : Specialized Clinical Services

Table III-10 PRODUCT-SPECIFIC ECONOMIES OF SCALE

Model B1 (142 Cases)

Output Group	Estimates
Y_1	1.712
Y_2	.286
Y_3	1.196

Y_1 : Blood Components Distributed
Y_2 : Specialized Laboratory Services
Y_3 : Specialized Clinical Services

Table III-11 GLOBAL AND PRODUCT-SPECIFIC ECONOMIES OF SCOPE

Model B1 (142 Cases)

Output Group	Estimates
$\{Y_1\} + \{Y_2\} + \{Y_3\}$	.224
$\{Y_1\} + \{Y_2 \& Y_3\}$	.180
$\{Y_2\} + \{Y_1 \& Y_3\}$	.530
$\{Y_3\} + \{Y_1 \& Y_2\}$	-.186

Y_1 : Blood Components Distributed
Y_2 : Specialized Laboratory Services
Y_3 : Specialized Clinical Services

CHAPTER IV

SUMMARY OF RESEARCH FINDINGS, CONTRIBUTIONS, LIMITATIONS, AND FUTURE EXTENSIONS

1. SUMMARY OF RESEARCH FINDINGS

By using Data Envelopment Analysis (DEA), the study first measured the relative efficiency of 48 blood centers from 1987 to 1989 using both the single output Model A and the three output Model B. Model A employed Blood Components Distributed (BCD) as the representative output of blood centers. In this analysis 13 percent of the centers were found to be relatively efficient, 23 percent were from 1 to 10 percent less efficient, another 40 percent were from 11 to 20 percent less efficient, and 24 percent were 21 percent or more less efficient.

Model B employed BCD, Specialized Laboratory Services (SLS) and Specialized Clinical Services (SCS) as the three outputs of blood centers. In this analysis 28 percent of the centers were found relative efficient, 7 percent were from 1 to 10 percent less efficient, another 15 percent were from 11 to 20 percent less efficient, 25 percent were from 21 to 30 percent less efficient, and another 25 percent were from 31 to 40 percent less efficient. While some of the variations in relative efficiency may have been the results of differences in input prices and other regional characteristics, 24 percent of the centers according to Model A and 50 percent of the centers according to Model B were at least 21 percent less efficient indicating an obvious need for management's immediate attention.

The exploratory study of factors affecting blood center efficiency identified five determinants which were significant at the 1 percent level. High input prices of material and capital were associated with low efficiency ratings at the .1 percent level. High hospital density per million population was associated with high efficiency ratings at the .1 percent level. Higher numbers of BCD were associated with higher efficiency ratings at the .1 percent level, suggesting economies of scale in blood center operations. And a high input price of labor was associated with high efficiency ratings at the 1 percent level.

Models A and B were further extended to Model A1, A2 and Model B1, B2 to study average scale and scope economies and frontier scale and scope economies. Models A1 and A2 concluded there exist economies of scale among large blood centers and diseconomies of scale among small blood centers, the average blood center with 100,000 units of whole blood collection per year appeared to have constant return to scale. Model B2 with the less efficient blood centers removed from the sample showed significant scale economies among large blood centers and notable diseconomies of scale among small blood centers. But results from Model B1 failed to reject the hypothesis of constant return to scale. Blood centers having whole blood collection of 100,000 units or more per year were estimated as having economies of scale. The savings increased as output increased from 100,000 units up to the largest blood center with approximately 300,000 units of whole blood collection per year.

Models B1 and B2 showed strong economies of scope with joint production of blood components distributed and specialized laboratory services; diseconomies of scope with joint production of blood components distributed and specialized clinical services; and slight or constant returns to scope with joint production of specialized laboratory and clinical services.

2. IMPLICATIONS

Both Models A and B showed there are wide differences of efficiency ratings among blood centers. Data Envelopment Analysis was selected not only to measure individual blood center's relative efficiency but also to indicate where the sources of inefficiency came from. For those blood centers which were at least 21 percent less efficient, managers should use DEA results to guide their actions in reducing excess inputs or increasing outputs. Managers of large, medium-size, and small blood centers could gain insights from the DEA results of the sources of inefficiency as well as ways to improve efficiency.

Because the input prices of material and capital were highly associated with the DEA efficiency ratings, some form of price adjustments such as cost of living indices could be implemented to obtain more comparable material and capital costs as inputs for individual blood center analysis in the DEA study. Rural small blood centers and urban large blood centers are different in terms of size as well as in their regional characteristics such as population density and hospitals per million population. Separation of the two type of blood centers might yield better measures of the relative efficiency among centers in each group.

Through the Translog cost function analysis, it was concluded that blood centers with 100,000 units of whole blood collection per year were operating in the range of constant return to scale. Centers with over 100,000 units WBC per year were operating in the area of economies of scale; centers with below 100,000 units of WBC per year were operating in the area of diseconomies of scale. By increasing

the scale of blood center operations, average production cost per unit of output should continue to decrease. This observation is of importance for policy purposes. Joint production of blood components distributed and specialized laboratory services showed strong economies of scope. On the contrary, joint production of blood components distributed and specialized clinical services
exhibited diseconomies of scope. These results suggest blood centers should pursue joint production of BCD with SLS but not with SCS.

3. CONTRIBUTIONS

This study developed two models to represent blood center operations: Model A was a three input and one output representation of the operations of a blood center; Model B was a more complete three input and three output representation. The study is the first to use DEA to measure blood center relative efficiency without the need to subjectively determine weights of individual inputs and outputs as required by traditional ratio or productivity index analyses. DEA results also provides managers with specific information useful in selecting ways to improve center efficiency, a result not available from ratio or regression analysis.

This is also the first study to simultaneously estimate various returns to scale and returns to scope properties of blood center operations using the most flexible functional form of the Translog cost function. Through structural tests, the homogeneous and Cobb-Douglas functional forms were rejected, meaning that results of previous studies using these restricted functional forms to study return to scale were biased and not properly structured.

Fourth, using efficiency ratings generated from the DEA study, the less efficient blood centers were excluded from further analysis of best management practice return to scale and return to scope. Information concerning the properties of return to scale and return to scope generated from the better managed blood centers was far more interesting and accurate than the results generated from the complete sample set which included both efficient and inefficient centers.

Fifth, through exploratory regression analysis, the study identified five

variables highly associated with blood center efficiency ratings. This suggests that future blood center efficiency evaluation studies should try to accommodate differences in these variables in order to generate better measures of relative efficiency.

Finally, the study illustrated how DEA results can be used as a decision-making and management planning tool for blood services.

4. LIMITATIONS

The primary limitation of the study is that the data on material and capital costs and input prices of material and capital were probably not very reliable because of a lack of a standardized cost accounting and reporting system for the blood centers. Inferences and implications drawn from this study must bear this limitation in mind.

Blood centers included in Models A2 and B2 did not all have DEA efficiency ratings of 1, so the best management practice estimates of return to scale and return to scope according to these models is only approximate by the study.

The number of input and output variables included in this study were relatively few. The three inputs (i.e., number of full-time equivalent employees, total material costs and capital costs) and three outputs of Model B could only provide managers with basic directions as to needed input reductions and/or output expansions for efficiency improvement. More input and output variables need to be included in any future study of blood center efficiency using the DEA approach.

5. RESEARCH EXTENSIONS

An obvious extension of the study would be to disaggregate labor inputs by functional areas such as donor recruiting, collection, preparation, specialized services, and administration as well as to further separate specialized clinical services into autologous collections and apheresis procedures. Given such a breakdown, DEA results could show how many employees in each functional area need to be eliminated for an inefficient center to become efficient. DEA could also be applied to measure blood center functional efficiency, for example in donor recruitment, collections, and component production.

Another extension might apply the stochastic statistical frontier approach to Model A in estimating blood center efficiency and compare the results with the DEA findings. It should be possible to develop a graphical presentations to assist managers to see the improvement of efficiency ratings resulting from different scenarios of input reductions and output expansions.

Results from the DEA efficiency study could also be used to obtain adjusted total costs, input prices, and outputs for the inefficient blood centers. With such input and output adjustments, inefficient blood centers could be fitted to the efficient frontier to obtain better estimates of best practice returns to scale and scope.

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