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Credit Scoring in a Hospital Setting

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Credit Scoring

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CREDIT SCORING IN A HOSPITAL SETTING

by

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in partial fulfillment of the requirements for the degree of

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Credit Scoring

Abstract

This is a study of the relationship between consumer credit scoring and the resolution of a patient's account for hospital services. Accounts studied were classified as Good accounts or Bad accounts based upon their final resolution. Bad accounts were those written-off to bad debt with Good accounts being all others.

The probability of predicting a patient's account being either Good or Bad was based upon a consumer credit scoring process. The null hypothesis of this study was that the consumer credit scoring process would not provide any indication about the outcome or resolution of the account. Analysis of the credit score and the outcome of the hospital account suggested the consumer credit score would indicate the patient's reliability in taking responsibility for the account. Based on the confidence given to credit scoring in consumer markets and the results of this study, the consumer credit score would have value for the health care industry.

I. Introduction

Hospitals are entering a competitive market. Employers and government are shouldering less and less of the cost of health care by sharing the risk of health expenditures through increases in patient deductibles and co-payments as well as through reduced reimbursement to providers.

Lower reimbursement to providers without proportionate reduction in expense will result in decreasing margins. Anti-dumping legislation and managed care contracting prohibits providers from being selective about the patients they treat, thus they are unable to avoid financial risk associated with costly, medically complex cases. Avoiding financial risk means the collection of every dollar will become increasingly more important as providers seek to maintain financial viability.

Collection of every dollar includes payment by the patient or compliance by the patient in providing evidence of an inability to pay. Either of these conditions results in satisfactory resolution of the account balance for the provider.

Credit scoring is widely used in consumer markets as a predictor of an individual's credit worthiness or compliance. According to Lewis (1992), credit scoring is a process whereby some information about a credit applicant is

converted into numbers that are combined to form a score. Based upon this score, the consumer is either granted credit or denied credit.

This research represents a correlational study of the consumer credit score, the independent variable, and the resolution of a patient's account for hospital services. Credit scoring as a predictor of collection may have value to the industry by assisting with issues of predicting collection or compliant behavior by the guarantor to bring the account balance to zero through acceptable methods.

The literature review addresses the value and status of the patient payment within the industry. Examination of health insurance as well as health care finance will demonstrate this value as well as support the growing value of predictability of account satisfaction.

The relationship between medical provider and the patient is not unlike other non-commercial business transactions. As such, many consumer credit laws apply to transactions related to the provision of health care. Examples of these include, but are not limited to the Fair Debt Collection Practices Act, Fair Credit Reporting Act, the Consumer Credit Protection Act, and the Equal Credit Opportunity Act (Hales, 1989). The literature in the field of credit scoring gives special emphasis to the Equal Credit Opportunity Act (ECOA).

The development of credit scoring as a consumer finance tool will be reviewed along with recent developments in its maturity and technological advancement. However, application of consumer credit scores to the health care industry in evaluating the collectability of an account was not found in the literature.

Due to the absence of published studies, the opportunity to evaluate the predictable resolution of a patient's hospital account based upon a consumer credit scoring process provides beneficial information that may be used by health care financial managers to support bad debt estimates and to forecast cashflow. Having a reliable source of predicting a bad debt account would assist health care managers proactively manage their business and, ultimately, their profitability.

II. Review of the Literature

Health Insurance

The purchase decision associated with any non-medical consumer item may include concern for price or financing; however this is not the case with regard to the purchase of medical care. With non-medical items, if there is a problem with price or financing, the purchase may be deferred. Feldstein (1993) suggests non-essential medical care might be deferred, and thus is comparable to a non-medical purchase. However, most health care can not be deferred. The lack of perfect knowledge by consumers of health care places the consumer in a position of reliance upon doctors to provide expert advice. Thus, as Donaldson and Gerard (1993) suggest the suppliers of health care are able to influence demand for that care.

Consumer moral hazard is an economic concept important to the understanding of behavior associated with the purchase of medical care. Consumer moral hazard as defined by Donaldson and Gerard (1993) arises when the financial cost of providing medical treatment is reduced to the point that being ill is not a condition to be avoided. Essentially, this means the patient is more willing to seek medical care if the cost of getting that care is low. With

minimal, if any, out-of-pocket cost, the patient will freely agree to any treatment without regard to its cost.

Consumer moral hazard, states Donaldson and Gerard (1993), has typically been countered in the following ways: use of co-payments or user charges, whereby the insured person pays some fraction or absolute amount of the supplier's charge. Other ways identified to counter consumer moral hazard include a fixed periodic per capita payment by consumers to the providers of comprehensive health care, such as a health maintenance organization (HMO) or incentives for consumers to obtain care from selected providers, as in the case of preferred provider organizations (PPOs). Additional ways of addressing moral hazard include placing financial limits or financial caps on insurance coverage and rationing care, which usually results in consumers incurring waiting costs for elective treatment.

Medical care is financed primarily through taxation and insurance, and from direct out-of-pocket expenditures. This financing is done through prepayment (taxes and insurance) or payment is made by the patient upon receipt of services.

The Health Care Financing Administration (Levit et al., 1996) reports private health insurance as a pre-payment method only pays about one-third of the average family's medical bills. Most families or enrollees in pre-payment plans do not have full coverage, which means they must pay a deductible, before any insurance benefits are paid to the

provider. Also, many policies have a co-insurance provision, whereby the enrollee pays a part of the bill and the insurance pays the rest. If the policy coverage is limited to only certain expenses and services, the enrollee would be required to pay the full cost of care in excess of these limits. While Acs and Sabelhaus (1995) report the percentage of out-of-pocket expenditure was 30.1% in 1980, the Health Care Financing Administration calculates these types of out-of-pocket payments represent more than 21% of the total personal healthcare expenditure in 1994. Despite the reduction, this direct outlay of funds by the patient remains substantial.

Cost-sharing, or co-payment schemes and deductibles were introduced by insurance companies to combat the problem of consumer moral hazard. Essentially, the aim of this practice is to place some financial burden on the consumer to eliminate or at least reduce unnecessary use of health care. Donaldson and Gerard (1993) indicate that co-payment schemes differ, but take four (4) main forms: (1) a flat charge for each unit of service; (2) co-insurance (the insured individual has to pay a certain proportion of each unit of health care consumed); (3) a deductible, or, (4) a combination of the last two.

Co-insurance or percentage participation aligns the interests of the patient or insured with that of the insurer. Feldstein (1993) advises that a co-insurance

clause in a health insurance contract requires that the insurer reimburse the patient for a fixed percentage of the loss. This means that as the price of medical care increases so will the portion paid by the patient. Feldstein further states this co-insurance clause can stipulate that as much as 20% of the charge for services be paid by the patient. The deductible represents the first dollars paid for services rendered. The deductible provision according to Feldstein may eliminate losses from small claims, but as a ratio of personal income, deductibles can be a substantial expense.

The alignment of the interests of the insured and insurer has been effective. Donaldson and Gerard (1993) state that introducing cost sharing does result in reduced utilization of health care relative to free care at the point of delivery. Effective treatments as well as trivial or placebo care utilization is reduced by low-income groups.

Patient participation in the cost of health care may not be limited to the co-payment, co-insurance or deductible. Feldstein (1993) indicates insurance companies may impose indemnity limits and cap their financial responsibility. If the patient's condition is severe and the required care is catastrophic in nature, the out-of-pocket cost to the patient may be substantial.

The cost of medical insurance premiums in addition to the cost of deductibles, co-insurance or co-payments have caused many patients to be uninsured. As identified by Donaldson and Gerard (1993), adverse selection may result in higher-risk groups (typically those with lower-income, the elderly and the chronically ill) paying higher experience-rated premiums to maintain coverage, which they may not be able to afford. As a result, these people may be left uninsured. Harris (1975) points out that deductibles, co-insurance and limits on insurance coverage reduce the attractiveness of medical insurance. Patients may be forced to use credit financing for the purchase of health care, if it is available. Hospitals are faced with the dilemma of providing treatment to these uninsured and underinsured individuals and then securing payment.

Consumer Credit

The basic theory of credit has remained the same over the centuries and continues today: lenders rent money to those who need it (Jensen 1992; Guide to Consumer Services, 1979). Due to the long standing acceptance of these theories, fundamental consumer credit concepts have received minimal attention and discussion in recent literature. As a result, discussions of consumer credit concepts are as relevant today as twenty years ago.

Money is a commodity someone borrows, or rents, and then pays for the privilege of using. The relationship of

debtor-creditor is created out of the legal relationship known as contract (Southwick, 1988). Morganstern (1972) states even the simplest consumer transaction of necessity involves a contractual relation.

The word credit is derived from the Latin credere - "to believe." Because of the customer's believability the promise of repayment has a real, precisely measurable value. But there are clues, according to Seder (1977), to the customer's state of mind and intentions-clues to his manner, his appearance, his life pattern and, most important, in his record. There is good reason to believe that he will not permit his credit and his credit rating to be damaged by failing to pay a particular bill.

The establishment of credit or the test of ones ability to keep their promise to pay is built around a variety of considerations. These considerations involve a formula known as the three Cs of credit --- character, capacity and collateral (Guide to Consumer Services, 1979). Character is measured by such things as continuous employment in the same area for a certain length of time. Capacity is measured by a level of income sufficient to pay off the loan plus any other debts outstanding. Collateral is measured by a potential borrower's assets, such as a car, a house, savings and securities, etc..

Some institutions red-flag persons in certain occupations as potential credit risks. Among those

considered credit risks are beauticians, bartenders, foreign diplomats, dock workers, noncommissioned military personnel, taxi drivers, free lance artists, writers and musicians (Guide to Consumer Services, 1979). Seder (1977) reports the best credit risk is a solid, stable, responsible person who is conscientious about keeping his commitments and promises.

Creditors look to credit bureaus or consumer reporting agencies for assistance in evaluating credit risk. Credit bureaus or consumer reporting agencies are defined as:

"any person which, for monetary fees, dues or cooperative nonprofit basis, regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports to third parties, and which uses any means of facility of interstate commerce for the purpose of preparing or furnishing consumer reports (Morganstern, 1972, p. 38)."

Credit bureaus are recognized as one of the most important sources of information about the paying habits of consumers. Cole (1980) describes credit bureaus as clearinghouses of information which is needed by credit granters to extend credit privileges promptly and with knowledge of the risk.

Consumer credit reports are, of course, a prime measure of one's personal integrity and financial dependability. If properly made and maintained as to their accuracy, these reports can be a measure of whether or not one can handle his financial obligations conscientiously. The term "consumer report" appears in The Fair Credit Reporting Act many times and means any written or oral communication provided by a consumer reporting agency (Morganstern, 1972). These reports pertain to credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics or mode of living. The information is to be used or expected to be used, or collected in whole or in part for the purpose of serving as a factor in establishing the consumer's eligibility for credit or insurance (Morganstern, 1972).

Credit reports have a high degree of reliability providing full and complete information, but not 100%. The accuracy and completeness of the information from which a report is prepared will determine the accuracy and completeness of the information provided to the creditor. The best thing a credit report can provide is that there has been not bad credit behavior in the past. Credit checking is necessary and important, but it offers no guarantees of payment to the creditor into the future. Seder (1977) states, even if everything is known about the customer from all available sources concerning the present circumstances

and his past record, the future will still be uncertain. People change and circumstances change. While a good past report provides a strong indication about the future behavior, extending credit is still taking a chance (Seder, 1977).

It is important to note that not all information obtained from the customer can be used in the credit granting decision. For example, Congress passed the Equal Credit Opportunity Act (ECOA), which became law in October 1975. The ECOA bars lenders from discriminating against borrowers on the basis of sex or marital status. Amendments to the ECOA also prohibit credit discrimination based on race, color, religion, national origin, age, receipt of income from public assistance programs and good faith exercise of rights under other Federal consumer protection laws, such as Fair Credit Billing and Truth-in Lending (Guide to Consumer Services, 1979). Only conditions relative to the customer's ability or past history of repayment may be used.

Under the Fair Credit Reporting Act, as reported by the Guide to Consumer Services (1979), the customer rejected for credit because of a credit bureau report is entitled to have the name and address of the credit bureau providing the report. Upon request and proper identification, the credit bureau must tell the customer "the nature and substance of all information" in its file, except for medical information

and must give the source of that information. In addition, the Guide to Consumer Services (1979) states credit bureaus must give the customer the list of those getting the report in the last six months and must reinvestigate any information which you say is incorrect or incomplete. Any incorrect or unverifiable data must be fixed or deleted.

Medical Care and Consumer Credit

A medical disability may result in a family becoming a large-scale health care consumer. Medical expenses associated with a disability due to illness or injury may well exceed the family income. Without the financial assistance provided by health insurance or other sources, the disabled person's credit may crumble and force the patient into bankruptcy. Acs and Sabelhaus (1995) indicate that consumers demonstrate their fear of credit problems and bankruptcy by purchasing more insurance for protection.

Large purchases on installment credit have become a way of American life. An important factor working against payment from the patient for medical care (post-payment) is that illness is usually an uncertain event and can not be planned as other purchases (Jacobs, 1991; Harris 1975). When a person becomes disabled and they are not covered by insurance, payments due on automobiles, refrigerators or televisions may not be made. Acs and Sabelhaus (1995) report that medical care purchased using out-of-pocket funds

compete for the same dollars used for the purchase of other goods and services from a limited income.

Unlike other business establishments, medical providers, specifically hospitals, are in a difficult position to deny credit. Generally, unless the services to be provided are elective, the hospital is obligated to render some services prior to evaluating the individual's financial capability for payment. Whatever the circumstances, the decision to purchase essential medical care on credit is a decision made after service is rendered. Purchasing medical care on credit reflects the option of distributing the cost of services received over time. As a result, Harris (1975) suggests offering of credit is not integral to the purchase of the medical service itself.

Assessing a patient's credit prior to treatment would not apply in hospital emergency departments (Sprinkle, 1995) as a patient's medical condition must be assessed prior to evaluating the patient's ability to pay. Applying the fundamentals of consumer moral hazard, this lack of credit assessment and, ultimately, the hospital's offer of credit may encourage patients to spend more and emergency department doctors to order more.

In contrast and for some patients, Donaldson and Gerard (1993) predict credit financing may discourage the use of unnecessary procedures. Credit financing of medical care is advantageous for post-payment of a short-term debt incurred

for a minor disorder. An advantage of credit financing in inflationary periods is that with credit terms fixed, rising income over time reduces the burden to the patient of financing medical care (Harris, 1975). In other words, the debt will remain constant while inflation increases income, as a result the proportion of income consumed by the debt decreases making the burden less for the debtor.

Since the income gap between the rich and the poor is increasing over time, even with a growing gross domestic product, the credit position of the poor is unlikely to improve in absolute terms without federal intervention. Jacobs (1991) reports the largest portion of those uninsured are working for small, low-wage firms. Low wages means less surplus cash which translates into less opportunity for post-payment for unexpected medical care. Therefore, knowledge of the patient's past behavior and commitment regarding credit and other financial information is important to a health care provider.

Hospital Finance

The management of accounts receivable is a complex problem that does not begin when the patient is discharged but rather with the preadmission process and continues until the account is paid or written-off as a bad debt.

"Hospitals are by necessity in the credit granting business. A hospital, even if well managed, can typically expect to hold about 25% of its total

assets and 75% of its current assets in accounts receivable. Thus, credit granting is an intrinsic and unavoidable operational fact of life for hospitals (Berman, Kukla, Weeks, 1994, p. 347)."

As such a significantly large element of current assets, accounts receivable also represent a major segment of working capital. The term "working capital" refers to both the current assets and the current liabilities of a health care organization (Neumann, Suver, Zelman, 1988). The challenge in the management of working capital is to ensure sufficient working capital to meet the financial obligations. One of the primary tasks of working capital management is to minimize delays in converting receivables into cash.

There are three costs incurred by a hospital organization as a result of delays in converting receivables to cash: (1) carrying cost or opportunity cost; (2) routine credit and collection costs; and (3) delinquency costs (Berman, Kukla, Weeks, 1994). These costs are reduced by a rapid cash conversion cycle.

Opportunity cost is equal to the return that could have been obtained if the funds were invested in some other alternative investment. In the case of accounts receivable, monies collected could have been invested in marketable securities or used to reduce a need to borrow funds. Possible loss of interest revenue from marketable securities

as well as interest expense for funds borrowed to meet daily cost of operation would be an opportunity cost.

The second classification of cost is the routine cost of collection and credit. These are operating costs associated with the fact that credit has been extended. For example, a hospital would have the cost of labor and supplies required to bill insurance companies, make adjustments for discounts, send statements to patients and follow-up on unpaid, unresolved accounts.

The third cost is delinquency cost, which naturally arises due to the uncertainties in the credit screening and granting process. Not all patients pay their bill on time and some do not pay at all. These accounts are referred to collection agencies and lawyers for collection. The expenses associated with the pursuit of these special accounts would be identified as the delinquency costs.

The billing of patients and the collection of payments under cost-sharing schemes, checking against fraud, etc., would likely be administratively expensive (Donaldson and Gerard, 1993). The value of this expense or cost of collection must be weighed against the potential loss due to a bad debt account. A cost-benefit analysis would provide necessary insight to the value of such an effort.

Environment and Industry

It is not unusual for lenders to retain only information from approved applicants. Without the data from

rejected applicants, Friedland (1993) reports the developer of the credit score process cannot collect a sample that represents the entire population of interest by inferring the performance of the unbooked applicants. Such a bias in the data may be a problem for a retail or other commercial establishment, but much less of a problem for a hospital emergency department as non-financial, medical criteria is usually the overriding consideration.

In a hospital environment a credit application and resulting score may be influenced by the Emergency Medical Treatment and Active Labor Act, which is part of the Consolidated Budget Reconciliation Act (COBRA) of 1985. COBRA prohibits "patient dumping" which is the transfer, discharge or refusal to treat a patient with an emergency medical condition or a woman in labor, on the basis of the patient's inability to pay (Sprinkle, 1995).

Following COBRA guidance means that the use of the Beacon score or other credit rating systems would not be a legal measure to reduce bad debt expense in a hospital emergency department prior to treatment or medical assessment. The use of this information would be most productive in approaching the patient for payment following discharge, or after the provision of triage care determining the condition is not an emergency.

Credit Scoring

There are two categories or types of systems that may be employed by lenders to evaluate applicants for credit. One system is referred to as a judgmental system. A judgmental system relies on the subjective judgement of experienced decision makers who evaluate each applicant on an individual basis in light of the experience accumulated by the decision-maker and his profession. The other type of system employed to predict repayment by a credit applicant is credit scoring. Schrader (1992) points out that credit grantors often use a combination of credit scoring and subjective judgement to make credit decisions.

The process of modeling the variables important in the extension of credit is referred to as credit scoring. Cole (1980) notes credit scoring provides credit grantors with the ability to grade prospective customers and to calculate the risk of extending credit. Many firms use credit scoring to determine the credit worthiness of their customers. This scoring process takes many forms depending upon the industry. For example, large commercial purchases by a firm may involve a specific inquiry to other vendors for references or negotiation relative to the principal value of the loan to the value of the item being purchased.

Three types of scoring products are available to credit grantors. The purest forms are application, behavior and credit bureau scoring. In some organizations these may be

combined or used in conjunction with one another; however, the source of the information evaluated provides distinctions among types.

Application scoring evaluates information on a consumer's application and a credit bureau report using characteristics that are relevant in predicting repayment. By assigning numerical values to each possible answer to selected questions on the application and characteristics on a credit report, credit grantors can objectively and consistently decide to grant or deny credit or to obtain additional information. Credit scoring of this type is used in revolving accounts (credit cards), installment loans (automobile loans) and open-ended lines of credit (cash reserve/checking overdraft protection) (Friedland, 1993).

Behavior scoring results from data analyzed from the customer's purchase and payment history with the credit grantor. Using data processing equipment, behavior scores interface with the account billing system and re-calculate scores on each customer monthly. This information is used by credit grantors to change credit limits of a customer, reissue credit cards, authorize transactions or prioritize collection activities. Based on this, Radding (1992) identifies the focus of most credit scoring innovation as behavior scoring.

Credit bureau scoring relies upon information from a consumer's credit report obtained from a credit bureau using

characteristics indicative of future payment behavior. Credit bureau scores reflect the customer's performance according to Radding (1992) with multiple credit accounts across multiple lenders. Thus, they are a superset of what the bank's own behavior score might be.

Credit bureau scores are, by nature, pooled scores. But, they are not ideally suited for use on application scoring because they do not take into account information from the credit application. Radding (1992) advises that the credit bureau score reflects only performance making it more like a behavior score than an application score.

Despite the lack of suitability, some characteristics of credit bureau scoring may appear in behavior as well as application scorecards. Because they are general scorecards developed using the experiences of many credit grantors, scores should be tracked against the credit grantors' decision-making processes for the scores to be most valuable. From this tracking, score distributions with associated odds can be configured and a cut-off score chosen to match acceptable levels of risks for credit grantors' business strategies (BEACON User's Guide, 1993).

Credit Scoring - The Purpose.

The appeal of credit scoring is its effectiveness, consistency and manageability (Radding, 1992). Credit scoring can play an important role as a critical strategic weapon in acquiring customers and servicing, maintaining and

managing the accounts (Jost, 1993). Jensen (1992) explains this is done through (1) lower processing cost, (2) improved credit control, (3) racially and ethnically non-discriminatory lending, (4) ease in adjusting credit standards and (5) faster credit approval decisions.

The primary purpose of a credit scoring system as Jensen (1992) demonstrates is to develop an indicator that will help to distinguish between good and undesirable accounts and relies on statistical techniques rather than subjective judgment. As a statistical tool there are two dimensions for evaluation of accounts. Brennan (1993) notes one of the dimensions is revenue and the other is risk.

Leonard and Banks (1994) summarize the reasons for the creation of a financial credit scoring model can be summarized as follows:

1. To quantify the mechanical procedures involved in credit scoring and gain the efficiencies of application processing that come through automation.
2. To gain control of and create consistency in lending practices for the entire credit portfolio.
3. To identify the variables which are important in the credit evaluation process.
4. To improve delinquency statistics while maintaining desired approval rates.

Credit Scoring - The Process.

Each scoring model is based upon its own unique mix of financial ratios and weighting factors. Therefore, Miller (1994) states varying conditions will produce differences in relative credit rankings from one model to the next.

Credit scoring relies upon proven statistical principles to determine the probability that a consumer will repay as agreed. A typical credit scoring system assigns points to certain characteristics that are deemed an indication of credit worthiness. Cole (1980) explains the points are added together to determine an applicant's score. A particular score must be measured against the standards of certainty of payment and found acceptable or unacceptable on the basis of the standards established by the credit policies of the firm (Cole, 1980).

Based on statistical analyses of historical data, certain financial variables are determined to be important in the evaluation process of the customer's financial stability and strength where the different variables are assigned different weights. An overall score is produced by adding these weighted scores (Leonard & Banks, 1994).

The first and often very time consuming process in any scorecard development must be the collection of suitable historical data (Credit Scoring: Setting Standards, 1992). A sample that is not representative of the population to be scored will result in a scorecard of limited reliability

regardless what technology is used for the development (Credit Scoring Development, 1993).

Selected applicant characteristics are then used as independent variables in discriminant or multivariate regression analysis which establishes the weights or scores for each characteristic. The shape, depth and availability of data play an important role in developing a credit scoring model. Generally a large random sample of known "good and bad" accounts is used to develop the model based on the actual applicant characteristics at the time the loan application was made. These statistical techniques require fairly large samples of good and bad loans to insure reasonably high predictive accuracy. For example, Jensen (1992) shares one typical study of 600 loan applications achieved a 73.7% correct classification using an 8-variable formula derived using stepwise regression.

Scoring systems may incorporate information on as few as 5 or as many as 350 characteristics. Cole (1980) reports credit scoring systems are developed by evaluating a pool of recently accepted and rejected applicants to determine the common characteristics of both good credit risks and applicants who subsequently defaulted or were slow to pay.

Schrader (1992) identified factors that have been used in various credit scoring systems are:

1. Income
2. Occupation

3. Time in job
4. Number of jobs currently held
5. Home ownership
6. Time at residence
7. Residence location
8. Amount of debt and debt ratio
9. Percentage of balance to available credit line
10. Ratio of amount of revolving credit to amount of installment debt
11. Type of credit references
12. Age
13. Credit bureau/delinquent history
14. Number of times recently applied for credit
15. Type of bank accounts

According to Friedland (1993), credit grantors avoid income information whenever possible because most applicants (1) misrepresent their income, (2) they confuse gross income with net income and (3) commissions or child support make income determination unreliable.

Schrader (1992) asserts any factor in a credit scoring system must be highly statistically correlated with repayment. Generally, a professionally contracted credit scoring system employs only factors that have an extremely high correlation with repayment. Harrington (1992) shares the most commonly used variables used are (1) debt ratio,

(2) number of credit inquiries, (3) number of accounts paid off, (4) number of outstanding accounts, (5) total monthly income, (6) employment tenure, and (7) number of payments 30 days late.

Credit scoring systems assign points for such applicant characteristics as income and job status, combine these with credit bureau information and produce a score that determines whether an applicant will be granted credit and how much. Most credit grantors set cut-off points for automatic acceptance and automatic rejection. Jensen (1992) points out that the definition of cut-off levels is quite complex because the scores of good and bad loans usually overlap. The region between these two scores is sometimes left to the judgement of a credit manager.

It is accepted within the credit industry that once a scorecard has been developed, it should be validated against an unbiased data sample (Credit Scoring: Setting Standards, 1992). One of the most important analytic decisions to be made is selecting the sample to be used (Credit Scoring Development, 1993). An institution needs 10,000-12,000 outstanding accounts to create its own statistically valid scoring model. Harrington (1992) advises that a large number of accounts is needed to determine the characteristics of a lender's good and bad borrowers.

In summary, Friedland (1993) offers the basic process of developing a credit score system:

1. Determine the portfolio of business to which the scorecard will be applied.
2. Define good and bad performance measures.
3. Gather and analyze information on applicants in the different performance categories.
4. Determine the set of predictors to be included in the scorecard with associated score weights via the use of score weights development algorithms.

Credit Scoring - Interpretation.

The scoring or grading should result in a prediction of future credit experience. Predication, or forecast, of future credit experience should reflect the best possible overall judgement considering all the evidence at hand. Cole (1980) suggests scoring or grading is recommended as a device which would assure that all pertinent factors are considered and would avoid undue influence by a single especially favorable or unfavorable piece of evidence. Inherent to credit scoring is objectivity and consistency.

According to Brennan (1993), these scores correspond to probabilities that translate into the possibility a given account will be a bad risk. As a group, people with scores in lower ranges statistically demonstrate greater risk of not paying as agreed than those with scores in higher ranges. For example, if possible credit scores range from 100 to 500, those with a score of 200 are less likely to pay than those with a credit score of 350.

Each scoring model according to Miller (1994) serves to structure the credit screening process, but no single numerical result can be considered the definitive answer for any but the most obvious credit decisions. A fundamental assumption in building a credit scorecard is that "history repeats itself" (Credit Scoring: Setting Standards, 1992). For an individual applicant, the scorecard is only a probability ranking based on the past credit record and characteristics of the applicant. Yet, no credit profile remains stable. Brennan (1993) shares the loss of a job or a spouse or other major life change can change future spending and paying behavior.

In concept credit scoring is simple. In practice, it is complex. Based on experience, it is possible to assign numerical scores to various characteristics of a potential borrower, those supplied by the borrower, those derived from the borrower's status, and those supplied by outside agencies such as credit bureaus (Brennan, 1993).

Difficult as it may be to set exact standards and intangible as this concept may prove to be, Cole (1980) states it is necessary in the daily operations of any credit department to compare specific cases against the standards established and accept those which meet those standards and reject those which are regarded as substandard. Miller (1994) advises the ability to understand the causes of a current or prospective customer's numerical rating, whether

comparatively strong or relatively weak, is essential to develop effective credit strategy.

Developers of experience-based scoring systems have made an important contribution to credit analysis by focusing attention on the key financial ratios that have proved their value in the decision-making process. Nevertheless, Miller (1994) explains the ability to identify the underlying causes of mixed or unfavorable numerical ratings and to exercise appropriate judgement about a customer's fundamental financial condition are the key skills continuously cultivated by credit professionals. Often times, it is the "it doesn't feel right" response on the part of the analytic reviewer that leads to an investigation to uncover underlying problems in the data (Credit Scoring Development, 1993).

Building a scorecard is as much an art as it is a science (Credit Scoring Development, 1993). The best scorecards combine the in-house expert's understanding of credit issues with the analytic experience in scorecard building that will be effective operationally (Credit Scoring Development, 1993). The problems with the in-house scorecard building process include the lack of specific expertise; the unavailability of personnel to train and, the hidden cost due to lengthy processing. (Credit Scoring: Setting Standards, 1992).

The objective is to breakeven for all accounts approved in the cut-off score range. Any accounts booked above this score will be profit generating on average. Identification of the cut-off score requires a fairly accurate estimate of the number of "goods" it takes to cover the losses from one "bad", which often falls in the range of five good to one bad. As a result, Leonard and Banks (1994) note credit scoring directly affects the delinquency or profitability of the portfolio that has been analyzed.

Current trends include supplementing traditional, internal scores, with external scores obtained from the major reporting bureaus. The bureau score provides a broader view by incorporating all the other credit accounts belonging to that customer (Robins, 1993b).

Most factors according to Schrader (1992) appear to have some common sense relationship to the likelihood of continued financial stability or the future ability to repay. The score model generally predicted a simple binary outcome, such as good or bad loan. Jost (1993) suggests forcing scoring models into dichotomous outcomes ignores the fact that there are at least four possible loan results: good, delinquent, charge-off and bankrupt.

The problem with credit scoring as identified by Harrington (1992) is that rather than being a tool, it becomes the decision maker. Collection scores predict the probability of a collection effort against the possibility

that a delinquent account will be successful. Recovery scores predict the probability that a bank will recover money from an account that has already been charged off. Radding (1992) points out that a bankruptcy profile looks different from the delinquent person's profile. There is a need for balance using professional judgement and evaluation as well as the objectivity of credit scoring. Before credit scoring, Jensen (1992) indicates that the traditional judgmental credit procedures were inherently subjective, as credit officer's past experience and the consideration of the evidence were done sequentially rather than simultaneously. The credit officer's judgement would be focused on predetermined and uniform credit factors. Further evidence of subjectivity was that the credit officer's assessment was not limited selected criteria, and the weight attached to any given factor is generally not predetermined (Schrader, 1992). Facing the problems of business volume of achieving margins and reducing bad debt, credit managers must turn to scoring systems for answers (Credit Scoring: Setting Standards, 1992). However, Harrington (1992) asserts human judgement will never be completely displaced from lending decisions.

Credit Scoring - Neural Models.

Neural computing has been a relatively small and obscure branch of the larger computer field known as artificial intelligence. This is opposed to another branch

of artificial intelligence called expert systems, where the knowledge of a human expert is captured and encoded into the logic of a computer system. The neural computing technology was inspired by the way neurological systems work, but has nothing to do with actual biological processes (Robins, 1993a).

Unlike expert systems, neural networks do not require the user to specify a number of "if-then" rules. The network only requires specific examples of input values along with the corresponding output values. Jensen (1992) reports the network determines rules that work for the specific examples.

On one hand, expert system technology has proven highly successful in solving problems where the rules for decision making are clear and the information is reliable. On the other hand, Jensen (1992) indicates that neural network software is now acknowledged as a viable means for reaching conclusions in situations where explicit decision rules are obscure or nonexistent and information is partially correct.

In reality, the neural network is a statistical technique for getting a close approximation to a solution for a particular problem. The difference between a neural-network approach and the traditional approach is that a neural network does postulating and testing automatically (Robins, 1993a). As a statistical technique, Jost (1993) reports a neural network calculates weights (score points)

for predictor characteristics (e.g., income, time on job) by "self learning" from data examples (e.g., good and bad loans). Neural networks learn from experience, so it is continually evolving, self-correcting and self-enhancing. According to Jensen (1992), training a neural network thus consists of repeatedly presenting related input-output sets so the backpropagation algorithm can incrementally adjust the connection weights for each neuron. Neural networks do not require an expert, just many examples in the form of data (Robins, 1993a).

All neural networks consist of layers of interconnected neurons. A simple neural network has three layers of neurons: input, hidden and output. The hidden layer forms an internal symbol set to represent concepts. Jensen (1992) reports multiple hidden layers are used to increase the generalization abilities of the network. With the data for Jensen's (1992) study, the network converged to a solution state faster with two hidden layers than with only one. There were three possible outcomes (1) delinquent, (2) charged-off, or (3) paid-off. Therefore, the network's output layer consisted of three neurons.

The neural network model yields a score similar to that of traditional statistical scoring models. Jost (1993) points out the neural network score value has the same characteristics and utility as a score developed with traditional statistical techniques. The key advantage is

neural networks are superb at spotting aberrant patterns (Brennan, 1993).

However, there is still danger. Although a neural network will provide a solution on its own, the quality of that solution is based on the quality of the input and the implementation or structure of the network. In other words, "junk in, junk out" still applies, even to neural networks (Robins, 1993a).

The easy use of neural net technology can help put the model development in the hands of the business domain experts (Jost, 1993). Building a neural network capable of analyzing the creditworthiness of loan applicants is quite practical and can be done easily according to Jensen (1992). In the past, it was called a scorecard, but today it is a decision system. The scorecard name as Jost (1993) suggests is a single-purpose tool delivered on paper, while decision system suggests a multi-purpose business support tool integrated into the automated computer environment.

Credit Scoring - Legal Considerations.

Credit scoring applications are a fast, mathematical way to infer the creditworthiness of an applicant. Brennan (1993) states such scoring is a strong defense against would-be litigants who might read bias into credit denial. The regulatory guides issued to date indicate that a credit scoring system may be easier to defend against such a challenge than a judgmental system (Schrader, 1992).

However, fear of litigation has slowed credit scoring systems' evolution. Artificial intelligence and neural networks, which learn from new data and past mistakes by detecting patterns in data, have not become as widespread as once anticipated because technology deviates from the norm. Merrick (1994) explains deviation attracts examiners' attention. Schrader (1992) expects credit scoring practices will be closely scrutinized in the future to determine whether the effect of such practices is to disproportionately deny credit to minorities.

Under the circumstances, Schrader (1992) continues, lenders employing credit scoring systems may need to obtain an expert's assurance that the system application and construction, is consistent with accepted statistical principles and methodology. When the system has been obtained through an external vendor the lender may want some form of written assurance to that effect from the vendor.

Any assault on credit scoring would be brought under the so-called "effects test" or the "disparate impact" doctrine developed under Title VII of the Civil Rights Act of 1964, as amended (Schrader, 1992). A number of different factors employed in credit scoring systems have been noted by regulators as being susceptible to challenge under the effects test. Schrader (1992) cites for example factors such as zip code or location of residence as these factors may be used to discriminate.

The Equal Credit Opportunity Act (ECOA), however, permits the use of a factor that has a disproportionate negative impact on minorities or females where the factor is demonstrated to meet " a legitimate business need that cannot reasonably be achieved as well by means that are less disparate in their impact." (Schrader, 1992).

The ECOA regulations provide that a creditor may initially purchase and use a system developed and validated on another lender's data. Even systems which are periodically "validated" may not escape this problem, notes Schrader (1992), unless the validation includes consideration of a much fuller range of personal financial characteristics which are in effect "class blind."

Guidelines of the Federal Trade Commission (FTC) require the consumer be told the basis of the credit denial. The FTC also requires that the consumer be provided with a simple explanation of the score's meaning. With neural credit scoring the score reported by the system would be applied to a credit grantor's standards. The question remains, according to Radding (1992), what explanation can the credit bureau give for credit denial as the credit bureau did not make the credit decision?

With neural credit scoring, the score reported would change with each new inquiry based on the level of reported credit activity. If the current score is to be given out, Radding (1992) states, it will obviously not be the same as

the score calculated when credit was denied. The score given to the bank no longer exists and could not be used anyway. The score is just a number. It does not mean anything by itself, but only has meaning in the context of the credit grantor's cut-off score.

Credit Scoring - Cautions.

Although statistical techniques, such as multiple linear regression and logic regression, play an important role in traditional scoring model development, Jost (1993) identifies several weaknesses in these statistical models which limit their effectiveness as long term decision tools. First, statistical models are manual and labor intensive process which requires specialized education, training and experience. Second, traditional score development procedures are not well suited for solving complex problems with more than two outcomes.

For example, factors like seasonality, inflation or blank application details can introduce questions of validity and reliability to the data and influence its effectiveness. As a result, a new statistical model needs to be developed each time they want to examine the influence of an additional complex characteristic. This is generally avoided and therefore, there is criticism for the lack of understanding and creation of "standard" scorecards. (Credit Scoring: Setting Standards, 1992). It is for this reason the development of computerized scoring models are more

popular to ease the burden of changes in the model creation process.

Credit scores have become the latest target in the ongoing disclosure skirmishes between the credit industry, consumer advocates and regulators. A credit score measures the likelihood that a borrower will default based on the pooled information in a credit report at the time the credit grantor gains access to a file. Radding (1992) indicates that the credit score, based in scorecards developed by credit scoring consultants for computer application, is usually recalculated each time a change is made to a borrower's file. Past credit scores are not saved. As stated before, this presents a serious legal issue should credit be denied based upon this score.

Another influence on a credit score would be the effort of prior creditors to collect the money due them. Harrington (1992) suggests a borrower with a good capacity to repay can be rejected by a scoring system simply because a previous lender made little effort to collect. In this instance the credit score is equally a reflection of the creditor's billing and collection process as it is of the debtors ability to pay.

Credit Scoring - Customized Models.

Generic credit scoring portfolios do not reflect the unique differences or needs of one creditor versus another. Harrington (1992) advises that the generic systems are not

as accurate in predicting applicant behavior as a customized system. Traditional statistical model performance depended upon the skill and experience of the model developer. However, Jost (1993) points out credit scoring statisticians seldom have the business domain experience and special customer knowledge necessary to design the most appropriate model for a particular industry.

Consequently, the trend within the finance industry is towards in-house score card development, which would reflect the input of those with the best understanding of the credit portfolio (Credit Scoring: Setting Standards, 1992). This trend has been supported by the flexibility and availability of personal computers and communication technology. With the purchase of a personal computer and a modem credit scoring would be available to the smallest business entity. In addition, assessment of that score would be sensitive to that entity.

Programs containing the scoring algorithms reside on a credit bureau's computer. In the on-line mode, each time a credit grantor requests a credit report, the score is dynamically calculated on information contained in the credit report at the time. On-line scoring is particularly appropriate for credit grantors who do not have portfolios which enable or justify a custom solution, do not have data processing capability to support a custom solution or simply

wish to supplement a customized system (BEACON User's Guide, 1993).

Custom scorecards are built for a specific use and they are usually developed using the specific credit grantor's experience with its customer base. Jost (1993) explains that scoring models are constantly developed and modified or redeveloped to reflect changing customer and competitor trends. Development time, using these new tools, is reduced to a matter of days or weeks instead of months.

The development of a credit scoring model typically costs between \$50,000 and \$100,000. Both the type of loan and the requirements of the creditor must be considered. In one case, Jensen (1992) describes an expert system with more than 2,000 rules were built into it to aid in the evaluation of loans. Although this may appear costly, this initial investment must be weighed against potential costs of bad debt. As Harrington (1992) recommends customized in-house scoring models be redesigned after four to five years to adapt to applicants' changing characteristics, ongoing maintenance costs must also be considered.

Credit Scoring - The Future.

Although the concepts, principles and procedures for developing and implementing a credit scoring model had been fully developed by the early 1970's (Jensen, 1992), credit risk prediction using a numerical formula has only been increasingly relied upon in the last decade. Lending

institutions, however, resisted credit scoring systems because of a reluctance to replace the expertise of loan officers, the known error rates for existing mathematical formulae and the absence of credit management personnel schooled in quantitative technique. Very simply, lending institutions felt that the credit granting process required human intervention.

Radding (1992) asserts there is a shift from account management and analysis to customer management and analysis. Credit scoring systems have evolved to meet the needs and challenges of increasingly sophisticated users in the dynamic and growing environment of credit granting. The scorecard building techniques introduced by Bill Fair and Earl Isaac 30 years ago no longer meet the demands of today's decision makers (Credit Scoring: Setting Standards, 1992).

Credit scoring systems have long been associated with avoiding risk. By avoiding risk, Brennan (1993) reports credit scoring systems have evolved into helping lenders predict profitability. In the past, credit bureaus have calculated and reported scores without differentiating as to which company was making the inquiry. Today, the consumer's relationship with the inquiring company is taken into account and the scoring is calculated differently based upon that relationship (Robins, 1993b).

With more accurate and complete data, sophisticated models and even multiple scorecards, banks and other creditors are pushing credit scoring techniques far beyond the original purpose according to Radding (1992). Ultimately, creditors have much of the information they need to make solid credit decisions with the assistance of computer technology.

Literature Review Summary

Health insurance plays a significant role in the financing of health care provided in a hospital setting. Its influence results in individuals receiving care with little concern for the cost. The portion of health care cost not paid by health insurance and related health care financing/delivery mechanisms (HMOs, PPOs), identified as a deductible, a co-payment, co-insurance or non-covered service, must be paid by the patient.

Credit as a normal part of a business setting is granted based upon a credit history. Services do not need to be provided or products are not required to be sold, if the applicant's record does not support the promise that payment will be made.

Credit bureaus are used by businesses to make that determination through the use of credit reports. Such reports are valuable tools, but they do not guarantee a debt owed will be a debt paid. Also, interpretation of credit reports is difficult and involves many factors.

Health care expenditures in a hospital setting can be substantial and can force a patient to declare bankruptcy. Unlike other creditors, a hospital by necessity provides services on credit with payment expected following service delivery from either insurance or some other third party and often some portion from the patient. Identified as accounts receivable on the balance sheet, this represents a substantial portion of a hospital's working capital.

Credit scoring reduces a complete credit report to one score. Although there are various names and uses, the ultimate use is to determine the probability of repayment. Having this information in advance can assist credit managers in reducing the costs associated with carrying accounts receivable and the cost of bad debts.

The use of a credit score based on valid and legal debtor characteristics removes some of the bias of a subjective evaluation. Using a credit score offers objectivity and consistency to the credit decision making process.

Credit scoring is statistically based using historical data on as many as 350 characteristics at one time. Any factor considered must be correlated with repayment. Equally important is the need for a large number of accounts to adequately provide a statistical comparison and a trend.

The probability of repayment is represented by the value of the score. However, there is still a need to

evaluate the score in relationship to the experience of a particular business or industry. One score or a particular range of scores will not necessarily be good when judged for credit across various businesses. There remains a need to evaluate the score and determine the range of scores appropriate for the particular business using that information, which re-introduces a subjective component to the use of a credit score. In application, this will mean movement of acceptable cut-off scores, as required to meet the requirements and expectations of the user. As a result, the score should not be viewed as concrete.

Credit score models have been developed as part of an artificial intelligence called neural computing. Neural model systems will self-correct and self-enhancing, while continually evolving. As with any decision making process, the neural model will only be as good as the facts it has to base a decision.

Neural credit scoring is not without critics. There is concern for discriminatory practices as certain inappropriate factors could be included in the analysis, but not be visible. Identification of discriminatory practices becomes most difficult if the scoring system is a result of a neural network process because the score would change continuously over time. Therefore, it is important that any system be validated as "class blind" in its application and use.

Without the use of personal computers, credit scoring can be expensive and time consuming. Multiple characteristics provide considerable opportunity for error. The potential for error should be known and considered as part of model development.

Generic scoring models do not provide the sensitivity to a particular business or industry that a customized model may offer. From the beginning, credit evaluation has been oriented toward the needs of the individual business evaluating the credit application. Customized models continue to offer needed attention to the special needs of the business. Customized models, however, are expensive and require a large data base of accounts to establish data ranges of good or bad scores. As a business changes, the model will need to be adjusted or redeveloped to meet the ever changing needs of the organization.

Credit scoring has come a long way over the last 20 years. The changes in computer technology will certainly contribute to better and more sophisticated credit models to generate better and more solid credit decisions.

III. Methodology

Research Design

Equifax, Inc. (formerly known as Retail Credit Company) was started by Cator Woolford in 1899. His original purpose was to report on the credit of consumers to the retail merchants of Atlanta, Georgia. As consumer credit reporting initially failed, the company focused on providing underwriting reports to insurance companies. In 1930, several retail credit bureaus were purchased by Equifax, which changed the direction only slightly as 75 percent of corporate revenues came from information services to insurance companies and only 20 percent from credit reporting and financial control (Cole, 1980).

The Beacon score was developed cooperatively by Equifax and Fair, Isaac and Company using Equifax's national database and scorecard development techniques from Fair, Isaac and Company. According to the BEACON User's Guide (1993) the Beacon score was developed by working with millions of Equifax records from May 1986 through April 1988. The pool of records represented consumer credit data from the entire United States as well as Puerto Rico, U.S. Virgin Islands, Guam and American Samoa.

The BEACON User's Guide (1993) states that statistical procedures were used to identify the most significant subset

of characteristics to determine good and bad credit performers. Bad credit performances include bankruptcy, charge-off, repossession, loan default, serious delinquency and other derogatory credit behaviors. The score development process ensured that insignificant or isolated bad credit behavior was not considered. For example, credit performance on medical and utility industry trades were discounted in the score development process.

A good classification was assigned to records displaying none of the bad credit behaviors or, at most, mild, isolated debt delinquency. The indeterminate classification pertained to records displaying neither the good nor the bad conditions (BEACON User's Guide, 1993).

The Beacon score, a neural network type of score, is dynamic reflecting the changing content of the credit file. The higher the Beacon score the lower the risk. BEACON User's Guide (1993) reports scores range from 363 to 830.

Beacon users are encouraged to validate the score on their own portfolios. BEACON User's Guide (1993) suggests two cut-off scores be chosen. One low cut-off score, below which applicants would be declined, and the other a high score, above which applicants would be accepted. A study to determine these scores is recommended after a 24 month period has elapsed.

In this study, emergency department registrations at Memorial Medical Center of Jacksonville were studied for a

period beginning December 10, 1992 through February 9, 1993. At the time the patient registered for services, data elements of name and social security number were electronically sent to Equifax. The Equifax system would then return a Beacon score, if there was a match. Of the total 1,476 emergency department registrations submitted to Equifax, 719 were matched to valid Beacon scores.

There are two reasons a Beacon score would not be matched and scores returned. Those names and social security numbers that did not have a match in the Equifax file would not return a score. A failure to match could be the result of a typographical error made in the entry of the name, the social security or both. Another reason for an unmatched file would be false information was provided by the patient at the time of registration. Incorrect information obtained may be due to the patient's state of confusion due to the emergency situation, which may simply be a matter of poor communication. Also, there may be a deliberate attempt on the patient's part to obtain care without their true identity being revealed. For example, someone may need care, but are unwilling to be responsible for the cost of the care.

Another reason a match may not be made is certain files can not be scored by Beacon. These files do not contain a trade line that has been open for six months or the trade line has not been updated in the last six months (BEACON

User's Guide, 1993). Absence of a trade line means the patient may not have established a credit file with Equifax prior to coming to the hospital for this emergency. A young patient, for example, may have only in the past five months made application for a credit card or loan.

The focus of this study is the final resolution or outcome of the patient account. Focus on the final resolution assumes that all accounts are resolved satisfactorily or unsatisfactorily. Even though some accounts reflect that charges were not paid in full, the accounts were in fact satisfied by means of a contractual adjustment, charity/uncompensated care adjustment or small balance write-off.

The research objectives of the study are as follows:

1. Determine if the Beacon score as a neural credit score is associated with the resolution of a hospital emergency department account, and
2. To determine the relationship and confidence of that relationship.

Toward these objectives the null hypothesis being tested is that the Beacon credit score and the outcome are independent. In other words, there will not be a relationship between the Beacon credit score and the outcome of the account. The alternative hypothesis is that the Beacon score and the outcome are related.

There is no opportunity to avoid financial risk in a hospital emergency department. The only opportunity to totally avoid financial risk is by denying care, but this is not an option (Sprinkle, 1995). As credit scoring is not a predictor of the health condition of the patient, it is impossible to suggest we will know the condition of the patient and, ultimately, the health care investment required from a credit score. For these reasons, the study of a credit score will not provide any information relative to the financial loss or gain to the hospital on a per case basis.

Measurement and Data Collection

All 719 accounts with a Beacon score were examined in March 1995, more than 24 months since the service was provided. Each account was reviewed to determine its final resolution. Final resolution was determined by the last transaction entered on the account that would bring the account balance to zero. All but eight of the 719 accounts had a zero account balance. Since these eight accounts had not been resolved, they were excluded from the study leaving 711 accounts remaining in this study.

The last transaction on each of the 711 accounts fell into one of six categories: (1) Adjustment, (2) Bad Debt, (3) Charity/Uncompensated Care, (4) Insurance, (5) Patient Payment and (6) Small Balance write-off. Each of these

categories reflect and describe the general nature of the last transaction. These categories are defined as follows:

Category One - Adjustment

Generally, this would indicate the account involved a payor that reimbursed less than full charges for the care rendered. When charges exceed the agreed reimbursement, an adjusting entry is made to the patient account to reflect the proper balance. If all payment was received, the account balance will be adjusted to zero.

These payors would include contracted managed care plans, Medicare, Medicaid and other government payors. Category one may also include special courtesy discounts for employees and others.

Category Two - Bad Debt

Category two applies to accounts that were determined unwilling to pay or comply with account resolution options. Such options may include a payment plan schedule or an offer of uncompensated care.

Category Three - Charity/Uncompensated Care

Category three involves compliance by the patient in submitting proper forms and other documentation that allowed for the charge to be discounted fully or in part. In the State of Florida, qualification for uncompensated care is not always

indigent status, but may include a ratio test comparing income to charges. The guidelines are specific for documenting income that some patients do not wish to share.

Category Four - Insurance

Category four identifies that the account obtained a zero balance as a result of an insurance or other third party payment.

Category Five - Patient Payment

Category five classified the account on the fact the last transaction that caused the account to have a zero balance was a payment from the patient.

Category Six - Small Balance Write-off

The sixth and last category identifies the account as having obtained a zero balance based upon an administrative decision to not pursue accounts with small balance. The value of accounts determined unworthy of further collection effort had a balance of less than \$25.00.

The distribution of the 711 accounts in each of these categories appears in Table I. The number of accounts reflecting the last transaction as being an adjustment totaled 103 or 14.49% of the total number of accounts in the study. Bad debt accounts totaled 276 and represented 38.8% of the 711 accounts. Charity or uncompensated accounts

contributed to only 1.69% of the study group with a total of 12 accounts. Insurance payments resolved 97 accounts or 13.64%, while 18.28% or 130 of the accounts were resolved by a patient payment. A remaining 93 for 13.08% of the accounts studied were written-off as small balances.

Table I

Payment Code Distribution

<u>Payment Code</u>		<u>Number of</u> <u>Accounts</u>	<u>Percent of</u> <u>Total</u>
Adjustment	(A)	103	14.49%
Bad Debt	(B)	276	38.82
Charity/Uncompensated	(C)	12	1.69
Insurance	(I)	97	13.64
Patient Payment	(P)	130	18.28
Small Balance	(S)	93	13.08

To provide a sense of the distribution of these accounts in relationship to the Beacon score, Table II presents the distribution using score intervals of ten. The first category with accounts to be recorded with two accounts within the Beacon Score range of 460 to 469. The last category was summarized as accounts with a Beacon score of 800 or more representing 27 accounts or almost 4% of the number in the study.

Arithmetic mean, median and mode were determined for each of the categories as well as the study group as a whole and presented in Table II. Although the data is presented in group form, the raw data was used in the calculations.

The arithmetic mean for the 711 accounts was calculated to be 641, while the median was 631 and the mode was 535.

In the categories of charity/ uncompensated care, insurance and patient payment and small balance write-off there was a tie in the frequency of several Beacon scores. For this reason, each of the tied scores is listed as the mode. For example, patient payment had four scores, 669, 760, 776 and 785, with highest, but equal frequency.

The Beacon score range with the largest number of accounts was 540 to 549 with 44 accounts or 6.2% of the total. The smallest number of accounts was represented by the Beacon Score range of 460 to 469 with two accounts or 0.3%.

As stated previously, the focus of this study is the predictability of a good account by using a Beacon score. A determination must be made as to which of the 711 accounts in this study represent a Good account and which represent Bad accounts. This will be determined by the acceptability of the last transaction on each account.

Five of the six categories used to classify each account's last transaction would be acceptable or Good accounts. These five acceptable categories are adjustment, charity, insurance, patient payment and small balance write-off. In each case the final transaction represented either a cash or non-cash benefit to the hospital.

Insurance and patient payments would result in positive cash benefits. Small balance write-offs also represent a positive cash benefit as the cost of carrying these accounts

is eliminated. An adjustment is made when all possible cash benefits have been received and the balance in excess of expected payments must be removed. Adjustments also eliminate carrying costs.

Charity or uncompensated care transactions do not have cash benefits. However, the hospital does receive non-cash benefit and the patient has demonstrated responsibility for the debt. Properly documented, charity accounts provide evidence of community benefit, as required of not-for-profit organizations. Further, charity transactions demonstrate patient compliance and cooperation by completing forms along with other documents to support their application for uncompensated care.

The only category without benefit is the category representing accounts with the final transaction of writing the balance off to bad debt. These accounts have not met the expected cash benefit and have a balance worthy of continued collection effort; however the patient has been non-compliant. As a result, any account written-off with a bad debt transaction as the final entry will be considered a Bad account. Accounts with the last transaction being a bad debt transaction will be considered a Bad account.

Dividing the data accordingly, Table III represents the number of bad debt accounts within the Beacon score range and the percentage of the total number of accounts within that interval range. Using the lowest and highest interval

Table III
Bad Accounts and Good Accounts within the Beacon Score
Range-Number and Percentage of Total Accounts within Beacon
Score Range

<u>Beacon Score Range</u>	<u>Bad</u> <u>Accounts</u>	<u>Percent</u> <u>of Range</u>	<u>Good</u> <u>Accounts</u>	<u>Percent</u> <u>of Range</u>
460 to 469	2	100.00%	0	0.00%
470 to 479	3	75.00	1	25.00
480 to 489	4	30.77	9	69.23
490 to 499	3	60.00	2	40.00
500 to 509	10	62.50	6	37.50
510 to 519	8	50.00	8	50.00
520 to 529	13	56.52	10	43.48
530 to 539	18	58.06	13	41.94
540 to 549	23	52.27	21	47.73
550 to 559	25	71.43	10	28.57
560 to 569	13	50.00	13	50.00
570 to 579	14	51.85	13	48.15
580 to 589	10	52.63	9	47.37
590 to 599	8	33.33	16	66.67
600 to 609	6	37.50	10	62.50
610 to 619	12	46.15	14	53.85
620 to 629	10	50.00	10	50.00
630 to 639	10	40.00	15	60.00
640 to 649	14	48.28	15	51.72
650 to 659	7	41.18	10	58.82
660 to 669	9	28.13	23	71.87
670 to 679	4	28.57	10	71.43
680 to 689	8	47.06	9	52.94
690 to 699	3	21.43	11	78.57
700 to 709	2	18.18	9	81.82
710 to 719	6	27.27	16	72.73
720 to 729	5	26.31	14	73.69
730 to 739	3	15.00	17	85.00
740 to 749	3	30.00	7	70.00
750 to 759	5	27.78	13	72.22
760 to 769	2	11.76	15	88.24
770 to 779	3	12.00	22	88.00
780 to 789	2	9.52	19	90.48
790 to 799	3	11.54	23	88.46
800 and more	5	18.52	22	81.48
Totals	276	38.82%	435	61.18%
	====	=====	====	=====

range as examples, the number of Bad accounts within the lowest range was 100% or in other words, all of the accounts

in this category were bad debt accounts. In a similar fashion, five of the 27 accounts in the interval with Beacon scores greater than 800 were Bad accounts or 18.52% of this interval was written-off to bad debt. The remaining 22 accounts or 81.48% in the Beacon score interval of 800 or greater were Good accounts.

Analysis

Brief examination of this table suggests a trend or pattern of debtor behavior. As the score increases the percentage of Good accounts within the range increases, while the percentage of the Bad accounts declines. For example, as observed within the interval from 490 to 499, the Bad accounts represented 60% of the accounts within the range and 40% were Good accounts. Yet, using the higher Beacon score values the relationship is reversed. Looking at the score interval of 770 to 779, Good accounts are 88% of the total, while only 12% were Bad accounts. Further analysis may offer more evidence of a relationship.

Due to the low frequency of observation within each of these intervals, consolidation of the interval range is recommended to improve the significance of further analysis. The chi-square test of independence was selected as the statistical tool as it is designed to make inferences about the existence of a relationship between two variables. Chi-square test of independence uses a contingency table method

of testing the significance of the relationship between two cross-tabulated variables (Polit, 1996).

The result of the consolidation resulted in 16 columns and two rows of data. Table IV reflects the consolidation as well as calculation of the expected frequencies required for chi-square analysis for each interval. The first two columns of the table represent the observed Good accounts and the calculated expected frequency of Good accounts for the consolidated interval range.

Table IV

Observed and Expected Frequency of Good Accounts and Bad Accounts within Beacon Score Intervals

Beacon Score Interval	Observed Good Accounts	Expected Good Accounts	Observed Bad Accounts	Expected Bad Accounts
460 to 499	12	14.68	12	9.32
500 to 519	14	19.58	18	12.42
520 to 539	23	33.04	31	20.96
540 to 559	31	48.33	48	30.67
560 to 579	26	32.43	27	20.57
580 to 599	25	26.31	18	16.69
600 to 619	24	25.70	18	16.30
620 to 639	25	27.53	20	17.47
640 to 659	25	28.14	21	17.86
660 to 679	33	28.14	13	17.86
680 to 699	20	18.97	11	12.03
700 to 719	25	20.19	8	12.81
720 to 739	31	23.86	8	15.14
740 to 759	20	17.13	8	10.87
760 to 779	37	25.70	5	16.30
780 to 820	64	45.27	10	28.73
Totals	435	435	276	276

The third and fourth column presents the observed Bad accounts and the calculated expected frequency of Bad

accounts for these same consolidated intervals. The relationship between the observed frequency and the expected frequency is graphically presented in Figure 1 and Figure 2. Using the mid-point of the interval ranges along the X axis, the bar graph in Figure 1 shows the greater than expected frequency at the higher score intervals for the observed Good accounts and less than expected frequency at the low end of the score intervals. Inversely, as shown in Figure 2, the greater than expected frequency for observed Bad accounts were at the low score intervals, while the less than expected frequency was at the high score intervals.

Using this information the chi-square statistic is calculated as demonstrated in Table V. Chi-square has a value of 79.23. Using a table of Critical Values of Chi-Square, a value of 79.23 well exceeds the table value of 37.70 identified at 15 degrees of freedom and a 0.001 level of significance. Based upon this computation, the null hypothesis, which stated the score and outcome would be independent of each other, should be rejected. The alternative hypothesis should be accepted indicating these two variables are related.

As further indication of a relationship between the credit score and the resolution of an account, represents the use of simple regression analysis to predict the percentage of Good accounts to be found within a credit

GOOD ACCOUNTS OBSERVED AND EXPECTED FREQUENCY

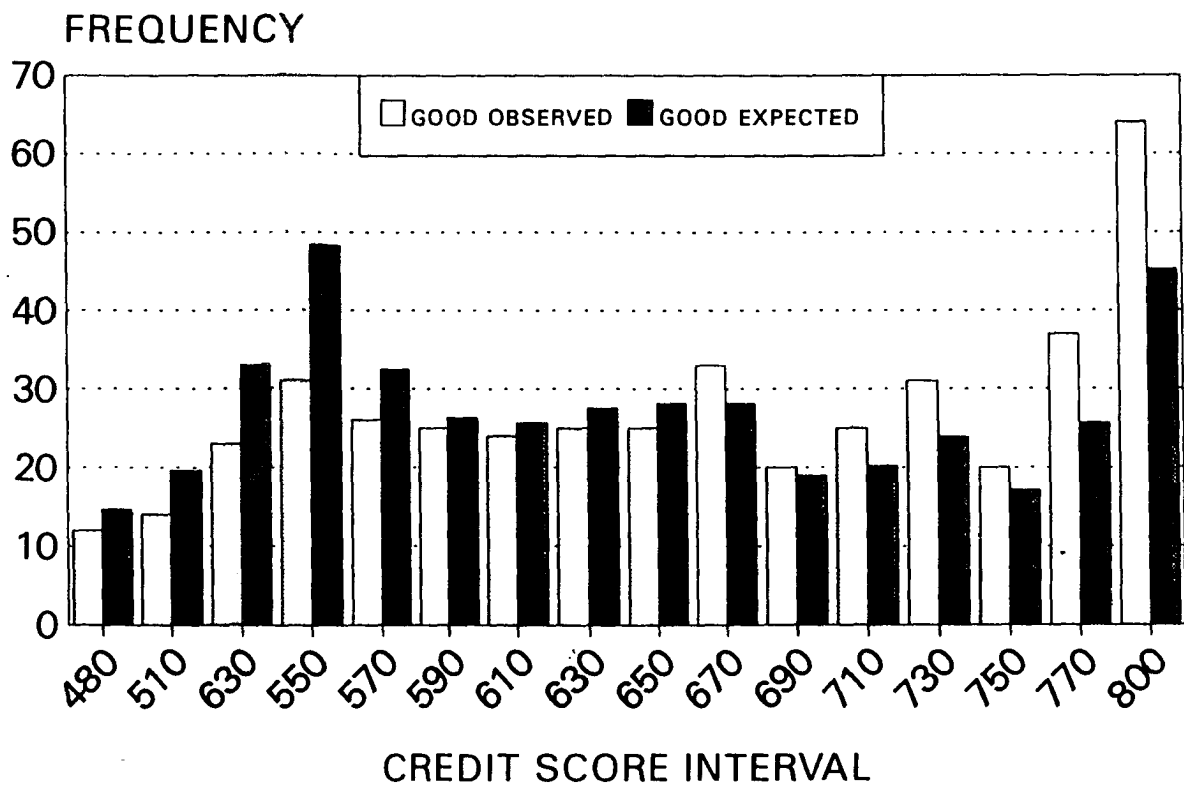


Figure 1

BAD ACCOUNTS OBSERVED AND EXPECTED FREQUENCY

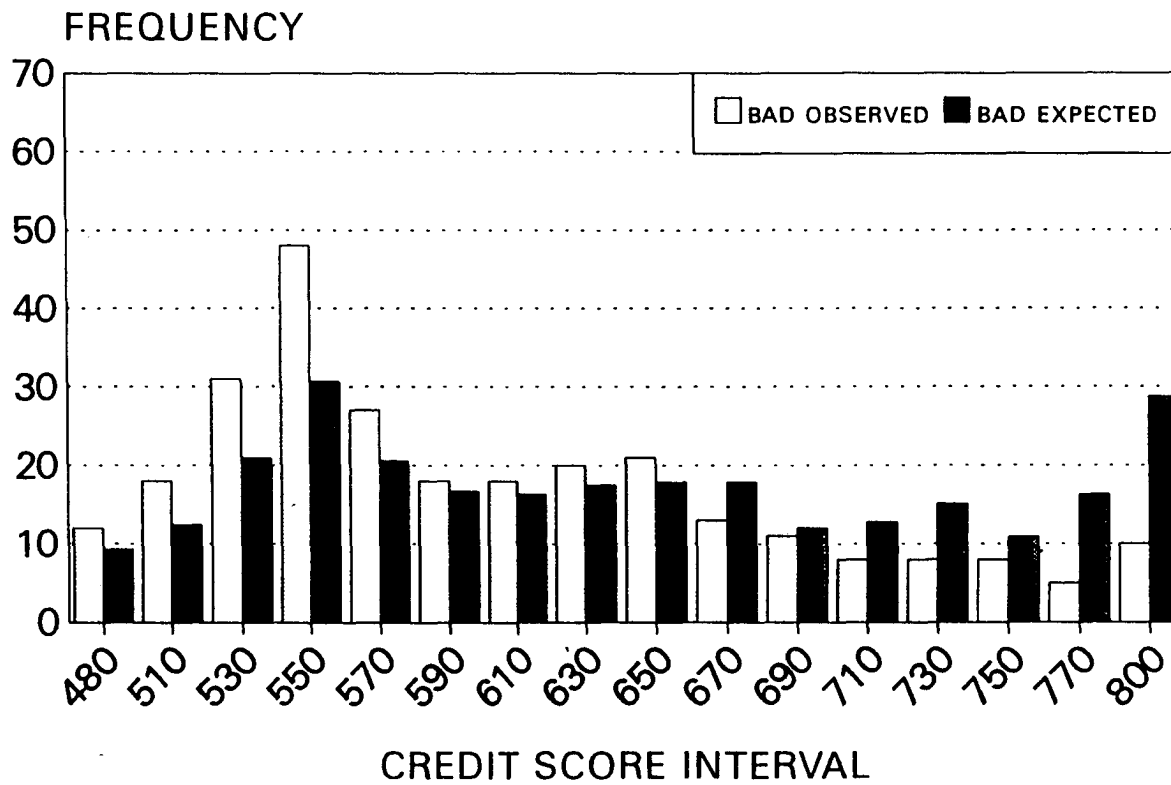


Figure 2

Table V
Chi-Square Statistic Calculation

CHI-SQUARE TEST OF INDEPENDENCE

RANGE	OBSERVED			EXPECTED			O-E	(O-E) ²	(O-E) ² /E	OBSERVED	EXPECTED			O-E	(O-E) ²	(O-E) ² /E
	GOOD	GOOD	GOOD	GOOD	GOOD	GOOD	GOOD	GOOD	GOOD	BAD	BAD	BAD	BAD	BAD	BAD	BAD
460 to 499	12	14.68	(2.68)	7.20	0.49	12	9.32	2.68	7.20	0.77						
500 to 519	14	19.58	(5.58)	31.11	1.59	18	12.42	5.58	31.11	2.50						
520 to 539	23	33.04	(10.04)	100.76	3.05	31	20.96	10.04	100.76	4.81						
540 to 559	31	48.33	(17.33)	300.44	6.22	48	30.67	17.33	300.44	9.80						
560 to 579	26	32.43	(6.43)	41.30	1.27	27	20.57	6.43	41.30	2.01						
580 to 599	25	26.31	(1.31)	1.71	0.07	18	16.69	1.31	1.71	0.10						
600 to 619	24	25.70	(1.70)	2.88	0.11	18	16.30	1.70	2.88	0.18						
620 to 639	25	27.53	(2.53)	6.41	0.23	20	17.47	2.53	6.41	0.37						
640 to 659	25	28.14	(3.14)	9.88	0.35	21	17.86	3.14	9.88	0.55						
660 to 679	33	28.14	4.86	23.59	0.84	13	17.86	(4.86)	23.59	1.32						
680 to 699	20	18.97	1.03	1.07	0.06	11	12.03	(1.03)	1.07	0.09						
700 to 719	25	20.19	4.81	23.14	1.15	8	12.81	(4.81)	23.14	1.81						
720 to 739	31	23.86	7.14	50.97	2.14	8	15.14	(7.14)	50.97	3.37						
740 to 759	20	17.13	2.87	8.23	0.48	8	10.87	(2.87)	8.23	0.76						
760 to 779	37	25.70	11.30	127.78	4.97	5	16.30	(11.30)	127.78	7.84						
780 to 820	64	45.27	18.73	350.65	7.75	10	28.73	(18.73)	350.65	12.21						
TOTALS	435				30.75	276				48.47						
TOTAL OBSERVED		711	CHI-SQUARE		79.23											

Table V

score interval range. This information is expanded to include the computed maximum and minimum percentage of Good accounts expected to be found with 95% confidence at that credit score interval. For example, the regression would predict the average percentage of Good accounts with a credit score of 700 to 719 would be 72.05% and with 95%

Table VI

Percentage of Observed Good Accounts within the Beacon Score Intervals with Regression and Maximum and Minimum Confidence Intervals

Beacon Score Interval	Percent Good Accounts	Regression	Confidence Interval Maximum	Confidence Interval Minimum
460 to 499	50.00%	38.07%	44.64%	31.50%
500 to 519	43.80	42.50	48.18	36.82
520 to 539	42.60	45.46	50.58	40.33
540 to 559	39.20	48.41	53.02	43.80
560 to 579	49.10	51.36	55.52	47.21
580 to 599	58.10	54.32	58.10	50.54
600 to 619	57.10	57.27	60.77	53.77
620 to 639	55.60	60.23	63.58	56.87
640 to 659	54.30	63.18	66.54	59.83
660 to 679	71.70	66.14	69.64	62.64
680 to 699	64.50	69.09	72.87	65.32
700 to 719	75.80	72.05	76.20	67.89
720 to 739	79.50	75.00	79.61	70.39
740 to 759	71.40	77.96	83.08	72.83
760 to 779	88.10	80.91	86.59	75.23
780 to 820	86.50	85.34	91.91	78.77

confidence the average percent of Good accounts will be between 67.89% and 76.20%. At the same time per the regression, a credit score between 520 to 539 will have an average of 45.46% Good accounts with 95% confidence the average percentage of Good accounts will be between 40.33%

and 50.58%. Plotting these percentages in graph form as noted in Figure 3, the positive slope of the line formed by the percentage of Good accounts and the regression suggests a positive relationship between these two variables.

Although the relationship is positive, the credit score is not a firm predictor of the resolution of the account. Using the minimum confidence level for a credit score of 460 to 499, the lowest credit score interval, there is still a 5% chance the percentage of Good accounts will be lower than 31.5% at this credit score interval. Decisions using the credit score as a predictor of account outcome must take this chance of error into consideration as the feasibility of the credit score as a tool is assessed.

CREDIT SCORE ANALYSIS

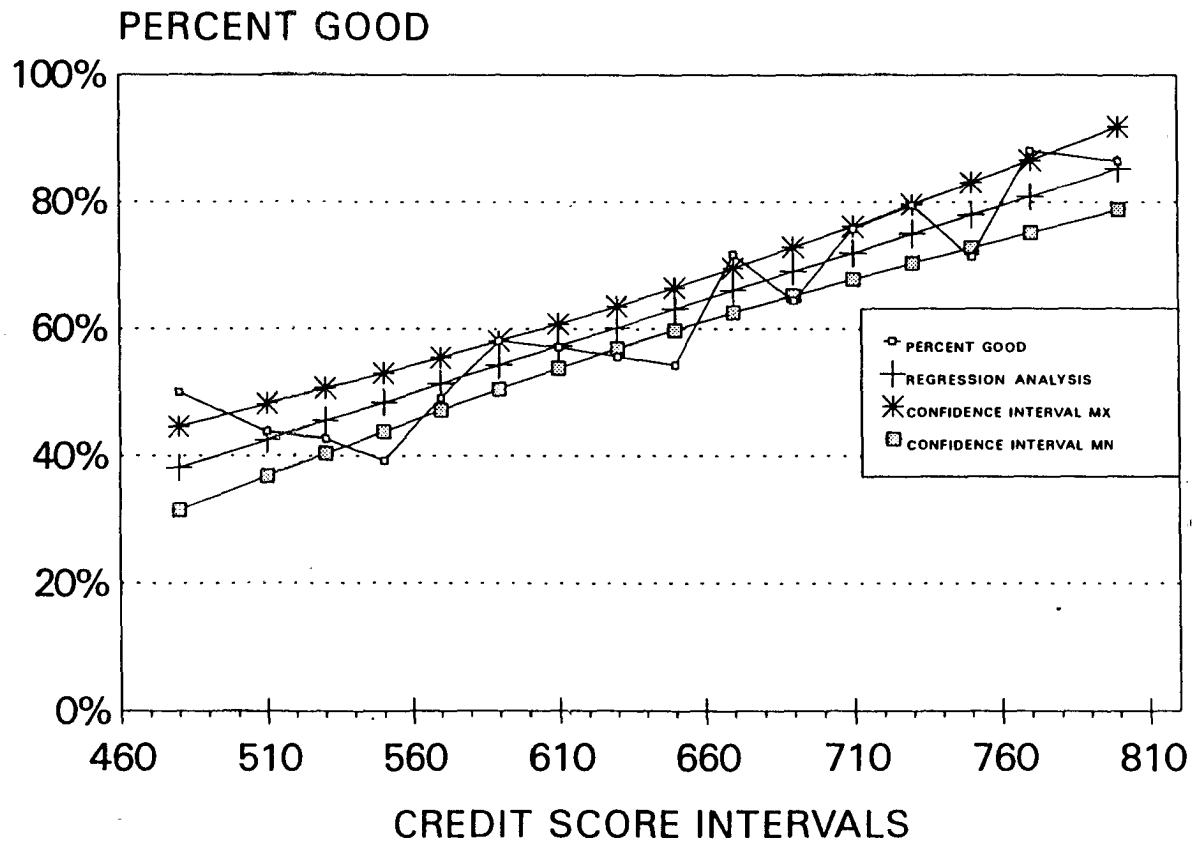


Figure 3

IV. Summary

Specific observation can be made from this study that offer some insight to the relationship of consumer credit scoring to resolution of hospital accounts. These observations are:

- (1) Across all ranges of credit scores there were both Bad accounts and Good accounts,
- (2) Using a Chi-Square Test of Independence, there is a relationship between the outcome of a patient account and the credit score,
- (3) With the application of simple linear regression, the relationship between the outcome and the credit score is positive,
- (4) The probability of the account being Good was greater when the credit score was greater and smaller when the credit score was lower, and
- (5) Credit scores are not an absolute predictor of patient account outcomes.

Although these facts are not surprising, they are reinforced by the evidence of this study.

V. Conclusions

It was determined there is a relationship between the credit score and account outcome proving the alternative hypothesis. Further, the relationship between these variables was determined to be a positive one, which suggests the increased probability of an account being Good increases as the Beacon credit score increases.

Worthy of note is the possible bias in the study data. Hospital emergency departments are often used by individuals with a poor payment record due to their inability to receive health care anywhere else. Emergency departments are used by indigent and others as a source of primary health care, which may be an influence on the data with a large segment of the study sample in the lower credit score range. Yet, this condition may serve as added motive to use a credit score to determine the exact credit status of the patient.

It was interesting to note that those with the highest credit score may still result in a bad debt. Accounts with high credit scores may be written-off to bad debt due to the fact a disability has reduced the patient's financial resources and they are unable to pay, and yet are unwilling to comply with charity/uncompensated care requirements. Or, patients may feel non-payment of medical bills is a way of protesting the high cost of health care.

Many operational, medical and social issues may have influenced the outcome of these accounts. The work load of those managing accounts may have provided more or less effort in the resolution of an account without knowing the credit score. Delays in patient waiting time provides time for hospital personnel to work toward account resolution. Delays in wait-time or patient discharge may be the result of other patients with more severe medical conditions. In addition, the wait-time may be the result of the patient being admitted to inpatient care, thus lengthening their stay.

Also, patients feel motivated to cooperate in the account resolution process feeling that the lack of compliance would be an obstacle to receiving necessary care. Essentially, a patient may comply by providing needed information for account resolution fearing that treatment would be withheld if they did not comply.

Another factor to account resolution is the social or family support of the patient. A patient's family can be a valuable source of information in resolving an account as they attempt to contribute to the patient's wellbeing by providing supporting financial information. However, if the patient has no family or social support, resolution of accounts may be slow at best as the source of information and compliance must come solely from the patient.

Recommendations for Future Research

The relationship of a credit score to a hospital account should be only the beginning. Additional study could determine if there is any correlation between a credit score and how quickly the account was resolved. Does a high credit score mean the account will be paid or resolved more quickly than a lower credit score? In other words, is the credit score a predictor of the patient's interest in prompt payment or compliance?

Another study to consider would be the relationship of a credit score to the existence of health insurance or other third party payor. Do those patients with a low credit score have health insurance? Further, is there any correlation between the credit score and the type of health plan or coverage? Do those with higher credit scores typically have indemnity insurance coverage or a managed care plan? In other words, do those with high personal, fiscal responsibility as demonstrated by a high credit score purchase expensive health insurance coverage representing a high adversity to risk or do they forego health insurance coverage altogether?

A close examination of the Bad accounts with high credit scores could be studied to determine the factors influencing this result. Why would a fiscally responsible individual as represented by their credit score allow this account to be resolved in this fashion? Equally important

would be knowledge of the factors influencing those in the low credit score range to be compliant in the resolution of their account. These factors would be of value to understanding debtor behavior psychology.

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