THE FINANCIAL IMPACTS OF BAD DEBT IN THE HEALTHCARE INDUSTRY: A MULTIVARIATE STATISTICAL ANALYSIS

C. Christopher Lee, B.P.S., M.B.A.

A Digest Presented to the Faculty of the Graduate School of Saint
Louis University in Partial
Fulfillment of the Requirements for the
Degree of Doctor of Philosophy

1996

Digest

The major purpose of this dissertation is to investigate the determinants of bad debt in the healthcare industry. Given the fact that the amount of bad debt exercises an adverse impact on the hospital profitability, hospitals need to control bad debt for their long-term survival. Studies of this subject are new and incomplete to the extent that previous studies used either simple naive statistical methods or less vigorous statistical methods investigating this important issue.

The Missouri State Hospital Database for this study includes 188 hospitals per year for the period 1991 through 1993, a total of 564 cases. To avoid organizational bias and measurement bias, only non-governmental, general medical and surgical hospitals are included.

This research develops a multivariate statistical model to explain bad debt behavior in hospitals. Three different multivariate models (regression, discriminant, and logistic regression) are estimated.

This study reports the following variables as significant determinants of bad debt: occupancy rate, Medicaid mix, Medicare mix, hospital size, and number of services. This dissertation also discusses policy implications regarding those bad debt determinants. This study provides additional input to our understanding of hospital financial statements.

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To my son Dennis

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CHAPTER 1

INTRODUCTION

This chapter presents the purposes of the dissertation and the reasons for this study. It, first, briefly describes the nature of bad debt in hospitals. Because bad debt and charity care were aggregated in financial statements until 1990, discussion of charity care will be presented. Next, the methodology section will describe data and research procedures. Finally, an outline of the remaining chapters will be provided.

Background

Bad Debt

Health Care Audit Guide (AICPA 1990) defines bad debt as the provision for actual or expected uncollectible resulting from the extension of credit. Accordingly, bad debt implies the amount of gross charges that will not be collected from patients from whom payment was expected. For example, if a patient had commercial insurance coverage that paid 80 percent of his/her bill of $10,000, the hospital would bill the patient for $2,000. If the patient refused to pay the $2,000 and no payment was expected, the $2,000 charge would be written off as a bad debt (Cleverly 1992, 103).

Charity Care

The new audit guide (AICPA 1990) defines charity care as healthcare services that were never expected to result in cash inflows. In other words, according to the hospitals' charity care policies, hospitals provide care without charge or at amounts less than established rates. The level of charity care depends upon the amount of charges foregone for services and supplies and upon the estimated cost of those services and supplies. Because hospitals do not pursue collection of amounts determined to qualify as charity care, they are not reported as revenue.

Charity care is characteristically different from bad debt, even if both come from unpaid account receivables (uncompensated care). Hospitals are said to have social responsibility to provide care to patients who can not afford to pay for the services. Therefore, hospitals are reluctant to improve profitability by reducing the charity care below a certain minimum level. If they do, the community may perceive hospitals as unwilling to provide care to those in need (Zollinger et al. 1991). In contrast, hospital management does not have any inherent problem in its effort to minimize the amount of bad debt. The definition for recognizing the difference between charity care and bad debt is often cited as the inability (charity care) versus an unwillingness (bad debt) to pay the entire account or the balance of an account not paid by insurance (Ferko 1993). As a matter of fact, an effort to minimize bad debt may be considered as efficient financial management.

Accounting Change on Bad Debt

Recently, the American Institute of Certified Public Accountants (AICPA) prepared a new guide that did not change existing accounting principles but did revise the format in which data are presented (AICPA 1990). The AICPA specifically addressed financial statement reporting issues related to bad debt and charity accounts. Based on the 1972 audit guide, bad debt and charity care were combined and, thus, were treated as a single deduction from revenues.

Under the new guidelines, bad debt is considered as an expense incurred through the extension of credit. Therefore, it is treated as an expense. The new guide requires a hospital to include footnote disclosure of the amount of charity care provided. When these changes in reporting requirements are coupled with the hospitals' ongoing budgeting needs, it is apparent that accurate identification and quantification of bad debt and charity care are vital processes in today's healthcare environment (Ferko 1993). Given the fact that the amount of bad debt exercises an adverse impact on the hospital profitability, a study investigating the determinants of bad debts will provide additional inputs to our understanding of hospital financial statements. A major change in accounting practice allows hospitals to separate bad debt from charity care accounts and, in turn, allows empirical study to focus on bad debt alone.

Research Purposes

The main goal of this dissertation is to investigate determinants of bad debt in the healthcare industry. Effects of the 1990 accounting change on bad debt will be discussed extensively. To achieve this goal, the following three purposes will be accomplished.

First, this study will examine the impact of environmental factors on hospitals' bad debt. Environmental factors include healthcare economic variables such as type of hospital ownership, efficiency of health service organizations, distribution of patients' health service payment methods, size and location of hospitals, occupancy rate, type of services, and level of community commitment.

The second purpose is to build a statistical model that can capture the nature of the determinants of the level of bad debt in hospitals.

The third purpose is to develop a comprehensive strategy for hospital bad debt management based on the statistical model.

Reasons for Study

The significant impact of bad debt on profitability in the healthcare industry needs to be further analyzed in light of the new healthcare audit guide (AICPA 1990). The healthcare industry has increasingly become an industry of profit making ventures. It is no longer uncommon in the healthcare industry to discuss the minimum operating margin needed to sustain long-term survival. This trend has become especially widespread since more consumers have joined Health Maintenance Organizations (HMOs) and providers give services on a capitated basis.

Maintaining a sound financial structure is also crucial when hospitals opt for debt-financing. Favorable ratings by financial institutions, such as Moody's Investors Services, will greatly lessen the amount of interest paid over the life of the debt. Accordingly, securing a minimum acceptable margin becomes an essential requirement for long-term survival. It may be even a reasonable assumption that hospitals set a certain target, or goal, for their minimum margin before they seriously consider allocating a portion of their revenue to bad debt or charity care. Johnsson (1991), for example, argues that a 4 percent margin is needed for the healthcare industry to be a viable operating industry.

Bad debt has been rising because third-party payers and employers have been shifting a greater portion of healthcare bills to individuals, forcing them to pay higher monthly premiums, annual deductibles and copayments (Nemes 1991). Dennen's study (1988) finds that about 3 percent of patient accounts is written off as a cost of bad debt. In 1987, the government spent $200 million on bad debt in the Medicare program (Mowll 1988). While governmental reimbursements to healthcare organizations for Medicare and Medicaid patients remain stagnant, the cost of healthcare increases. A growing trend toward managed care, especially capitated managed care, without even addressing the issue of indigent care, has intensified the financial hardship on the healthcare industry. As the environment surrounding the healthcare industry tends to limit their revenue, hospitals need to control the expense more than ever. Since bad debt is treated as an expense account, control of bad debt will eventually improve the profitability of hospitals. Consequently, effective bad debt management becomes an important issue for the healthcare industry.

Furthermore, in recent years, management of bad debt has become increasingly important to all healthcare entities, in particular hospitals, as a result of a change in the AICPA reporting requirements as stated earlier.

The literature shows a lack of financial analysis of bad debt in the healthcare industry. There have been numerous financial studies on profitability in the healthcare industry, some of which find several significant financial as well as environmental variables that explain the degree of hospital profitability (McCue 1988; McCue and Furst 1986). However, no studies have focused on bad debt alone from the managerial finance perspective. This study will attempt to find statistically significant variables that explain bad debt behavior. In addition, most studies of the determinants of bad debt used uncompensated care (bad debt plus charity care) (e.g., Saywell et al. 1989; Zollinger et al. 1991; and Weissman, Lukas, and Epstein 1992). However, as Buczko (1994) indicates, the behavior of bad debt in the healthcare industry is markedly different from that of charity care. Accordingly, studies of uncompensated care do not fully comprehend the problems and causes of bad debt. The healthcare industry needs a new business strategy for bad debt management that is based on a comprehensive understanding of factors influencing bad debt, including financial and economic attributes.

Finally, most studies of uncompensated care and bad debt utilized either simple descriptive statistics (Saywell et al. 1989; Weissaman, Lukas, and Epstein 1992; Zollinger et al. 1991) or stepwise regression analysis (Buczko 1994). This study proposes to use multivariate statistical methods to investigate an interaction among determinants that influence bad debt behavior.

Methodology

Data

The Missouri Department of Health has collected annual report of all Missouri hospitals since 1980 (Missouri Department of Health 1995). Data contain approximately 188 hospitals each year. There are about 156 variables in the annual data, which cover hospital characteristics, patient characteristics and hospital financial information. However, the Missouri Department of Health Reports include financial data only from 1985. Because a major reason for this study is to investigate the impact of the 1990 accounting change on hospital bad debt, this study plans to utilize information contained in the reports for three years (1991 - 1993), the most recent years available. After screening, the total hospitals remaining for this analysis are 98 hospitals. Thus, 294 cases during the three year period will be sufficient for cross-sectional analysis that this study will employ. Screening criteria will be discussed in detail in Chapter 3.

Research Procedure

This dissertation will use the following research procedures to accomplish the stated purposes. There are three parts.

In the first part, bivariate statistical models will be estimated to analyze the relationship between explanatory variables and bad debt; First, bad debt will be evaluated in terms of ownership type of a hospital. Investor-owned hospitals are expected to have less bad debt than not-for-profit hospitals because investor-owned hospitals are said to be more aggressive and efficient (Lewin et al. 1988). Second, statistical models will be built to investigate a possible linkage between hospital efficiency and the amount of bad debt. More efficient hospitals are assumed to have less bad debt than less efficient hospitals. Third, patient characteristics will play a role in hospital financial statements. Hospitals with more recipients of prospective payment systems such as Medicare are expected to report less bad debt than hospitals with fewer Medicare patients.

For the second part, this study will employ multivariate statistical methods to build exploratory models. Based on financial and environmental variables, the model will explain bad debt behavior. A multiple regression analysis, a discriminant analysis, and a logistic regression analysis will be explored.

Finally, a strategy of bad debt management will be discussed. Review of existing literatures on bad debt management, coupled with results from the previous two parts, will lead to formulating effective and efficient ways of controlling bad debt.

Expected Contributions to Literature

This study has several contributions to the understanding of bad debt behavior. First, this study attempts to isolate bad debt from charity care cost and investigates the determinants of bad debt. No comprehensive studies on bad debt alone are available in the literature.

Second, this research proposes to use multivariate statistical analyses in constructing the bad debt model. Multivariate statistical models have not been employed in bad debt study before.

Third, this study analyzes the bad debt behavior as a part of hospital profitability model. As such, a linkage will be sought between bad debt and hospital profitability.

Fourth, this study also proposes to study whether a relationship exists between the amount of bad debt and the amount of charity care. Since bad debt and charity care focus their emphasis on different aspects of hospital operations (bad debt as an efficiency measure and charity care as a commitment to the community), it is interesting to investigate whether hospitals can improve their efficiency without reducing their commitment to the community.

Finally, a strategy of bad debt management will assist hospital decision makers in their effort to improve the overall hospital profitability.

Organization of Dissertation

This dissertation consists of six chapters. Chapter 2 will include a review of literature dealing with bad debt studies of hospitals and attempt to derive research hypotheses. Chapter 3 will cover data descriptions and the model building process for this research. Chapter 4 will present empirical results on statistical analyses. Chapter 5 will discuss the results and implications of the results. Finally, Chapter 6 will summarize the findings and conclude this study. Limitations of the study and future research directions will also be provided in Chapter 6.

CHAPTER 2

REVIEW OF LITERATURE

Chapter 2 will review studies on bad debt and other related areas, such as charity care, uncompensated care, profitability and bad debt management. At the end of this chapter, hypotheses for this study will be formulated.

Determinants of Uncompensated Care

Uncompensated care is often defined as the sum of charges for charity care and bad debts. Sloan et al. (1986) report that about two-thirds of uncompensated care expenses are attributed to bad debt and one-third to charity care. Due to reporting procedures on bad debt and charity care prior to 1991, studies on bad debt have been always a part of large studies on uncompensated care. Consequently, a lack of separate data on charity care and bad debt has forced researchers to combine these two categories into a single unit of measure in their studies. Therefore, a review of the literature on uncompensated care will provide direction that may benefit to study on bad debt behavior.

According to Buczko study (1994), uncompensated care has become a major issue in hospital finance as the number of uninsured persons has increased while the hospital revenues have stagnated. The stagnation is due mainly to prospective payment systems and, to some extent, managed care. Green (1993) reports that the 20 most successful hospital systems in this country provide \$550.1 million in charity care in 1991, or 2.5 percent of hospital net revenues; when bad debt of \$729.1 million is added to charity care, those systems provide total uncompensated care of \$1.26 billion in 1991, or 48.2 percent of net income. Responding to this serious issue, several studies have attempted to investigate significant determinants of uncompensated care.

Saywell et al. (1989) conduct a descriptive statistical analysis to determine the demographic and clinical characteristics of the uncompensated care patients in Indiana hospitals. They select a sample of 1,689 patients classified as 'charity' plus 'bad debt' cases in 1986 from 27 general acute care hospitals. The descriptive statistical analysis shows that the typical uncompensated care patients are young, female, and single, with a total hospital charge of \$1,688, of which \$751 remains uncollected. According to their study, the most common diagnoses for these patients were pregnancy, childbirth with injury, and poisoning. As expected, patients with large debts are unemployed. In addition, their study seems to suggest that the amount of uncompensated care differs substantially by location of hospitals, average length of stay, and types of payer.

In investigating significant determinants of uncompensated care, Zollinger et al. (1991) employ a multiple regression analysis on the data that Saywell et al. (1989) used. They use a ratio of uncompensated care to total expense as a dependent variable and host of pertinent variables as independent variables in the regression model. Independent variables include age (years), length of stay (days), total charged, percent of bill collected, marital status (married, single, widowed), gender, insurance type (self-pay, commercial, HMO, other), employment status (unemployed, employed), location of hospital (rural, urban), discharge (self-care, home care, other), diagnosis (pregnancy; child birth with injury; poisoning; mental disorders; digestive system disease; circulatory system disease; ill-defined conditions; other gastrointestinal disorders; endocrine, nutritional deficiency; nervous system disease; muscular-skeletal system disease; neoplasm; newborn aftercare; congenital anomalies; other infectious disease; skin diseases; other aftercare; prenatal disorders; mother aftercare; blood diseases). Among clinical factors, they classify the following as pregnancy-related diagnosis: pregnancy, childbirth, newborn aftercare, congenital anomalies, prenatal disorders, and mother aftercare. The results reveal that insurance coverage, total hospital charge, pregnancy-related diagnoses, marital status, employment status, discharge status, urban location, and total hospital revenue are significant factors in predicting unpaid hospital bills. Their study also reveals that 60 percent of the patients have some form of insurance and are responsible for 40 percent of the uncompensated amount; this information justifies the need to examine the adequacy of patient insurance coverage.

Also investigating uncompensated care, Weissman, Lukas, and Epstein (1992) provide descriptive statistics in six hospitals in the state of Massachusetts. These hospitals include one urban public hospital, two major urban teaching hospitals, and three suburban/small city community hospitals. They study data on all patients (2,332) whose hospital charges are written off as uncompensated care during the 3rd quarter of fiscal year 1988. According to the study, the majority of write-off cases (1,364) are from one of the private hospitals. Half of the patients with unpaid bills fall between ages 25-64 years old and account for more than 70 percent of the total write-off. Only approximately 6 percent of write-off patients are age sixty-five or older. The average unpaid amount is $2,119 per case. About 33 percent of write-off cases are admitted through the emergency department. The majority of these patients is female (55 percent) and receives care from mainly obstetric services.

According to their study, the most common and the most expensive clinical conditions of patients in the write-off pool (33 percent of cases) are from two major diagnostic categories: (1) pregnancy, childbirth, and puerperium, and (2) newborns and other neonates. On the other hand, diagnoses relating to digestive and circulatory systems are the two categories with the highest total write-off amounts; together these diagnoses account for 16 percent of cases and 26 percent of write-off amounts. While uninsured patients account for much of uncompensated care, 73 percent of the bad debt and nearly one fourth of the charity care expenses can be traced to insured patients who have some forms of insurances. A small number of cases with large unpaid bills account for a substantial portion of the write-off amounts.

Hultman(1991) attempts to determine whether hospital location, types of ownership, and Medicare's prospective payment system (PPS) on inpatients has any impact on the level of uncompensated care. A non-equivalent group design is used with repeated measures of uncompensated care on 137 system hospitals for two study periods: pre- and post-Prospective Payment System (PPS). Investor-owned system hospitals demonstrates the largest increase in uncompensated care (37 percent) under the Prospective Payment System. The results suggest that not-for-profit and investor-owned system hospitals are becoming more similar in levels of uncompensated care provided. The study also reports that the prospective payment system has had a negative effect on rural hospital profitability.

Buczko (1994) in his study on bad debt and charity care for 82 hospitals in the state of Washington argues that aggregation of bad debt and charity care yields a measure of uncompensated care effort whose mean is influenced by the distribution of bad debt far more than the distribution of charity care. Therefore, study of uncompensated care provides a biased estimate of charges and effort incurred in the provision of hospital care to indigent persons. Accordingly, a need for separate studies on bad debt and charity care is not only justified, but, more importantly, essential for unbiased estimations of each one of these important financial segments.

Determinants of Charity Care

Because both bad debt and charity care are components of uncompensated care and because segregated accounting was not available until 1990, the findings from charity care studies may provide additional information in understanding bad debt behavior. This study will attempt to establish a relationship between the amount of bad debt and charity care.

Several studies have attempted to estimate the behavior of charity care alone. Most of these studies utilize simple statistical methods such as descriptive statistics or bivariate statistics to isolate the determinants of charity care. Charity care and bad debt are characteristically different as discussed by Buczko (1994). Weissman, Lukas, and Epstein (1992) also find that charity care patients are clearly indigent while bad debts usually are results of an inefficient collection process.

Ashby (1992) in his study of charity care shows that the level of charity care is negatively related to the gross revenue per bed and the location of hospitals. This relationship is due mainly to a significant variation of patient mix by the location of hospitals. These regional and local variations in hospital performance have been also reported in other studies (Kwon et al. 1988; Martin and Kwon 1995). Generally, there are more indigent patients in larger urban areas than in rural areas. Relative to rural hospitals, those hospitals in urban areas usually offer more aggressive and costly treatment, impacting their level of charity care. Therefore, it is anticipated that hospitals in urban locations provide more charity care than their counterpart.

Cost-shifting is prevalent in the healthcare industry and compensates for lost revenues (charity care and bad debt) in treating Medicaid and indigent patients. Lewin, Eckels, and Miller (1988) suggest that hospitals may shift income from patients with commercial insurance to an indigent care fund to recover some of the revenue necessary to fund charity care. The study also argues that type of hospital ownership makes a significant difference; investor-owned hospitals provide proportionally less charity care than not-for-profit hospitals. In addition, the study reports that investor-owned hospitals are more efficient in terms of profit margin than not-for-profit hospitals. However, Zollinger et al. (1991) report that the patients of hospitals having larger total revenues leave a greater portion of their total charges unpaid. Also, it has been argued that investor-owned hospitals have not provided their share of charity care relative to not-for-profit hospitals (Ashby 1992). On the other hand, Hezlinger and Krasker (1987) imply that although not-for-profit hospitals receive more social subsidization than investor-owned hospitals, not-for-profit hospitals do not appear to have provided more benefit (charity care) to society. However, a modified replication of their study by Arrington and Haddock (1990) dispute the Herzlinger and Krasker results.

Determinants of Bad Debt

Buczko (1994) performs three separate regression analyses to investigate the determinants of charity care, bad debt, and total uncompensated care. The study uses data on patient charges assigned to charity care and bad debt in 1987 for 82 acute care hospitals in the state of Washington. Attributes included in the models are occupancy rate, Medicare case-mix index, percent of Medicare to total inpatient days, percent of Medicaid to total inpatient days, percent of Medicare discharges that are outliers, hospital bed size, government owned hospitals, proprietary ownership, major and minor teaching hospital status, fund balance, presence or absence of obstetric care unit, coronary intensive care unit, neonatal intensive care unit, burn care unit, HMO contract, PPO contract, member of multihospital system, member of alliance, swing beds, and emergency visits as a percentage of total outpatient visits. His study is the first attempt in the literature to investigate the determinants of bad debt using a multivariate statistical model.

In Buczko’s study, the amount of bad debt as a percent of total expense is the dependent variable. The stepwise regression analysis shows that the percentage of emergency outpatient visits, government control, and provision of organ transplants all are associated with an increasing percentage of bad debt charges, but occupancy rate and membership in a multihospital system are associated with a lower percentage of bad debt charges.

In contrast, charity care and uncompensated care models produce different results. The stepwise regression analysis for the percentage of charity care charges to the total expense indicates that occupancy rates, presence of a burn care unit, and presence of a hospice all were associated with an increase in charity care cost. The stepwise regression analysis for the percentage of total uncompensated care charges to the total expense, on the other hand, shows that Medicaid share of total discharges, presence of a burn care unit, and swing beds were associated with increased uncompensated care.

As shown, the results indicate that the determinants of the charity care, bad debt, and total uncompensated care differ markedly. Buczko suggests that bad debt should be isolated from charity care when estimating a hospital's level of effort in providing care to indigent patients.

Although the study employs separate estimating models for bad debt, charity care, and uncompensated care, and thereby contributes significantly to understanding these important areas, a use of stepwise regression models is unfortunate. Stepwise regression models suppress the behavior of other independent variables (variables deleted from the models because of a low tolerance level). These deleted variables could have shed additional light on hospital bad debt models.

Over the past several years, one of the most frequently litigated issues before the Provider Reimbursement Review Board (PRRB) has been providers' entitlement to Medicare reimbursement for bad debts attributable to Medicare deductibles and coinsurance (Sutter 1994). While the PPRB sometimes has been sympathetic to providers, the Health Care Financing Administration (HCFA) has invariably reversed in favor of Medicare intermediaries.

Historically, Medicare has furnished only limited payments for bad debt cost. It has reimbursed only deductible and coinsurance amount owed, but unpaid, by Medicare patients where providers have made reasonable collection effort. However, the percentage of total Medicare payment attributable to Medicare bad debt is traditionally so small that bad debt seldom receives serious attention from the Medicare administration. Similar findings have also been reported by Saywell et al. (1989), Zollinger et al. (1991) and Weissman, Lukas, and Epstein (1992).

Determinants of Profitability

There have been quite a few studies on the determinants of hospital profitability. The new auditing guide (AICPA 1990) mandates the amount of bad debt to be treated as a part of expense. Such a change inevitably alters the process of profit configuration since the profit is basically a difference between total revenue and total expense. Accordingly, determinants of profitability may play a role in explaining the behavior of bad debt. For this reason, the literature on profitability studies may add a further understanding of the bad debt behavior in hospitals.

Using the 1989 data in Florida, Vogel, Langlan-Orban, and Gapenski (1993) examine exceptionally high and exceptionally low profitability hospitals among 169 acute-care hospitals. Operating margin is used as a measure of hospital profitability. Using a logistic regression model, they test 22 independent variables which included age of plant, area wage rate, average length of stay, case mix index, debt utilization, hospital concentration, hospital size, intensive care mix, labor intensity, managed care mix, Medicaid mix, Medicare mix, non-operating revenue, outpatient mix, ownership, patient income, physician density, service index, sub-acute care mix, system status, teaching status, uncompensated care mix. Among the independent variables, the authors identify four significant determinants of profitability: debt-to-asset ratio, Medicare mix, labor intensity, and uncompensated care. According to their study, these four variables have a negative effect on high profitability. The study also reports that a patient's length of stay in hospital has a negative impact on the profitability but hospital size has no relationship with the profitability.

Gapenski, Vogel, and Langland-Orban (1993) develop five cross-sectional multiple regression models to determine hospital profitability with the same data set and independent variables that Vogel, Langland-Orban, and Gapenski (1993) used. They classify the independent variables into four categories: organizational, managerial, patient-mix, and market variables. Organizational variables include teaching status (0 for non-teaching and 1 for teaching hospital status), types of ownership (0 for not-for-profit hospitals and 1 for investor-owned hospitals), and system status (0 for free standing hospitals and 1 for system hospitals). Managerial variables include age of plant (accumulated depreciation divided by annual depreciation expense), debt utilization (total debt including current liabilities divided by total assets), service index (weighted sum of services offered), labor intensity (total hospital full-time equivalent employees divided by total inpatient days adjusted for outpatient visits), and non-operating revenue mix (non-operating revenue divided by total revenue). Patient-mix variables include Medicaid mix (total Medicaid inpatient days divided by total inpatient days); sub-acute care mix (sub-acute inpatient days divided by total inpatient days); uncompensated care mix (charity and bad debt deductions divided by gross patient care revenue); Medicare mix (total Medicare inpatient days divided by total inpatient days); case-mix index (average Medicare diagnosis-related group weight); average length of stay (total number of inpatient days divided by total number of admissions); outpatient mix (total outpatient revenue divided by total patient care revenue);

intensive care mix (total intensive care inpatient days divided by total inpatient days); and managed care mix (total managed inpatient days divided by total inpatient days). Finally, market variables include area wage rate (earnings per worker by county), physician density (number of physicians per 1,000 population by county), patient income (per capita income by county), and hospital concentration (Herfindal index by county).

Their study reveal that among organizational variables, teaching status and hospital size have a significantly negative relationship with profitability. The ownership variable shows a weak but significant relationship with profitability. Four of the five managerial variables are important factors in determining profitability; they are age of plant, debt utilization, service index, and labor intensity. Nearly one-half of the patient-mix variables (Medicaid mix, sub-acute care mix, uncompensated care mix, and Medicare mix) are important in explaining variations in profitability. Three market variables (area wage rate, physician density, and patient income) are found to have some influence on profitability.

McCue (1991) examines financial distress of hospitals from the standpoint of cash flow. The data consists of two samples from acute care hospitals from the state of California; the first one includes 421 hospitals for the 1984-1985 period and the other sample of 395 hospitals for the 1986-1987 period is used to test the model's prediction power. The study employs logistic regression analysis. First, if cash flow ratios (average cash flow to total beds) are negative and within the bottom quartile, then the hospitals are classified as financially distressed. On the other hand, when cash flow ratios of hospitals are positive and within the top quartile, the hospitals are treated as high positive cash flow hospitals. Second, following the same rule, the profitability ratio (net income to beds) is used to categorize hospitals. Thus, two binary dependent variables are created and used for constructing two logistic regression models. McCue compares the cash flow ratio model with the profitability ratio model in terms of predictability of hospitals' financial distress and found the superiority of the profitability model. In addition, the author generalizes the results that financially distressed hospitals show lower occupancy rates, slower collections of receivables, and higher amounts of debt. However, since his study excludes hospitals belonging to the second and the third quartiles from the estimating models, an issue of sampling bias could have entered into the models; patterns found in each group might exist also in the excluded groups (second and third quartiles).

McCue, Clement, and Hoerger (1993) examine the relationship between ownership and profitability for inpatient psychiatric hospitals. They include 151 short-term psychiatric hospitals from 6 nationwide data bases for two periods (1986 and 1989), excluding all levels of governmental hospitals. Data are pooled by a dummy variable for two years and analyzed using ordinary least squares. Their results indicate that ownership has a significant role for determining profitability; i.e., investor-owned-hospitals are more profitable than not-for-profit hospitals. The study also reports that average length of stay (measured by the total inpatient days divided by total discharge) and hospital size have no impact on the profitability.

Cleverly and Harvey (1992a) show that hospital size has statistically significant and positive relationship with profitability among urban hospitals. However, in another study they find that hospital size is significantly and negatively related to profitability among rural hospitals (Cleverly and Harvey 1992c). Both studies also report that Medicare case-adjusted length of stay is significantly and negatively related to profitability among urban as well as rural hospitals.

Cleverly and Harvey (1992b) attempt to determine critical relationships between business strategy and financial performance of urban hospitals. They examine financial and operating data of 1,025 U.S. hospitals that are defined as large urban hospitals under the Medicare prospective payment system for 1988 only. The study employs a multiple regression model, which uses return-on-asset investment as a dependent variable and includes 18 independent variables that reflect hospital management strategy. They are capital expense (percent), FTEs per adjusted patient day, Medicare case-adjusted length of stay for cost leadership strategy, market share (percent) for market share factor, gross prices/cost for pricing strategy, Medicare (percent), Medicaid (percent), Medicare case mix, outpatient revenue (percent), non-operating revenue/total outpatient revenue (percent) for product line/diversification strategy, revenue/fixed asset, revenue/current assets, discharges/beds for investment strategy, current ratio, long-term debt/fixed assets for financing factors, size of hospitals and control status. They find that hospital size has a significant effect on profitability.

In another study, Cleverly and Harvey (1992c) use the 1988 database of 1,876 rural, non-teaching hospitals in the U.S. as defined by the Medicare Prospective Payment System. The study uses the same model from Cleverly and Harvey (1992b). The results show that all variables for cost leadership strategy, market share factor, pricing strategy, financing factors, and two variables for product line/diversification strategy, Medicaid (percent) and non-operating revenue/total outpatient revenue (percent) show statistical significance in explaining hospital's profitability. They also find that revenue/fixed assets for investment strategy and control status are also significantly related with the profitability.

Sear (1992) compares efficiency and profitability of investor-owned multi-hospital systems with those of not-for-profit hospitals in Florida. The study uses three largest investor-owned multihospital system hospitals in Florida during the years 1982-1989. The author tests this hypothesis: Because investor-owned hospitals maximize output and minimize corresponding inputs, this higher efficiency should result in higher operating margins. According to descriptive and F-statistics, the results support this hypothesis: Investor-owned hospitals yield higher operating margins than not-for-profit hospitals. The study also reports that the average length of stay in a hospital has a negative impact on the profitability and that case mix is positively related with the profitability.

Walker and Humphreys (1993) test the hypothesis that there are fundamental differences in financial decision-making by hospital decision makers in different ownership categories. Using 1989 data from the Health Care Financing Administration and cross-sectional analysis with ordinary least squares, they find that decision makers in investor-owned hospitals are more efficiency and profitability oriented in financial decision-making than are voluntary hospital decision makers.

Rosko and Carpenter (1994) examine hospital profitability by linking the markup ratio (gross patient revenue divided by total expenses) to several internal and external attributes in hospital operations. These attributes are severity-of-illness index, case-mix index, Medicare revenue/total patient revenue, Medicaid revenue/total patient revenue, teaching hospitals, multihospital system, Herfindahl index, proportion of the population enrolled in HMOs, personal per capita income, and civilian unemployment rate. Cross-sectional data in 1989 include all 201 general acute hospitals in Pennsylvania. In a multiple linear regression model, severity of illness, the proportion of revenue earned from Medicare and Medicaid, unemployment rate, teaching status, and personal per capita income are positively related with the markup ratio.

Cleverley and Harvey (1992d) propose several financial measures in evaluating hospitals' financial performance (rate of return on the investor's equity); The measures are liquidity (current ratio-current assets divided by current liabilities), financial risk (average days in accounts receivable), asset management and replacement (average age of plant, HFMA's replacement viability ratio), and debt capacity (long-term debt to equity ratio). The study attempts to compare the financial performance of the hospital industry with that of the industrial, transportation and utility sectors, using the same financial measures. The descriptive statistical results reveal that hospitals exhibit weaknesses in several areas.

Accounting Change on Bad Debt

The new reporting practice adopted by the American Institute of Certified Public Accountants (AICPA 1990) has significant implications in the financial reporting systems. The new guide makes the hospital financial reporting statements more realistic, in large part, because the new guideline prohibits the hospitals from combining uncollected debt and charity care in a single line. Financial analysts have complained about such practice as it blurred the distinction between two different types of expenses and, in many cases, has concealed the large amount of charity care that hospitals have been providing for many years (Pallarito 1990). The overall response from the healthcare industry has been positive to the new guide.

Pallarito (1990) describes the way hospital revenues and expenses would be calculated under the new auditing guide as follows:

Profit or Loss = Income from Operations
- Net non-operating revenue or expense,

where Income from Operations = (N.P.S.R.[1] + O.O.R.[2]) - T.O.E.[3]

Note:

[1] Stands for Net Patient Service Revenue.

[2] Stands for Other Operating Revenue and does not include charity care, which is listed in a footnote as a separate item.

[3] Stands for Total Operating Expenses and includes bad debt.

Pallarito also adds that patient accounting system traditionally has started with gross patient related service revenues (sum of all conceivable revenues) and then subtracted contractual allowances and other uncollected accounts, such as bad debt and charity care. The presentation of gross revenues became misleading partly because hospitals were deducting full charges for uncompensated services, even though most payers, including Medicare, Medicaid and managed-care insurers, pay discounted charges. Under the new guide, hospitals start their calculations with net patient related service revenues, which disallows any subtractions.

As Rode (1990) mentions, this change in patient accounting systems allows hospitals to practice uniform accounting standards, which reflects accurate comparisons. The lack of uniformity left the financial information open to criticism and undermined efforts to compare patient accounting processes and estimate the value of receivables.

Kovener (1990) also expects a positive impact from this accounting change. The author argues that gross revenue has become an increasingly inaccurate measure of appropriate payments. Thus, the new guidelines require a hospital's revenue to reflect the amount that the patient has an obligation to pay. In addition, the footnote disclosure gives management an opportunity to describe charity care more fully than before. This realistic disclosure displays the hospital’s level of commitment to the community. Hospitals should clearly establish criteria for charity services and differentiate those services from bad debts. Accordingly, reclassifying an uncollectible amount as either charity or bad debt should be carefully controlled.

Bad Debt Management

Given that approximately 25% of insured patients' bills unpaid (uncompensated care), Weissman, Lukas, and Epstein (1992) argue that uncompensated care is likely to continue to be an institutional concern even if universal health insurance is achieved. They imply that adequate insurance system alone may not be the solution to reduce the amount of bad debt. Zollinger et al. (1991) also argue for the need to examine the adequacy of patient insurance coverage based on their study on determinants of uncompensated care. They also point out that providing insurance would not entirely eliminate the problem of uncompensated care. They stress a hospital's need to increase collection efforts for all unpaid bills.

The preceding studies appear to suggest that hospitals should not only depend on healthcare insurance reform to reduce bad debt, but, more importantly, they should find other means to resolve bad debt problems. This argument has merit to the extent that as more people enter into contracts with HMOs, more and higher deductibles/co-payments are inevitable. This change in the healthcare environment is highly conducive to higher bad debt.

Ferko (1993) suggests that prior to classifying and subsequently writing off an account as a bad debt, the hospital must set policy, define appropriate criteria, implement procedures for identifying and processing accounts, and monitoring compliance. The hospital's collection control points serve as a map for the identification of charity care situations and for collection of potential bad debt accounts. The principal control points are (1) during the preregistration process, (2) at the time of admission and registration, (3) while the patient is in-house, (4) at the time of discharge, and (5) during post-service follow-up and collection. The author argues that effective management techniques for bad debt and charity care accounts can reduce days outstanding in accounts receivable. Furthermore, investigation into the appropriateness of bad debt and charity care write-offs can result in increased revenues, improved management reporting information, and increased patient satisfaction.

Rode (1991) also discusses several approaches that can be helpful in estimating bad debt allowance. He argues that the characteristics of bad debts are critical to determine bad debt allowances and to identify ways that patient accounting staff could have better handled cases. He suggests that an institution should start to obtain data from an electronic format to make an allowance estimate and improve its patient accounting process which would help reduce bad debts. Some or all patient accounts staff members should be asked to help determine a bad debt allowance model, which is based on a particular set of accounts that reside in a facility's accounts receivable on a given date. The model should document charity care and adjustment activity at each step in billing and collection process.

Typically, healthcare institutions hire collection agencies for a contingency fee to collect first-party bills that are 4- to 6-months-old. Scott (1993) argues that selling distressed receivables gives healthcare companies another, and faster, way to reduce bad debt and thereby improving cash flow. Collection agencies working under standard contingency arrangements keep 20 percent to 35 percent of the money they collect. However, few hospitals or physician groups sell bad debt outright because they fear negative publicity and loss of control of their accounts.

In summary, the literature suggests that occupancy rate, ownership type, Medicare mix, hospital size, average length of stay, Medicaid mix, type and number of services and location may have significant impact on determining the level of bad debt in hospitals. Table 2-1 lists the major studies in each area.

Table 2-1

Summary of Studies

Subjects	*Literature*
Uncompensated Care	Buczko (1994); Green (1993); Hultman (1991); Saywell et al. (1989); Sloan et al. (1986); Weissman, Lukas, and Epstein (1992); Zollinger et al. (1991)
Charity Care	Arrington and Haddock (1990); Ashby (1992); Buczko (1994); Hezlinger and Krasker (1987); Lewin, Eckels, and Miller (1988) Weissman, Lukas, and Epstein (1992); Zollinger et al. (1991)
Bad Debt	Buczko (1994); Saywell et al. (1989); Sutter (1994); Weissman, Lukas, and Epstein (1992); Zollinger et al. (1991)
Profitability	Cleverly and Harvey (1992a,b,c,d); Gapenski, Vogel, and Langland-Orban (1993); Joo (1995); Kwon et al. (1988); Martin and Kwon (1996); McCue (1991); McCue, Clement, and Hoerger (1993); Rosko and Carpenter (1994); Sear (1992); Vogel, Langland-Orban, and Gapenski (1993); Walker and Humphreys (1993)
1990 Accounting Change	AICPA (1990); Pallarito (1990); Kovener (1990); Rode (1990)
Bad Debt Management	Ferko (1993); Rode (1991); Scott (1993); Weissman, Lukas, and Epstein (1992); Zollinger et al. (1991)

Statement of Hypotheses

The literature review appears to indicate that bad debt is related to four broad categories of determinants: efficiency, ownership type, prospective payment system, and other factors. Based on these factors, four research hypotheses for this study are formulated as follows:

Hypothesis 1: More efficient hospitals will have significantly less bad debt than less efficient hospitals, where the hospital efficiency is measured by occupancy rate.

Hypothesis 2: Investor-owned hospitals will have significantly less bad debt than not-for-profit hospitals.

Hypothesis 3: Hospitals with more recipients with prospective payment systems such as Medicare will have significantly less bad debt than hospitals with fewer Medicare patients.

Hypothesis 4: Variations of bad debt will also be explained simultaneously by a set of other mediating factors, such as Medicaid mix, operating margin, size and location of hospital, average length of stay, the amount of charity care, and type and number of services.

Chapter Summary

Chapter 2 presented a review of literature on determinants of bad debt, charity care, uncompensated care and bad debt management. In addition, this chapter discussed about bad debt management. Based on the literature, several variables appeared to be significant in explaining bad debt behavior. Hypotheses on bad debt behavior were constructed accordingly.

Chapter 3 will describe study methodology. It will describe in detail the data used in this study, the characteristics of variables that will be included in the bad debt estimating models, and the univariate and multivariate statistical models.

CHAPTER 3

METHODOLOGY

The main purpose of this research as described in Chapter 1 is to investigate the financial impacts of bad debt in hospitals. To achieve this purpose, bivariate and multivariate statistical models will be utilized. Chapter 3 will describe the normative research procedure to test hypotheses outlined in Chapter 2. First, a description of data will be provided. Next, the dependent and independent variables will be introduced and discussed. Last, the details of each statistical modeling process will be discussed.

Description of Data

The Missouri Department of Health has collected annual report of all Missouri hospitals since 1980 (Missouri Department of Health 1995). The reports contain approximately 188 hospitals each year. There are about 156 variables in the annual data, which cover hospital as well as patient characteristics and hospital financial information. However, the Missouri Department of Health reports include financial data only from 1985. Given that one of the major reasons for this study is to review the impact of the 1990 accounting change on bad debt behavior, this study plans to utilize information contained in the reports for three years (1991 - 1993), the most recent years available.

Next, hospitals in the data set are categorized according to ownership. In the healthcare industry, hospitals with different types of ownership are assumed to have different goals and operating characteristics (Joo 1995, 47). For example, hospitals owned by governments such as state, county, city, and hospital districts will have different missions and, therefore, operate under the financial protection of direct government subsidies (Gapenski, Vogel, and Langland-Orban 1993; McCue, Clement, and Hoerger 1993; Vogel, Langland-Orban, and Gapenski 1993). Therefore, organizational bias may enter the measurement process if vastly different units (characteristics) are brought into the modeling process. To avoid such bias, this study uses the 1991-1993 data from all non-governmental hospitals in the state of Missouri. Saywell et al. (1989) also exclude governmental hospitals for the same reason. In the data set, there are ten different ownership types as shown in Table 3-1.

Table 3-1

Ownership Type

Ownership Code	*Ownership Type*
12	State
13	County
14	City
16	Hospital district
21	Church operated
22	Church affiliated
23	Other not-for-profit
31	Investor-owned, individual
32	Investor-owned, partnership
33	Investor-owned, corporation

In addition, hospitals with different service categories have different goals and missions as reflected by mental hospitals, veteran hospitals, and children's hospitals (Clement, D'Aunno, and Poyzer 1993; Walker and Humphreys 1993; Zucker 1987). Special hospitals, such as psychiatric, mental hospitals and long-term care facilities, are also excluded in order to avoid the measurement bias. Hospitals in the data set are categorized according to service types. There are ten different service categories in the data set as listed in Table 3-2.

Table 3-2

Service Categories

Service Code	*Service Category*
10	General medical and surgical
22	Psychiatric
33	Tuberculosis and other respiratory
46	Rehabilitation
48	Chronic disease
49	Other
50	Children’s general medical and surgical
52	Children’s psychiatric
57	Children’s orthopedic
82	Alcoholism/other chemical dependency

The total hospitals remaining for this analysis after screening are 98 hospitals per each year. Total number of cases for cross-sectional analysis is 294 during the three year period (1991-1993).

Variables

Dependent Variable

(Percent of Bad Debt to Total Operating Expense; BADDEBT):

This study uses the percent of total bad debt to total hospital operating expenses as a dependent variable. Buzcko (1994) utilizes the same variable in his study of the determinants of hospital bad debt. In contrast, Weissman, Lukas, and Epstein (1992), Zollinger et al. (1991), and Saywell et al. (1989) use the ratio of total uncompensated care (bad debt plus charity care) to total hospital charge as their dependent variable. Due mainly to unavailability of bad debt information, their studies, however, do not focus on bad debt, but rather on uncompensated care.

Independent Variables

This study utilizes four categories of explanatory variables as discussed in Chapter 2. They are (1) indicators of hospital efficiency (occupancy rate), (2) type of hospital ownership (investor-owned vs. not-for-profit hospital), (3) prospective payment system variable (percent of Medicare discharge to total hospital discharge), and (4) other mediating variables which may impact the hospital bad debt behavior: for example, location of hospital, percent of Medicaid discharge to total hospital discharge, size of hospital, number and type of services available, and amount of charity care.

1. Efficiency Variable (Occupancy Rate; OCRATE):

Most studies use operating margin as a hospital efficiency indicator (Cleverley 1994; Cleverley and Harvey 1992a; Friedman and Shortell 1988; Gapenski, Vogel, and Langland-Orban 1993; Vogel, Langland-Orban, and Gapenski 1993; Kwon et al. 1988; Joo 1995; Kwon et al. 1995). Since the amount of bad debt is a part of the accounting process in computing operating margin, the use of operating margin may distort the true nature of bad debt behavior. In contrast, occupancy rate is measured by total inpatient days divided by licensed bed days and is not directly linked to the dependent variable (bad debt). Therefore, this study uses occupancy rate as a hospital efficiency indicator. Zucker (1987) also utilizes occupancy rate as a hospital efficiency indicator in his study of the hazard of change in healthcare organizations. His study indicates that routine change in hospital service lines had a positive effect on improvement of hospital occupancy rate. However, a study by Joo (1995) shows that changes in hospital product lines have a negative impact on hospital profitability. Since a higher occupancy rate implies a higher hospital revenue, a negative relationship is expected between this variable and the amount of bad debt. A similar result is reported by Buczko's study (1994).

2. Ownership Type (TYPE):

Motivated by profit, it has been reported (Lewin et al. 1988) that investor-owned hospitals (TYPE=1) are more efficient than not-for-profit hospitals (TYPE=0). Walker and Humphreys (1993) test the hypothesis that there are fundamental differences in financial decision-making by hospital decision makers in different ownership categories. They find that decision makers in investor-owned hospitals are more efficiency and profitability oriented in financial decision-making than are not-for-profit hospitals' decision makers.

Accordingly, it is assumed that investor-owned hospitals show a lower percent of bad debt to total operating expense than not-for-profit hospitals. A lower proportion of bad debt expense implies a relatively higher operating margin. Accordingly, this study assumes a negative relationship between this variable and the percent of bad debt to total operating expense for investor-owned hospital (TYPE=1). A study by Buczko (1994) appears to support this hypothesis.

3. Prospective Payment Systems (Medicare Mix; MCRMIX):

Most Medicare patients are under the prospective payment system. Historically, Medicare has furnished only limited payments for bad debt. It has reimbursed only deductible and coinsurance amounts owed, but unpaid, by Medicare patients where providers have made reasonable collection efforts (Sutter 1994). However, the percentage of total Medicare payments attributable to Medicare bad debt traditionally was so small that bad debt seldom received serious attention from Medicare. Accordingly, a negative relationship is expected between this variable and hospital bad debt, where Medicare mix is measured by total Medicare inpatient days divided by total inpatient days. Similar findings have been reported by Saywell et al. (1989), Zollinger et al. (1991), and Weissman, Lukas, and Epstein (1992).

4. Mediating Variables:

Several additional variables are included in this bad debt estimating model. Based on literature review, these variables have shown impact on hospital bad debt behavior.

Medicaid Mix (MCDMIX):

This variable is included in this study as a substitute variable for community wealth. Numerous studies indicate that most, if not all, patients who left their bills unpaid had some form of insurance coverage. It is implied that those who left bills unpaid were probably underinsured rather than uninsured who may become eligible for charity care. Hospitals with an unusually high proportion of Medicaid population are usually located in the area where the community income is lower than average. Kwon et al. (1988) and Martin and Kwon (1995) employ a similar approach in their hospital profitability study. A positive relationship is expected between these two variables (MCDMIX and Bad debt); the higher the Medicaid discharge, the higher the rate of bad debt to the total operating expense. Medicaid mix is measured by total Medicaid inpatient days divided by total inpatient days.

Hospital Size (SIZE):

This variable includes only the number of licensed beds. Cleverley and Harvey study (1992a) show a statistically significant and positive relationship between profitability and hospital size among urban hospitals, but a significant and negative relationship among rural hospitals (Cleverley and Harvey 1992b). Gapenski et al. (1993) also find that hospital size is significant and negatively related to two out of three pre-tax measures of profitability. In contrast, McCue (1991) and McCue, Clement, and Hoerger (1993) report that hospital size is not significantly related to total profit margin. The findings of these studies appear to have been supported by Vogel, Langland-Orban, and Gapenski's study (1993).

Since hospital size is often linked to the location of the hospitals (e.g., larger hospitals more likely are located in urban area where more bills unpaid (Kwon et al. 1988)), hospital size is assumed to have a positive impact on the size of bad debts. A similar finding is reported by Saywell et al. (1989) in a study on behavior of hospital bad debt.

Average Length of Stay (ALOS):

This variable measures the total inpatient days divided by total discharge (McCue, Clement, and Hoerger 1993). Cleverley and Harvey (1992b and 1992c) find that Medicare case-adjusted length of stay is significantly and negatively related to profitability among urban as well as rural hospitals. Similar findings are reported by Sear (1992) and Vogel, Langland-Orban, and Gapenski (1993). However, Gapenski, Vogel, and Langland-Orban (1993) and McCue (1991) report no significant relationship between this variable and profitability. Since the length of stay is negatively related to profitability, it is assumed in this study that a positive relationship is expected between this variable and the amount of hospital bad debt. A similar finding is reported by Saywell et al. (1989).

Location (SMSA):

This variable represents the location of hospitals within or outside the standard metropolitan statistical areas (SMSA): value one (1) for hospitals within the standard metropolitan statistical area and zero (0) for hospitals outside the standard metropolitan statistical area are assigned respectively. This variable is not shown to be significant in the study of the financial performance of selected system hospitals (Friedman and Shortell 1988). However, this study hypothesizes that hospitals within the standard metropolitan statistical area will treat more underinsured patients than hospitals outside standard metropolitan statistical area. Accordingly, a positive relationship is expected between this variable and the amount of hospital bad debt. Studies on uncompensated care (bad debt plus charity care) indicate that the amount of uncompensated care is generally higher for hospitals in urban areas than those in rural areas (Saywell et al. 1989; Zollinger et al. 1991; Weissman, Lukas, Epstein 1992). In this study, a positive relationship is assumed between the amount of bad debt and hospitals located in urban area (SMSA=1).

Charity Care (CHARITY):

Both bad debt and charity care are components of uncompensated care. But the hospital accounting system did not separate these two items until 1990. Nevertheless, behavior of charity care may provide additional information in understanding of the bad debt behavior, if a relationship is established between the amount of bad debt and charity care. Most studies (Saywell et al. 1989; Weissman, Lukas, Epstein 1991; Zollinger et al. 1992) use uncompensated care (bad debt plus charity care). Accordingly, this study uses percent of charity care to total operating expense as an additional explanatory variable.

Type of Services (SERVTYPE):

Several studies on bad debt and charity care report that there are a few hospital services which appear to draw excessive amount of bad debt and charity care (Saywell et al. 1989; Weissman, Lukas, Epstein 1991; Zollinger et al. 1992; Buzcko 1994). Presence (SERVTYPE = 1) or absence (SERVTYPE = 0) of emergency service, obstetric services, prenatal care, and poisoning seem to draw heavy uncompensated care. Accordingly, this study proposes to use these four services as dummy variables to capture any significant variation in bad debt.

Number of Services (SERVNUM):

Neither bad debt nor charity care studies have used the number of services that hospitals offer as an explanatory variable of bad debt. However, it is reasonable to speculate that as more services are offered, the likelihood of unpaid charges increases. Accordingly, this study proposes to use the number of services that hospitals offer as an additional independent variable to investigate the bad debt behavior.

Table 3-3 lists the variable names to be used in this study along with corresponding coding formats.

Table 3-3

Summaries of Variables

Variable	*Acronym*	*Coding Format*
Bad Debt Amount	BADDEBT	Percent of bad debt to total operating expense
Occupancy Rate	OCRATE	Total inpatient days divided by licensed bed days
Ownership Type	TYPE	0 for not-for-profit 1 for investor-owned
Medicare Mix	MCRMIX	Total Medicare inpatient days divided by total inpatient days
Medicaid Mix	MCDMIX	Total Medicaid inpatient days divided by total inpatient days
Hospital Size	SIZE	Number of licensed beds
Average Length of Stay	ALOS	Total inpatient days divided by total discharges
Location	SMSA	o for outside SMSA 1 for inside SMSA
Charity Care	CHARITY	Percent of charity care amount to total operating expense
Emergency Service	SERVTYPE1	1 for presence of the service 0 for absence of the service
Obstetric Service	SERVTYPE2	1 for presence of the service 0 for absence of the service
Prenatal Care	SERVTYPE3	1 for presence of the service 0 for absence of the service
Poisoning	SERVTYPE4	1 for presence of the service 0 for absence of the service
Number of Services	SERVNUM	Number of services offered by a hospital

Statistical Models

Descriptive Statistics

Several studies on bad debt related subjects (charity care and uncompensated care) use only descriptive statistics (Saywell et al. 1989; Weissman, Lukas, and Epstein 1992). Therefore, results from descriptive statistics in this study will be compared with those from previous studies. Adequacy of data on each variable will be reviewed to ascertain whether any data transformation is needed to normalize the data for the bivariate and multivariate models described below. Major statistical tools include descriptive statistics, tests for outliers and t-test for mean differences between two groups of hospitals: investor-owned and not-for-profit hospitals.

Bivariate Model

Bivariate statistical models will attempt to analyze the relationship between various explanatory variables and bad debt. Simple regression models will be used for this purpose. The direction of the regression coefficient and the statistical significance for the coefficient will be used as measures of reliability of simple regression models. These models will be used to test three major hypotheses (H1, H2, H3) stated in Chapter 2.

First, bivariate statistical analyses will investigate a possible linkage between hospital efficiency (Occupancy Rate; OCRATE) and the amount of bad debt. It is hypothesized that more efficient hospitals have less bad debt than less efficient hospitals (H1). A negative regression coefficient is expected. Second, bad debt will be evaluated in terms of ownership type of a hospital (TYPE). The proposed hypothesis (H2) stipulates that investor-owned hospitals (TYPE=1) have less bad debt than not-for-profit hospitals (TYPE=0). Accordingly, a negative regression coefficient is also expected. Third, patient characteristics will play a role in hospital financial statements. It is hypothesized that hospitals with more recipients of prospective payment systems such as Medicare (MCRMIX) will have less bad debt than hospitals with fewer Medicare patients (H3). A negative regression coefficient is expected.

Multivariate Models

Bivariate models have a certain limitation as they assume all other pertinent variables that would impact the amount of bad debt remain unchanged. This assumption is highly unrealistic. As literature on bad debt indicates, bad debt is a result of many inter-related attributes; Market and financial variables, organizational structure, and patients all contribute to a formation of bad debt behavior. Accordingly, to understand the bad debt behavior to the fullest extent, all factors influencing bad debt should be investigated simultaneously. For this purpose, multivariate statistical models (multiple regression, discriminant, and logistic regression models) are suggested.

Multiple Regression Analysis

First, this study will employ a multiple regression analysis to build an exploratory model. Based on independent variables described above, the model will explain the size and directional relationship between bad debt and explanatory variables.

Linear regression models or ordinary least square models are the most popular methods employed by hospital profitability studies (Gapenski, Vogel,and Langland-Orban 1993; Vogel, Langland, and Gapenski 1993). Because linear relationship is convenient and easy to understand, regression models are frequently applied to hospital profitability studies. Borrowing a theoretical framework from these studies, the following multiple regression model is proposed:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + e_i$$

$$= \beta_0 + \sum_{j}^{p} \beta_j X_j + e_i \qquad \ldots\ldots\ldots\ldots \quad (3.1)$$

where Y_i = the amount of bad debt as percent of total operating expense for the *i*th hospital,
X_j = independent variables ($j = 1,2, \ldots, p$),
e_i = random error, and
i = $1,2, \ldots, m$ (hospitals).

Coefficients of determination and F-values will be used as measures of validity and reliability of multiple regression models. Individual t-values will be employed as reliability measure of each explanatory variable. Variance inflation factors (VIF) will be computed to estimate whether multicollinearity problems exist.

Discriminant Analysis

Like ordinary least squares, discriminant analysis is a linear model and frequently applied to cross-sectional analysis. Discriminate analysis assesses predictors separating two or more groups from each other. In addition, a discriminant function extracted from a model can be used to determine group membership for new subjects and observations.

Zazac and Shortell (1989) integrate a two-group discriminant analysis into their study along with other methods. They estimate predictors for isolating hospitals experiencing change in strategy.

Kwon et al. (1988) and Martin and Kwon (1995) apply discriminant analysis to a two-group classification. They are interested in examining indicators that could separate financially healthy and unhealthy Catholic hospitals.

For this study, the data will be separated into two groups (high bad debt and low bad debt), in terms of percent of bad debt to total operating expense. The low bad debt group (BD = 0) includes the first quartile of hospitals and the high bad debt group (BD = 1) will be fourth quartile of hospitals. Independent variables discussed in the previous section will be used as discriminators. With two groups, the discriminant analysis is transformed into its simplest form: one dimension. The one-dimensional canonical discriminant function transforms multiple individual variable values to a single discriminant score which is then used to classify the subjects. The generalized composite canonical discriminant model of this research is expressed in the following mathematical form (Klecka 1989, 15):

$$f_{km} = \mu_0 + \mu_1 X_{1km} + \mu_2 X_{2km} \ldots + \mu_P x_{pkm}$$

$$= \mu_0 + \Sigma\ \mu_j X_{jkm} \qquad \ldots\ldots\ldots\ldots \quad (3.2)$$

where f_{km} = the value (score) on the canonical discriminant function for case m in the group k;
μ_j = coefficients which produce the desired characteristics in the function; and
X_{jkm} = the value on discriminating variable X_j for case m in group k.

where k = 1 for high bad debt group, and 0 for low bad debt group;
m = case number of hospitals; and
X_j = independent variables (j = 1 through p).

Canonical coefficients and Wilk's lambda will be used as measures of validity and reliability of discriminant models.

Logistic Regression Analysis

Logistic regression models are based on the logistic distributions function and are usually estimated with maximum likelihood. Logistic regression models take a binary (dichotomous) dependent variable and offer probabilities and odds for the interpretation of parameters. A binary dependent variable, probabilistic interpretation, and maximum likelihood estimation are major differences between linear regression analysis and logistic regression analysis. Probabilistic interpretation and maximum likelihood estimation are attributes differentiating logistic regression models from discriminant models (Joo 1995, 40).

Several studies in the healthcare area use logistic regression models; McCue (1991) dichotomizes financial ratios such as average cash flow to total beds and net income to beds, for a study of financially distressed hospitals. Thus, instead of linear regression analysis, logistic regression analysis was employed to find factors contributing to financially distressed hospitals. Vogel, Langland-Orban, and Gapenski (1993) also use logistic regression models to identify factors influencing exceptionally high and low profitability among hospitals in Florida. They dichotomize continuous measures such as pre-tax operating margin and basic earning power, and applied logistic regression analysis.

Many researchers prefer logistic regression approach to discriminant model for several reasons. Logistic regression models require less vigorous assumptions in a model building process than discriminant analysis. As a result, results from logistic analysis are more robust than those from discriminant model. Second, the odd ratios from logistic model can be used as policy guidelines in strategic management planning in hospitals. Since one of the major purposes of this study as described in Chapter 1 is to provide hospital decision makers with policy guidelines on bad debt management, the use of logistic analysis seems to be an ideal tool for this study.

For this model, the same framework suggested for the discriminant model will be used. Accordingly, the logistic regression model can be written as (Kleinbaum 1994, 7):

$$P(X_k) = P(BD = k \mid X_1, X_2, \ldots, X_p)$$

$$= \frac{1}{1 + e^{-z}} \quad \ldots\ldots\ldots\ldots\ldots \quad (3.3.1)$$

where $z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots. + \beta_p X_p$

$$= \alpha + \Sigma\ \beta_j X_j \quad \ldots\ldots\ldots\ldots\ldots \quad (3.3.2)$$

where BD = a dichotomous dependent variable (Bad Debt),
k = value of BD (1 or 0),
X_j = independent variables (j = 1 through p),
$P(X)$ = conditional probability of an event k occurring, and
X = a vector of independent variables.

The logistic regression model (Equation 3.3.1) can be rewritten in terms of the odds of an event occurring. The odds of an event 'k' occurring (BD = k) are then estimated as:

$$\text{Odds} = \frac{P(X_k)}{1 - P(X_k)} \quad \ldots\ldots\ldots\ldots\ldots \quad (3.3.3)$$

With odds for each k (Equation 3.3.3), odds ratio can be determined as:

$$\text{Odds Ratio } (X_1, X_0) = \frac{\text{Odds for } X_1}{\text{Odds for } X_0} \quad \ldots\ldots \quad (3.3.4)$$

A logit also can be computed by the odds (Equation 3.3.3) as:

$$\text{logit } P(X) = \text{Log (Odds)} \quad \ldots\ldots\ldots\ldots\ldots \quad (3.3.5)$$

Chi-square value of model improvement will be used as a measure of model reliability.

Chapter Summary

Chapter 3 described methodology, including data, variables, bivariate and multivariate statistical models that will be used to explore the behavior of bad debt. Simple regression analysis and t-test were presented for the bivariate and univariate models, while multiple regression analysis, discriminant analysis, and logistic regression analysis were chosen for the multivariate models. Chapter 4 will present the results of these models.

CHAPTER 4

STATISTICAL RESULTS

This chapter presents the statistical results of models discussed in Chapter 3. The sample selection process will be discussed initially, followed by descriptive statistics for all variables discussed in Chapter 3. Because one of the major hypotheses of this study is to ascertain whether the amount of bad debt varies by type of hospital (not-for-profit vs. investor-owned hospitals), t-tests will be carried out on all variables, including the amount of bad debt, based on the type of hospitals. Finally, three different multivariate statistical models (linear multiple regression model, discriminant model, and logistic regression model) will be constructed to study the determinants of hospital bad debt.

Data

Since 1980, the Missouri Department of Health has collected annual report of all Missouri hospitals (Missouri Department of Health 1995). The annual reports include data from approximately 188 hospitals. There are about 156 variables in the annual data, which include hospital as well as patient characteristics and hospital financial information. Because this study examines the impact of the 1990 accounting change on bad debt behavior, it utilizes information contained in the reports for the three years 1991 through 1993, the most recent years available. To avoid organizational bias, this study uses only non-governmental hospitals in the state of Missouri. Hospitals with different types of ownership may have different missions and operating characteristics. In addition, special hospitals, such as psychiatric, mental hospitals and long-term care facilities, are excluded in order to avoid measurement bias.

In summary, the Missouri State Hospital Database for this study includes 188 hospitals per year for the period 1991 through 1993, a total of 564 cases. As stated, only non-governmental, general medical and surgical hospitals are included.

Of the 564 cases, 216 cases were deleted from this study due to either governmental or non-general medical surgical nature (57) or missing service codes (159). Of the remaining 348 cases, 54 cases were further deleted due to missing information, leaving 294 usable cases as a valid sample size for this study.

Descriptive Statistics

Table 4-1 lists descriptive statistics for categorical variables. Continuous variables are summarized in Table 4-2.

Table 4-1
Descriptive Statistics for Categorical Variables

Variable	Value	Frequency	Percent
Ownership Type	0 (not-for-profit) 1 (investor-owned)	264 30	90 10
Location	0 (rural) 1 (urban)	105 189	36 64
Emergency Department	0 (absence) 1 (presence)	5* 234*	2 98
Neonatal Intensive	0 (absence) 1 (presence)	219* 20*	92 8
Obstetrics	0 (absence) 1 (presence)	71* 168*	30 70

Note: *The sum of two categories does not match 294, due to missing values in each variable.

According to Table 4-1, 264 cases (90 percent) are classified as not-for-profit hospitals and 30 cases (10 percent) are investor-owned hospitals. The majority of the hospitals are within the urban area (64 percent), and most of the hospitals are equipped with emergency rooms (98 percent) and obstetrics service (70 percent). Very few hospitals provide neonatal intensive care (8 percent). Given that emergency room service is provided by virtually every hospital (98 percent), its unique contribution to the variation of the hospital bad debt may be muted. Accordingly, this variable will be deleted from further model building process.

Table 4-2
Descriptive Statistics for Continuous Variables

Variable[a]	Mean	Std Dev	Minimum	Maximum	n
OCRATE	0.42	0.15	0.10	0.88	189
CHARITY	1.63	2.77	0.00	18.86	190
BADDEBT	4.78	3.53	0.00	14.42	190
ALOS	5.48	4.56	0.06	34.72	172
MCDMIX	11.31	12.57	0.00	86.07	184
SERVNUM	41.29	13.58	15.00	71.00	157
MCRMIX	57.77	14.38	3.78	87.82	184
SIZE	233.76	218.48	42.00	1208.00	190

Table 4-2 shows that the average length of stay during the study period is 5.48 days; Medicaid mix accounts for more than 11 percent of the total inpatient days, and almost 58 percent of the total inpatient days comes from Medicare inpatient days. The average occupancy rate of hospitals is 42 percent during the study period and the average hospital size is almost 234 licensed beds. Each hospital provides almost 41 different service lines during the observation period. Each hospital contributes 1.63 percent of its total operating expense to the community as charity care and also incurs 4.78 percent of its operating expense as bad debt. Together, each hospital expends 6.41 percent (1.63 + 4.78) of its operating expense as uncompensated care. This level of uncompensated care is comparable to that of other studies such as Buczko (1994), Saywell et al. (1989) and Weissman, Lukas, and Epstein (1992).

Bivariate Correlation

Multicollinearity in multivariate statistical models always provides a challenge. Bivariate measures of collinearity may provide preliminary information regarding interrelationships among independent variables. This preliminary information indicates a need for special care in managing multicollinearity in the model building process.

Table 4-3 provides bivariate measures of collinearity among independent variables. It is unreasonable to expect no statistically significant relationships among independent variables; In research such as this study, many attributes and variables are assumed to influence simultaneously the dependent variable. As shown in Table 4-3, several independent variables exhibit statistically significant relationships among themselves: for example, average length of stay and number of services that each hospital provides, and number of services and occupancy rate. However, the central issue in multicollinearity is level of correlation (tolerance level) rather than statistical significance (Neter, Wasserman and Kutner 1996). As shown in Table 4-3, the smallest tolerance level is 0.459; This level occurs between the number of services and the hospital size and is well above the conventionally accepted size of tolerance level of 0.1. Nevertheless, the issue of multicollinearity will be closely monitored in the multivariate model building process.

Table 4-3

Bivariate Correlation Coefficient Matrix

	BADDEBT	ALOS	CHARITY	MCDMIX	MCRMIX	OCRATE	SERVNUM	SIZE	SMSA	TYPE	SERVT2	SERVT3
BADDEBT		0.03	0.17*	0.31	-0.18*	0.01	-0.12	-0.13	-0.06	-0.00	0.07	0.06
ALOS			0.32**	0.16*	-0.14	0.28**	0.22**	0.38**	0.18*	0.00	-0.02	-0.04
CHARITY				0.30**	-0.30**	0.43**	0.07	0.38**	0.16*	-0.16*	-0.01	0.11
MCDMIX					-0.55**	0.23**	-0.13	-0.07	-0.06	0.15*	0.04	0.07
MCRMIX						-0.28**	-0.07	-0.20**	-0.16*	-0.03	-0.08	-0.21**
OCRATE							0.55**	0.47**	.24**	0.07	0.08	0.17*
SERVNUM								0.73**	.44**	0.07	.22**	0.18*
SIZE									.43**	-0.09	0.19*	0.23**
SMSA										-0.08	-0.03	0.09
TYPE											-0.00	-0.09
SERVT2												0.14
SERVT3												

Note: $*p < 0.05$ $**p < 0.01$

SMSA (Location: 1=Urban, 0=Rural);
Type (Ownership type: 1=Investor-owned, 0=Not-for-profit);
SERVT2 (Obstetrics unit);
SERVT3 (Neonatal intensive care)

t-test Results

Because one of the major hypotheses of this study is to ascertain whether investor-owned hospitals have significantly less bad debt than not-for-profit hospitals, t-tests will be carried out on the amount of bad debt along with other pertinent independent variables, based on the type of hospitals. The results are listed in Table 4-4.

Contrary to the expectation, no significant difference exists between the amount of bad debt as a percent of operating expense for not-for-profit hospitals and investor-owned hospitals. According to Table 4-4, not-for-profit hospitals incur 4.79 percent of their operating expense as bad debt, whereas the corresponding amount for investor-owned hospitals is 4.74 percent. However, not-for-profit hospitals donate 1.79 percent of their total operating expense to the community as charity care, whereas investor-owned hospitals commit only 0.43 percent to the community ($p < 0.01$).

Investor-owned hospitals exhibit a higher occupancy rate than their counter-part (45 percent vs. 42 percent) and such a difference is statistically significant only at $p < 0.1$. Investor-owned hospitals have higher Medicaid patient days (16.3 percent) than not-for-profit hospitals (10.6 percent); This result is unexpected to the extent that the total reimbursement ratio for Medicaid patients has been lower than other conventional discharges such as commercial insurance as well as Medicare programs.

Table 4-4
t-test Results by Ownership Type (TYPE)

Variable	Not-for-profit		Investor-owned		t-value
	Mean	SD	Mean	SD	
ALOS	5.47	4.75	5.59	3.03	-.11
BADDEBT	4.79	3.55	4.74	3.48	.07
CHARITY	1.79	2.88	.43	1.34	3.87***
OCRATE	0.42	.16	.45	.07	-1.75*
MCDMIX	10.60	12.52	16.30	12.05	-2.05**
MCRMIX	57.98	14.71	56.27	11.97	.53
SIZE	241.26	229.46	181.83	106.15	2.12**

Note: *** $p < 0.01$
** $p < 0.05$
* $p < 0.10$

Multivariate Statistical Models

The decision variables discussed in Chapter 3 and reviewed separately in this chapter seldom behave disjointedly. A more realistic scenario is that all pertinent variables (categorical as well as continuous) act jointly to influence the variation in the amount of bad debt. Accordingly, it is possible that one or a group of independent variables which play a significant role in univariate models may become less important variable(s) in multivariate statistical models. Multivariate statistical models will capture the partial contribution that one variable makes as other variables enter into the models.

Regression Model

A. Reduced Models

Three reduced regression models are constructed to test the first three hypotheses stated in Chapter 2. The first model regresses the amount of bad debt against the occupancy rate that measures hospital efficiency. According to the first hypothesis in Chapter 2, more efficient hospitals should have less bad debt than less efficient hospital. The result from the simple regression model shows no statistically significant relationship between the occupancy rate and the amount of bad debt. However, as shown below, the directional relationship is negative, as expected.

$BADDEBT = 4.846 - .086OCRATE$ ($R^2 = 0.0+$, $F=0.002$)

where BADDEBT = Percent of bad debt to total operating expense,
OCRATE = Occupancy rate.

In Chapter 2, this study hypothesized that investor-owned hospitals would have significantly less bad debt than not-for-profit hospitals. Statistical results indicate, as shown below, that the relationship between these two variables is not statistically significant. However, the evidence suggests that investor-owned hospitals have less bad debt in terms of total operating expenses than their counter-part.

$BADDEBT = 4.819 - 0.083TYPE$ ($R^2 = 0.0+$, $F=0.012$).

where TYPE = Ownership type of hospitals
(1 = Investor-owned hospitals,
0 = Not-for-profit hospitals).

Finally, in Chapter 2 this study hypothesized that hospitals with more recipients with prospective payment systems such as Medicare would have significantly less bad debt than hospitals with fewer Medicare patients. A reduced regression model shows a significant negative relationship between the amount of bad debt and Medicare mix variable, as hypothesized. The statistical result is as follows:

$BADDEBT = 7.513 - .045MCRMIX$ ($R^2 = 0.03$, $F=6.58^{**}$)

where MCRMIX = Medicare Mix.
$^{**}p < 0.05$.

B. Full Model

Table 4-5a shows the results from the multiple regression model along with other pertinent information. The overall model is significant (F-value = 1.93, $p < 0.05$) with $R^2 = 0.142$. No serious multicollinearity problem exists in the model as none of the variance inflation factor (VIF) exceeds 10 (Neter et al. 1996). A mild correlation between the number of services and hospital size was expected as discussed in Table 4-3.

Table 4-5a
Results of Regression Model[a]

Variable	Regression Coefficient	Beta[b]	VIF[c]	t-value
ALOS	0.070	0.09	1.39	1.00
CHARITY	0.184	0.13	1.79	1.26
MCDMIX	0.079	0.29	1.74	2.74***
MCRMIX	0.009	0.04	1.61	0.40
OCRATE	-5.860	-0.26	2.12	-2.20**
SERVTYPE2	0.586	0.08	1.13	0.94
SERVTYPE3	1.202	0.07	1.18	0.89
SERVNUM	0.040	0.16	3.59	1.09
SIZE	-0.003	-0.25	3.29	-1.73*
SMSA	0.325	0.04	1.44	0.50
TYPE	0.043	0.00	1.14	0.05
Constant	3.861			1.90*
R^2 = 0.142 F value = 1.93**				

*$p < 0.10$
**$p < 0.05$
***$p < 0.01$

[a]Dependent variable = Percent of bad debt to total operating expense.
[b]Beta stands for the standardized regression coefficient.
[c]VIF stands for the variance inflation factor.

According to Table 4-5a, hospitals with higher occupancy rates appear to have relatively lower amounts of bad debt, as hypothesized, and such a relationship is statistically significant ($p < 0.05$). Higher occupancy rates usually imply higher net revenue as the average fixed cost decreases because more beds become occupied.

Although statistically not significant, results indicate that investor-owned hospitals recognize more bad debt than not-for-profit hospitals. According to Table 4-5a, investor-owned hospitals recognize more than 0.04 percentage points higher bad debt than not-for-profit hospitals, ceteris paribus. However, hospital size shows a significantly negative relationship with bad debt; Larger hospitals tend to have less bad debt.

As expected, the addition of expensive services such as neonatal intensive care and obstetrics services increase bad debt. According to Table 4-5a, Medicaid patient mix adds significant amount of bad debt to the overall hospital financial burden ($p < 0.01$). Possibly, however, some of the bad debt associated with Medicaid patient mix may be, and/or should be, treated as charity care since the eligibility of Medicaid insurance often becomes unclear. Under such circumstances, some hospital administrators classify uncollectibles as bad debt instead of charitable deductions. Medicare mix, on the other hand, appears to play an insignificant role in determining the size of bad debt. Such a result is not totally unexpected because the Medicare insurance, by definition, leaves very few items uncollected (Buzcko, 1994).

Table 4-5a also shows a positive relationship between the amount of bad debt and the amount of charity care although such relationship is statistically insignificant. Apparently, hospitals with high levels of charitable contributions also have large amounts of bad debt. Since one measures efficiency (bad debt) and the other measures societal commitment of quality care (charity), further analysis of these two seemingly conflicting variables is invited.

Table 4-5a reports a positive relationship between Medicare mix and bad debt. As discussed in the reduced model for Medicare mix variable and hypothesized in Chapter 2, a negative regression coefficient was expected. It is possible that the addition of a Medicaid mix variable to the full model may have caused this unexpected direction of relationship. Medicaid is also considered a prospective payment system with lesser degree than the Medicare system in terms of their commitment to the system. Therefore, a full regression model without the Medicare mix variable is constructed, as shown in Table 4-5b.

Results from Table 4-5b show a negative relationship between Medicare mix and bad debt variables, as hypothesized. Characteristics of other variables essentially remain the same, as reported in Table 4-5a with Medicaid.

Table 4-5b
Results of Regression Model without Medicaid Mix

Variable	Regression Coefficient	Beta	VIF	t-value
ALOS	0.092	0.12	1.37	1.29
CHARITY	0.211	0.16	1.78	1.47
MCRMIX	-0.024	-0.10	1.17	-1.17
OCRATE	-4.535	-0.20	2.05	-1.69*
SERVTYPE2	0.704	0.09	1.12	1.10
SERVTYPE3	1.317	0.08	1.18	0.95
SERVNUM	0.020	0.11	3.53	0.71
SIZE	-0.000	-0.31	3.23	-2.00**
SMSA	0.180	0.02	1.43	0.28
TYPE	0.480	0.05	1.10	0.58
Constant	6.690			3.73***
$R^2 = 0.091$	F value = 1.31 ($p = 0.23$)			

*$p < 0.10$
**$p < 0.05$
***$p < 0.01$

Discriminant Model

In order to further confirm the validity of the variables included and discussed in the multiple linear regression model (Table 4-5a and 4-5b), the data were separated into two groups (high bad debt and low bad debt) in terms of the percent of bad debt to total operating expense. The low bad debt group (BD = 0) includes the first quartile of hospitals (bad debt ranging from 0 to 2.25 percent of the operating expense), and the high bad debt group (BD = 1) includes the fourth quartile of hospitals (bad debt ranging from 6.83 to 14.42 percent of the operating expense). Independent variables discussed in the previous section will be used as discriminators. The results are shown in Table 4-6.

According to Table 4-6, the model appears to be acceptable with a Chi-square value of 26.7 ($p < 0.01$) for Wilk's lambda (8) of 0.628. Because the centeroid for Group 1 (-0.792) is distinctly different from the centeroid for Group 2 (0.722), a clear separation of group membership is indicated. The discriminant model also reports an 80 percent correct classification rate. The model=s canonical correlation coefficient shows 0.609.

Table 4-6
Results of Discriminant Model

Variable	Unstandardized Canonical Discriminant Function	Standardized Canonical Discriminant Function Coefficients
ALOS	0.07	0.40
CHARITY	0.15	0.44
MCDMIX	8.18	0.11
MCRMIX	3.41	0.05
OCRATE	-2.45	-0.37
SERVTYPE2	0.46	0.20
SERVTYPE3	1.01	0.27
SERVNUM	0.12	1.48
SIZE	-5.10	-1.07
SMSA	0.82	0.39
TYPE	0.30	0.09
Constant	-4.91	
Group Centroids	Group 1 (low bad debt) = -0.792	
	Group 2 (high bad debt) = 0.722	
Canonical Correlation = 0.609		
Wilk's Lambda = 0.628 Chi-square= 26.7***		
Correct Classification Rate =80.0 percent		

Note: ***$p < 0.01$

Table 4-6 reveals that occupancy rate and hospital size are only two discriminators which appear to contribute to lower amounts of bad debt. The rest of the discriminators appear to have an opposite effect. The preceding findings are also in line with findings in the linear multiple regression model (Table 4-5a). As discussed in Table 4-5a, Medicare mix is a minor player in determining the size of debt. It is also clear from Table 4-5a that the number of services that a hospital provides, hospital size, and the amount of charity care have significantly more segregating power than other discriminating variables.

Logistic Regression Model

As discussed in Chapter 3, some researchers prefer logistic regression to discriminant analysis. First, logistic regression models require less vigorous assumptions in the model building process than discriminant analysis. Hence, results from logistic analysis are more robust than those from the discriminant model. Second, the odd ratios from a logistic model can be used as policy guidelines in strategic management planning in hospitals.

For this model, the same framework used for the discriminant model will be used; the low bad debt group (BD = 0) includes the first quartile of hospitals (bad debt ranging from 0 to 2.25 percent of the operating expense), and the high bad debt group (BD = 1) will include the fourth quartile of hospitals (bad debt ranging from 6.83 to 14.42 percent of the operating expense). The results from a logistic regression model are presented in Table 4-7.

The model appears to be acceptable because model reliability is good (Chi-square value = 61.10, $p < 0.01$) and the model improvement is also reliable (Chi-square value = 30.179, $p < 0.01$). The model reports the correct classification rate is 81.5 percent, a rate which is slightly improved from the discriminant model (80.0 percent).

According to Wald statistics in Table 4-7, two variables, number of services (SERVNUM) and hospital size (SIZE), show statistically significant relationships with the level of hospital bad debt. The location variable (SMSA) is marginally significant. Presence of neonatal service and urban location have the largest odds ratios, followed by presence of obstetrics service and investor-owned hospital. According to Table 4-7, the odds would increase by 2.47 times and 3.87 times, respectively, if hospitals decide to add expensive services such as obstetrics unit (SERTYPE2) or neonatal intensive care unit (SERVTYPE3). The logistic regression model also reveals that the odds of being in the higher bad debt group (75 percentile) will be 3.73 times greater if the hospitals are operating within the SMSA area rather than outside the SMSA.

The results in Table 4-7 are comparable to those in the discriminant model (Table 4-6). In addition, the directional relationships between the dependent variable (bad debt) and the selected independent variables (occupancy rate and size of hospitals) in Table 4-7 are comparable to those in the multiple linear regression model (Table 4-5). However, the reliability of the relationship between the amount bad debt and the occupancy rate that exists in multiple linear model is no longer true in the logistic regression model.

Table 4-7
Results of Logistic Regression Model

Variable	Beta	Wald	Odd Ratio
ALOS	0.11	1.62	1.12
CHARITY	0.31	2.46	1.37
MCDMIX	0.02	0.40	1.02
MCRMIX	0.02	0.50	1.02
OCRATE	-3.21	1.04	0.04
SERVTYPE2	0.90	0.97	2.47
SERVTYPE3	1.35	0.80	3.87
SERVNUM	0.19	11.55***	1.21
SIZE	-0.00	5.75**	0.99
SMSA	1.31	2.90*	3.73
TYPE	0.73	0.42	2.08
Constant	-9.15	7.23***	
Chi-square for Naive model = 89.97***			
Chi-square for Goodness-of-fit = 61.110*** Chi-square for Improvement = 30.179***			
Correct Classification Rate = 81.54 percent			

Note: *p < 0.10
**p < 0.05
***p < 0.01

Chapter Summary

Chapter 4 presented descriptive statistics, bivariate correlation estimates, univariate statistics, and the results of multivariate statistical models. Among independent variables, Medicaid mix, hospital size and occupancy rate were found to be statistically significant in explaining the amount of debt in the multiple linear regression model. The number of services that the hospital provides, hospital size and the amount of charity care have significantly more segregating power than other variables in the discriminant model. In the logistic regression model, the number of services, the size of hospital, and the location of hospital are three major variables in separating one group of hospitals (hospitals with low bad debt) from other group of hospitals (hospitals with high bad debt).

In Chapter 5, the implications based on results in Chapter 4 will be discussed along with hypotheses formulated in Chapter 2.

CHAPTER 5

DISCUSSION OF STATISTICAL FINDINGS

This chapter will discuss the implications of the statistical results presented in Chapter 4. Based on the hypotheses formulated in Chapter 2, the relationship between sets of independent variables and the dependent variable (bad debt) will be interpreted and discussed. Policy implications will be addressed based upon interpretation of the statistical results.

Efficiency Variable (Occupancy Rate)

The first hypothesis in Chapter 2 states that more efficient hospitals will have significantly less bad debt than less efficient hospitals; In this study, efficiency is measured by the occupancy rate. As discussed in Chapter 2, Buczko (1994) reports a negative relationship between bad debt and occupancy rate. McCue (1991), in his profitability study, on the other hand, finds a positive relationship between occupancy rate and profitability, inferring a negative relationship between occupancy rate and bad debt.

The bivariate statistical result from the reduced regression model of this study reveals no significant relationship between occupancy rate and bad debt. However, the directional relationship is found to be negative, as suggested by Buczko (1994) and hypothesized in this study.

Results from the full regression model (Table 4-5a) reveal a statistically significant relationship ($p < 0.05$) between the amount of bad debt and the occupancy rate. This finding seems to be consistent with that of Buczko (1994). The direction of the relationship is also consistent with our hypothesis (negative) as shown in Table 4-5a and 4-5b. In addition, results from the discriminant model (Table 4-6) appear to support the findings from the multiple regression model. As shown in Table 4-6, the occupancy rate is one of the two discriminators that contribute to lowering the amounts of bad debt in hospitals. Although the relationship is statistically insignificant, such an inverse relationship between the amount of bad debt and the occupancy rate is further confirmed by the logistic regression model (Table 4-7).

Accordingly, the first hypothesis that more efficient hospitals as measured by occupancy rate will have significantly less bad debt is confirmed by this study. As discussed in Chapter 3, since a high occupancy rate implies high hospital revenue, a negative relationship between these two variables is not unexpected.

Ownership Type

According to the hypothesis in Chapter 2, investor-owned hospitals will have significantly lower percentage of bad debt in terms of operating expense than not-for-profit hospitals. Numerous studies indicate that decision-makers in investor-owned hospitals are more efficiency and profitability oriented in financial decision-making processes than are not-for-profit hospitals' decision makers. Accordingly, investor-owned hospitals are expected to show a lower percentage of bad debt to total operating expense than not-for-profit hospitals.

The bivariate test results in Table 4-4 reveal no significant difference between the amounts of bad debt of investor-owned hospitals and not-for-profit hospitals ($p > 0.1$). However, the average amount of bad debt in not-for-profit hospitals (4.79 percent) is slightly greater than that of the investor-owned hospitals (4.74 percent). A reduced model from regression analysis also indicates the same result: a negative relationship between the amount of bad debt and the type of hospital (TYPE = 1 for investor-owned hospitals and TYPE = 0 for not-for-profit hospitals).

Multivariate regression models reveal that ownership type has virtually no impact on determining the amount of bad debt. In addition, the directional relationship between the amount of bad debt and the type of hospitals in all three multivariate models is positive; This result is inconsistent with the results of univariate models and hypothesis. However, the relationship is statistically insignificant, leaving the impression that such a relationship could happen by a chance. A similar result is also noted in the discriminant model (Table 4-6); the standardized discriminant coefficient for TYPE (0.09) is the second lowest among 11 discriminators. Although statistically not significant, the logistic regression model (Table 4-7) indicates that the odds of being in the higher bad debt group (75 percentiles) will be 2.08 times greater than not-for-profit hospitals if the hospitals are owned by for-profit investors.

Accordingly, this study does not appear to support the second hypothesis that the investor-owned hospitals incur less bad debt than the not-for-profit hospitals. As discussed in Chapter 2, this hypothesis was formulated based on numerous findings of relationships between ownership of hospital and profitability (Lewin, Eckels, and Miller, 1988; Gapenski, Vogel, and Langland-Orban, 1993; McCue, Clement, and Hoerger, 1993; Sear, 1992; Walker and Humphreys, 1993). In addition, several studies on charity care also concluded that the amount of charity care is significantly related to type of ownership (Ashby, 1992; Lewin, Eckels, and Miller, 1988; Arrington and Haddock, 1990).

However, the following two studies appear to suggest no apparent difference in the amount of charity care between investor-owned hospitals and not-for-profit hospitals. Hezlinger and Krasker (1987), for example, report that the amount of charity care provided by investor-owned hospitals is not significantly different than the amount of charity care provided by not-for-profit hospitals. Hezlinger and Krasker's study (1987) seems to be supported, at least, in part by Hutman's study (1991) on uncompensated care (charity care plus bad debt); Hutman found that relationship between uncompensated care and ownership type tends to disappear. If such a trend indeed exists as noted by Hezlinger and Krasker (1987) and Hutman (1991), it is entirely possible that the difference in the amount of bad debt between investor-owned hospitals and not-for-profit hospitals may also be disappearing.

Prospective Payment System (Medicare Mix)

If the payment for treatment is pre-arranged as was the case under the prospective payment system, it is highly unlikely that hospitals would experience a serious bad debt problem as they are under the fee-for-service systems. Accordingly, hospitals with a higher proportion of revenue generated from the prospective payment system would have a lower percentage of bad debt than hospitals whose major revenues stem from the fee-for-service systems. Since most Medicare patients are under the prospective payment system, this research attempts to test the existence of the inverse relationship between the proportion of Medicare discharge in a hospital and the proportion of bad debt to total operating expense.

The Medicare variable has been used with mixed results in studies on hospital profitability (Vogel, Langlan-Orban, and Gapenski, 1993; Gapenski, Vogel, and Langland-Orban, 1993). Buczko (1994) uses this variable to determine the level of charity care and reports a significant relationship between uncompensated care and Medicare mix. Accordingly, in Chapter 2 this study formulated a hypothesis that hospitals with more

Medicare patients would have significantly less bad debt than hospitals with fewer Medicare patients.

Statistical results from a reduced regression model show that Medicare mix indeed has a negative effect on bad debt, as hypothesized. The relationship between Medicare mix and bad debt is also statistically significant ($p < 0.05$). This statistical result is consistent with Buczko's (1994) finding in his uncompensated care. Mixed results, however, are observed in multivariate statistical models. A full regression model with the Medicaid mix variable (Table 4-5a) shows a positive relationship between Medicare mix and bad debt, but a negative relationship between these two variables is noticed in a full regression model without the Medicaid mix variable (Table 4-5b).

The positive relationship between Medicare mix and the amount of debt is not totally unexpected. Profitability studies also reveal mixed conclusions on the prospective payment system. Hultman (1991), Vogel, Leanlan-Orban, and Gapenski (1993) report a negative relationship between the Medicare variables (prospective payment system) and hospital profit; This result implies that a positive relationship between Medicare and bad debt is, at least, tenable, as shown in this study. Secondly, a review of the results from two multiple regression models (Table 4-5a and Table 4-5b) may provide an additional explanation for the positive relationship between Medicare mix variable and the amount of bad debt. Medicaid is also considered a prospective payment system to some extent; The Medicaid system almost mimics the Medicare prospective system in many states, including the sample state of this study (Missouri). Thus, the addition of a Medicaid mix variable to the model may alter the directional relationship between Medicare mix and the amount of bad debt. A statistically significant relationship ($p < 0.01$) between these two variables (Medicare mix and amount of debt) found in Table 4-3 would support this contention. Finally, outcomes may be different if other measures of the prospective payment system are used. For example, Rosko and Carpenter (1994) use Medicare as a proportion of total revenue to measure the impact of the prospective payment system on profitability of hospitals.

Mediating Variables

As discussed in Chapter 2 and Chapter 3, this research indicates that the behavior of bad debt also varies with other mediating variables. In this section, several such mediating variables will be discussed, based upon the statistical results reported in Chapter 4.

Medicaid Mix

Medicaid mix variable was included in this study as a surrogate variable for community wealth. Hospitals with an unusually high proportion of Medicaid population are usually located in areas where community income is lower than average. In their profitability studies, Kwon et al. (1988) and Martin and Kwon (1995) argue an inverse relationship between community wealth and Medicaid variables. Accordingly, it was hypothesized in Chapter 2 that the Medicaid mix variable would have a positive relationship with bad debt.

Results from a multivariate statistical model (Table 4-5a) appear to support such a hypothesis.

As shown, a statistically significant positive relationship ($p < 0.01$) is noted between the Medicaid mix variable and the amount of bad debt in hospitals. Statistical results from the discriminant model (Table 4-6) also appear to confirm the positive relationship between these two variables. Results from this study are consistent with study results by Gapenski, Vogel, and Langland-Orban (1993), who report a negative relationship between Medicaid mix and profitability. In addition, Rosko and Carpenter (1994) and Cleverly and Harvey (1992b) show similar results, although their studies use different scales in measuring the impact of Medicare patients on hospital profitability. The former study (Rosko and Carpenter, 1994) employs Medicaid dollar per total revenue while the latter (Cleverly and Harvey, 1992b) uses Medicaid revenue as a percentage of total revenue.

This study suggests that in order to reduce the level of hospital bad debt, hospitals need to be located in neighborhoods where fewer Medicaid patients reside. For example, in the early 1980s St. Luke Hospital moved from the City of St. Louis, where a majority of the population received Medicaid services, to its current location in West County, where most of the patients used commercial insurance. An alternative suggestion is to control the number of Medicaid patients in an effort to sustain a long-term financial survival. However, if the current managed care systems encompass Medicaid patients, as is the case in Minnesota, Tennessee, Arizona, and Missouri, the level of hospital bad debt may be reduced as was the case under the Medicare prospective system.

Hospital Size

Several profitability studies have reported a negative relationship between hospital size and profitability (Gapenski, Vogel, and Langland-Orban, 1993; Cleverly and Harvey, 1992b and 1992C). Given that bad debt has an adverse effect on profitability, a positive relationship is inferred between hospital size and the amount of bad debt.

On the contrary to expectations, multiple regression models reveal a significantly negative relationship between these two variables (hospital size and bad debt), as shown in Table 4-5a and Table 4-5b. Results from a discriminant model (Table 4-6) and logistic regression model (Table 4-7) also appear to support such negative directional relationship.

Although a negative relationship between the size of hospitals and the amount of debt seems to be contradictory to a hypothesis developed in this study (Chapter 2), it is consistent with a finding from Cleverley and Harvey (1992a).

They find a statistically significant and positive relationship between hospital size and profitability among urban hospitals; This result appears to indicate an inverse relationship between bad debt and hospital size.

Another possible reason for an inverse relationship between these two variables may be that a large hospital has a higher occupancy rate. As indicated in Table 4-3, there is a high and statistically significant correlation between the occupancy rate and the size of hospitals ($p < 0.01$). It was shown in the previous discussion that occupancy rate has a statistically significant inverse relationship with the level of bad debt ($p < 0.05$). Therefore, a negative relationship between the size of hospitals and the level of hospital bad debt is, at least, tenable, as hypothesized and as implied by Saywell et al. (1989).

Average Length of Stay

In Chapter 2, this study hypothesized that average length of stay would be positively related to the amount of bad debt. The logic behind the hypothesis is that: as more patients are covered and treated under the managed care payment system and/or prospective payment system, the total amount of payment (revenue to hospitals) would become fixed, regardless of length of stay in hospitals for treatment. Consequently, the likelihood is high that patients with longer hospital stays would incur more bad debt than the patients with shorter hospital stays. This logic is consistent with a study on uncompensated care by Saywell et al. (1989), who find average length of stay has a positive effect in determining the uncompensated care amount. In addition, numerous profitability studies have used this variable as one of the determinants and reported a negative relationship between these two variables (average length of study and operating margin)(Sear, 1992; Vogel, Langlan-Orban, and Gapenski, 1993).

Location

Several studies on uncompensated care have reported a positive relationship between the amount of uncompensated care and an urban location (Saywell et al. 1989; Zollinger et al. 1991; Weissman, Lukas, Epstein 1992). Accordingly, this study hypothesized that urban hospitals would have a higher level of bad debt than hospitals located outside the SMSA area.

As shown in Table 4-5a and Table 4-5b, regression results seem to support the hypothesis. The finding of a positive relationship between two variables (BADDEBT and SMSA) is also consistent with findings on profitability studies by Kwon et al. (1988) and Martin and Kwon (1995), as well as those studies on uncompensated care (Saywell et al. 1989; Zollinger et al. 1991; Weissman, Lukas, Epstein 1992). Asby (1992) also reports a similar result in his study of charity care. However, the relationship is not statistically significant, a result which is consistent with findings of Friedman and Shortell (1988).

They report no significant relationship between hospital location and financial performance. The discriminant model also confirms the positive directional relationship (Table 4-6).

As shown in Table 4-7, the logistic regression model shows that the location variable (SMSA) has a marginally significant relationship with the level of hospital bad debt ($p < 0.10$). The corresponding odds ratio indicates that the odds of being in the higher bad debt group (75 percentile) will be almost four times greater if the hospitals are located in urban areas rather than outside the SMSA area. Accordingly, the hypothesis that a negative relationship exists between the amount of bad debt and the location of hospital is partially confirmed.

Charity Care

Until 1990, hospitals treated bad debt as a part of uncompensated care (charity care plus bad debt). Although *Health Care Audit Guide* (AICPA 1990) is clear how these two attributes (amount of bad debt and amount of charity care) should be treated in financial statements (bad debt as a cost and charity care as lost revenue reported in a footnote), hospitals may have treated these two attributes interchangeably, especially at the early implementation stage of this new guideline. Buczko (1994), for example, finds that charity care and bad debt are components of uncompensated care but the behavior of charity care is different from that of bad debt. Accordingly, the behavior of charity care may provide additional information for understanding bad debt behavior, if a relationship is established between the amount of bad debt and charity care.

Two studies on profitability use uncompensated care as a determinant of profitability (Vogel, Langlan-Orban, and Gapenski, 1993; Gapenski, Vogel, and Langland-Orban, 1993). Saywell et al. (1989), Weissman et al. (1991) and Zollinger et al. (1992) also use uncompensated care as one of the main determinants in their studies of bad debt behavior.

Statistical results from all three multivariate models in this study reveal a positive but statistically insignificant relationship between charity care and bad debt. The direction of relationship has been uncertain. Since charity care is a hospital's commitment to a community and bad debt is a measure of hospital efficiency, the behavior of charity care, as discussed, has been considered different from that of bad debt. This study indicates a positive relationship between the two variables, indicating that hospitals with more charity care tend to incur more bad debt. Possible reasons for the positive relationship between these two variables (amount of charity care and amount of bad debt) may include the level of Medicaid revenue of hospitals. As discussed earlier, there was a statistically significant and positive relationship between the level of bad debt and the proportion of Medicaid discharge of hospitals (Table 4-5a). As discussed, hospitals at the early stages of implementation of the new guideline were not sufficiently careful in separating the charity care from the bad debt. As a result, accounting practices may have caused a linear positive relationship between these two attributes.

Type of Services

As hypothesized in Chapter 2, certain types of hospital service make a significant difference in incurring bad debt. Based upon the literature review, this study proposed the following four services as significant types of service that would have contributed to change in the amount of bad debt: emergency service (SERVTYPE1), obstetric service (SERVTYPE2), prenatal care (SERVTYPE3), and poisoning service (SERVTYPE4). However, as discussed, emergency service and poisoning service variables were deleted from this study for these reasons; Missouri hospital database does not list a poisoning service, and most hospitals in state of Missouri (98 percent) have emergency service, thereby making statistical analysis of this variable (emergency service) virtually meaningless in differentiating the amount of bad debt based on this service. In addition, this study replaces prenatal care with a neonatal care unit because prenatal care is not listed in the database.

<u>1. Obstetrics unit service</u>

Saywell et al. (1989), Zollinger et al. (1991), and Weissman, Lukas, and Epstein (1992) report the importance of this service in their studies of uncompensated care. Multivariate models report a positive relationship between these two variables, indicating that addition of this service to hospital operation appears to contribute to an increase in the amount of bad debt. However, the relation between two variables (bad debt and obstetric service) is not statistically significant. A discriminant model also reveals that this variable has insignificant segregating power (Table 4-6). Results of the logistic regression model (Table 4-7), however, reveal interesting information. According to Table 4-7, the odd will be almost 2.5 times greater of being in the higher bad debt group (75 percentile) if a hospital adds an obstetrics unit to its services. Obstetrics service requires a large financial commitment, including malpractice insurance, but users of this service may not be the type of patients who are able to afford to subscribe to the advanced technology already provided. Accordingly, the high odds ratio reported in this study is not surprising.

2. Neonatal intensive care

Saywell et al. (1989) and Zollinger et al. (1991) report a significant impact of this service on estimating the amount of uncompensated care. As was the case in obstetric service, neonatal intensive care is an expensive service. Multivariate models reveal a positive relationships between neonatal intensive care and bad debt, but the relationship is statistically not significant. Results from the logistic regression model indicate that the odds of being in the higher bad debt group (75 percentile) will be almost four times greater if the hospital adds this service (Table 4-7). This result appears to confirm the study findings by Saywell et al. (1989) and Zollinger et al. (1991).

Number of Services

In Chapter 2, this study hypothesized that as hospitals add more medical services to their operations, the likelihood of unpaid bills would increase. A positive relationship, therefore, between this variable and the amount of bad debt is expected.

Statistical results of this study appears to confirm a positive directional relationship between these two attributes (Table 4-5a and Table 4-5b). The relationship is statistically not significant. This variable, however, appears to have the largest discriminating power among independent variables to separate the hospitals in the low bad debt group (25 percentile) from hospitals in the high bad debt groups (75 percentile) (Table 4-6). Logistic regression results also support the results from the discriminant model ($p < 0.01$).

Policy Implications

This study reveals that most of the variables assumed to have significant impacts on the level of bad debt are managerial in nature. Occupancy rate, for example, can be adjusted (increased) by management by streamlining products (services) to the community. Required is sound strategic planning that situates hospitals in places that provide financially sound services. In addition, the trend of health care in this country is preventing hospitalization and avoiding expensive inpatient treatment. Currently managed care actively seeks outpatient and ambulatory treatments rather than inpatient treatment; This trend reduces occupancy rate.

Given that this study appears to indicate an inverse relationship between the volume of patients under the prospective payment system and the amount of bad debt, decision makers in hospitals are in position to manage bad debt as more patients are covered under the prospective payment systems, such as managed care. This trend will be augmented by the growing Medicare volume (as the population of this country ages) and by the growing number of Medicaid patients. (Many states are entering into managed care reimbursement platforms for Medicaid patients.)

This study also reveals that the decision makers in hospitals require careful strategic planning to determine the types and numbers of services that are offered to the community. This study clearly demonstrates that certain types of service are expensive and would become sources of financial drain (bad debt). Accordingly, decisions to provide services to the community should be carefully evaluated.

Finally, according to this study, hospital size may play a role in lowering the amount of bad debt. A careful review of bivariate relationships among and between variables (Table 4-3) reveals a strong and statistically significant negative relationship between the size of hospitals and the occupancy rate ($r = 0.47$, $p < 0.01$). In other words, this result appears to imply that hospitals operating at sub-optimum levels, as measured by occupancy rate and the number of licensed beds, may incur a substantial amount of bad debt. The preceding implication is consistent with stories reported almost daily by communities, especially in urban areas; These communities have too many licensed beds (large size) compared to the community needs (occupancy needs). As discussed earlier in this section, hospitals would be able to lower their bad debt by improving the occupancy rate through maintaining the optimum size of services.

Chapter Summary

Chapter 5 presented the implications of the results. In summary of hypotheses, Hypothesis No. 1 is strongly supported; The efficiency variable as measured by occupancy rate has a significant and positive relationship with the amount of bad debt.

This study does not appear to support Hypothesis No. 2; Investor-owned hospitals will have less bad debt than their counterparts (not-for-profit hospitals). This study indicates that the amount of bad debt as measured by percentage of operating expense is essentially identical between investor-owned hospitals and not-for-profit hospitals.

According to Hypothesis No. 3, hospitals with more patients under the prospective payment systems as measured by Medicare mix will have significantly less bad debt than hospitals with fewer patients under the prospective payment system. Hypothesis No. 3 is marginally supported. There is some evidence, although statistically insignificant, that the prospective payment system appears to lower the amount of bad debt.

Among mediating variables, Medicaid mix ($p < 0.01$), hospital size ($p < 0.1$), and number of services ($p < 0.01$) are significantly related to bad debt.

Chapter 5 also presented the implications of the results and provided policy implications. Chapter 6 will provide a summary, conclusion, limitations and directions of future research of this study.

CHAPTER 6

SUMMARY AND CONCLUSION

This chapter will summarize the findings and limitations of this dissertation and suggest directions for future research. Finally, this chapter will conclude the study.

Summary and Contributions

The significant impact of bad debt on profitability in the healthcare industry needs to be analyzed in light of the new healthcare audit guide. The healthcare industry has increasingly become an industry of profit making ventures. At the same time, bad debt has been rising because third-party payers and employers have been shifting a greater portion of healthcare bills to individuals, forcing individuals to pay higher premiums, annual deductible and co-payments. As a result, the likelihood that a hospital incurs bad debt also has risen. Nevertheless, the literature shows a lack of financial as well as statistical analyses of bad debt in the healthcare industry.

This study, therefore, attempted to investigate determinants of bad debt in the hospital industry. Three major purposes of this study were designed to achieve this goal. They were the following; (1) to examine the impact of healthcare economic variables on hospitals' bad debt; (2) to build a multivariate statistical model that can capture the nature and extent of the determinants of the level of bad debt in hospitals;

and (3) to develop a comprehensive operational strategy for hospital bad debt management based on the statistical model. Four hypotheses were constructed to achieve the purposes of this study:

H1: More efficient hospitals will have significantly less bad debt than less efficient hospitals, in which the hospital efficiency is measured by occupancy rate.

H2: Investor-owned hospitals will have significantly less bad debt than not-for-profit hospitals.

H3: Hospitals with more patients with prospective payment systems, such as Medicare payment recipients will have significantly less bad debt than hospitals with fewer Medicare patients.

H4: Variations of bad debt will also be explained simultaneously by a set of other mediating factors, such as Medicaid mix, operating margin, size and location of hospital, average length of stay, the amount of charity care, and type and number of services.

Results of this study indicate that Hypothesis No.1 is accepted, Hypothesis No. 2 is not accepted, Hypothesis No. 3 is accepted, and Hypothesis No. 4 is accepted.

This dissertation offers several contributions to the understanding of bad debt behavior. First, this study isolated bad debt from charity care cost and investigated the determinants of bad debt. No comprehensive studies on bad debt alone have been available in the healthcare literature. Second, this research used multivariate statistical analyses in constructing the bad debt model. Multivariate statistical models have not been employed previously in bad debt studies. Third, this study analyzed the bad debt behavior as a part of hospital profitability model. As such, a linkage was established between bad debt and hospital profitability. Fourth, this study investigated whether a relationship exists between the amount of bad debt and the amount of charity care. Finally, a strategy of bad debt management was discussed which would assist hospital decision makers in their effort to improve overall hospital profitability.

Study Limitations and Directions for Future Studies

There are several limitations of this study. First, the data base of this study did not include data prior to 1991. Accordingly, no serious attempt was made to investigate the effect of the 1990 accounting change in the healthcare industry. If data prior to 1990 were available, a comparative study of the bad debt behavior prior to and after the 1990 accounting change could have been conducted. Second, the literature review indicates that economic variables, such as unemployment rate and per capita income may have significant impact on hospital profitability. These variables were not included in this study. Third, future studies can include healthcare specific variables, such as teaching status, burn care service, oncology, and hospice into the bad debt behavioral model. Buczko (1992) used these variables in his study on uncompensated care and charity care. Fourth, it would be interesting to apply this model to more recent data from hospitals who have undergone big changes in terms of their payment arrangement (from fee-for-service to managed care) and the philosophy of healthcare management (from acute care to preventive care). Fifth, this study used the percent of bad debt to total operating expense as a measure of bad debt amount, based on Buczko's study (1992). However, this measure can be biased by a change in and/or manipulation of financial information. A new measure, such as the amount of bad debt per bed, could be tested in future studies as a measure of bad debt. Finally, a national data base could be utilized to test the validity of this model on hospital bad debt.

Conclusion

This research developed a multivariate statistical model to explain bad debt behavior in hospitals. Three different multivariate models (regression, discriminant, and logistic regression) were estimated. This study reported the following variables as significant determinants of bad debt: occupancy rate, Medicaid mix, Medicare mix, hospital size, and number of services. This dissertation also discussed policy implications regarding those bad debt determinants.

BIBLIOGRAPHY

Aldrich, John H. and Forrest D. Nelson. *Linear Probability, Logit, and Probit Models.* Berverly Hills, CA: Sage Publications, 1984.

American Institute of Certified Public Accountants. *Audits of Providers of Health Care Services*, New York, N.Y.: AICPA, 1989.

American Institute of Certified Public Accountants. *Health Care Audit Guide*, New York, N.Y.: AICPA, 1990.

Arrington, B., and Hadock, C. "Who Really Profits from Not-for Profits?" *Health Service Research* 25(2). June 1990: 291-304.

Ashby, J. L. "The Burden of Uncompensated Care Grows." *Healthcare Financial Management* (April, 1992): 66-81.

Buczko, William. "Factors Affecting Charity Care and Bad Debt Charges in Washington Hospitals." *Hospital & Health Service Administration* 39:2 (1994): 179-191.

Clement, Jan P., Thomas D'Aunno, and Barbara Lou M. Poyzer. "The Financial Performance of Diversified Hospital Subsidiaries." *Health Service Research* 27 (February 1993): 741-763.

Cleverley, William O. *Essentials of Health Care Finance*. Gaithersburg, MD: Aspen Publishers, Inc., 1992.

Cleverley, William O. "Trends in the Hospital Financial Picture." *Healthcare Financial Management* 48 (February 1994): 56-63.

Cleverley, William O. and Roger K. Harvey. "Is There a Link between Hospital Profit and Quality?" *Healthcare Financial Management* 46 (September 1992a): 40-45.

______________. "Competitive Strategy for Successful Hospital Management." *Hospital & Health Services Administration* 37 (Spring 1992b): 53-69.

______________. "Critical Strategies for Successful Rural Hospitals." *Health Care Management* Review 17 (Winter 1992c): 27-33.

______________. "Does Hospital Financial Performance Measure Up?" *Healthcare Financial Management* (May 1992d): 21-25.

Dennen,Taylor. “Cleaning Up Compensation Claims.” *Business and Health* 5:8 (June 1988): 35-37.

Ferko, Patrice. "Managing Bad Debt and Charity Care Accounts." *Topics in Health Care Financing* 20:1 (1993): 66-70.

Friedman, Bernard and Stephen Shortell. "The Financial Performance of Selected Investor-Owned and Not-for-Profit System Hospitals Before and After Medicare Prospective Payment." *Health Services Research* 23 (June 1988): 237-267.

Gapenski, Louis C., W. Bruce Vogel, and Barbara Langland-Orban. "The Determinants of Hospital Profitability." *Hospital & Health Services Administration* 38 (Spring 1993): 63-80.

Graham, Judith, *Modern Healthcare* 17:8 (April 10, 1987): 108.

Herzlinger, R.E., and Krasker, W.S. "Who Profits from Nonprofit?" *Harvard Business Review* (January-February, 1987): 93-106.

Hultman, Cheryl I. "Uncompensated Care before and after Prospective Payment: The Role of Hospital Location and Ownership." *Health Services Research* 26:5 (December 1991):613-622.

Johnson, Julie. "Uncompensated Care before and After Prospective Payment: The Role of Hospital Location and Ownership." *Health Services Research* 26 (December 1991): 613-622.

Joo, Seong Jong. *Determinants of Hospital Profitability: An Event History Analysis*. Ph.D. Dissertation. The Graduate School, Saint Louis University, St. Louis, Missouri, 1995.

Klecka, William R. *Discriminant Analysis.* Newbury Park, CA: Sage Publications, 1980.

Kleinbaum, David G. *Logistic Regression: A Self-Learning Text.* New York, NY: Springer-Verlag, 1994.

Kwon, Ik-Whan, Scott R. Safranski, David G. Martin, and William R. Walker. "Causes of Financial Difficulty in Catholic Hospitals." *Health Care Management Review* 13 (Winter 1988): 29-37.

Lewin, L. S., T. J. Eckels, and L. B. Miller. "Setting the Records Straight." *New England Journal of Medicine* 318:18 (May 1988): 1212-1215.

Martin, David and Ik-Whan G. Kwon. "Wealth Shifting and Capital Structure Choice in Not-for-Profit Hospitals: An Agency

Approach." *International Association of Management Journal* 8:2 (1996): 20-28.

Mowll, Charles A. "Documenting Medicare Bad Debt." *Health Financial Management* 42:2 (1988): 102-104.

McCue, Michael J. "A Profile of Preacquisition Proprietary Hospitals." *Health Care Management Review* 13 (Fall 1988): 15-24.

______________. "The Use of Cash Flow to Analyze Financial Distress in California Hospitals." *Hospital & Health Services Administration* 36 (Summer 1991): 223-241.

McCue, Michael J., Jan P. Clement, and Thomas J. Hoerger. "The Association of Ownership and System Affiliation with the Financial Performance of Inpatient Psychiatric Hospitals." *Inquiry* 30 (Fall 1993): 306-317.

McCue, Michael J. And Richard W. Furst. "Financial Characteristics of Hospitals Purchased by Investor-Owned Chains." *Health Services Research* 21 (October 1986): 515-527.

Missouri Department of Health. *Annual Missouri Hospital Reports: 1980-93*. Jefferson, MO: Missouri department of Health, 1992.

Nemes, Judith. "Hospitals put teeth into efforts to collect bad debt." *Modern Healthcare* (June 17, 1991): 41-50.

Neter, John, William Wasserman, Michael H. Kutner. *Applied Linear Statistical Models*. Burr Ridge, Illinois: Richard D. Irwin, Inc. (1996).

Pallarito, Karen. "New Auditing Rules to Better Document Charity-Care Costs." *Modern Healthcare* (May 28, 1990): 43.

Rode, Dan. "Determining an Allowance for Bad Debt." *Healthcare Financial Management* 45:4 (April 1991): 92-94.

Saywell, Robert M., Terrel W. Zollinger, David K. W. Chu, Charlotte A. MacBeth, and Mark E. Sechrist. "Hospital and Patient Characteristics of Uncompensated Hospital Care: Policy Implications." *Journal of Health Politics, Policy and Law* 14:2 (Summer 1989): 287-307.

Scott, Lisa. "Firm Offers to Sell Bad Debt to Highest Bidder." *Modern Healthcare* 23:6 (February 8, 1993): 34.

Sloan, F., J. Valvona, F. Sloan, J. Blumstein, and J. Perrin, eds. *Uncompensated Hospital Care: Rights and Responsibilities*. Baltimore, MD: Johns Hopkins Press, 1986.

Train, Kenneth. *Qualitative Choice Analysis: Theory, Econometrics,* *and an Application to Automobile Demand.* Cambridge: The MIT Press, 1986.

Vogel, W. Bruce, Barbara Langland-Orban, and Louis C. Gapenski. "Factors Influencing High and Low Profitability Among Hospitals." *Health Care Management Review* 18 (Spring 1993): 15-26.

Walker, C. Langford and L. Wade Humphreys. "Hospital Control and Decision Making: A Financial Perspective." *Healthcare Financial Management* 47 (June 1993): 90-96.

Weissman, Jpel S., Carol Van Deusen Lukas, and Arnold M. Epstein. "Bad Debt and Free Care in Massachusetts Hospitals." *Health Affairs*, (Summer 1992): 148-161.

Zazac, Edward J. And Stephen M. Shortell. "Changing Generic Strategies: Likelihood, Direction, and Performance Implications." *Strategic Management Journal* 10 (September/October 1989): 413-430.

Zollinger, T. W., R. M. Saywell, Jr., D. K. W. Chu, A. Ziegart, J. R. Woods, and LaBov, D. "A Determination of Institutional and Patient Factors Affecting Uncompensated Hospital Care," *Hospital & Health Services Administration* 36:2 (Summer 1991): 243-56.

Zucker, Lynne G. "Normal Change or Risky Business: Institutional Effects on the 'Hazard' of Change in Hospital Organizations, 1959-1979." *Journal of Management Studies* 24 (November 1987): 671-700.

VITA AUCTORIS

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Chris Lee had taught Business Statistics, Operations Research and Production Systems, Intermediate Statistics, Management Information Systems, and Production and Operations Management from 1987 to 1994 at Saint Louis University. Since 1994, he has presented eight papers at ORSA/TIMS, ASA, INFORMS, ISI, SWFAD, and MBAA conferences. Recently, his three papers were published at *Southwest Review of International Business Research, the Midwest Review of Finance and Insurance,* and *Midwest Review of International Business Research*. Two additional papers are under review for publication in *Marketing Research* and *International Journal of Operations Management*. More recently, his statistical paper was accepted for presentation at the 1996 ASA Meetings.

Mr. Lee has consulted several companies in a variety of fields: Mail Survey, SPC, TQM, Credit Scoring Model, Neural Network, Survival Analysis, etc.. His latest two consulting projects are to build a Survival Analysis model to estimate the loss rate from loans at a large financing institution in St. Louis and to implement the Data Envelopment Analysis model to measure the efficiency at a large hospital in St. Louis. In September 1995, the Statistics Division of ASQC awarded the Doctoral Student Grant to Mr. Lee for his achievement in the area of quality improvement.

Chris Lee also enjoyed writing a monthly column on securities investment in *Beauty Times* from 1994 to 1995. He is a diehard fan of St. Louis *Cardinals* and Miami *Dolphins,* and a liberal Democrat. Chris has a good sense of humor and friends often call him a comedian. He releases his stress by sharing jokes with colleagues or sampling various ethnic foods in town.