BANKRUPTCY PREDICTION: A MODEL
FOR THE CASINO INDUSTRY

by

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ABSTRACT

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This study shows the development of a discriminant model to predict failure or non-failure in the casino industry. The objective of the study is to provide a model developed for the casino industry using financial data from a sample of failed and non-failed casinos. The data was provided by the Nevada Gaming Control Board from information they collect from all licensed casinos with over $1 million in annual revenue.

The theoretical model developed for the study includes five constructs that indicate success or failure in the casino business. The five constructs are: Management, Location, Ambiance, Marketing and Financial Strength. Due to limitations in the data, two of these constructs were not included in the development of the discriminant model; Location and Ambiance.

The model includes twelve predictor variables: A&P/Total Revenues, Cash Flow/Liabilities, Net Income/Assets, Sales/Assets, Operating Margin, Payroll/Revenues,

Payroll/Assets, % Change in A&P/Total Revenues, % Change in Cash/Liabilities, % Change in Sales/Assets, % Change in Operating Margin, % Change in Payroll/Revenue and % Change in Payroll/Assets.

The model accurately predicted group membership for 100% of the cases included in the study. The model was shown to be statistically valid using a Wilks' Lambda test. The model was also tested using data that were not included in the development of the model. The classification accuracy of this data set was 100% for failed firms and 89% for the non-failed firms, with an overall classification accuracy of 92.3%.

The model predicted failure more accurately than three traditional models using casino data had done in a previous study. The three models were the Altman Z score model, which had a prediction accuracy rate of 50% one year prior to failure, the Deakin model, which had a prediction accuracy rate of 29% one year prior to failure and the Zavgren model, which had an accuracy prediction rate of 21% one year prior to failure.

The study shows that a financial analysis model that is developed specifically for the casino industry provides much more accurate information to its users.

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CHAPTER 1

INTRODUCTION

Twenty-five years ago, in 1976, the only legal casinos in the United States were located in the state of Nevada. These casinos were financed primarily by individual investors (there were some limited exceptions, such as loans from the Teamster's pension fund, controlled by Jimmy Hoffa, and loans from Perry Thomas' Valley Bank). The casino industry has grown from a market value of a few hundred million dollars in those days, to several billions of dollars during the last several years. Much of this growth has been accomplished through public stock offerings, public debt offerings and an increasingly large amount of bank debt. Not only has there been an increase in the magnitude of the investment in the casino industry, the number of individuals directly and indirectly investing has also increased significantly. With this increased investment and increased investor base has come a more complex vulnerability to potential losses caused by business failure.

Despite many success stories in the casino industry, there have also been casinos that have failed, causing their investors and their creditors to suffer significant losses. Not all casino failures are singularly because of financial reasons either, other factors such as location and marketing strategy can be just as important. If there were a means of predicting the combination of characteristics of casinos that are likely to fail, corrective measures could be taken to alter their underlying problems, redefine strategies and procedures or in some instances avoid or reduce investments in questionable firms that cannot be salvaged.

One method used in evaluating the likelihood of success or failure of a business is to examine its financial ratios. Since failure of a company, as defined by bankruptcy, is the inability of the company to be able to meet its credit obligations as they become due, there is by definition a relationship between the company's financial position and its status as a failed or non-failed company. But, the purpose of bankruptcy prediction is to be able to identify characteristics that are likely to lead to bankruptcy, not to define a bankrupt firm. One method of predicting business success or failure that has been widely used over the past thirty years is the statistical bankruptcy prediction model, first presented by Edward I. Altman in his 1967 Ph.D. dissertation (Altman, 1988).

Why use bankruptcy prediction models? Bankruptcy prediction models present their users with the opportunity to assess the quality of a business's financial performance and position relative to other businesses through the use of a single index figure, whose value indicates success or failure (Altman, 1968; Aziz, Emanuel & Lawson, 1988; Aziz & Lawson, 1989; Blum, 1974; Bukovinsky, 1993; Deakin, 1977; McGurr, 1966; Ohlson, 1980). But, while traditional bankruptcy prediction models have been shown to work well for predicting the classification of specific types of businesses into failed and non-failed groups (Altman, 1988), none were developed for use specifically in the casino industry.

The rationale for the need to have a bankruptcy prediction model that is based on the industry being examined is that different factors could be more significant in predicting the success or failure of a business in a particular industry because of the way that industry works. Edward Altman developed what is generally considered the first modern bankruptcy analysis (Platt, 1985). This original bankruptcy prediction model relied on information that was available from public records about industrial (manufacturing) companies (Altman, 1967). Fifteen years after publishing his initial model, Altman authored a book (1983) recapping the evolution of bankruptcy prediction efforts. In this book Altman points to the need for industry specific studies:

> We realize that the relative heterogeneity of industrial firms, both manufacturers and retailers constrains the model as to its expected accuracy for firms whose affiliation differs from that of the "average" industrial company...The ideal would be to construct individual models for specific industries (p. 273).

There have been some studies on other industries such as a study of failures in the Savings and Loan business done by Pantalone & Platt in 1985. Edminister (1971) studied small firms with defaulted SBA loans. Altman also did a study of railroads (Altman, 1983). There are no published studies of casinos.

The casino industry is a service industry, but at the same time can involve a large capital investment. Operationally, casinos are highly labor intensive, there is only a small part of the casino revenue generating process that involves the conversion of a raw material into a sales product. Unlike a manufacturing or retail business, casinos do not convert an inventory into a product. The venue of a casino, like a retail business, is highly visible and important to the customers' patronage. Significant portions of a casino's fixed assets have relatively short lives (compared to the buildings and equipment in a typical manufacturing business).

Problem Statement

Bankruptcy prediction models present their users with the opportunity to assess the financial health of an organization, if they work properly. An earlier study (Patterson, 1999) tested three traditional bankruptcy prediction models (Altman, 1967; Deakin, 1972; Zavgren, 1985), using financial data from failed and non-failed casinos. None of these three models predicted failure and non-failure with better results than would be expected using a priori probabilities. The objective of this study is to develop a statistical model that will differentiate between casinos that are likely to fail and those that are not likely to-fail with a higher classification rate than existing bankruptcy prediction models.

Limitations

A limitation of this study is the availability of financial information on individual casinos. The relatively small number of casinos that have filed bankruptcy further limits the scope of the study, and the availability of sufficient data for tests of statistical reliability.

There are alternative statistical methods that have been employed in bankruptcy prediction studies. The only statistical methodology used in this study was discriminant analysis.

The Nevada Gaming Control Board supplied the financial ratio information used in this study. Due to Nevada state law, the Board is not allowed to release any financial information that could be identified as coming from a specific casino. One of the limitations related to this restriction was that additional information concerning the data was not readily available, subsequent to the initial request for the data. In addition, since the providing of the data was unprecedented, additional requests were determined to be inappropriate to future relations with the Gaming Control Board. The result of this limitation was that some of the data supplied could not be used in the study.

Delimitation

Two of the problems facing any analysis that requires financial operating data are consistency and availability. The casino industry has a history of being particularly secretive about its financial data, and there are no uniform standards that are generally applied to the manner in which casinos keep their records. An exception to this generality is the information that casinos in Nevada with gross revenue of $1 million or more are required to submit to the Nevada Gaming Control Board on an annual basis (NGCR 6.070).

Similar information has been collected and compiled by the Gaming Control Board for each of the past fifteen years. While the information needed for the study is available from these reports, Nevada state law prohibits the Gaming Control Board from divulging financial information about the casinos, except in the aggregate. In order to obtain permission to obtain the necessary information to complete this study, it was necessary to establish the significance of the study and to provide a format that would conceal the identity of the properties. By restricting the information requests to ratios rather than absolute numbers and by not asking for the dates of the information, the possibility of identifying the properties through a process of elimination was virtually eliminated. An additional requirement for obtaining the information was that in order to maintain the confidentiality of the process, the actual gathering of the raw data would have to be performed by staff of the Gaming Board's audit division.

Once the Gaming Board had agreed to provide the data needed for the study, additional meetings were held with audit division personnel to discuss specifics of the data requirements. The firms to be studied would be limited to those Nevada firms that had been in bankruptcy proceedings during the past fifteen years (failed casinos). The financial information was to be from each of the two years prior to the date of the individual casino's bankruptcy filing.

The Gaming Board also agreed to supply similar financial ratios for firms that had not been involved in bankruptcy proceedings (non-failed casinos). The non-failed casinos chosen were casinos of similar size (as determined by casino square footage) and the financial information was to be from the same years as that for the failed casinos of a similar size. The non-failed casinos were also to be chosen from the same type of market area and geographic location.

Several kinds of statistical analysis have been used in bankruptcy prediction models, including: univariate analysis (Beaver, 1966), multiple discriminant analysis (Altman, 1967; Deakin, 1972), linear probability models (Myer & Pifer, 1970), logit analysis (Ohlson, 1980; Zavgren, 1985; Gentry, Newbold & Whitford, 1985), probit analysis (Grablowsky & Talley, 1981) and neural network analysis (Tam, 1991; Tam & Kiang, 1992). Only one of these methods will be utilized in this study: multiple discriminant analysis. Despite some limitations, this is the method that has been used in more studies than any other method and it is the method that has consistently produced the most accurate prediction/classification accuracy.

Definitions

A priori probabilities. Probabilities that are based on prior knowledge about the sample. In an analysis where there are two equal sized groups of cases, the a priori probability of choosing the correct group for a case chosen at random would be 50%.

Business Failure. The inability of a firm to meet its obligations when due. For purposes of this study, the filing of bankruptcy proceedings (either voluntary or involuntary) indicates business failure.

Capital Replacements. The amount spent to upgrade or replace the capital assets of a firm. For purposes of this study, capital replacements were determined by taking the difference between beginning and ending property and equipment, not including construction-in-progress and not including any deductions for accumulated depreciation.

Cash Flow from Operations. The amount of cash received from operating activities. For purposes of this study cash flow from operations is calculated by adding net income plus depreciation plus decreases in current assets plus increases in current liabilities.

Casino Industry. The population of all casino companies that offer casino games, including table games and slot machines, includes casinos in all jurisdictions. This study only includes casinos doing business in the state of Nevada. Since the financial characteristics of these casinos may or may not be similar to casinos in other jurisdictions, the results may or may not be valid for the casinos in other jurisdictions.

Classification Accuracy. The percentage of cases that are classified into the correct group through a prediction model.

Collinearity. Exists when there is a statistical relationship between two variables.

Current Assets. Cash plus marketable securities plus receivables plus inventories plus prepaid expenses.

Current Liabilities. Accounts Payable plus Accrued Expenses plus Deposits plus the Current Portion of Long Term Debt.

Failed Firm. A firm that has been a subject of bankruptcy proceedings, either voluntary or involuntary.

Gaming Revenues. The amount of money wagered by customers less the amounts paid out to customers for winnings. Also called "Win".

Marketing Costs. For purposes of this study, the amounts spent for advertising and promotion.

Multi-collinearity. Problem that occurs in a correlation matrix when variables are too highly correlated. Can occur when there are two or more variables that measure the same thing.

Multiple Discriminant Analysis. A statistical analysis technique for distinguishing among defined groups by developing a linear combination of discriminating independent variables. Inputs are variables that discriminate between the groups. The analysis defines each group as a vector of attributes that constitute a density function. The process maps the multi-dimensional characteristics of the density function of the population's attributes onto a one-dimensional measure by forming a linear combination of the attribute along some axis. The purpose of the analysis is to derive relationships that minimize the variances within a group while maximizing the variances between groups.

Naïve determination. The likelihood of predicting a particular outcome based on the a priori probabilities of the data being examined.

Non-failed firms. Firms that have not the subject of a bankruptcy proceeding.

Operating Income. Revenues less operating expenses.

Operating Margin. Operating Income divided by Revenues.

Quick Assets. Cash plus marketable securities plus receivables.

Total Revenues. The amounts received by the operation from customers for purchases of goods and services plus Gaming Revenues.

Type One Errors. Classifying a failing firm as non-failing. These are generally considered the more serious errors for investors or lenders, as investments could be made which otherwise might not have been made.

Type Two Errors. Classifying a non-failing firm as failing.

Univariate Analysis. The technique of looking at only one variable at a time to explain a result. Assumes implicitly that all other variables are equal. This is the method used by Beaver to analyze financial ratios and develop values that indicated the ratio level to be expected in a failed or a non-failed firm.

Working Capital. Current Assets less Current Liabilities.

Tests of Results

To test the classification accuracy of the model developed for the study, the model will be tested using data from casinos that are not used in the development of the differentiation model. The results of the tests will be compared to results from the three models tested in a prior study (Patterson, 1998) and to the a priori probabilities of failure and non-failure based on the mix of casinos used in the test (an equal number of failed and non-failed casinos would result in a 50% likelihood of proper classification by predicting either failure or non-failure for the entire group). The Null Hypotheses and the Alternative Hypotheses to be tested are as follows:

$H_{Null\ 1}$: A statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than a naïve prediction.

$H_{Alternative\ 1}$: A statistical bankruptcy prediction model developed using casino data will predict bankruptcy more accurately than a naïve prediction.

$H_{Null\ 2}$: A statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Altman Z Score model (1967).

$H_{Alternative\ 2}$: A statistical bankruptcy prediction model developed using casino data will predict bankruptcy more accurately than the Altman Z Score model (1967).

$H_{Null\ 3}$: A statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Deakin model (1972).

$H_{Alternative\ 3}$: A statistical bankruptcy prediction model developed using casino data will predict bankruptcy more accurately than the Deakin model (1972).

$H_{Null\ 4}$: A statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Zavgren model (1985).

$H_{Alternative\ 4}$: A statistical bankruptcy prediction model developed using casino data will predict bankruptcy more accurately than the Zavgren model (1985).

Organization of Paper

Chapter 2 traces the history of financial statement analysis and bankruptcy prediction studies. It also reviews a recent study of the effectiveness of traditional bankruptcy prediction methods for predicting bankruptcy in the casino business.

Chapter 3 describes the data that were collected for use in the analysis and the methods that were used to construct the predictive model.

Chapter 4 presents the model that was developed to predict failure or non-failure and the results of the predictions. Tests of casinos not included in the development of the model are used to validate the model.

Chapter 5 summarizes the results of the tests and conclusions about the applicability of the test results to the casino industry. Opportunities for additional research and future studies are also presented.

CHAPTER 2

LITERATURE REVIEW

The process of understanding and being able to interpret the meaning of financial statements has been an evolutionary process. Before the type of analysis that is being used for statistical bankruptcy prediction was possible, reliable and consistent financial statements had to be available. The fundamental financial ratios that are used in for statistical bankruptcy prediction analysis had to be developed, and the relevancy of those ratios had to be established. This literature review section will trace the history of accounting in the United States, financial ratio analysis and classic bankruptcy prediction models.

Accounting in the United States

In order to have meaningful financial analysis, one must first have good accounting records. The keeping of accounting records in the United States is as old as its discovery by Columbus. On his famous 1492 voyage, one of his crew of forty men was the royal controller of accounts. This controller was sent to keep track of Columbus and to keep records of the gold and spices Columbus was expected to discover during his voyage (Cooke, 1973).

Even the pilgrims had accountants, although there were apparently some problems with the way one of their first kept the accounting records. According to Willard Stone (1979), as early as 1620 they were concerned about their finances and that their treasurer, Mr. Martin, had not fulfilled his responsibilities. Less than a year later, they were asked by their London financier-merchant, Thomas Weston to, "Give us accounts as (sic) perticulerly as you can how our moneys were laid out."

Although there were accountants practicing in the United States throughout the 1700s and 1800s, it was not until the late 1800s that public accounting became an organized and regulated profession that would begin to wield some influence in the business world. During the last half of the 19th century, business in the United States was dominated by giant trusts in railroads, oil, steel, banking, tobacco, sugar and coal. But by the end of the century, the autonomy of these companies was being eroded by events such as the passage of the Sherman Antitrust Act in 1890, a European money market panic in 1873 that had resulted in the failure of more than 5,000 companies and losses of $220 million (Fels, 1951) and the panic of 1893, which initiated one of the most severe depressions in United States history (Previts & Merino, 1979).

It was in this climate that the role of the public accountant and the practice of financial analysis began to emerge. According to Previts and Merino (1979), three of the earliest advocates of financial analysis were Thomas F. Woodlock, John Moody and Henry Clews. Clews was a well known financial author who felt that public accountants would provide publicity to corporate financial records. Woodlock published a book in 1895, <u>The Anatomy of a Railroad Report</u>, that was considered the authoritative resource for understanding railroad reports. Moody also wrote about railroad company financials in his book, How to Analyze Railroad Reports. It was also during this period that the first organized accounting professionals organizations were begun in the United States.

The first organized professional association of accountants, The Institute of Accountants and Bookkeepers, was formed in New York on July 28, 1882. The association was later renamed the Institute of Accounts. The purpose of the organization was to try to lend an image of professionalism to what was viewed by some as a less than honorable endeavor. According to Previts and Merino (1979), James T. Anyon, an early CPA, suggested that, the "back parlor" (moonlighting) nature of many American accounting practices raised doubts among the public about the quality, ability and character of early native accountants. He noted that accountants were viewed as "men of figures" – those who dealt in and loved figures for themselves, who calculated balances in accounts, prepared elaborate statements and looked for errors. Accountants were viewed as the type of persons who thought figures, sometimes juggled them, and always wrote and talked them." Previts and Merino (1979) cite another early accountant's view of accounting, which seems to be more of the image the profession wanted to establish with the public:

> The professional accountant is an investigator, a looker for leaks, a dissector and a detective in the highest acceptation of the term; he must have a good knowledge of real estate, machinery, buildings and other property. His business is to verify that which is right and to detect and expose that which is wrong; to discover and report facts as they exist, whether they be plainly expressed by clear and distinct records or whether they be concealed by the cunning naive or hidden under plausibly arranged figures or as is frequently the case omitted from the records

entirely. He is a reader of hieroglyphics, however written, for every erasure, altercation, (sic) interlining, dot, dash or character may have a meaning. He must interpret, rearrange and produce in simple but distinct from self explanatory and free from mysteries of bookkeeping, the narrative of facts, the relation of each other in results. He is the foe of deceit and the champion of honesty (Keister 1896). (p. 90)

The second accountants' society to be formed was the American Association of Public Accountants, on September 20, 1887. This group would later become the American Institute of Certified Public Accountants (AICPA). While the Institute of Accounts had a entrance exams that tested practical and technical competence as early as 1884, it was not until 1897 that the first public accounting law was passed by the New York legislature, through the combined efforts of the two organizations.

With the emergence of the professional accountant, creditors and investors were in a position at the beginning of the twentieth century to start being more comfortable relying on the financial statements of companies when making credit and investment decisions. Before this time, most credit decisions were based on the creditor's personal knowledge of the debtor's ability to pay (Brown, 1955). According to Brown, the use of financial statements for granting credit was only beginning to be accepted prior to 1900. She attributes one of the earliest written documentations of credit analysis to Peter R. Earling, who wrote a paper entitled, Whom to Trust: A Practical Treatise on Mercantile Credits. His recommendations included an examination of asset valuation, the relationships between assets, liabilities and net worth.

Brown's dissertation also describes the contributions of James Graham Cannon, who presented a paper in 1905 to the New Jersey Bankers Association. Cannon maintained that the most important feature of credit science was the interpretation of the borrower's statement (balance sheet). According to Cannon, an unanalyzed statement was worse than no statement. His rules for credit were fairly simple, only quick assets should be considered in making a loan, and total credit should not exceed fifty percent of the quick assets. Cannon also presented an analysis of a set of "typical balance sheets", for four groups of borrowers. In this analysis Cannon calculated quick assets, fixed assets, liabilities and net worth, each as a percentage of total assets. He also computed sales per dollars of quick assets and total assets. He then compared the percentages for the different groups. According to Brown, this analysis "opened a wide field for use of percentages and proportion in the analysis of financial statements" (Brown, 1955, p. 12).

Cannon's use of percentages in the analysis of financial statements was not widely used during this early period, but it did foreshadow a way of looking at companies of various sizes and types of businesses in a different manner. This was one of the first examples of financial ratio analysis.

Financial Ratio Analysis

Financial ratios were the first analytical method of assessing the financial performance of a company. Financial ratios were also one of the first tools for predicting the future performance of a company.

James Horrigan introduces his anthology of articles on financial ratio analysis with the following observation:

In a fundamental sense, the development of financial ratios was probably inevitable. Accounting statements themselves report absolute numbers and those numbers only convey information about the size of the firm. Big firms have big numbers and small firms have small numbers. Some kind of relative numbers had to be developed if analysts were to make any sense out of accounting data. Therefore, financial ratios really represented the first attempt to measure various underlying relationships that would reveal the true essence of firms. (p. 1).

Woodlock's The Anatomy of a Railroad Report (1900) discussed such financial measures as "the percentage of operating expenses to gross earnings", "the ratio of fixed charges to net income" and "the relative proportion which the funded debt and stock of a company should bear to the actual cost of the property". In regard to current position, Woodlock said, "In general, current items on each side of the account should at least fairly offset each other, year by year." In his 1911 The Principles of Bond Investment, Lawrence Chamberlain used Woodlock's ratio of operating expenses to gross earnings, calling it the "operating ratio" (Myer, 1939, p. 6-7).

The need for a measurable method of making credit and investment decisions was the primary reason for the initial development of financial ratio analysis. "Analysis of financial ratios began in the early 1900's with the development of the current ratio and the creation of a benchmark level for an acceptable relationship" (Beaver, 1966, p. 71). "Other ratios were developed in the 1890's, but this ratio, the current ratio, was to have a more significant and long lasting impact upon financial statement analysis than any other ratio" (Horrigan, 1968).

A classic report issued in 1919 to the Federal Reserve Bank, "Study of Credit Barometrics", by an employee of the National Bank of Commerce, a Detroit bank, Alexander Wall, used seven different financial ratios from nearly a thousand firms to establish a norm for analysis. Wall had collected this information over a seven year period from financial statements he obtained from the files of commercial paper brokers (Horrigan, 1968). In the article Wall criticized bankers who based their decisions on the amount of the current ratio alone. He gave hypothetical examples showing the volatility of the current ratio and its components, and discussed factors that could explain differences in current ratios between different companies. He maintained that to get a complete picture of the financial condition of a firm other relationships should be used as a check on the current ratio (Wall, 1919). According to Horrigan (1968), "Wall had, in effect, popularized the ideas of using many ratios and using empirically determined relative ratio criteria" (p. 286).

The twenty years following Wall's original presentation was a period of increasing interest in the financial world on the subject of ratios. There were several compilations of financial ratio data averages, the process at the time being described as, "scientific ratio analysis" (Justin, 1924). There were many new ratios developed during this period, and in an attempt to control the proliferation, Wall developed an index for many of these by weighting the ratios according to a relative value he assigned to each ratio Horrigan (1968). Another analyst who made significant contributions during this period was James Bliss who presented a set of principles for the use of ratios in management. He maintained that there were more or less normal relations that must exist within a business if it was to be profitable (Brown, 1955).

While many new ratios were developed in the 1920's and many financial scholars and practitioners were enthusiastic about the potential of using these new methods, there were others who disagreed. One such critic was Stephen Gilman, who did not feel that ratios portrayed the fundamental relationships within a business. He listed four reasons for not using ratios to analyze companies in his book Analyzing Financial Statements. The objections were: 1. Their changes over time cannot be interpreted because the numerator and the denominator of the ratio both vary, 2. The ratios are "artificial" measures, 3. They divert the analyst's attention from a comprehensive view of the firm, 4. Their reliability as indicators varies widely between ratios (Horrigan, 1968).

Studies conducted in the 1930's found that failing firms had significantly different financial ratios than those of non-failing firms (Altman, 1988). Arthur Winakor and Raymond Smith published a study for the University of Illinois, Bureau of Business Research in 1930, Bulletin No. 31, A Test Analysis of Unsuccessful Industrial Companies, which analyzed the financial statements of 29 companies in an attempt to discover characteristics that would assist in anticipating probable failure. Their second study, Changes in the Financial Structure of Unsuccessful Industrial Corporations, expanded the original study to 183 companies. They found that the most accurate and consistent indicator of failure was the ratio of working capital to total assets. Their study also showed significant differences in the ratios of companies from different industries and differences depending on the amount of time between the dates of the financial information and the dates of failure, some ratios improved and others got worse with the proximity of the failure date (Smith & Winakor, 1935).

Paul FitzPatrick in his 1931 study, Symptoms of Industrial Failure, studied trends in thirteen ratios over a period of three years for twenty failed and nineteen non-failed companies. FitzPatrick discussed each of the ratios and the conventional thinking about the minimum acceptable level of each. The minimum level for the current ratio was 200%, the quick (or acid-test) ratio was 100%, net worth to total liabilities was 100%. The other ratios were all, to some extent dependent upon the type of company. FitzPatrick also looked at the trend of the ratios over time; did they improve or did they decline. He found that levels of the majority of the ratios were "satisfactory" for the majority of the successful companies and that the unsuccessful companies all had a number of unsatisfactory ratio levels. He also found that the successful companies had better ratios than the unsuccessful ones. Finally, he noted the increasing importance of the net worth to debt and net profit to net worth ratios, and the decreasing importance of the current ratio and the quick ratio in predicting business failure. His final comment was on the unavailability of data on failed companies (FitzPatrick, 1931).

In 1942, Charles Merwin published a study, Financing Small Corporations: In Five Manufacturing Industries, 1926-36. He analyzed trends in ratios over a six-year period for "continuing and discontinuing" firms, comparing mean ratios for the discontinued firms against the average ratio values for the continuing firms. His conclusion was that three ratios accurately predicted failure, net working capital to total assets, net worth to debt and the current ratio. According to Horrigan, "Merwin's study was the first really sophisticated analysis of ratio predictive power" (Horrigan, 1968, p.290). The next stage in the development of financial analysis was the use of statistical methodologies to predict the future of companies. The most well known univariate study was done by William Beaver and the most well known multivariate study was done by Edward Altman. Each of these studies will be reviewed next, as will some of the other more well-known bankruptcy prediction studies.

William H. Beaver, 1966

William H. Beaver did a classic study using univariate analysis to examine the ability of financial ratios to predict business failure in 1966. According to Edward Altman, this study "set the stage for the multivariate attempts, by this author and others, which followed" (Altman, 1993, p. 181). Horrigan said, "This study will undoubtedly become a landmark for future analysis in ratio analysis." (Horrigan, 1968, p. 291).

Beaver first selected a set of thirty existing financial ratios that he felt were the best measures of a firm's health. He then grouped these ratios into six groups according to what they measured. The six groups were cash flow ratios, net income ratios, debt-to-total assets ratios, liquid assets to total assets ratios, liquid assets to current debt ratios and turnover ratios. The ratios studied are shown in Table 1.

Table 1
Beaver's List of Ratios Tested

Cash Flow Ratios

1. Cash flow to sales
2. Cash flow to total assets
3. Cash flow to net worth
4. Cash flow to total debt

Net Income Ratios

1. Net income to sales
2. Net income to total assets
3. Net income to net worth
4. Net income to total debt

Debt to Total Asset Ratios

1. Current liabilities to total assets
2. Long-term liabilities to total assets
3. Current + long-term liabilities to total assets
4. Current + long-term liabilities + preferred stock to total assets

Liquid Assets to Total Asset Ratios

1. Cash to total assets
2. Quick assets to total assets
3. Current assets to total assets
4. Working capital to total assets

Liquid Asset to Current Debt Ratios

1. Cash to current liabilities
2. Quick assets to current liabilities
3. Current ratio

Turnover Ratios

1. Cash to sales
2. Accounts receivable to sales
3. Inventory to sales
4. Quick assets to sales
5. Current assets to sales
6. Working capital to sales
7. Net worth to sales
8. Total assets to sales
9. Cash to expenditures for operations
10. Defensive assets to expenditures for operations
11. Defensive assets minus current liabilities to expenditures for operations.

These ratios were selected based on three criteria. First the ratio had to generally be considered, by the financial literature, to be reflective of the crucial relationships of a firm's condition. He cautioned that the popularity of a ratio did have a drawback, in that, "the most popular ratios will become those most manipulated by management (an activity known as window dressing) in a manner that destroys their utility" (Beaver, 1966, pp. 79-80).

The second criterion was that the ratio had performed well in one of the previous studies of bankrupt companies. The third criterion was that the ratio be defined in terms of a cash-flow concept. Beaver felt that "cash-flow ratios offer much promise for providing ratio analysis with a unified framework..." (Beaver, 1966, p. 80). Satisfaction of any of the criteria was sufficient for inclusion in the study. In order to have each of the ratios provide as much additional information as possible; Beaver excluded any ratio that was a "transformation" of another ratio that had already been selected.

Beaver's model was based on four propositions, all else being equal. First that the more net liquid assets a firm has, the smaller the probability of failure. Second that the larger the net cash flow from operations, the smaller the probability of failure. Third that the larger the amount of debt of the company, the greater the probability of failure. Finally that the larger the amount of liquid assets required to fund operating expenditures, the greater the probability of failure.

He used these propositions to test the predictive ability of the ratios. Using a set of 79 failed companies and a matched set of 79 non-failed companies; he calculated each of the thirty ratios. His results showed that, "The difference in the mean values is in the predicted direction for each ratio in all of the five years before failure. Failed firms not only have lower cash flow than non-failed firms but also a smaller reservoir of liquid assets. Although the failed firms have less capacity to meet obligations, they tend to incur more debt than do the non-failed firms" (Beaver, 1966, p. 80).

He found that the data was very consistent and that it suggested that there is a difference in the ratios of failed firms and non-failed firms. This was consistent with earlier studies. Fitzpatrick had published a study of nineteen pairs of failed and non-failed firms in 1932, which indicated repeated differences in the ratios for at least three years prior to failure. Winakor and Smith in a 1935 study had found deterioration in the mean values of failed firms for ten years prior to failure, with the rate of deterioration increasing as failure approached. These were the same results observed by Charles L Merwin in his 1942 study, (Beaver, 1966, pp. 81-82).

Having demonstrated that there was a difference in the ratios, Beaver wanted to answer the question of how large the difference was. To accomplish this he then determined the relative frequency distribution of each ratio for each group, failed and non-failed. Using these distributions, he was able to identify the ratio value at which the likelihood of the firm being classified in the appropriate company group (failed or non-failed) was high and the likelihood of the firm being classified in the wrong company group was low, for each of the ratios he tested.

The six ratios that had the lowest classification error rate were cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratio and the no-credit interval ratio. The best performing ratio was cash flow to total debt, which had a classification error of 13% in the year prior to failure. The next best performing ratio was net income to total assets.

Beaver concludes that the predictive ability of certain financial ratios, particularly cash flow to total debt provide useful information in assessing the likelihood of a firm failing. However, he acknowledges that further research using the combination of several ratios or changes in ratios might provide better predictive information. (Beaver, 1966 & 1968).

Edward I. Altman, 1968

The first study to look at the effect of using a combination of financial ratios to predict business failure was done by Edward I. Altman in 1968 (Altman, 1968). Altman used a statistical technique known as multiple discriminant analysis (MDA) to analyze the ratios of the groups of failed and non-failed firms in his study. The Altman Z score model is the most widely quoted model for predicting business failure and it is generally considered the standard by which other models are measured.

Based on previous studies, Altman selected a set of twenty-two ratios that he felt might be significant indicators of failure. Using the financial statements of 33 failed and 33 non-failed companies, Altman used a step-wise multiple discriminant analysis program to establish which ratios would most contribute to a formula that could differentiate the failed and non-failed companies. The results of his analysis yielded a formula that used five of these ratios; Working Capital/Total Assets (X_1) Retained Earnings/Total Assets (X_2), Earnings before Interest and Taxes/Total Assets (X_3), Market Value of Equity/Book Value of Total Debt (X_4) and Sales/Total Assets (X_5). Altman's formula is presented below in Model One.

Model 1

Altman Z-Score Multiple Discriminant Analysis Model

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5$$

Where X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Market value equity/Book value of total debt

X_5 = Sales/Total Assets

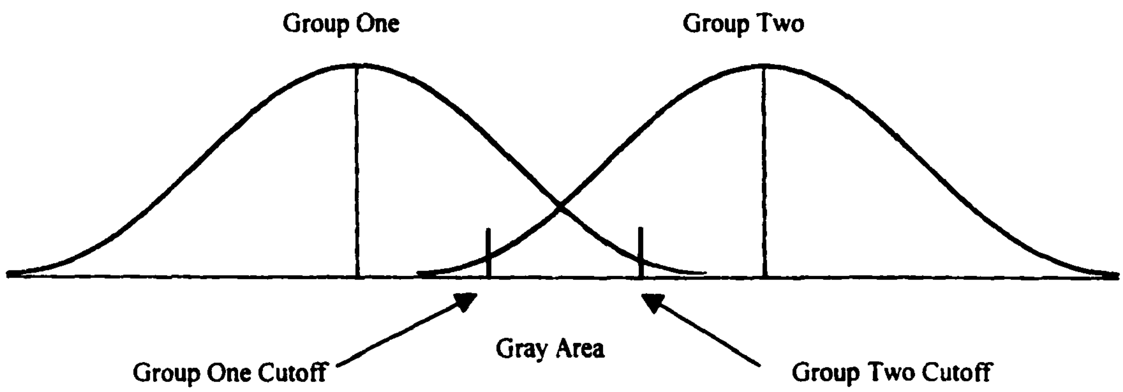
Z = Overall Index

(Altman, 1968, p. 594).

One purpose of multiple discriminant analysis is to predict group membership using a set of predictor variables. This is accomplished by determining the set of coefficients which, when applied to the observed values of the predictor variables creates a discriminant function whose solution (the Z-score) maximizes the differentiation between one group and another. The distributions of the solutions to the discriminant function from each group will provide a range of acceptable values at a given significance level for each group. Figure One is a graphical example of how these distributions might look. The graph shows the tails of each distribution intruding fairly far into each other; this is for illustrative purposes so that it is easier to label the relevant points, in an actual discrimination the tails would create a much smaller gray area.

Figure 1

Discriminant Function Distribution



The cutoff points are determined by assigning an acceptable significance level to each distribution. In the graph above, the Group Two Cutoff represents a point on the Group One distribution where one would expect that a value less than that amount would, with a high level of confidence, belong to the population of Group One. The Group One Cutoff represents a point on the Group Two distribution where one would expect that a value more than that amount would, with a high level of confidence, belong to the population of Group Two. The Gray Area represents the overlap of the two distributions, where a value could be from either of the two group populations.

Although he did not identify them as such, the ratios in Altman's model represent the constructs of failure prediction. These constructs are liquidity, cumulative profitability, productivity, return on investment and competitiveness.

There are understandable rationales behind the predictive ability of each of the ratios. The working capital to total assets ratio measures the firm's liquid assets relative to its total capitalization. A firm experiencing consistent operating losses will usually have a shrinking proportion of current assets relative to its total assets.

The retained earnings to total assets ratio measures cumulative profitability. Since the retained earnings account is a cumulative account, younger firms will have had less time to build it up. This creates a bias against younger firms, which is consistent with the reality that the incidence of failure is higher in a firm's early years.

The earnings before interest and taxes to total assets ratio is a measure of the firm's productive use of its assets. Insolvency occurs when a firm's liabilities exceed the value of its assets. Since earning ability is in fact the true measure of the value of the firm's assets, this ratio provides a basis for assessing the earning ability.

The market value of equity to book value of total debt ratio shows the level that the firm's value can decline before its liabilities exceeds its assets. The fifth ratio, sales to total assets measures management's ability to deal with competition.

Once the discriminant function had been determined, Altman plotted each firm's Z score in a matrix to show how the individual scores line up with respect to the actual status of the firm (failed or non-failed). This evaluation matrix is presented in Table Two.

Table 2
Evaluation Matrix

	Predicted Group Membership	
Actual Group Membership	Bankrupt	Non-Bankrupt
Bankrupt	H	M_1
Non-Bankrupt	M_2	H

The H's stand for correct classifications (Hits) and the M's stand for misclassifications (Misses). M_1 represents Type 1 errors and M_2 represents Type 2 errors. The sum of the correct hits divided by the total number of firms being classified gives the percent of firms correctly classified. This percentage is similar to the coefficient of determination (R^2) in regression analysis, which measures the percent of the variation of the dependent variable explained by the independent variables. (Altman, 1968).

When the original sample of failed and non-failed firms were tested using this formula, the overall classification error rate one year prior to failure was 5%. Secondary samples used to test the accuracy of the model also validated the accuracy of the model.

To make the model usable without having to replicate the study for each application, Altman further studied the results of his initial tests and derived cut-off values that would provide a basis for classification. The cut-off values Altman established was that all firms with Z scores less than 1.81 were failed, all firms with Z scores greater than 2.99 were non-failed and Z scores greater than 1.80 but less than 3.00 were in a "zone of ignorance" or gray area.

In his conclusions, Altman said, "A limitation of the study is that the firms examined were all publicly held manufacturing corporations, for which comprehensive financial data were obtainable, including market price quotations. An area for future research, therefore, would be to extend the analysis to relatively smaller asset-sized firms and unincorporated entities where the incidence of business failure is greater than with larger corporations" (Altman, 1968, p. 609).

Edward B. Deakin, 1972

Deakin's study combined the research of Beaver and Altman into a single model. His perception was that while Beaver's method had a superior predictive ability, Altman's approach was intuitively more appealing. Using the fourteen ratios from Beaver's study that best predicted failure, Deakin used the same MDA approach that Altman had used to derive a linear function that weights and combines the ratios in order to maximize the difference between the failed and non-failed groups.

In replicating the Beaver study, Deakin used a smaller sample, 32 failed firms instead of 79, and took the data from a different time period, 1964 to 1970 instead of 1954 to 1964. He also ranked the values of the ratios and then selected a cut-off point for each ratio that would minimize the occurrence of misclassification errors. He compared his results to Beaver's and found that the results "would tend to confirm Beaver's observations." (Deakin, 1972, p.169).

Deakin also performed a Spearman rank-order correlation coefficient test to determine the correlation of the predictive ability of the ratios. This test showed "a rather high correlation of relative predictive ability of the various ratios." (Deakin, 1972, p. 169).

The correlation coefficient in the third year before failure, while still significant, was 20 to 30 points lower than the other years. Through an analysis of the financial statement items that were used to calculate the ratios, Deakin concluded that the failed firms tended to expand rapidly in the third or fourth years prior to failure. This expansion was financed by increased debt and preferred stock rather than from funds provided by operations or additional common stock. Subsequently the firms were unable to generate sufficient increases in sales and net income to repay this bigger debt load, therefore causing them to lose assets.

Deakin's analysis yielded a different relationship for each of five years preceding failure. While some of the ratios showed a low contribution to the function, he found that leaving out any of the fourteen ratios increased the number of classification errors significantly. Rather than establishing a cut-off score, as Altman had done, Deakin classified firms according to their score's deviation from the mean score for each group.

Despite an error rate of less than 5% in the three years prior to failure, Deakin's original model was criticized for having different models for each year (Altman, 1993). Expanding on a technique used by Robert Libby (1975) in his study of the usefulness of accounting ratio information, Deakin revised his model in 1977.

Using principal-components analysis, Libby had identified only five independent sources of variation in the fourteen ratios used in Deakin's original study: profitability, activity, liquidity, asset balance and cash position. He then determined through an analysis of the rotated factor matrix which of the original ratios best represented each of the five financial dimensions. He then provided the reduced set of five ratios and the entire set of the fourteen Deakin ratios to a group of loan officers to test how well they would classify the failed and non-failed firms using the two sets of information. His test showed that the predictive ability with the reduced number of ratios was only slightly reduced.

Deakin developed a new model based on the five ratios identified by Libby. The model was tested against his original sample, as well as an additional sample of 31 firms that failed during 1970 and 1971 and another sample of 47 firms that failed during the period 1972 to 1974. For the last sample, the model correctly predicted 39 of the failures, misclassified one firm and identified seven companies as in need of further investigation, two years prior to failure, (Deakin, 1977).

Classification into the failed group or the non-failed group was based on the relative distance of its index from the average of the failing and non-failing groups. Deakin did not specify cutoff values or ranges of non-determinability in his study. However, from the information he did provide about his results it is possible to estimate cutoff values. Deakin provided the results of the calculation of the group mean for each ratio. Using these means to solve the linear and the quadratic equations it is possible to determine a solution for each equation for each group's mean values. The values that result from solving the linear equations are –1.381 for failed firms and +1.053 for non-failed firms. The values for the quadratic formula are –37.84 for failed firms and –54.24 for non-failed firms. Using these values however does not provide a zone of ignorance. If a firm's score is closer to the failed group, it is classified as failed, if it is closer to the non-failed group it is classified as non-failed. In order to resolve any differences between the two tests, Deakin used the decision rule that when both of the tests showed that the firm was failing or non-failing, the firm was so classified. If the two tests classified the firm differently, the firm fell into the "investigate further" category. Deakin's business failure prediction formulas are shown in Model 2.

Model 2

Deakin's Multiple Discriminate Analysis Model

Linear Equation:

$$I = -1.369 + 13.855X_1 + 0.060X_2 - 0.601X_3 + 0.396X_4 + 0.194X_5$$

Quadratic Equation:

$$I = 1.78 - 8.242X_1 - 70.06X_1^2 - 31.57X_2 - 5.65X_1X_2 - 22.06X_2^2 + 12.93X_3 + 20.49X_1X_3 + 50.82X_2X_3 - 204.7X_3^2 - 5.79X_4 + 0.68X_1X_4 - 2.06X_2X_4 - 1.0X_3X_4 - .88X_4^2 - .42X_5 - .57X_1X_5 - 1.46X_2X_5 + 2.5X_3X_5 - .34X_4X_5 + .17X_5^2$$

Where I = Overall Index

X_1 = Net Income/Total Assets

X_2 = Current Assets/Total Assets

X_3 = Cash/Total Assets

X_4 = Current Assets/Current Liabilities

X_5 = Sales/Current Assets

(Deakin, 1977, p. 79).

Altman also produced a model using both the linear and quadratic approach. This new model uses seven ratios that are different from the five used in his first model. The seven ratios measure return on assets, stability of earnings, debt-service, cumulative profitability, liquidity, capitalization and size. The new model yields what Altman terms a Zeta score that produces superior accuracy to the old model in classifying firms and has received generally high reviews in financial literature. However, the model cannot be independently utilized for testing, as Altman has not released the details of the model. He has a firm that markets the use of the model for testing firms, (Altman, 1993).

Marc Blum and Robert Edmister conducted two other studies that are often included in financial literature concerning business failure prediction. Blum's 1974 study was similar to Altman's, except he broadened the definition of failure and he used a different set of ratios. Edmister's study also used multiple discriminant analysis, but his study only looked at smaller companies.

Robert O. Edmister, 1972

Edmister's study was the first to focus on small business failure. He used a sample drawn from Small Business Administration loans. Edmister tested five methods of ratio analysis on a set of 19 ratios. All the ratios were chosen from ratios used in prior studies by Beaver, Altman and Blum. The first method tested was using the ratio itself as a predictor of failure. The premise was that the level of the ratio itself might be a predictor of failure. To test his theory, Edmister compared the values of individual ratios to the average ratio of other small businesses in the same industry. The comparison showed that the failed firms' ratios were consistently lower.

The second method tested was the accuracy of a test using a three-year trend in the ratios. Only ratio values that went in the same direction all three years were considered trends. Upward trends were considered positive and downward trends were considered negative. Variables for up-trends and downtrends were assigned a value of one if the ratios exhibited either an upward trend or a downward trend; otherwise those variables were assigned a value of zero.

The third test looked at the combination of the ratio's trend and the ratio value. The fourth test looked at the three-year average of the ratios. The fifth test looked at a combination of the industry trend and the industry level of the ratios, by dividing each ratio by the corresponding industry average ratio.

Edmister's study did not result in an accurate function for data within one year of failure. However, an accurate prediction function was developed using data three years prior to failure. This equation is shown below in Model 3.

The study achieved a classification accuracy of 93%, with a Z-score below .47 indicating failure, above .53 indicating non-failure and scores between those values being a "gray zone" similar to Altman's. The most significant contribution of Edmister's study was the concept of using industry averages to calculate standardized ratios and the converting of the ratios to dichotomous variables, which added to the significance of the results. (Edmister, 1972).

Model 3

Edmister's Small Firm Multiple Discriminate Analysis Model.

$$Z = 0.951 - 0.423X_1 - 0.293X_2 - 0.482X_3 + 0.277X_4$$
$$0.452X_5 - 0.352X_6 - 0.924X_7$$

Where Z = Overall Index

X_1 = 1 if funds flow/current liabilities < 0.05

= 0 otherwise

X_2 = 1 if equity/sales < 0.07

= 0 otherwise

X_3 = 1 if (net working capital/sales)/industry average ratio < -0.02

= 0 otherwise

X_4 = 1 if (current liabilities/equity)/industry average ratio < 0.48

= 0 otherwise

X_5 = 1 if (inventory/sales)/industry average ratio < 0.04 and trends upward

= 0 otherwise

X_6 = 1 if quick ratio/industry average < 0.34 and trends downward

= 0 otherwise

X_7 = 1 if quick ratio/industry average trends upward

= 0 otherwise

(Edmister, 1972, p. 1487-1488).

Marc Blum, 1974

Blum's definition of failure went beyond looking at just bankrupt firms. He also included firms that could not pay their debts when due and firms that had entered into an agreement to reduce debts. Using this definition, he was able to obtain a data set that contained 115 failed and 115 non-failed companies from the years 1954 to 1968.

As a framework for his study, Blum used a set of six propositions for predicting failure that was very similar to the set of propositions that Beaver had used. The first proposition was that the smaller the pool of net liquid assets, the greater is the likelihood of failure. The second proposition was that the smaller the inflow of resources from operations the more likely the probability of failure. The third proposition was that the larger the claims on the resources by creditors, the greater the probability of failure. The fourth proposition was that the greater the outflow of funds required by the operation of the business the higher the probability of failure. The fifth proposition was that the more highly variable earnings and claims against resources, as shown by outflows to maintain current operations and by obligations to creditors, the higher the probability of failure. Finally, the more "failure-prone" the industry locations of a firm's business activities are expected to be, the higher the likelihood of failure.

To measure these propositions Blum grouped twelve ratios into three general classifications: liquidity, profitability and variability. He further broke down liquidity into short-run liquidity and long-run liquidity, and measured both the flow and the position of each.

The ratios he used to measure short-term liquidity were the "quick flow" ratio and the ratio of net quick assets to inventory. The "quick flow" ratio was defined as cash +

notes receivable + market securities + (annual sales ÷ 12) ÷ (cost of goods sold – depreciation expense + selling and administrative expense + interest) ÷ 12. He defines net quick assets as cash and equivalents plus accounts and notes receivable less short-term resource claims.

Long-run liquidity was measured by three ratios, cash flow to total liabilities, net worth at fair market value to total liabilities and net worth at book value to total liabilities. He used the harmonic mean of the bounds of the range of stock prices during a year as the measure of fair market value, in order to eliminate speculative upsurges in market value.

Profitability was measured as the rate of return to common stockholders who invest for a minimum of six years. Rate of return was the internal rate of return computed over the six years. Initial investment was defined as the average stock price during the first year and cash flows over the period were defined as dividends received plus a presumed sale at the end of the six years in an amount equal to the average stock price for the sixth year.

Blum's inclusion of measures of variability was the most extreme departure from the conventional analyses. He used six ratios to determine variability and trend of resource inflow and to determine the variability of his short-term liquidity indicator – net quick assets to inventory. For both net income and for the net quick assets to inventory ratio he computed the standard deviation over each year, trend breaks and slope. Trend breaks were defined as a decline in either net income or the ratio from one year to the next. Slope is the trend line fitted to the observations using the least-squares method.

Blum reported a 93-95 percent predictive accuracy for his model in the first year before failure. He found, like Beaver, that cash flow/total debt was the best predictor ratio. He also developed functions using raw accounting data, which had a better predictive accuracy than the models using ratios, but he offered no explanation for this, suggesting the need for additional research. He also suggested that his study indicated that the use of non-traditional ratios and non-traditional approaches to looking at ratios might yield more discriminating results. Blum did not publish his actual formulas for failure prediction, and none of the other studies reviewed attempted to present a formula. (Blum, 1974).

James A. Ohlson, 1980

There have been several other studies that have attempted to improve on the ability to predict financial failure. The primary distinctions among these studies have been the method of selecting the ratios to be used, the statistical technique used to evaluate the relationship of the variables, the method of selecting the data sample and the types of businesses being reviewed.

In 1980, James Ohlson developed a model using the logit technique that was later to be used by Zavgren in her 1985 study. Ohlson cited three primary problems with prior studies that had been done using the more popular MDA technique. First he objected to the statistical requirements imposed on the distributional properties of the ratios. Among these requirements were that the variance-covariance relationships of the ratios had to be the same for both groups and that the predictors (ratios) had to be normally distributed. However, he also stated, "A violation of these conditions, it could perhaps be argued, is unimportant (or simply irrelevant) if the only purpose of the model is to develop a discriminating device" (Ohlson, 1980, p. 112).

Ohlson also felt that the use of a score, which is the output of the MDA approach, was only a ranking method, and did not provide the opportunity for interpretation. Finally, he did not feel that the use of the procedure of matching failed and non-failed firms provided any benefit to an analysis. He felt that, "The use of use of conditional logit analysis, on the other hand, essentially avoids all the problems discussed with respect to MDA." (Ohlson, 1980, p. 112).

In addition to his preference for the logit analysis technique, Ohlson also objected to the data used in prior studies. He felt that by using financial statement information from Moody's Manual, the source for most prior studies, no consideration had been given to the dates that information was available to the public. He noted that all the prior studies had assumed that the information was available as of the date of the financial statements, which is of course not the case. To overcome this limitation, he used SEC reports that were dated.

According to Ohlson, "No attempt was made to select predictors on the basis of rigorous theory. To put it mildly, the state of art seems to preclude such an approach." (Ohlson, 1980, p.118).

Ohlson chose nine ratios for his analysis, based on "simplicity". Five of the ratios were ones often cited in the literature; total liabilities divided by total assets, working capital divided by total assets, current liabilities divided by current assets, net income divided by total assets and funds provided by operations divided by total liabilities. He also used size of the firm as defined by the equation: log(total assets/GNP price-level index).

He also used two variables that were defined as decision variables. One of these variables compared total liabilities to total assets, assigning a value of one if liabilities exceed assets and zero otherwise. The other assigned a value of one if net income was negative for the two years prior to failure and zero otherwise. The final factor measured the change in net income. The change was determined using the following formula: $(NI_t - NI_{t-1})/|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period.

While Ohlson's results were not as good as Altman's or Deakin's, he concluded that his methodology was more sound. He also reached some other interesting conclusions from his study. He found that size of the firm was the most important predictor in his model, with financial structure being the next. Ohlson's model is shown in Model 4.

Model 4

Ohlson's Logistic Regression Model.

$$Y_i = -1.32 - 0.0407X_1 + 6.03X_2 - 1.43X_3 + 0.0757X_4$$

$$2.37X_5 - 1.83X_6 + 0.285X_7 - 1.72X_8 - 0.521X_9$$

And

$$P = (1 + \exp\{-Y_1\}^{-1}) \text{ so that } Y_1 = \log[P/(1-P)]$$

Where P = Overall Probability of Failure

X_1 = log (Total Assets/GNP price-level index)

X_2 = Total Liabilities/Total Assets

X_3 = Working Capital/Total Assets

X_4 = Current Liabilities/Current Assets

X_5 = Net Income/Total Assets

X_6 = Funds from Operations/Total Liabilities

X_7 = 1 if net income was negative for the last two years

= 0 otherwise

X_8 = 1 if total liabilities > total assets

= 0 otherwise

X_9 = $(NI_t - NI_{t-1})/|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period.

(Ohlson, 1980, p. 118-119).

Rose and Giroux, 1984

Peter Rose and Gary Giroux developed a model in their 1984 study that used ratios that had not been used in previous studies. They developed 130 new ratios and tested a set of 92 firms, 46 failed and 46 non-failed. Their analysis showed that 34 of these ratios showed significant differences between the two groups.

They combined these 34 ratios with 27 ratios that had been used in other bankruptcy prediction studies. The ratios were then used in a MDA procedure that resulted in a model using 18 of the ratios. Of these 18 ratios, 13 had not been used in prior models.

The study developed both a linear prediction equation and a quadratic prediction equation. The overall classification accuracy of their model was 92%. The linear equation accurately classified the firms from 88% to 97.4% over the seven-year period of the study. The quadratic equation's accuracy ranged from 74.5% to 86.7%. While the results were not consistent enough to make the model a more reliable predictor than either the Altman model or the Deakin model, there were some findings that could influence future studies.

The performance of the new ratios they used indicates that creative ways of choosing ratios could improve the accuracy of new models. Their study also showed that the quadratic function had less variance than the linear function, perhaps indicating the need to include a quadratic equation in future studies (which Zavgren did in her study). The actual equation developed by Rose and Giroux was not presented in their study, only the results. (Rose & Giroux, 1984).

Christine V. Zavgren, 1985

Zavgren used a different statistical analysis technique than Altman and Deakin used. She used a technique called logit. Logit, like multiple discriminant analysis, is a multivariate technique that considers all the predictive factors in a problem taken simultaneously. Unlike MDA, logit weighs each of the variables in such a way that the formula generates a probability of classification of the total set of weighted variables into one of two separate groups. MDA generates a linear relationship whose solution will maximize the difference between two possible classifications.

Zavgren chose the ratios to be used in her study based on a 1973 study by Pinches, Mingo and Caruthers that used factor analysis to identify the most appropriate grouping of factors affecting a firm's financial position and financial performance. The seven areas their study showed as the most critical were return on investment, capital intensiveness, inventory intensiveness, financial leverage, receivables intensiveness, short-term liquidity and cash position, (Bukovinsky, 1993).

Using 48 separate ratios, Zavgren selected the seven ratios that provided the best measure for each of the seven factors. The seven ratios were total income to total capital, sales to net plant, inventory to sales, debt to total capital, receivables to inventory, quick assets to current liabilities and cash to total assets. Zavgren's final formula is shown in Model 5.

Model 5

Zavgren's Logistic Regression Model.

$$Y_i = 0.23883 + 0.00486X_1 + 0.001110X_2 - 0.00108X_3 - 0.0435X_4$$
$$0.01583X_5 + 0.03074X_6 - 0.1078X_7$$

Where Y_i = Overall Probability of Failure

X_1 = Net Income/Total Equity

X_2 = Total Sales/Net Plant

X_3 = Total Inventory/Total Sales

X_4 = Total Liabilities/Total Equity

X_5 = Total Receivables/Total Inventory

X_6 = Quick Assets/Current Liabilities

X_7 = Total Cash/Total Assets

(Zavgren, 1985, p. 24, 29).

According to Zavgren, the expected results of her study were not supported by the analysis. The model she developed had less accurate results than the Altman model or the Deakin model. Using probabilities as a financial risk measure in the pattern of the financial attributes and the information provided the primary significance of her study. (Zavgren, 1983).

Cash Flow Models

Prior to the issuance by the Financial Accounting Standards Board (FASB) of Statement of Financial Accounting Standards No. 95, Statement of Cash Flows, in 1987, consistent information concerning actual cash flow was generally not available. The studies conducted prior to 1987 generally used a proxy for cash flow, net income plus depreciation, for their ratios that required a cash flow factor. In addition to ignoring the impact of changes in other current assets and changes in current liabilities on cash flow from operations, the use of net income plus depreciation also leaves out the funds provided/used in financing and investing activities. Measures of actual cash flow were used in several bankruptcy studies during the 1980's. (Bukovinsky, 1993).

Unfortunately, the results of the cash flow based studies showed very little incremental value to traditional accrual based prediction models (Altman, 1984). Although cash flow is considered in many of the traditional bankruptcy prediction models, using information from accrual statements provides adequate information.

In the FASB Statement of Financial Accounting Concepts No. 1 an objective of financial accounting was said to be the providing to decision-makers of useful information to assess the amount, timing and uncertainty of future cash flows. The FASB and accounting academics agree that accrual accounting provides the best information about a firm's current and future performance (Shroff, 1998).

Casey & Bartczak, 1984 & 1985

In their first study, Casey and Bartczak used a sample of 60 companies that filed for bankruptcy from the period 1971-1982 and matched them with 230 non-failed companies. For each of these companies they computed three variables, operating cash flow, operating cash flow divided by current liabilities and operating cash flow divided by total liabilities.

Their conclusion was, "that none of the variables could discriminate between the bankrupt and non-bankrupt companies with reasonably good accuracy. In fact, overall accuracy for operating cash flow was only slightly better than chance (50%) for the first and second years before failure and was worse than chance for the remaining years" (Casey & Bartczak, 1984, p.64).

In a letter to the editor of the Harvard Business Review, Edward Altman commented on Casey & Bartczak's study. "Casey and Bartczek are absolutely correct in their assertion that OCF or its variation measures are poor predictors of insolvency, either by themselves or as parts of a multivariate model of the type that I have been discussing ever since the original Z-score approach for bankruptcy prediction was developed. Indeed, my own skepticism about liquidity measures in general and cash flow variables in particular has caused me to almost eliminate them from consideration" (Altman, 1984, p. 176).

In a follow-up study, Casey and Bartczak tested the effect of adding operating cash flow information to existing accrual-based models in order to enhance their predictive ability. The results again showed that the operating cash flow data do not provide incremental predictive power over accrual-based ratios. They suggested that a broader definition of cash flows, like total cash flow might lead to improved classification accuracy. (Casey & Bartczak, 1985).

Gentry, Newbold & Whitford, 1985

Using a matched sample of 33 failed and 33 non-failed companies, Gentry, Newbold & Whitford used both MDA and logit techniques to analyze eight funds flow variables. The eight variables were funds provided by operations, flows provided by changes in working capital, fixed coverage expenses (interest and rent), funds used for capital expenditures, dividends, other asset and liability flows and change in cash and marketable securities.

Using a probit model to develop a formula that predicts the probability of failure for each of the firms, they were only able to achieve 79% accuracy in predicting failure using their funds flow variables. They also tested the effect of combining accrual-based ratios to their model. Their conclusion was "that the addition of cash-based funds flow components to the traditional financial ratios used to discriminate between failed and non-failed companies results in significantly improved predictive performance" (Gentry, Newbold & Whitford, 1985).

However, according to Bukovinsky, "this conclusion is based only on the statistical significance of the models. The ultimate test of the incremental predictive ability of the models would involve the use of the models to classify a sample of firms and to compare the classification accuracies of the models. No such test of the comparative classification accuracies of the models was performed" (Bukovinsky, 1993).

Aziz & Lawson, 1988

Aziz and Lawson formally tested the differences between the predictive accuracy of Altman's Z and Zeta models, a cash flow based model and a model that combines the cash flow based model with Altman's Z-model. What they found was that in the first year before failure the combined model showed better classification accuracy than that shown by any of the other three models. However, in terms of overall accuracy they found that the ability to discriminate between bankrupt and non-bankrupt firms was about the same for all the models.

In terms of predictive accuracy, the cash flow model and the combined model were superior to either the Z-model or the Zeta model, particularly in the second through the fifth years before failure. Their conclusion was that while the study showed mixed results, it did indicate that cash flow information was important and should be considered in future studies. (Aziz, Emanuel & Lawson, 1988; Aziz & Lawson, 1989).

Summary of Traditional Bankruptcy Prediction Models

While there are many studies that have been conducted in the field of predicting business failure and many failure prediction models developed, there is no consensus on which model is the best or which variables are the most effective. A limitation on all of the studies has been the lack of sufficient data to perform extensive testing or satisfactory validation procedures.

The studies of bankruptcy prediction that have been done in the past have concentrated on identifying the symptoms of a failed firm, what a failed firm looks like after it has entered into a failure mode, rather than what has caused the failure. Additional research into the underlying causes of failure could potentially help prevent bankruptcy rather than just predicting it.

A recent study evaluating existing bankruptcy prediction models showed that no one model in the existing literature was entirely satisfactory at differentiating between bankrupt and non-bankrupt firms. The study concluded that the different models might have different uses and that the challenge for new research is to make full use of all readily available data within a better model of the bankruptcy process. (Mossman, 1998).

Application of Traditional Models to the Casino Industry

In a study of the effectiveness of three of the traditional bankruptcy prediction models for predicting failure and non-failure in the casino business, it was shown that none of the models predicted bankruptcy with any greater accuracy than a naïve prediction (Patterson, 1999).

In the study, the three models chosen for the analysis were the models developed by Edward I. Altman, the models developed by Edward Deakin and the model developed by Christine Zavgren. Each of the models was tested using published financial data for an equal number of failed and non-failed casinos.

The Altman model was chosen because it is generally considered the landmark model in bankruptcy prediction; it was the first published study that used multi-variant analysis to study the differences between failed and non-failed firms, by using multiple ratios simultaneously. The Altman model, which was first published in 1968, is still the most widely used and widely quoted bankruptcy prediction model.

The Deakin model was used because it is another early multi-variant analysis model that is generally cited and used as a standard for evaluating new approaches to bankruptcy prediction. It uses different ratios than the Altman model and may produce different results when applied to gaming analysis.

The Zavgren model was chosen because it uses a different approach than either the Altman or the Deakin model, and may yield different conclusions from those of the other two models.

The basis for evaluating the contributions of the models was a naïve prediction. The naïve prediction would be that in a sample population that contained exactly the same number of failed and non-failed firms, assigning an individual firm to one group or another on a random basis would, on average, result in a correct classification 50% of the time (Patterson, 1999).

The Altman model had an accuracy rate of 50% one year prior to bankruptcy and 58% two years prior. These results do not suggest any incremental value to the prediction decision. The major weakness of the Altman model is that it predicts failure for all but two firms in each of the two years tested. While it is generally agreed that a type two error, predicting failure for a non-failing firm, is less costly than a type one error, predicting failure in all cases except absolutely certain successes would preclude almost all investment decisions.

The Deakin models presented different results. Deakin's linear model has an overall accuracy rate of 79% one year prior to failure and 75% two years prior. While these results are clearly superior to the results of a naïve selection process, they do not come close to the 97.5% success rate he achieved in his original study. The other two models do not come close to the accuracy of a naïve selection process. The quadratic function only achieved an accuracy rate of 29% one year prior to failure and 42% two years prior. The combined model results were 29% and 33% respectively for one and two years prior to failure.

Like the Altman model's variables, the Deakin model variables are heavily influenced by the value of the total assets of the firm. In the linear equation, the highest weight is attributed to the net income to total assets ratio, which measures the return on the total investment. This relationship is not considered in any of the other models, and may explain the reason this model exhibits the best prediction accuracy of all the models. By comparing net income to total assets, which is the same as total investment, both the needs of the equity holders and the debt holders are considered. This would tend to indicate that the casino's ability to generate or not generate an appropriate return could represent a good predictor of its likelihood of success.

The significance of cash and of current assets relative to the total capitalization of the casinos is the primary reason for the failure of the quadratic equation to accurately predict failure in the casino business. The required levels of cash in the casino industry are highly dependent upon regulatory requirements, and do not really vary significantly between a successful firm and an unsuccessful firm. The levels of cash and working capital are to the Deakin model, as in the Altman model, important factors about which the casino industry should probably be more attentive, but they do not appear to be significant discriminators between failing and non-failing firms.

The relationships of the Deakin quadratic model do not appear to provide any discriminating information concerning the viability of a casino. According to Deakin, all the casinos are going to fail. Due to the differences in predictive ability between his linear model and his quadratic model it would appear that the primary distinguishing characteristic is the return on investment, and that the coefficients of the quadratic model are not appropriate for casinos.

The Zavgren model has the lowest classification accuracy of the three models. One year prior to failure, the model only classified 75% of the firms at all, and then correctly classified only 21% of those. Two years out classified a higher percentage of the firms, 96%, but only did slightly better at classification, 29%. This accuracy level is significantly lower than what would be expected from a naïve classification.

The Zavgren model uses inventory levels in two of the variables of the model. In the casino business, inventory levels are not as important as they would be in a manufacturing or a retailing firm. Relationships between inventory levels and sales would generally not be indicative of any poor management decisions in the casino business.

The return on equity ratio also does not seem to work for a casino. Because of the high leverage rates of many casinos, equity holders may appear to be achieving acceptable returns if the debt holders are ignored. Since this is the effect of computing return on equity without any return on liabilities or total investment being considered, the result is non-discrimination. The other ratios in the Zavgren equation reflect the same measurement problems of the casino industry as seen in the Altman and Deakin models.

Summary of Literature Review

While accounting records in the United States date back to its earliest days, it was not until the end of the nineteenth century that accounting finally began to emerge as a profession. One impetus of this emergence was the growing need for reliable financial records as the country moved from a primarily agricultural and mercantile economy to an industrial economy.

The transition of the country's economy was accompanied by a heightened interest in measuring the financial condition and stability of companies. The first ratio used to measure a firm's financial condition was the current ratio in the early 1900's. During the 1920's and 1930's, several additional ratios were developed to provide a more comprehensive means of evaluating companies. New methodologies of analyzing these ratios were also developed and the process of distinguishing between failed and non-failed companies through various manipulations were also developed and studied.

Beginning with the work of Beaver in 1966, statistical analysis of multiple financial ratios began to be used for predicting business success or failure. Edward Altman developed the first analysis of a combination of financial ratios, using multiple discriminant analysis, in 1968. Since that time several other studies have been done that have looked at various industries and that have used several different statistical techniques. None of these studies was done specifically for predicting failure or non-failure in the casino business. Patterson's study (1999) examined the results of using three of the most recognized bankruptcy prediction models to test failed and non-failed casinos.

The traditional bankruptcy prediction models tested do not provide significant incremental information for predicting bankruptcy in the casino industry. Only a part of one of the models showed results that were superior to what would be expected from a naïve classification. A possible explanation for the inability of the models to perform adequately in the casino industry is that the original studies were done using manufacturing companies, which typically exhibit financial structures that are different than what is seen in the casino industry.

The Altman Z score, which is often quoted in investment banker reports has been widely used in all types of businesses, including casinos, had an accuracy classification rate of only 50% in year one of the test, and 58% in year two. While it accurately predicted failure for 92% of the firms that failed, it did this at the expense of erroneously predicting failure in 92% of the firms that did not fail. The same rate would have been achieved by saying that all casinos are going to fail.

The Deakin linear model did better than the Altman model, achieving a prediction accuracy rate of 79% in year one and 75% in year two. While this represents a positive contribution to overall knowledge of the firm's total financial information, the rates and types of errors can confuse this information. The type one errors were fairly high at 25% and 33%, and would probably not represent an acceptable level relative to the risk of investing in a firm that is likely to fail.

The Deakin quadratic model and the combined results model did not perform as well as a naïve prediction, at 29% in year one and 42% and 33% for year two. The models also produced conflicting results in three of the years. The type two errors were higher than the type one errors in both years for the quadratic model, at 100% and 92%

versus 42% and 25%, but both types of errors are higher than acceptable. While the error rates were higher in the combined model, only 46% of the firms were classified.

The Zavgren model achieved the lowest classification accuracy at 21% and 29% for year one and year two respectively. The Zavgren model also had a high rate of non-classified firms, 25% in year one and 4% in year two. The type two errors for those firms classified by the Zavgren model were 100% in each test period and 33% type one errors in year two. The accuracy level would have been much higher by simply saying that all casinos will fail.

The conclusion of this literature review is that there is a need for a bankruptcy prediction model that is developed specifically for the casino industry. Since none of the traditional approaches seems to work better than the Altman Z score model, the statistical approach used by Altman seems to be appropriate for this analysis.

CHAPTER 3

RESEARCH METHODOLOGY

The purpose of this study was to develop a model, which would differentiate between casinos that are likely to fail and those that are likely to succeed, by using the financial ratios of the casinos. The first step in the process was to make a determination as to what the critical factors might be that distinguish the two groups of firms. What is different between a successful casino and an unsuccessful casino? The development of the constructs of the model and the development of a theoretical model are discussed in this chapter.

The next step in the development of the differentiation model was to examine the information that is available that could be used to measure the factors that have been identified as constructs for the model. For this study this step in the process was complicated because of the data source that was utilized. The procedures that were used to select and obtain the data for the study are discussed in this chapter.

Finally a statistical method had to be selected to analyze the numbers and develop the actual differentiation model. To select the appropriate method, the model assumptions had to be examined relative to the information that was to be used. The alternatives and final determination of model choice are discussed in this chapter, together with a discussion of the methods that were used to evaluate the results of that modeling effort.

A possible outcome of this study is that a model cannot be developed that will significantly differentiate between casinos that are likely to fail and those that are likely to succeed. An alternative outcome is that the model does significantly differentiate between the two groups of casinos.

Development of Theoretical Model

In addressing the question of what distinguishes failed and non-failed casinos, there is obviously no simple answer. Failure can occur in any business for numerous reasons and at other times it occurs for no apparent reason. In order to determine likely characteristics of failed firms versus non-failed firms, a qualitative analysis was performed. This consisted of interviews of casino industry experts who had experience with failed and non-failed firms.

Although the interviews were open-ended discussions and not structured question and answer sessions, the same basic concepts were discussed in each interview. Each interviewee was asked about his personal experience and observations of failed casinos and non-failed casinos. What were the primary differences in the two groups? What types of controllable factors may have led to the failure of certain casinos. Why do some casinos fail while others do not. What types of operational adjustments are typically made after a casino enters bankruptcy protection? What would they look at to determine the likelihood that a particular casino would fail in the future?

The groups of industry experts that are involved with financial statements on an almost daily basis are the casino industry independent auditors, accountants and investment bankers. The independent auditors who were interviewed for this study are senior partners for two of the leading CPA firms in the casino industry. Steve Comer is the senior partner responsible for the gaming practice of Arthur Anderson, which has been responsible for the audits for numerous gaming companies, including Harrahs, Hilton, MGM, Mandalay Resort Group and Caesars. Jeff Cooper is the managing partner for Bradshaw Smith, which is a Las Vegas based CPA firm that has been extremely involved in the casino industry in Las Vegas for many years.

Other CPA's that were interviewed concerning their thoughts and opinions on bankruptcy in the casino business were Saul Leonard, Larry Bertsch and David Vorce. Saul Leonard was the senior gaming industry partner for the CPA firm of Laventhol and Horwath, and now has his own gaming consulting business in Los Angeles. Larry Bertsch is a Las Vegas CPA who now serves at a court appointed bankruptcy trustee. He was the controller for the management company that ran both the Aladdin Casino and the Marina Casino during their bankruptcy periods. David Vorce was a senior manager with the Bradshaw Smith firm.

Two senior analysts for investment banking firms that have large gaming clientele were also interviewed. Jason Adler is a senior gaming industry analyst for Bear Stearns. He has been responsible for financing of both successful and failed casinos and is a well-known and respected expert on gaming financial information. Bruce Turner is a senior gaming industry analyst for the Smith Barney firm.

Numerous gaming industry executives were also interviewed to get their perspectives on bankruptcy in the casino industry. William Dougall is the former president of Del Webb Nevada and has managed both bankrupt and very successful casinos. William was appointed by the bankruptcy trustee and approved by the Nevada Gaming Control Board to manage both the Marina Casino and the Aladdin Casino when they were in bankruptcy. In both cases, the casinos were turned around financially under his management. Mr. Dougall's insights into the real-world experiences of turning around a bankrupt casino were invaluable to the development of the constructs that were identified for this study.

The process of seeking expert opinions on bankruptcy was ongoing for more than two years and involved many people. Shannon Bybee is the Executive Director of the UNLV International Gaming Institute, a member of the Board of Directors of the Claridge Casino (currently in Chapter 11), the former President of the Golden Nugget Casino and the Claridge Casino in Atlantic City and a former member of the Nevada Gaming Control Board. Jim Palmer works for the audit division of the Nevada Gaming Control Board and maintains a database of financial information on gaming licensees, including a bankruptcy prediction analysis performed on the annual reports of the casino companies. Bob Fry is the CFO for Global Cash Access; he was the CFO for the Gold Strike properties owned by Bill Ensign and became the Assistant Treasurer of Circus/Circus after the merger of Gold Strike and Circus. H.S. Duffy Stanley, Jr. is the bankruptcy trustee for Southern Mississippi who was assigned as the receiver for the three bankrupt riverboats in Southern Mississippi (the Palace, Treasure Bay and the Belle of Biloxi).

Pulling together all the information related by this informal group of experts, there were several specific items that were identified consistently. Grouping the responses according to similarity, five constructs were identified that seem to represent the consensus of what described the primary indicators of business success or failure. These five constructs are: Management, Location, Ambiance, Marketing and Financial Strength. The next step in developing a theoretical model was to define what observed variables would represent each of the constructs and what empirical data would need to be collected to measure each of the observed variables. Constraining the decision making process of selecting empirical data to be used in the model was the availability of data. In some cases an alternative ratio had to be chosen when some other measure might have been more informative simply because there was no way to get at the data. A graphic representation of theoretical model is shown in Figure Two, Figure Three, Figure Four Figure Five and Figure Six below.

Figure 2

Theoretical Model

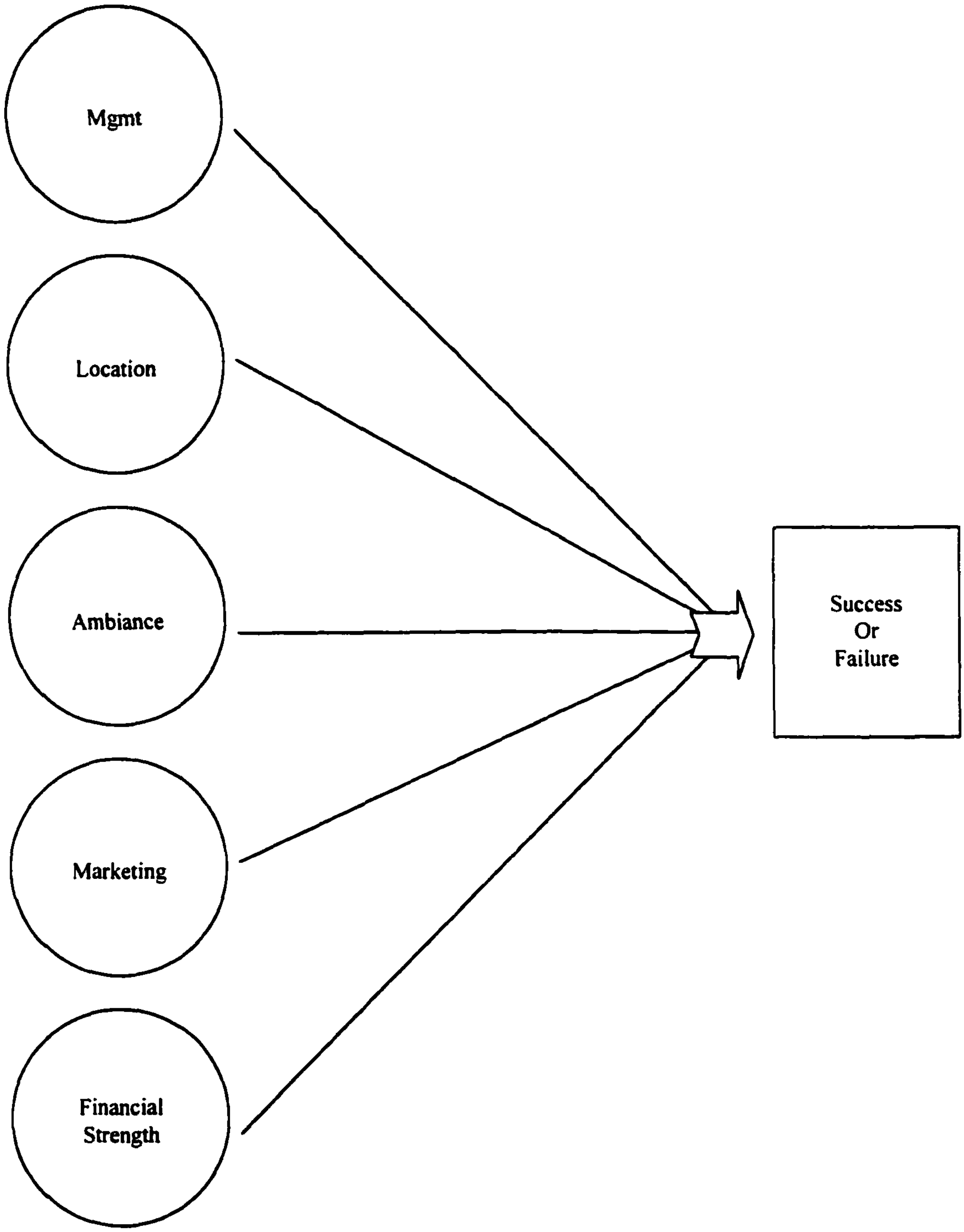


Figure 3

Management Construct

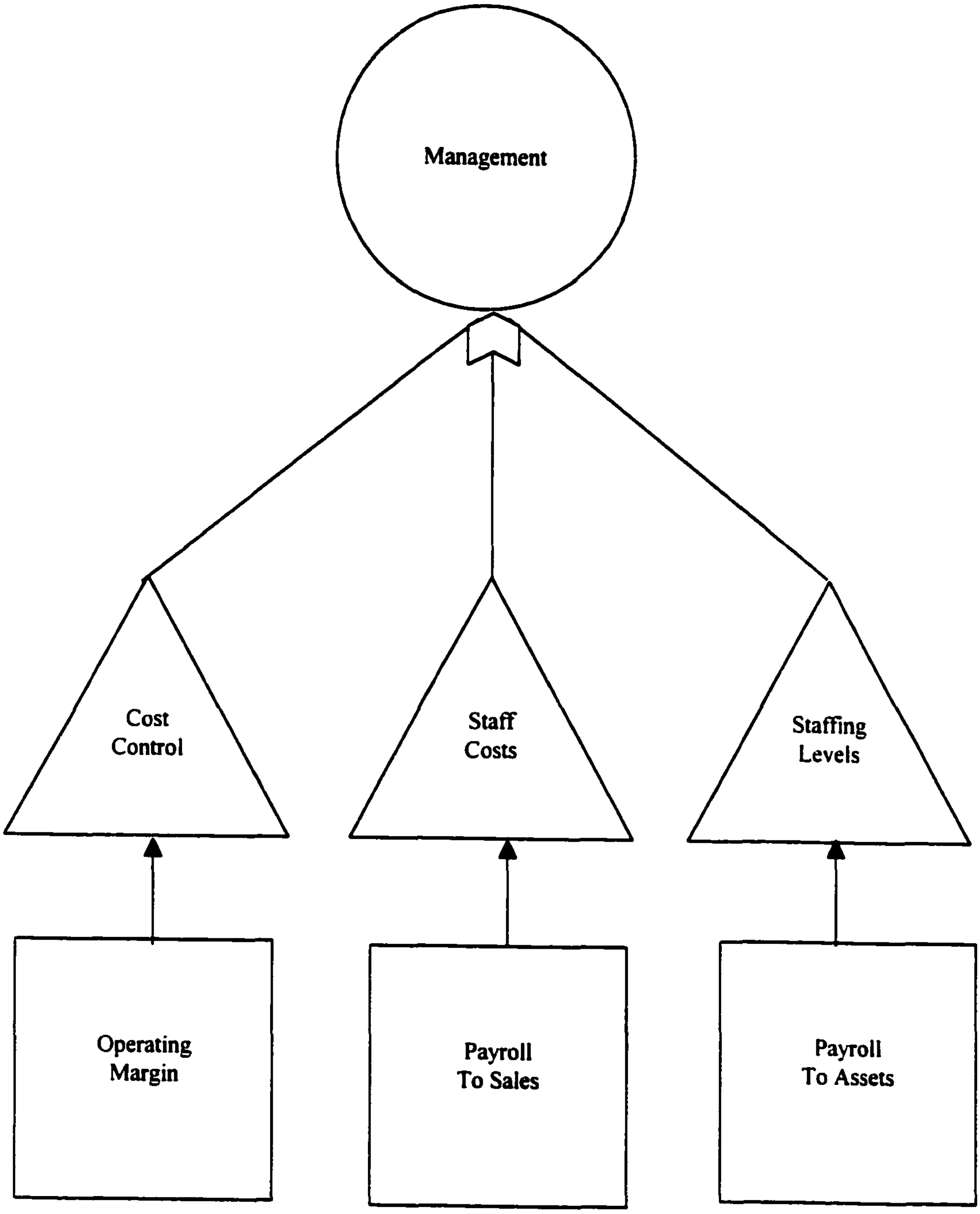


Figure 4

Ambiance Construct

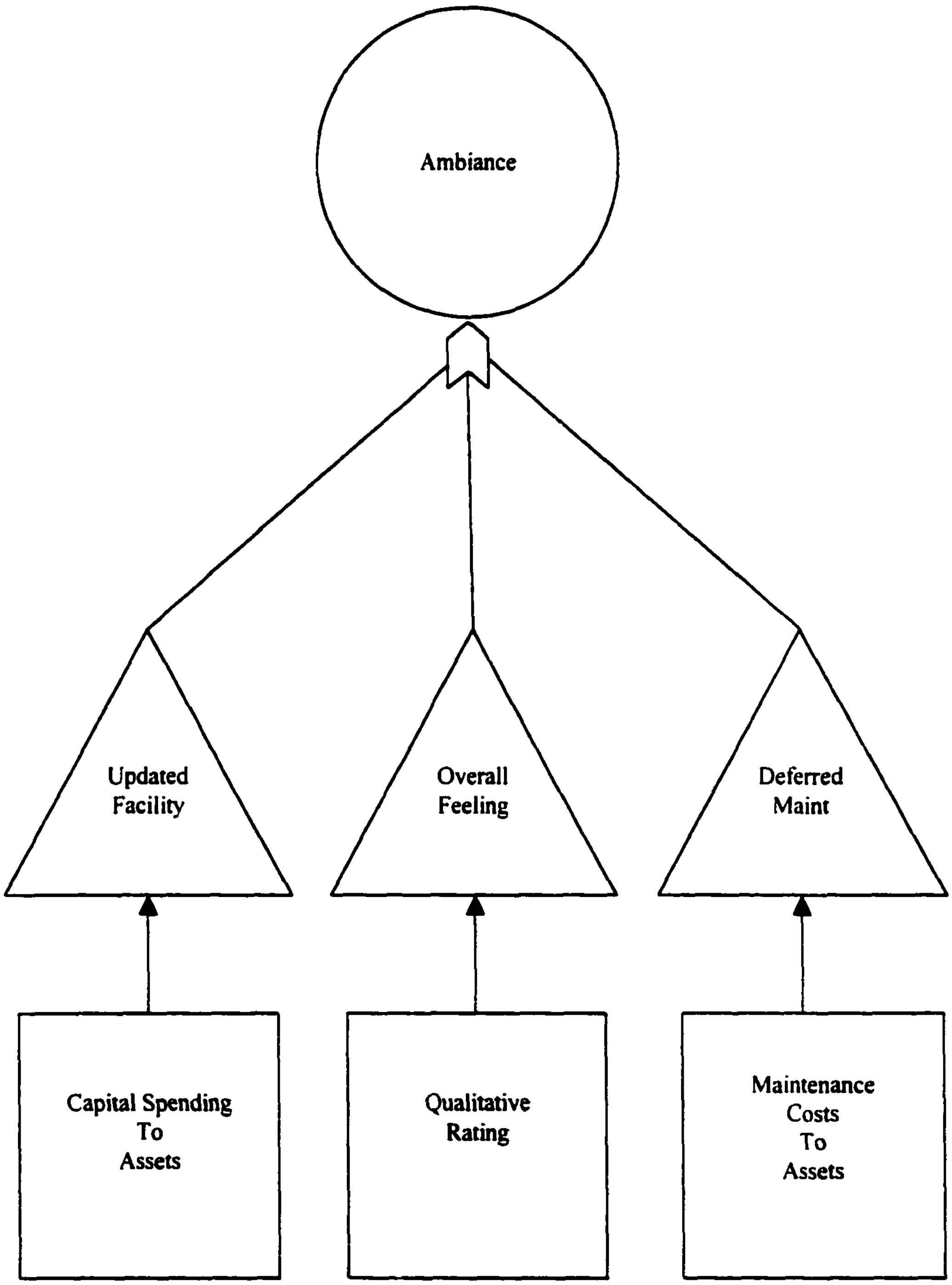


Figure 5

Marketing Construct

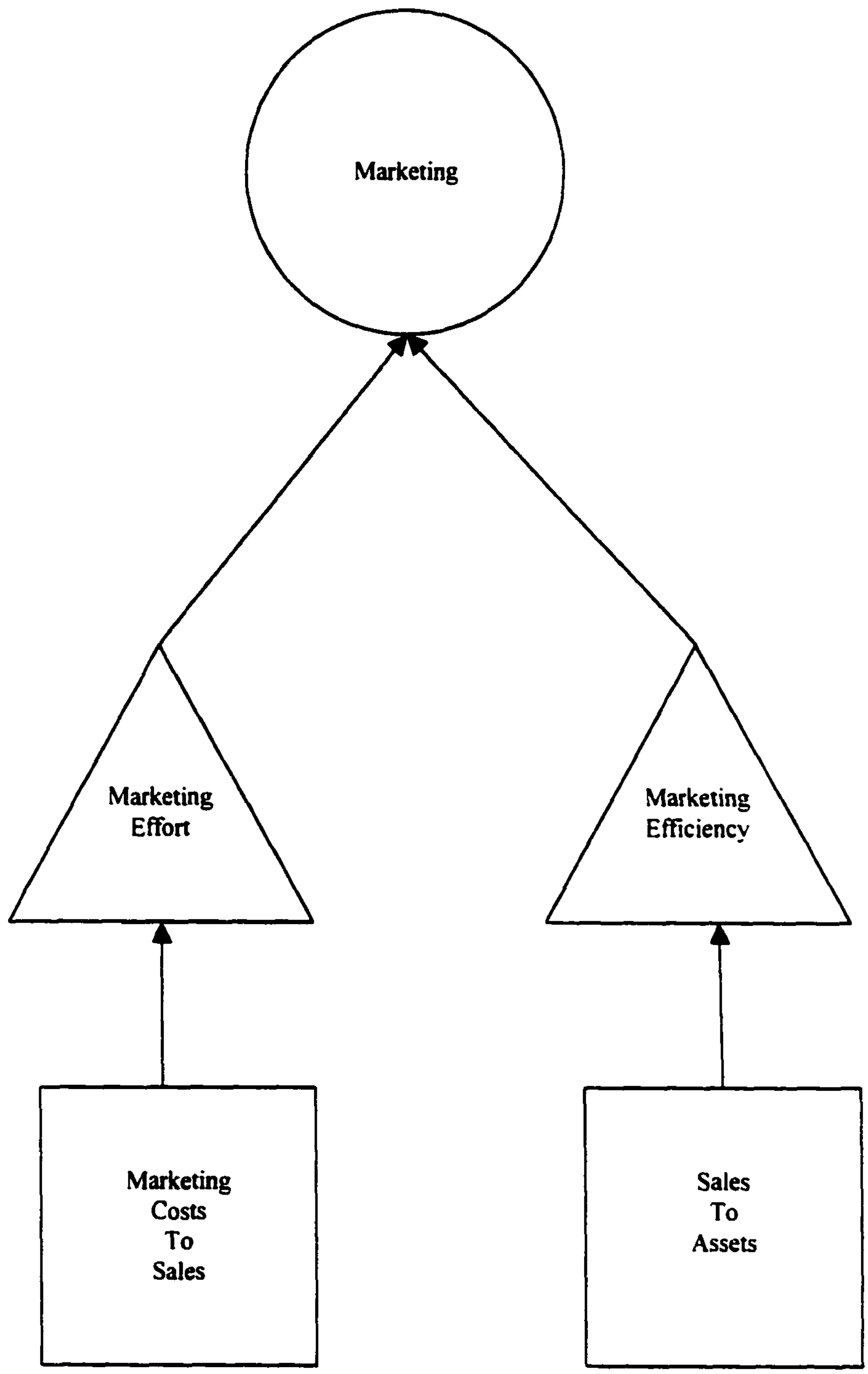
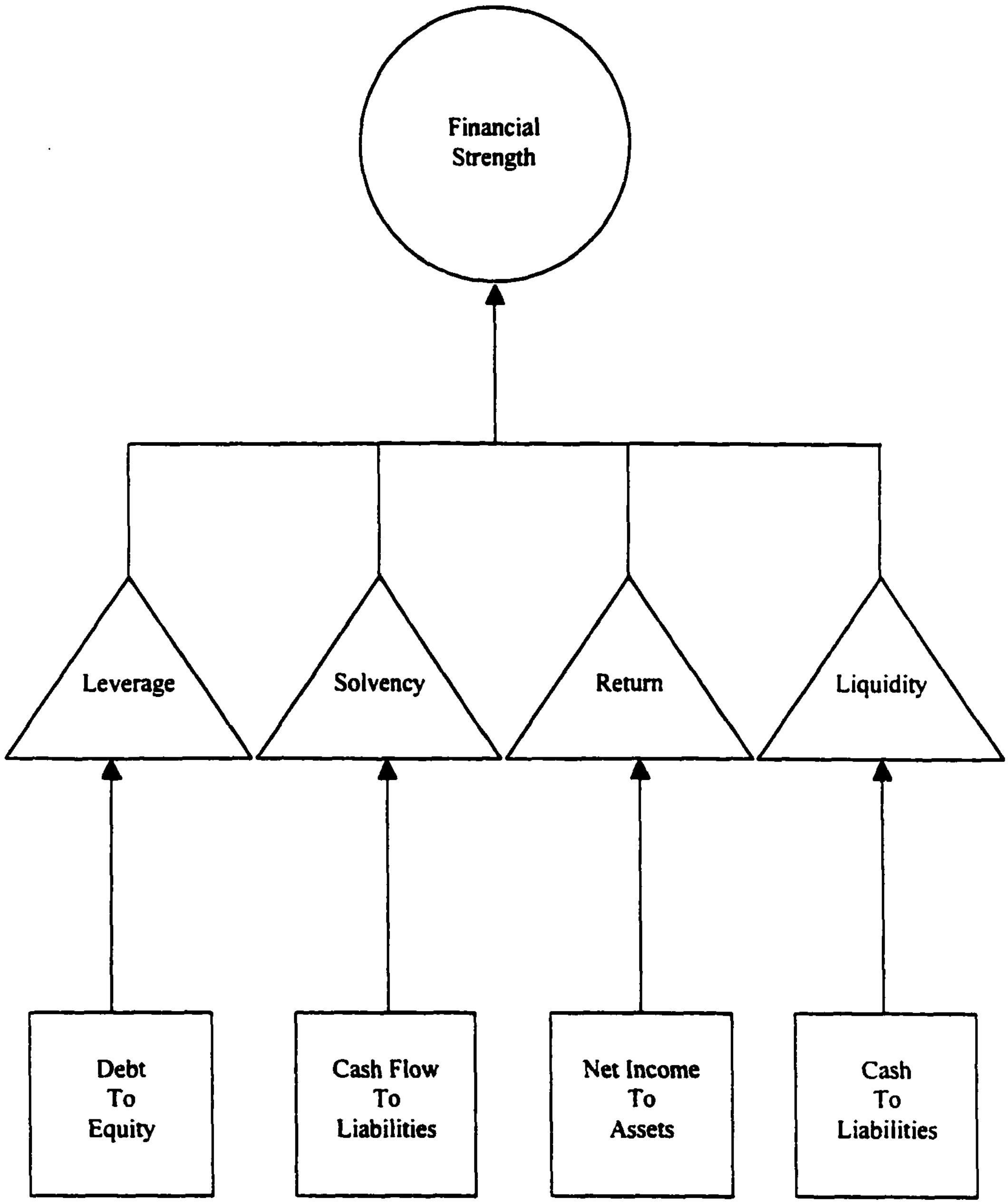


Figure 6

Financial Strength Construct



The Management construct relates to the operating areas of the business that are controlled by the property's management. The experts all agreed that the majority of bankrupt casinos do not adequately control their operating costs. In order to measure overall control of operating costs the operating margin was used, which is operating income divided by total revenues. According to Steffy, Zearley and Strunk (1974), the operating margin ratio indicates management's ability to control costs.

The theory behind using the operating margin to measure overall operating efficiency is that the ratio represents a generalized way of looking at the total operation, and is not dependent upon a particular mix of revenue sources or the size of the operation. Although operating costs do have a fixed component, which tends to make a larger operation have a better operating margin than a smaller operation, casinos do not have many operating costs that are fixed at different revenue levels, the costs are primarily variable and therefore this measure should adequately measure operating efficiency. It is believed that a successful casino would have a higher operating margin than would an unsuccessful casino.

Payroll costs are the largest operating expense in any casino, and by measuring the amount of payroll costs as a percentage of sales the efficiency of payroll cost control relative to the level of business is possible. While this measure is important when looking at two casinos of the same size, it does not provide for any differences in payroll that might be attributable to the size of the facility (there would be both positive and negative results that could result from a bigger or smaller casino). The other payroll efficiency measure, payroll costs to total assets, is designed to measure the level of staff relative to the size of the casino. By utilizing two ratios, the economies of scale that might make a bigger casino more efficient are softened, and the additional staff necessary to operate the bigger casino is taken into consideration.

The second construct is location. The problem with this construct was how to measure the quality of one location versus another. All the experts agreed that there were casinos that they knew of where location had been a factor in the failure of the property. This factor seems to be more of a qualitative assessment than a quantitative one, and therefore a rating scale was used to measure location. The scale used was a 5-point Lickert scale, with 1 being poor, 2 below average 3 average, 4 above average and 5 prime. Some of the qualities that were considered in rating each property were such things as proximity to other casinos, quality of neighborhood, ease of access and distance from target market. The measure is strictly a subjective judgment, but represents an overall assessment of the property's location.

Ambiance has to do with the overall feel of the property. It was generally felt that one of the things that happen to a property is that the customer does not like the décor, cleanliness, and/or general quality of a property. While this too is a somewhat subjective distinction, it was felt that there were some measurable things that happen that cause a property to have an uncomfortable feel. One of the things that happens to properties in an effort to save money is the deferral of maintenance programs. The result of a sustained program of deferred maintenance is that the property falls into disrepair. Not only do mechanical problems begin to occur, the brightness and cleanliness of the property begin to suffer. Another thing that can happen to a property that could create an ambiance that is not attractive to customers occurs when capital replacements are not made when they are needed. This situation can cause a distressed situation or could be a reaction to being in a distressed situation. Excessive capital replacements might also be a cause of financial distress if the level is more than can be supported by the property.

To measure the level of deferred maintenance and the level of capital replacements, it was decided to compare the maintenance costs and the capital spending to the total assets of the company, not including capital replacements for expansion of facilities. This method gives a perspective of how much is being spent for maintenance and for capital replacements relative to the total overall magnitude of the facility. A third observed variable that was added was a qualitative assessment of the facility. As with location, this measure is a subjective judgment about the overall feeling of the facility. A five-point Lickert scale was used for this variable, with 1 representing an old or poorly maintained facility, 2 being a substandard facility, 3 was for average facilities, 4 for a relatively new, well maintained facility and 5 being a superior facility.

The fourth success/failure construct is marketing. The general opinion of the experts is that when properties start having financial difficulties, one of the first areas that face reductions is the area of marketing costs. It was felt that neglecting a marketing program would soon lead to a diminution of customer awareness and an erosion of the property's ability to attract new customers. To measure the marketing effort the relative amount of marketing expenditures to sales was computed. While this measure does not address the effectiveness of the marketing effort, at least it tells whether or not there is some type of marketing program being pursued and how that effort on a cost basis compares from one property to another. The other empirical measure is marketing efficiency measured in the analysis is total sales to assets. This measure when compared to other companies will show if the sales level adjusted for the size of the investment is in line between successful and unsuccessful companies. Marketing effectiveness could also be measured as a qualitative variable, but it seemed that this was just too subjective to try to measure.

The final construct is Financial Strength. The observed variables that measure this construct are traditional financial ratios that have been used in other prediction models to measure financial strength: Leverage, Solvency, Return and Liquidity. These types of ratios have consistently been utilized in previous bankruptcy studies (Jones, 1987).

Leverage refers to the financing mix of the company, how much of the overall investment comes from creditors and how much comes from the owners. In general, creditors want the owners to have a large enough investment so that the creditor position is protected in the case of liquidation. Owners on the other hand want as much debt as possible (as long as the rate is lower than the required return on equity level) so that they can have a fixed level of return that has to be paid on that investment and so they can deduct the payments made on that portion of the investment. Also, if the venture is profitable, debt holders generally do not share in the profits above their predetermined interest rate. The ratio of debt to equity was used as the empirical data to measure this variable. According to Steffy, Zearley and Strunk (1974), this ratio measures the relative amount of capital supplied by the owners and too high of a ratio can increase the authority of the creditors, decrease the freedom of management and burden the company with interest payments.

Solvency refers to the firm's ability to repay its debts when they become due. Solvency is different than liquidity or profitability. Solvency relates to a firm's ability to sustain an operating cash flow that will service its debts as they become due in the future. Liquidity refers to the structure of a firm's assets, how much of the total assets are cash or can be converted to cash, and how that cash relates to the total liabilities of the firm. Profitability relates to the measurement of income, the amount by which revenues exceed expenses (or the inverse in the case of an unprofitable company). Since profitability is not based on cash or when cash might be ultimately realized, profitability does not indicate whether a firm can pay its debts, though certainly sustained lack of profits would make it difficult for a company to be able to pay its bills eventually. Solvency is affected by many factors, including the amount of the company's asset base, the level of its existing debt, the amount of cash it is generating and the amount it will generate in the future. For purposes of this study, the ratio that was chosen was cash flow from operations as a percentage of total liabilities. While this ratio does not address the long-term ability of the firm to meet its future obligations, it does provide a measure that is at least representative of the amount by which the current cash flow is capable of meeting existing obligations.

Return refers to the income that is made by the company. Return can be compared to debt levels, equity levels, revenue levels, asset levels or most any other financial measurement. By using net income to assets to measure return, the portion of debt or equity does not have to be considered. Other measures were not considered since they were being considered elsewhere in the analysis of financial strength. It is felt that overall acceptability of a level of return should be related to the total investment in the company by all of its stakeholders.

Liquidity is the amount of cash the company has relative to the amount it needs to meet its current obligations. While a firm does not need to have cash equal to all its obligations, it does need to be able to pay those obligations that are due or will become due in the short term. Not having enough cash will seriously impede the ability of a company to negotiate favorable purchasing arrangements, it may lead the company to make short term decisions that are not in the best interests of the company simply because of the cash situation not for sound business reasons and it may keep the company from pursuing activities that could make the business more successful.

Financial Data Used in Study

The primary limitation of this study was the availability of consistently prepared financial information from failed and non-failed casinos. Casino managers and owners are traditionally very sensitive to revealing financial information about their operations. People whose lives were often shrouded in secrecy and who had very little trust of anyone outside their own organization began the industry. This tradition of secrecy still continues.

For a previous study, data from public reports was used to test the accuracy of the Altman, Deakin and Zavgren models for predicting casino failure. This information was obtained from old annual reports and from SEC filings. While these reports provided sufficient information to test these historical models, which had been originally developed using information from public documents, there was not sufficient information available in these reports to conduct the current study.

Even if the information that was needed had been available from these sources, there are only a small group of casinos that are required to file this type of report. Also there are no consistent standards for the ways the information in these reports are presented. Public financial statements are typically presented in a very abbreviated format.

Individual state regulatory agencies each have reporting requirements for the casinos in their jurisdiction. Only three of these jurisdictions have had casinos that meet the criteria of failure: Mississippi, Atlantic City and Nevada. Of these three jurisdictions, only Atlantic City makes data on individual casinos available to the public. Nevada and Mississippi both have provisions in their casino laws that specifically prohibit the release of property specific data. While most of the information for creating a model based on the constructs identified for this study could be obtained from the reports of Atlantic City casinos, there have not been enough cases of bankruptcy in Atlantic City (only Resorts International, the Atlantis, the Sands: Greate Bay, and the Claridge) to perform a meaningful study using only their data. Mississippi has also had a few bankruptcies; Splash, Biloxi Belle, Treasure Bay, the Sahara and the Palace, but again not a sufficient number to do a valid study (even if the information was available on these properties, which it is not). Nevada has had several casino bankruptcies through the years, but Nevada law prohibits the release of individual casino financial data.

Since Nevada is the only state with a sufficient number of bankrupt casinos to allow an analysis of data that is prepared under exactly the same set of guidelines, it was the only logical choice as a possible source of data.

In the state of Nevada, all casinos with gross revenue of $1 million or more are required to submit to the Nevada Gaming Control Board an annual information report. This report includes detailed information concerning the financial operating results and the financial status of the casino. Aggregated information from these reports is made available to the public through Gaming Board publications and press releases. But, as stated earlier, state law prohibits the release of data that could possibly identify financial information as belonging to any specific casino.

Two significant factors in being able to obtain the release of data for this study were that the format (ratios) provided assurance of the confidentiality of individual property identities and the fact that the data being requested was for purposes of academic research and would be beneficial to both the state and the casino industry in general.

Three of the items needed to compute the ratios in a traditional manner are not included in the reports filed by the casinos, and substitutions were necessary. The three items were capital spending, cash flow from operations and marketing costs. Using the data that was included in the casino reports, acceptable definitions for these three items were determined.

For capital spending, balance sheet information was used. Capital spending was approximated by taking the change in gross property and equipment plus building (excluding construction in progress) from one year to the next.

Cash flow from operations was defined as net income (excluding extraordinary items), plus depreciation and amortization, minus the net increase in current assets plus the net increase in current liabilities. While not 100% accurate, this approximation is the ordinary definition of cash flow from operations as long as there are no gains or losses on sales of assets or treasury stock included in the net income number.

Marketing costs are not reported on the annual report, but advertising and promotion costs are reported. Since the advertising and promotion figure contains most of the marketing costs except for marketing payroll, which is included with the total payroll costs, the number seemed like an appropriate measure of sales effort. Payroll costs are included in the staffing levels and staff costs ratios, so they are not being ignored in the analysis, only aggregated.

Once the data requirements were determined, the set of casinos from which the data would be collected were identified. The Gaming Board's database of financial information in its current format is only available for the years after 1985. All the casinos that had declared bankruptcy since that time were selected as the failed firms. This list consisted of 16 casinos. Due to the confidentiality requirement, the identity of these casinos was not provided with the data.

For each of the failed casinos, it was agreed that the ratios would be based on the reports for each of the two years before the year they entered the bankruptcy process. Ratios for each of these two years were provided separately.

In order to minimize the differences between the failed casinos and the non-failed casinos that would be used in the modeling process, five parameters were agreed to for the selection of the non-failed casinos. First, one non-failed casino would be selected to correspond to each failed casino. Second, the non-failed casino would be one of approximately the same size (based on square footage of casino space) as its corresponding failed casino. Third, the corresponding failed and non-failed casinos would be located in approximately the same market area. Fourth, the two casinos would have similar amenities (i.e. if the failed casino had a hotel so would the non-failed casino, or if the failed casino did not have a hotel neither would its non-failed correspondent). Finally, the ratios for the non-failed casino would be computed based on the same year's report as its corresponding failed casino. As with the failed casinos, the identity of the non-failed casinos was not disclosed due to confidentiality requirements.

Since the identities of the casinos were not known, except to the Gaming Control Board, the two subjective evaluations (quality of location and quality of property) were also provided by them. The Board agreed to be as objective as possible and to try to employ the same sort of criteria when scoring each casino for each of the two years of the dataset.

While the resulting dataset is not very large, it has as many observations as many of the traditional bankruptcy prediction studies, and should be sufficient to provide a meaningful analysis. Only Nevada data will be used in the creation of the model, due to its consistency. Data from casino financials that are not part of the design of the model will be used as a holdout sample to test the accuracy of the model.

Statistical Method Used for Analysis

Many bankruptcy prediction studies have used a discriminant analysis method for developing the model that they used to predict business failure. This statistical technique is a multivariate method of data analysis. Edward Altman (1967) was the first person who used discriminant analysis for the classification of firms into failed and non-failed categories. This 1967 study resulted in the Altman Z score model that is widely used in finance textbooks and in the business world to this day. Although the method has been criticized over the years, most of the critics have not been able to attain the classification accuracy of the Altman Z score model even with more sophisticated techniques (Zavgren, 1985; Deakin, 1972).

R. A. Fisher first proposed the discriminant analysis approach in 1936 as a statistical tool for use in the classification of plants (Tatsuoka, 1970). The goal of discriminant function analysis is to predict group membership into one of two or more mutually exclusive and exhaustive categories from a set of predictor or classification variables. Classification is done by means of a linear discriminant function: $y = b_1x_1 + b_2x_2 + \ldots + b_nx_n$; where x_i = the i^{th} predictor variable, b_i = the coefficient value of x_i, and y = the discriminant score (Von Frederikslust, 1978, p. 5). The discriminate function solution is determined by finding the discriminate score, which best differentiates between two groups where the classification of each group member is known. A distribution of the scores for each group is developed and the point at which the overlap of the distributions of the two groups is sufficiently insignificant becomes the cutoff for membership in the other group (see Figure 1). The form of the model to be used in this analysis is presented in Model 6.

Model 6

Form of model for casino bankruptcy prediction

Prediction Score = $\beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 - \beta_5X_5 - \beta_6X_6 - \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} - \beta_{11}X_{11} - \beta_{12}X_{12} - \varepsilon$

Where:

X_1 = Marketing Costs/Total Revenues

X_2 = Net Income/Total Assets

X_3 = Total Revenues/Total Assets

X_4 = Operating Margin

X_5 = Payroll Costs/Total Revenues

X_6 = Payroll Costs/Total Assets

X_7 = % Change in Marketing Costs/Total Revenues Ratio

X_8 = % Change in Cash Balance/Liabilities Ratio

X_9 = % Change in Total Revenues/Total Assets Ratio

X_{10} = % Change in Operating Margin Ratio

X_{11} = % Change in Payroll Costs/Total Revenues Ratio

X_{12} = % Change in Payroll Costs/Total Assets Ratio

ε = Error or constant

"Classification makes fewer statistical demands than does inference" (Tabachnick & Fidell, 1996, p. 512), however there are some assumptions about the predictor variables that need to be considered. The sample size of the smallest group should exceed the number of predictor variables (Tabachnick & Fidell, 1996). There is an assumption of multivariate normality, which means that the sampling distribution of any linear combination of predictors is normally distributed, but using discriminant analysis for classification is not very sensitive to violations of normality (Hair, Anderson, Tatham & Black, 1998). Discriminant analysis is very sensitive to outliers (Tabachnick & Fidell, 1996).

Discriminant analysis for purposes of classification is sensitive to heterogeneity of variance-covariance matrices. If heterogeneity is found, the predictors can be transformed, separate covariance matrices can be used for classification, quadratic discriminate function analysis or nonparametric classification can be used (Tabachnick & Fidell, 1996).

Discriminant analysis assumes linear relationships among all pairs of predictors within each group, however a violation does not increase the likelihood of a Type I error. Multicollinearity or singularity may occur if the predictor variables are redundant, making matrix inversion unreliable (Hair, Anderson, Tatham & Black, 1998).

The logistic regression approach avoids many of these constraints of discriminant analysis and is another approach that has been used in bankruptcy prediction. The difficulty with using a logistic regression approach is that the model equation will contain log transformations of the variables used in the analysis, which do not display as directly the impacts of changes in the various components of the equation. The results would tend to be more difficult for a non-statistician to understand and interpret. In the studies that have used logistic regression, the classification accuracy has not been as good as that achieved by those studies that used discriminant analysis (Patterson, 1999).

The accuracy of the model is determined by how well it classifies companies as failed or not failed. A classification matrix, which shows the number and percentage of firms that are classified appropriately is the measurement device used in discriminant analysis. The model will be tested using both the data from the casinos that are used to develop the model and a sample of firms that are not used in the model development. A classification matrix will be used to determine the accuracy of the model and this will be compared to the prediction accuracy of classic bankruptcy models applied to casino data and to the a priori probabilities of the data.

CHAPTER 4

DESCRIPTIVE ANALYSIS OF FINDINGS AND RESULTS

This chapter presents the tests that were conducted to select the predictor variables that would be used in the discriminant model and the results of those tests. It then shows the results of the development of the discriminant model and the tests that were used to measure the reliability and significance of the model.

Selection of Predictor Variables

Before beginning the discriminant analysis procedure, the data provided by the Gaming Control Board was examined to understand and evaluate each ratio provided. The data consisted of the requested ratios as well as some additional information that had not been requested. The additional information included several ratios based on hotel occupancy, gaming revenues per square foot, bad debt expense as a percent of revenues, complimentary expenses to revenues, gaming revenues to total revenues, current ratios and a ratio of fixed assets to total assets. Each of these ratios was tested in the discriminant model, but none of them added to the model's classification accuracy.

Five of the ratios used in the theoretical model were not used in the analysis; quality of location, quality of the property, long-term debt to equity, capital spending to assets and maintenance costs to assets. The two subjective variables, quality of location and quality of the property, were eliminated because of the lack of any definitive description of the methodology used to determine the ratings and the resulting inability to replicate a similar index for casinos not included in the data set. The capital spending to assets and maintenance cost to assets ratios were not used because it was determined by the Gaming Board that the information in their database did not permit them to accurately measure the level of deferred maintenance or the amount spent on maintaining an updated facility.

The reason for not using the debt to equity ratio is three-fold. First, the reported debt numbers were not reliable in many cases. For example, casinos that were part of a group of casinos often did not report any debt, since it was all carried on the books of the parent organization. Another problem has to do with the levels of debt that casinos have been able to obtain relative to their equity investment. Many casinos in recent years have been financed with debt offerings that either had equity conversion features or appealed to a market desire to invest in the casino business. There is also another factor that is difficult to measure in a traditional financial statement; this factor could be described as "off-balance sheet" equity. This phenomenon of closely held businesses occurs when the owner guarantees the debt of the business, thus providing (from the lender's point-of-view) an implicit level of equity to secure the debt. Finally, the negative retained earnings that can result from accumulated losses can partially or totally obscure the contributed capital of the company. Although they were not used in the analysis, all the variables were tested in the discriminant model and none were found to add to the classification accuracy of the model.

The data provided by the Gaming Control Board was for two one-year periods, one year and two years prior to the bankruptcy filing of the failed firm (same time period for the non-failed firm chosen to correspond to each of the failed firms). The data for one year prior to failure plus the percentage change from two years prior to one year prior.

The final count of ratios that were used in the analysis was eight from each year and the percentage change in each of the eight ratios. The eight ratios were: operating margin, payroll to sales, payroll to assets, marketing costs to sales, sales to assets, cash flow to liabilities, net income to assets and cash to liabilities. Before running the discriminant analysis, the data to be used was screened to assure the data met the assumptions of discriminant analysis.

Assumptions of Discriminant Analysis

Discriminant analysis has several requirements for its proper application. The key assumptions for discriminant analysis are multivariate normality of the independent variables and unknown (but equal) variance-covariance matrices for each of the groups. Despite the fact that according to Hair, Anderson, Tathum and Black (1998), "Mixed evidence exists concerning the sensitivity of discriminant analysis to violations of these assumptions" (p. 259), tests were conducted to determine the multivariate normality of the data, and the equality of the variance-covariance matrices of the two groups.

In order to test for multivariate normality, all linear combinations of sampling distributions of means of predictors would have to be tested for normality. There is currently no statistical test for accomplishing this (Hair et al.,1998; Tabachnick and Fidell, 1996). Since discriminant analysis is fairly robust to failures of normality, as long as the failure of normality is due to skewness and not outliers, a test was made for univariate normality for each of the predictor variables. Once univariate normality is achieved, multivariate normality will be assumed, for purposes of this analysis.

Although univariate normality of the individual predictor variables does not assure multivariate normality, lack of univariate normality might indicate a lack of multivariate normality. To test for univariate normality, each predictor variable was tested individually using the using the Kolmogorov-Smirnov test for normality. The results of each of the tests are shown in Appendix A. Using a significance level of 5%, eighteen of the thirty-two variables did not pass the normality test.

Examination of the graphs from the tests seems to indicate that the cause of the failure is primarily the presence of outliers. One acceptable method of reducing the impact of univariate outliers is to change the score of the variable for the outlying case so that it is not as deviant. A way to accomplish this is to assign the outlier the value of the next most extreme variable (Tabachnick and Fidell, 1996). After making this adjustment, the Kolmogorov-Smirnov tests were rerun for the variables that did not pass. Only four of the variables did not show significant tests for univariate normality after the adjustment: % Change in Cash Flow/Liabilities Ratio for failed casinos, Cash/Liabilities for non-failed casinos and % Change in Net Income/Total Assets Ratios for both failed and non-failed casinos. The three predictor variables associated with these variables were eliminated from the analysis.

Having established univariate normality for each of the predictor variables, tests were conducted to determine the homogeneity of the variance-covariance matrices of the remaining variables of the two groups. The first procedure is an examination of within-group distributions of each variable individually by studying boxplots. The boxplots of each pair of data are presented in Appendix B. The plots show that some of the variables exhibit within-group distributions that are markedly different between the two groups, but overall the distributions are fairly close. Levene tests for equality of variance were also performed on each set of predictor variables. The Levene tests indicated that for four of the variables, the within-group variances were not equal. Since the tests for inequality were not extreme however, none of the variables was eliminated at this stage of the analysis.

To examine how the variables covary, a scatterplot matrix for each variable was created. In the scatterplots, the appearance of a similarity between the dispersions of variables between the two groups is desired. The scatterplots are presented in Appendix C. In general, the dispersions appear similar and homogeneity of covariance is assumed.

Other statistical tests of the equality of covariance matrices were conducted for the entire combination of variables for each group. To conduct the tests, a multivariate analysis of variance technique was used. The tests for equality of covariance matrices used were: Box's M, Pillai's True, Wilk's Lambda, Hotelling's True and Roy's Largest Root. The null hypothesis for each of the tests is that the observed vector of means for the dependent variables is equal across groups. All tests failed to reject the null hypothesis at a p-value of less than .0005. Based on the scatterplots and the statistical tests, equality of the variance-covariance matrices seems reasonable.

The other requirements of discriminant analysis are: adequate sample sizes, linearity of the predictor variables, lack of multicollinearity or singularity (Tabachnick & Fidell, 1996). Since the two samples have an equal number of cases, adjustments to probability of group assignment are not necessary in this analysis. There are also no missing data in this analysis. According to Tabachnick and Fidell (1996), the sample size of the smallest group should exceed the number of predictor variables. Using the reduced number of predictor variables, there are thirteen to be used in the analysis. Since there are sixteen cases, there should be no problem with overfitting, which is the producing of results so close to the sample that they do not generalize to other samples (Tabachnick & Fidell, 1996). Multicollinearity and singularity occur when there are predictor variables that are redundant (Hair, Anderson, Tatham & Black, 1998). This situation was avoided both by the definitions of the variables and by the exclusion of variables that test for low tolerance within the differentiation program itself (Tabachnick & Fidell, 1996). Examination of the correlation matrix confirmed that the variables did not indicate multicollinearity, none of the correlations exceeded 0.90 (Hair, Anderson, Tatham & Black, 1998).

Having satisfied all the assumptions for using discriminant analysis, the final selection of predictor variables was used in the SPSS Version 10 statistical package's discriminate analysis program.

Development of the Discriminant Model

There are two ways of performing discriminant analysis, stepwise estimation and simultaneous estimation (Tabachnick & Fidell, 1996). The stepwise estimation process involves introducing the predictor variables one at a time into the discriminant function, based on their discriminating power. The program first selects the variable with the best discriminating power, and then adds additional variables one at a time based on their ability to improve the discriminant function. The simultaneous estimation procedure introduces all of the predictor variables into the model concurrently. For this study, only the simultaneous method was used. The reason for selecting this method is that SPSS excludes a variable if it contributes the same improvement as another variable, without regard for its contribution to the overall classification accuracy. Stepwise estimation is also not as accurate with smaller samples (Tabachnick and Fidell, 1996).

The results of discriminate analysis are measured by the degree of accuracy with which the model predicts classification into the proper category (Hair, Anderson, Tatham & Black, 1998). The results of the casino discrimination model produced a classification accuracy of 100%. All failed casinos were predicted to be in the failed group and all non-failed casinos were predicted to be in the non-failed group.

Strictly as a comparison, the discriminant analysis function was applied to several other combinations of predictor variables. The classification accuracy of the models for combinations of alternative predictor variables ranged from a low of 59.4% to a high of 93.8%, as variables were removed from the original model to the final one.

The final discriminant model is shown in Model 7 and a graphical view of the discriminant test results is shown in Figure 7. The cutoff score is determined by averaging the centroid values of the two groups. The mean of the failed group scores is –2.09 and the mean of the non-failed group scores is 2.09, therefore the cutoff score is 0, which can be seen in Figure 7.

One variable, Cash Flow/Liabilities had a coefficient of zero in the model, and is left out of the equation.

Model 7

Casino bankruptcy prediction model

Prediction Score = $.256X_1 - .178X_2 + .365X_3 + .223X_4 + .603X_5 - .949X_6 - .025X_7 + .923X_8 - 26.885X_9 + .023X_{10} - 6.328X_{11} + 24.454X_{12} - 24.393$

Where:

X_1 = Marketing Costs/Total Revenues

X_2 = Net Income/Total Assets

X_3 = Total Revenues/Total Assets

X_4 = Operating Margin

X_5 = Payroll Costs/Total Revenues

X_6 = Payroll Costs/Total Assets

X_7 = % Change in Marketing Costs/Total Revenues Ratio

X_8 = % Change in Cash Balance/Total Liabilities Ratio

X_9 = % Change in Total Revenues/Total Assets Ratio

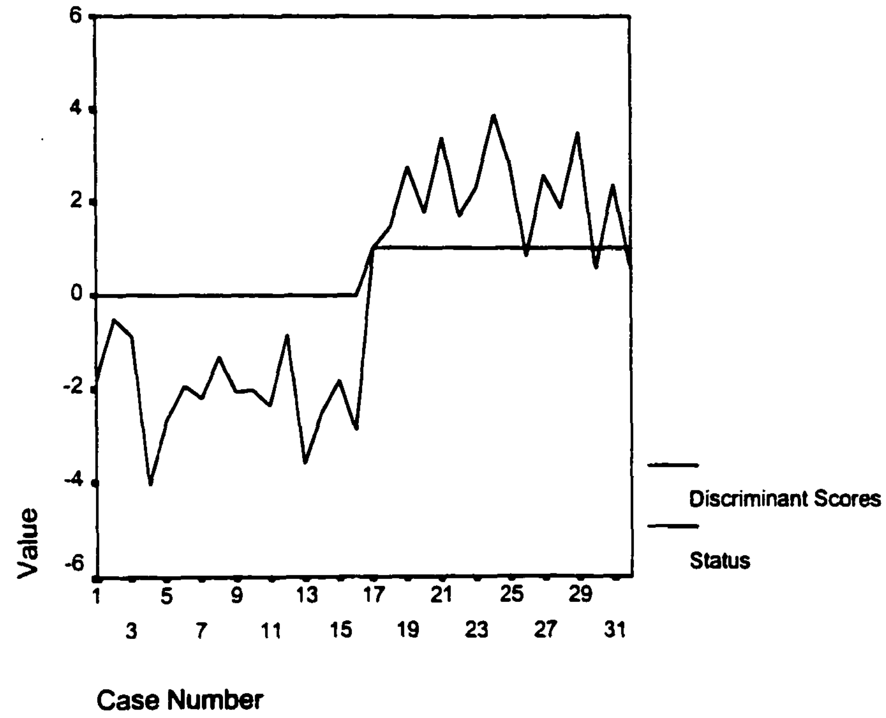
X_{10} = % Change in Operating Margin Ratio

X_{11} = % Change in Payroll Costs/Total Revenues Ratio

X_{12} = % Change in Payroll Costs/Total Assets Ratio

Figure 7

Graph of discriminant scores for failed and non-failed casinos



Assessing the Statistical Significance of the Model

The statistical significance of the model was evaluated using the Wilks' Lambda statistic, which measures the statistical significance of the discriminatory power of the model. According to Tabachnick and Fidell (1996), "Wilks' Lambda is the criterion of choice unless there is reason to use Pillai's criterion" (p. 401). Wilks' Lambda expresses the proportion of unexplained variance, it is the ratio of the within group variance to the total variance of a matrix. The values range from 0 to 1.0, with small values indicating strong group differences and values close to one indicating no differences. For the casino bankruptcy prediction model, the Wilks' Lambda was .176, which with 13 degrees of freedom has a significance level of less than .0005.

The canonical correlation value of the model is .908, which measures the association between the discriminant scores and the groups. For discriminant analysis with two groups, the canonical correlation is equivalent to the Pearson correlation, which measures standardized covariance.

Statistically, the model is strong and its classification accuracy is excellent. To test the model's effectiveness, a test was made using data provided by the Gaming Control Board that were not included in the design of the model.

Test of the Model

To test the external validity of the model, data not used in the development of the model are tested using the discriminant model (Hair, Anderson, Tathan & Black, 1998). External validity relates to how well the model works for predicting failure for firms that were not included in the original analysis. To test the internal validity of the model, the data used in the development of the model are used.

Two sources of data were examined to determine if the data necessary to run the model might be available for casinos that were not located in Nevada. The Research Insights database of all SEC reports was examined, as well as the monthly and annual reports of the New Jersey Casino Control Commission. While much of the data was found in these sources, there was no information on two of the variables in either source; advertising and promotion costs and payroll costs.

The Nevada Gaming Control Board data that was used to develop the model included all the bankrupt casinos in their database. There were no failed casinos that were not included in the study for which the required information was available to test the model. Information on non-failed casinos that were not included was available from the Nevada Gaming Control Board.

An alternative test was produced. A decision was made to use financial information for failed casinos that were used in the model development, but from different years. While this test is not as conclusive as one using different casinos, it was felt that it would give an indication using new data. The non-failed casinos would be ones that were not used in the model development. The test period would be two years prior to failure.

After obtaining the new information, the data were entered into an Excel worksheet to calculate the discriminant scores for the casinos in the test sample. Using the cutoff score of zero, the model correctly classified 100% of the failed firms and 89% of the non-failed firms, for an overall classification accuracy of 92.3%.

CHAPTER 5

CONCLUSIONS AND SUMMARY

The purpose of this study was to develop a bankruptcy prediction model for the casino industry that would incorporate financial relationships that are significant to the casino business that might not be significant in other types of businesses. The study began by reviewing the history and evolution of financial analysis in America. Classic bankruptcy prediction studies were each examined to understand the methodologies and procedures that had been used by other researchers. A review of a prior study (Patterson, 1999) showed that the classic bankruptcy prediction models that are currently being used in the casino industry do not accurately predict failure or non-failure for casinos.

Next, a group of experts were interviewed in order to collect and understand information and opinions they had concerning bankruptcy in the casino business. Using the information collected through these interviews, a theoretical model of the factors that contribute to success or failure in the casino business was designed. The theoretical constructs of this model are: Management, Location, Ambiance, Marketing and Financial Strength.

For each construct a measurement indicator was defined and the type of empirical data that would be used for the measurement was identified. For the management construct, the measurement indicators selected were: cost control, as measured by the operating margin ratio; staff costs, as measured by the ratio of payroll costs to sales; and staffing levels, as measured by the ratio of payroll costs to assets. Location was measured by a subjective rating of the property, taking into account such things as accessibility, proximity to competition, proximity to target market and esthetic quality of surroundings. Ambiance relates to how the property is maintained and how comfortable and satisfied with the appearance of the property the patrons are. The ambiance of the property was measured by how updated the property was kept, as shown by the capital spending to assets ratio. Another consideration in assessing ambiance is the level of deferred maintenance as indicated by the ratio of maintenance costs to assets. Finally a subjective evaluation of the overall quality of the property was made.

Marketing was evaluated only in financial terms, as a comparison to the levels of marketing or the failed and non-failed firms. Another important factor in marketing is the effectiveness of the marketing effort, but direct measurement of this attribute did not lend itself to this study. The two measures of the marketing construct chosen for this model were marketing effort and marketing efficiency. Marketing effort relates to the relative amount of money spent on marketing to the size of the property, the ratio of marketing costs to sales was used to measure this factor. Marketing efficiency is the amount of sales that is generated relative to the size of the property, and is measured by the ratio of sales to assets.

Financial strength was measured using the four classic aspects of a firm's financial position: leverage, solvency, return and liquidity. The amount of debt a firm has relative to its overall capitalization (leverage) is shown by the ratio of debt to equity. A firm's ability to pay its obligations as they become due (solvency) is measured by the ratio of cash flow to liabilities. The level of return generated relative to the size of the investment in the firm is measured by the ratio of net income to assets. Liquidity relates to the firm's ability to pay its current obligations, and is measured by the ratio of cash to liabilities.

Having developed a theoretical model of the constructs that indicate success or failure in the casino business, a statistical technique for establishing a model that would accurately classify a firm as failing or not failing was selected. The approach chosen for this study was discriminant analysis, using the SPSS statistical analysis package, version 10.0. This approach was picked over the other techniques primarily because it is the method that has been used in the majority of the classic bankruptcy prediction studies that were reviewed for this study. Discriminant analysis also has the advantage of producing a result that is easier to understand by non-statisticians than some of the other approaches, such as logistic analysis. Discriminant analysis is also considered more appropriate for smaller samples and its accuracy at classification is often superior to the other methods that could be used.

The data used in the study was obtained from the Nevada Gaming Control Board. They provided the requested ratios for each of the bankrupt casinos in their database, which included all casinos with gross revenues in excess of $1 million. The database has information on casinos from 1985 to 2000. They also provided the same types of information for an equal number of non-bankrupt casinos that were considered comparable properties. For each casino, two years of data were provided for each ratio.

Before beginning the analysis of the data, the entire set of data was reviewed with the auditor from the Gaming Control Board who had prepared it. From the original set of thirteen ratios requested, it was determined that the information reported by the casinos that was used in the computation of three of the ratios was not suitable for inclusion in the study. It was also determined that the qualitative evaluations of location and property quality were too subjective and that they would not be appropriate for inclusion in the study.

To avoid the problem of having separate models for each of the two years of data provided, after reviewing the data, the % change in the ratios from one year to the next was included as a variable in the analysis. It was felt that the deterioration of a ratio could be as predictive as the ratio itself. The inclusion of these percentage change ratios resulted in a total of sixteen ratios for the analysis.

Results of Tests

Before performing a discriminant analysis, the data to be used in the analysis must be examined to assure that the requirements for the proper application of discriminant analysis are met. Key assumptions include multivariate normality of the independent variables, homogeneity of variance-covariance matrices for each group, the absence of significant outliers, absence of missing data, sufficient sample size, mutually exclusive and fully exhaustive group definitions, lack of multicollinearity or singularity.

Plots of each of the variables and pairs of variables were studied and statistical tests were performed to determine that the assumptions necessary for discriminant analysis were satisfied. As a result of these tests, three of the ratios were eliminated from the data set to be analyzed, leaving thirteen ratios in the final analysis.

The results of the discriminant analysis produced a model that used twelve of the variables and produced a classification accuracy of 100%. The model was found to be statistically significant. Wilks' Lambda was used to measure the significance of the discriminatory power of the model (.176, $p<.0005$). Canonical correlation, which measures the strength of the association between the discriminant scores and the groups, had a value of .908, indicating a strong association.

The model was also tested using data that were not included in the development of the model. The model accurately classified 100% of the failed casinos and 89% of the non-failed casinos, for an overall classification accuracy of 92.3%, for this test data. A Classification Matrix showing the results of the test is presented in Table 3.

Table 3
Classification Matrix for Casino Model

Status	Predicted Group Membership: Failed	Predicted Group Membership: Non-Failed	Total Correct
Failed	100%	0	100%
Non-Failed	11%	89%	100%
Total	38.5%	61.5%	92.3%

Since the identity of the casinos in the test group were not known, it was not possible to gather the additional financial information for the test group that was necessary to test the Altman, Deakin and Zavgren models using the same casinos. However, since the original tests on the Altman, Deakin and Zavgren models included all the bankrupt Nevada casinos for the test period (Patterson, 1999), the results of those tests were used to compare their accuracy to the accuracy of the new casino bankruptcy prediction model. The ratios that were used for the test of the casino prediction model were from financial reports filed two years prior to bankruptcy (for the failed firms). The results of the tests in the Patterson 1999 study were performed both one year prior to failure and two years prior to failure, for this comparison only the results of the tests two years prior to failure were used. The overall classification results of each of the models are presented in Table 4.

Table 4

Comparison of Classification Accuracy

Naïve Prediction	50%
Altman Z Score Model	58%
Deakin Linear Model	75%
Deakin Quadratic Model	42%
Deakin Combined Model	33%
Zavgren Model	29%
Casino Prediction Model	92.3%

Tests of Null Hypotheses and Conclusions

Null Hypothesis One, that a statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than a naïve prediction, is rejected. The casino prediction model showed a classification accuracy rate of 100% and 92.3% for the holdout sample. A random selection process based on a priori probabilities would be expected to have a classification accuracy rate of 50% with equal sized groups.

Null Hypothesis Two, that a statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Altman Z Score model (1966), is rejected. The Altman Z-score model using casino data showed a classification accuracy rate of 58% two years prior to failure, in a prior study (Patterson, 1999).

Null Hypothesis Three, that a statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Deakin models (1972). is rejected. The Deakin linear model using casino data showed a classification accuracy rate of 75% two years prior to failure, in a prior study (Patterson, 1999). The Deakin quadratic model showed a classification accuracy of 42% two years prior to failure. The Deakin combined models showed a classification accuracy rate of 33% two years prior to failure (Patterson, 1999).

Null Hypothesis Four, that a statistical bankruptcy prediction model developed using casino data will not predict bankruptcy more accurately than the Zavgren model (1985), is rejected. The Zavgren model using casino data showed a classification accuracy rate of 29% two years prior to failure (Patterson, 1999).

Based on the data available for analysis, the conclusion is that the study was able to develop a statistically significant model for predicting bankruptcy in the casino industry.

Areas for Future Research

This study indicates that the financial characteristics of the casino industry are sufficiently different from other industries that financial analysis techniques specifically designed to address these differences are necessary. Utilizing techniques and standards that were developed for other industries may yield misleading indications of the financial health of a casino. Through the development of standards and methods of measurement that are appropriate for casinos, it is possible that the performance and future of individual casinos and the industry can be improved.

As Altman observed in his classic study, the ideal would be to construct individual models for specific industries. This study has shown that the results of looking at casino ratios does in fact make a significant difference in the accuracy of the classification of casinos into failed and non-failed groups. Similar analysis of other industries, such as the hotel industry and the food and beverage industry would likely result in more accurate models.

Building on the research done for this study, the results should be studied to determine if it is possible to develop a way to use the casino prediction score as a measure of the overall financial health of a casino. If it can be shown that the casino prediction score can be used as an index of a casino's financial health. and that the magnitude of the score is meaningful, it could become a standard for the industry.

A different approach to measuring the constructs that were excluded from the model needs to be developed. While it would not be possible to improve the classification accuracy of the model, the inclusion of these variables (at least intuitively) could make it a much more powerful tool.

Additional data needs to be analyzed. Other jurisdictions require casinos to report financial information. It is possible that the information needed to replicate this study could be obtained, based on the results of this study and the approach to the format of the data that was approved by the Nevada Gaming Control Board.

Other statistical techniques should be tested. Some of the assumptions for discriminant analysis are hard to explicitly describe and some other method might produce results that are more statistically sound.

The benefits of having financial tools that are designed for the casino industry must be communicated to the industry leaders who control access to the information necessary to develop those tools. Uniform accounting and reporting standards need to be developed for the industry that incorporate an adequate level of detail and consistency for meaningful analysis. Governmental organizations that mandate the use of these standards need to understand exactly what is needed, and they must demand that the data provided be accurate and complete. Financial reporting in the casino business today looks a lot like the reporting that was done in the transportation and industrial sectors in the nineteenth century.

Summary

The model developed in this study was able to predict failure or non-failure of casinos with 92.3% accuracy. This classification accuracy rate is significantly better than the classification accuracy rate achieved by conventional bankruptcy prediction models that were developed for industrial companies. The study indicates that there is a need to develop similar indicators of financial health for other sectors of the hospitality industry using more specific measurements of the drivers of success that are peculiar to those sectors.

The model developed can enhance the ability of investors to quantitatively assess their casino investments and potential investments. Regulators and auditors should use the model to determine the scope of financial reviews. It should become a part of the "going-concern" assessment process. Lenders should use the model when considering new loans, loan extensions or requests for renegotiation of loan terms. It can provide management with information that could indicate necessary changes in operating policies and cost controls. It should be used as a budgeting and long-term planning tool to assess the impact of proposed changes and planning assumptions.

The study provided an example of why more consistency in reporting financial results is essential to the ability to develop analytical tools that can enhance the future of the business. Billions of dollars are now invested in the casino business, and it is still considered a high-risk investment by many. Through an enhanced understanding of the business through new ways of analyzing the business, it may be possible to improve this high-risk perception.

APPENDIX A

NORMALITY TESTS OF PREDICTOR VARIABLES

Figure A1

Test for normality – A&P/Total Revenues for failed casinos

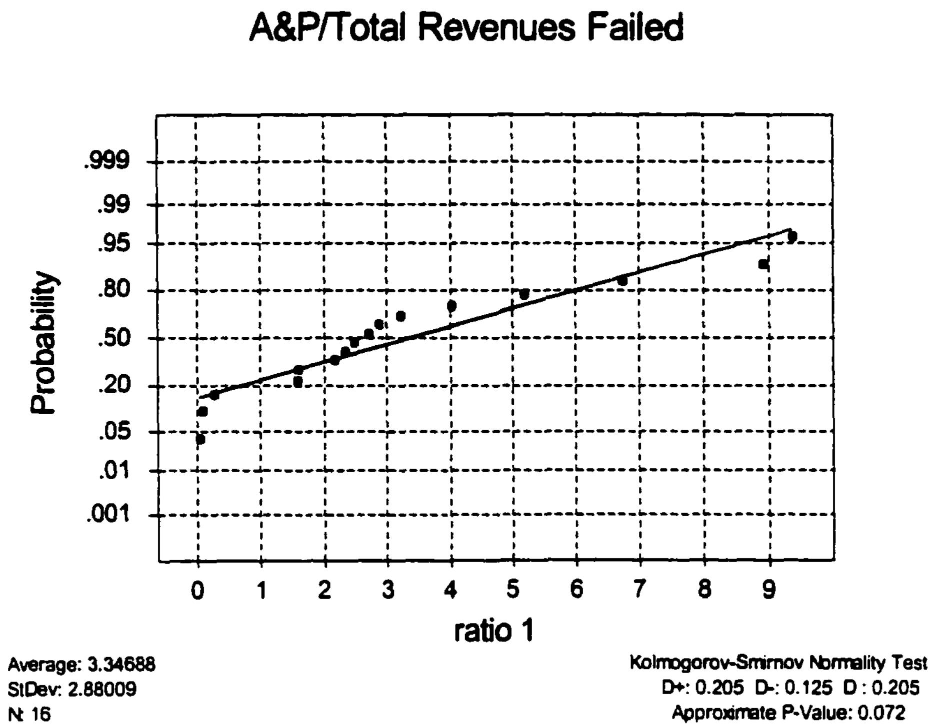


Figure A2

Test for normality – Cash Flow/Liabilities for failed casinos

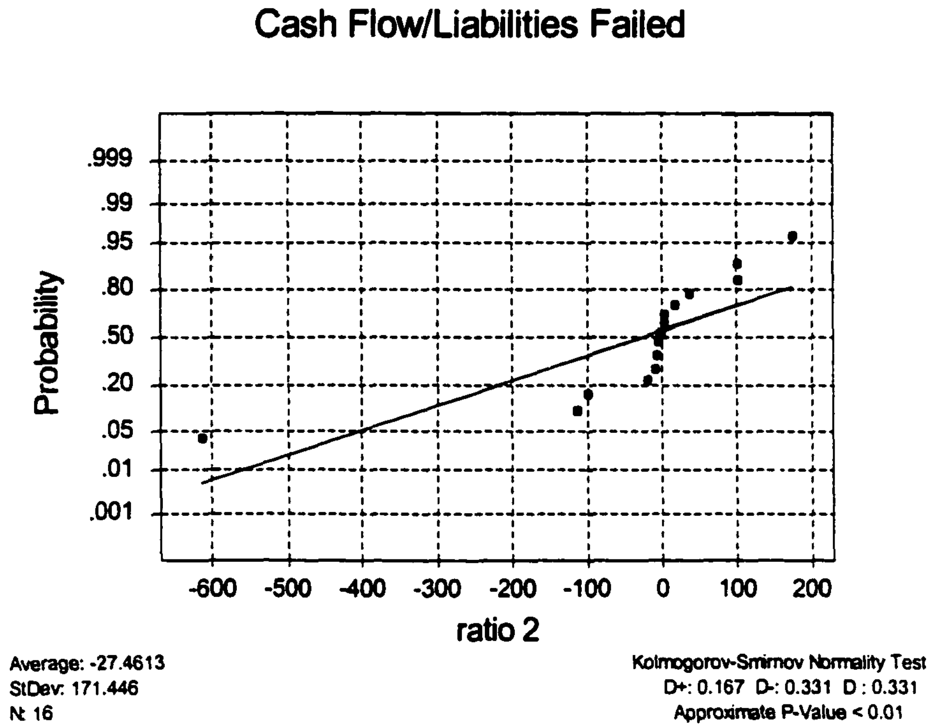


Figure A3

Test for normality – Cash/Liabilities for failed casinos

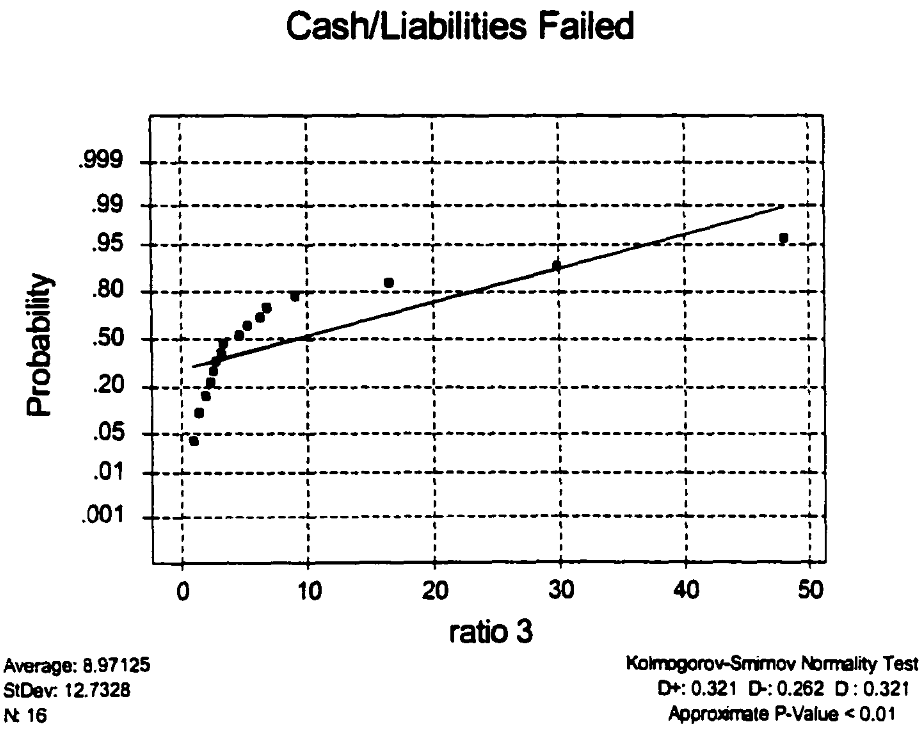


Figure A4

Test for normality – Net Income/Assets for failed casinos

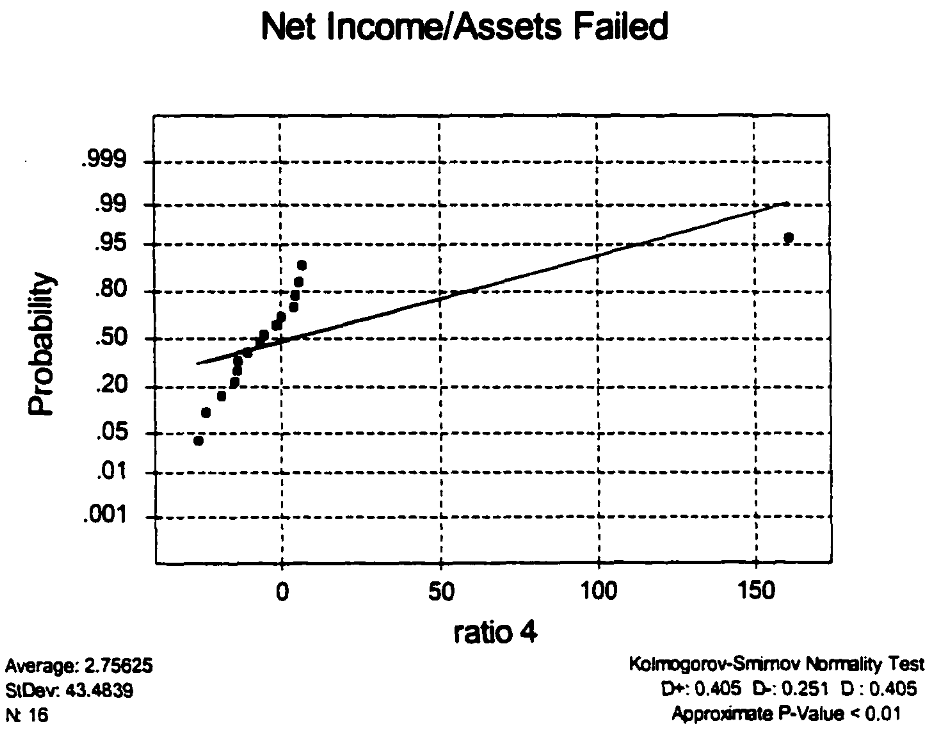


Figure A5

Test for normality – Sales/Assets for failed casinos

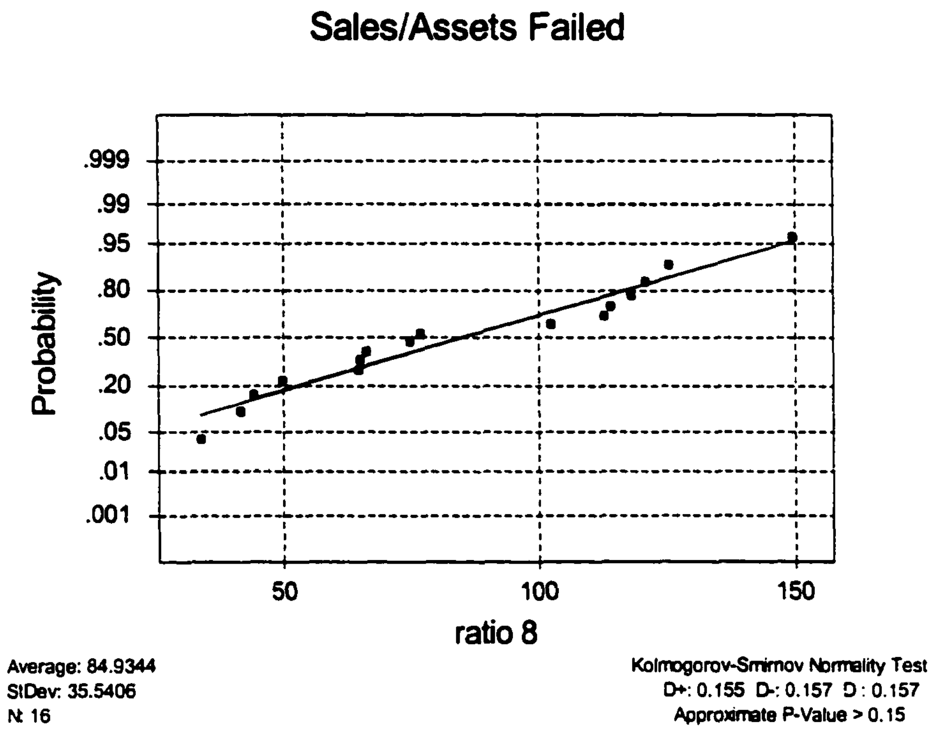


Figure A6

Test for normality – Operating Margin for failed casinos

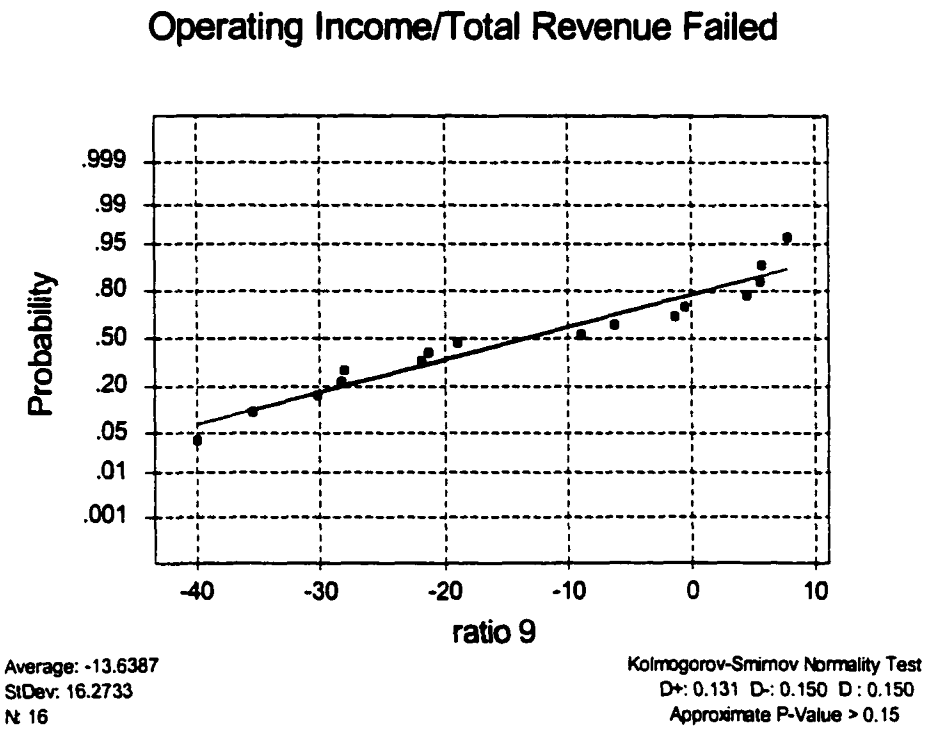


Figure A7

Test for normality – Payroll/Revenues for failed casinos

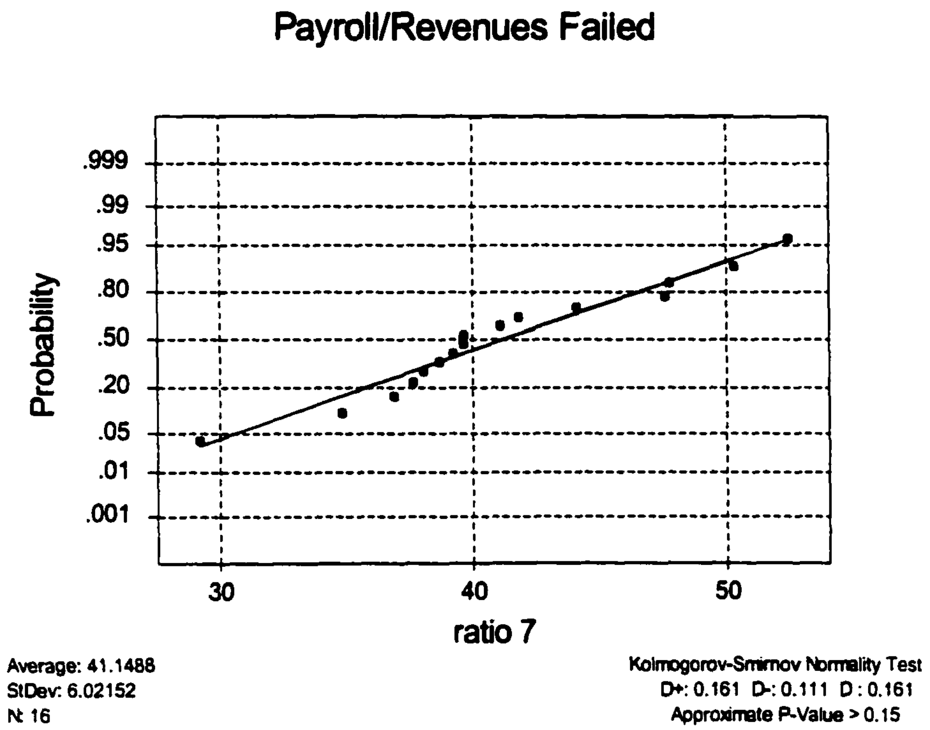


Figure A8

Test for normality – Payroll/Assets for failed casinos

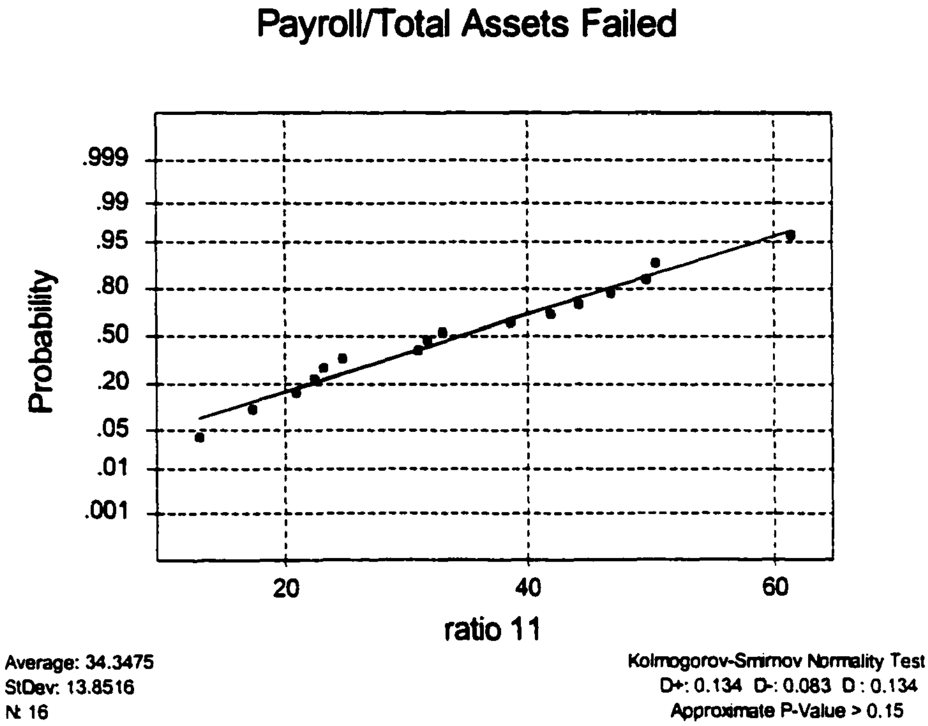


Figure A9

Test for normality -- % Change in A&P/Total Revenues Ratio for failed casinos

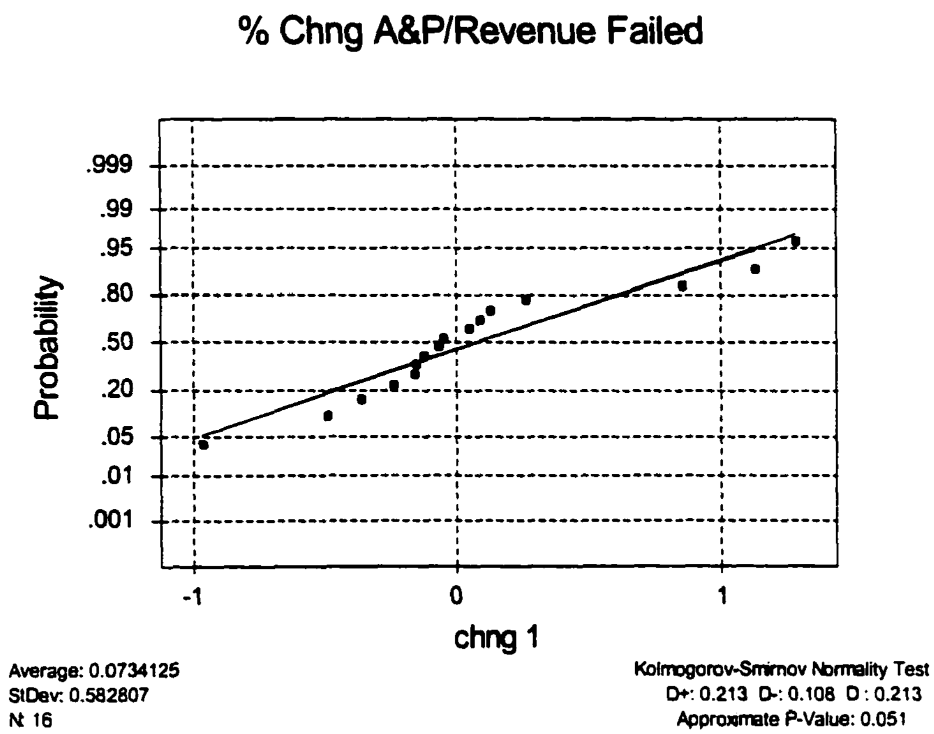


Figure A10

Test for normality -- % Change in Cash Flow/Liabilities Ratio for failed casinos

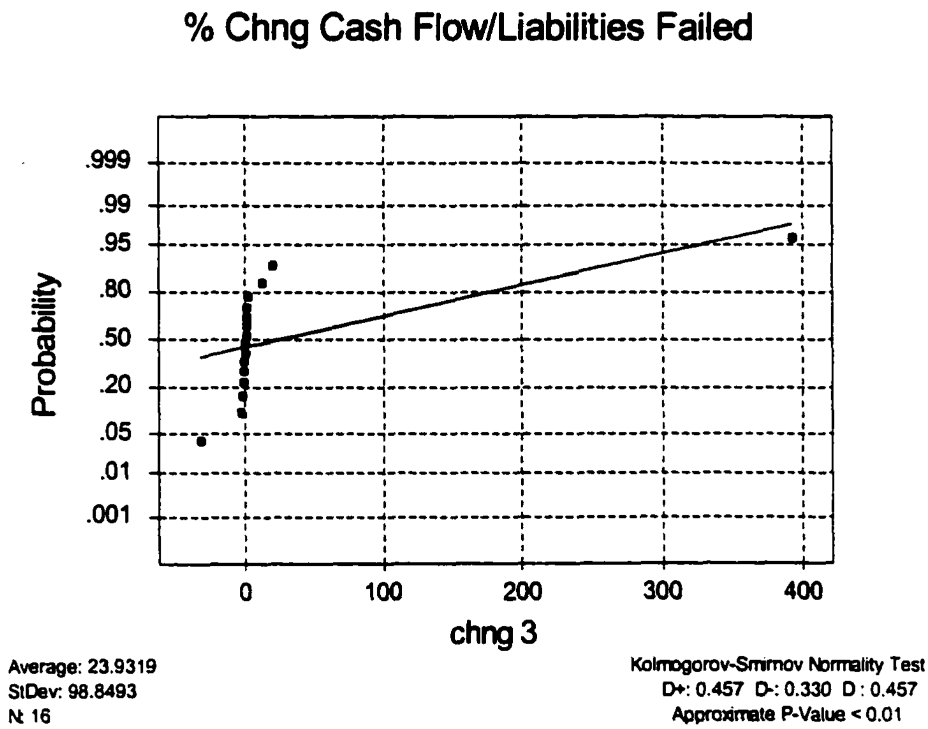


Figure A11

Test for normality -- % Change in Cash/Liabilities Ratio for failed casinos

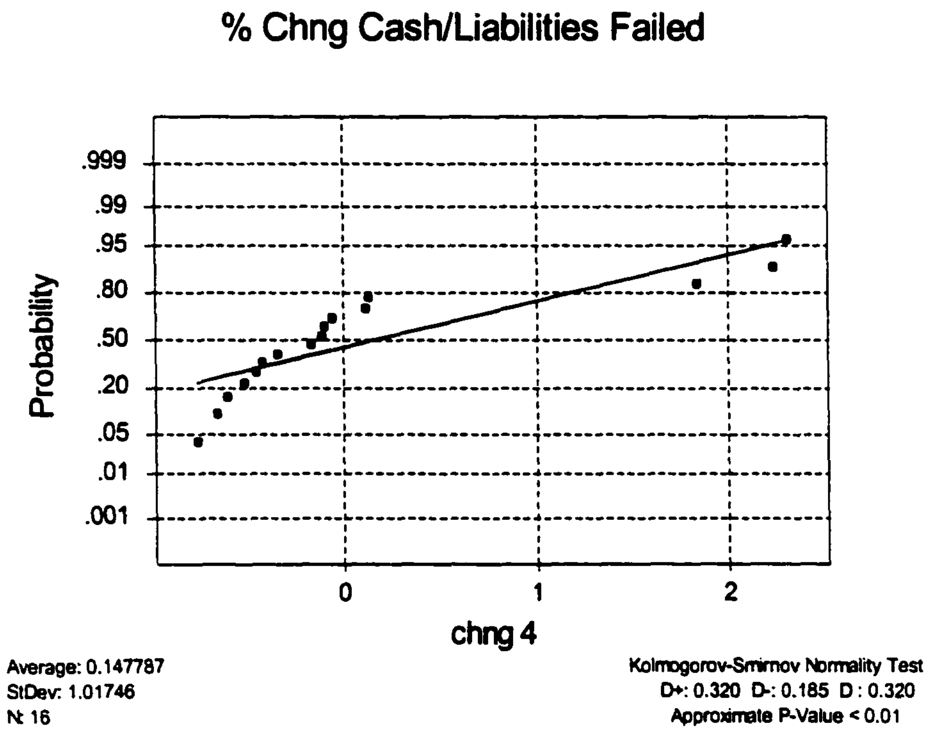


Figure A12

Test for normality -- % Change in Net Income/Assets Ratio for failed casinos

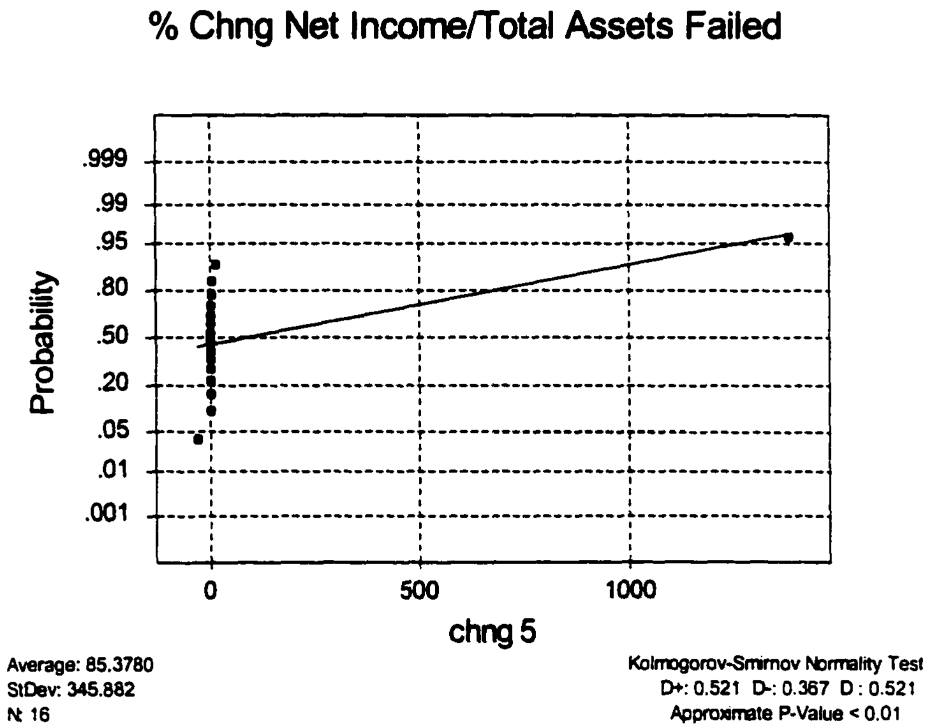


Figure A13

Test for normality -- % Change in Sales/Assets Ratio for failed casinos

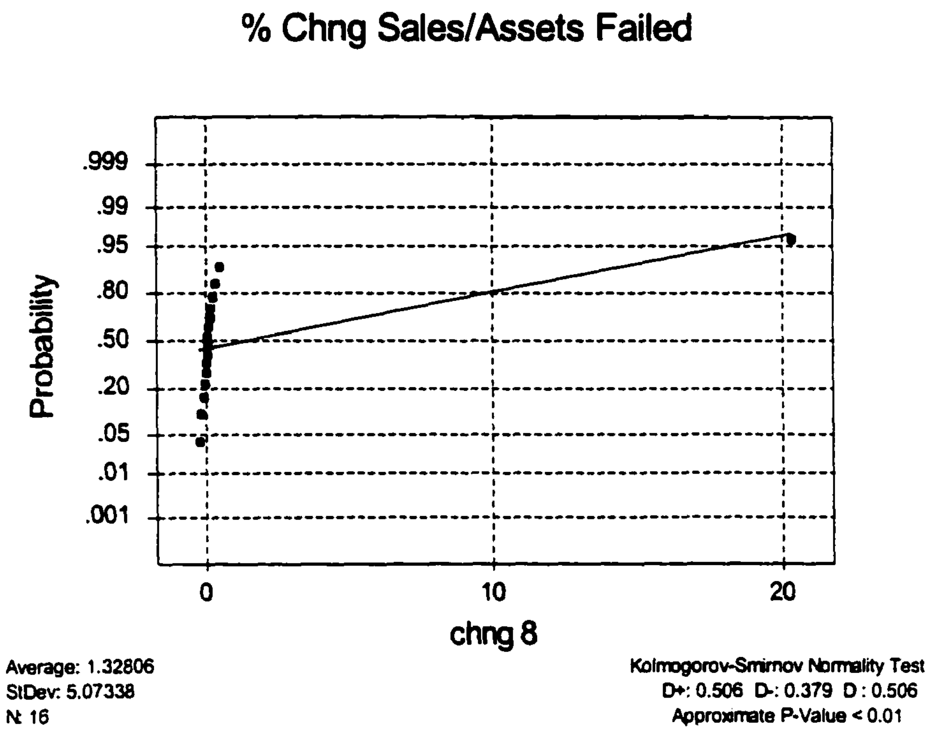


Figure A14

Test for normality – % Change in Operating Margin Ratio for failed casinos

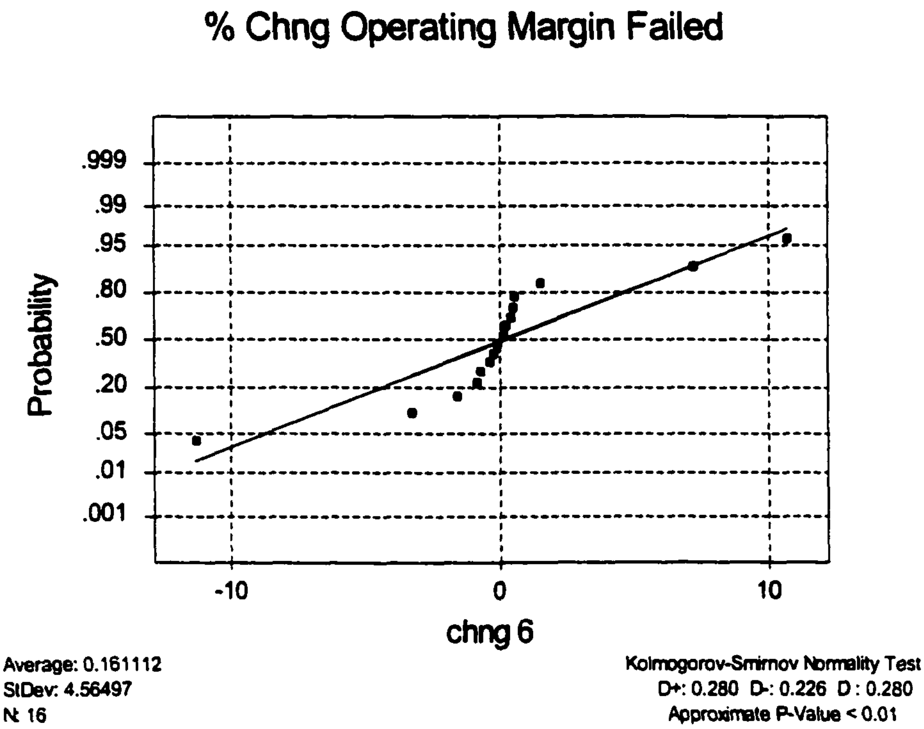


Figure A15

Test for normality -- % Change in Payroll/Revenues Ratio for failed casinos

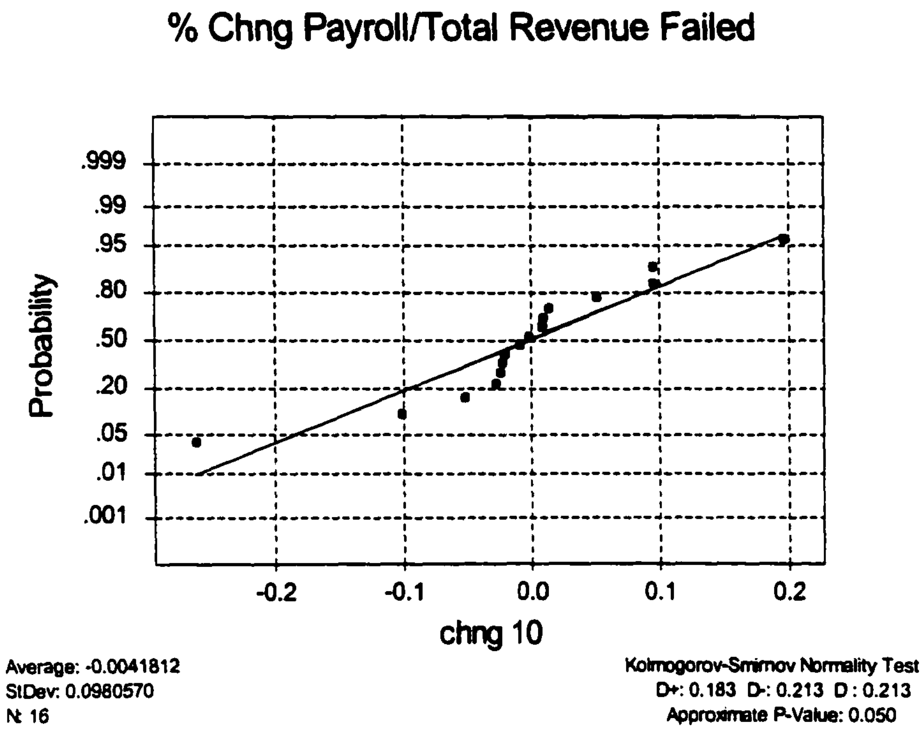


Figure A16

Test for normality -- % Change in Payroll/Assets Ratio for failed casinos

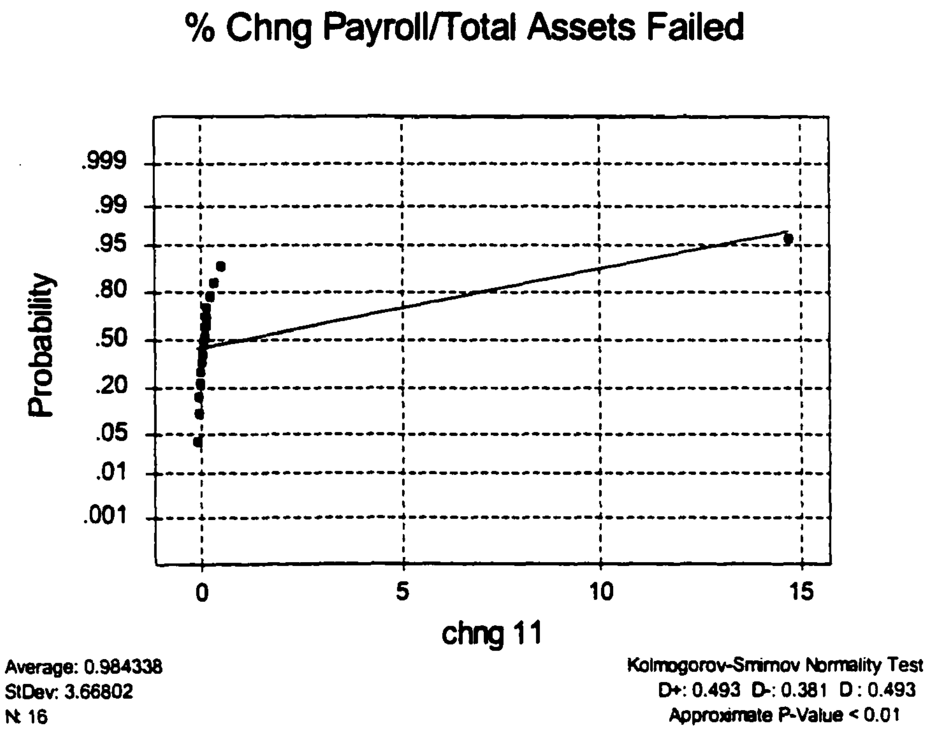


Figure A17

Test for normality – A&P/Total Revenues for non-failed casinos

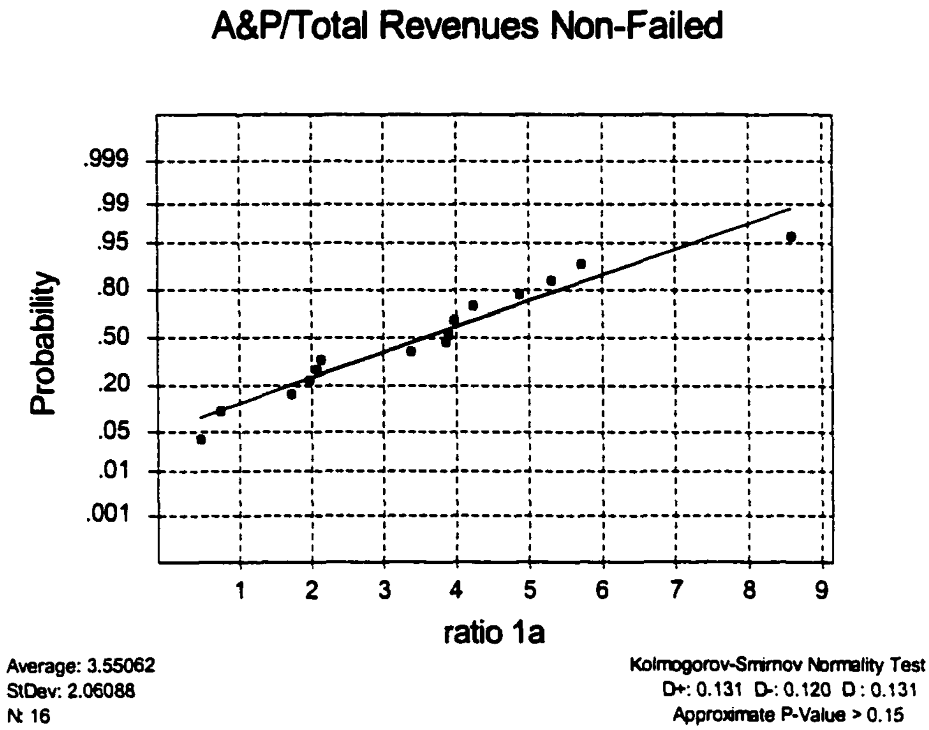


Figure A18

Test for normality – Cash Flow/Liabilities for non-failed casinos

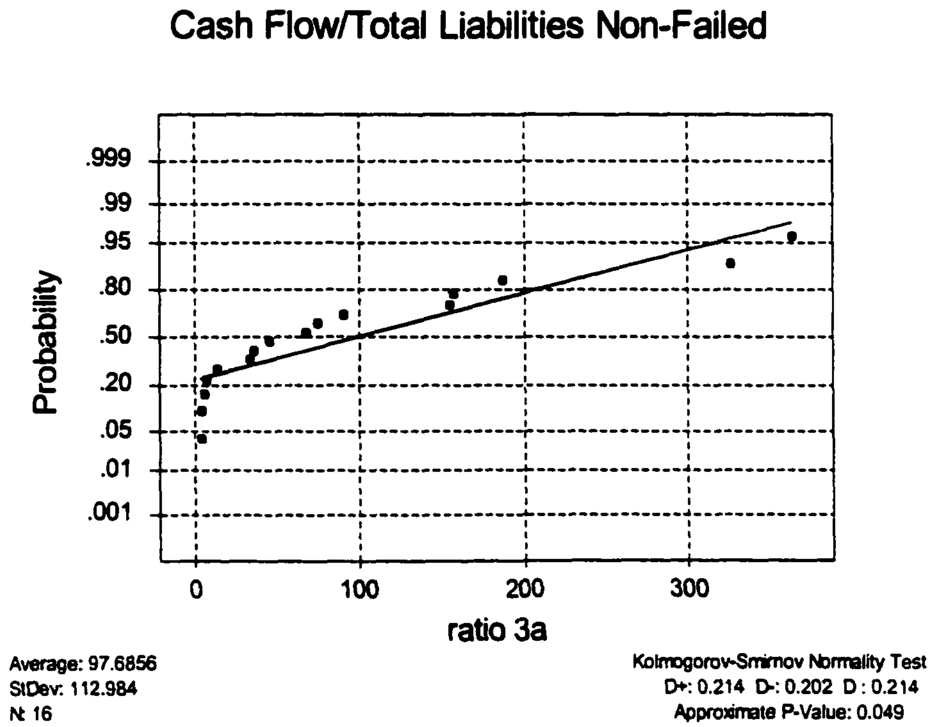


Figure A19

Test for normality – Cash/Liabilities for non-failed casinos

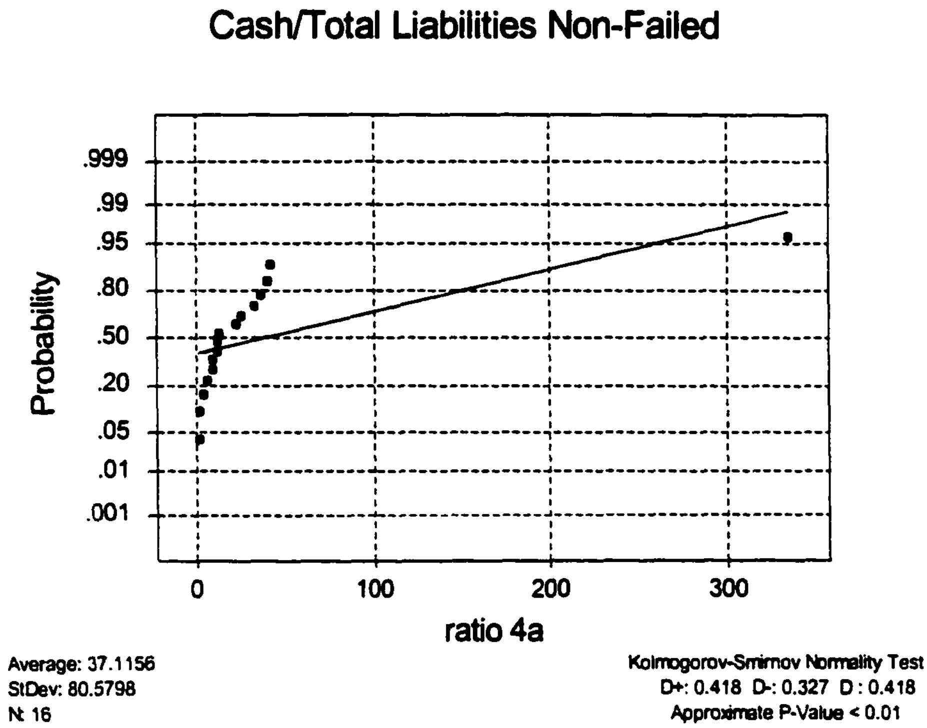


Figure A20

Test for normality – Net Income/Assets for non-failed casinos

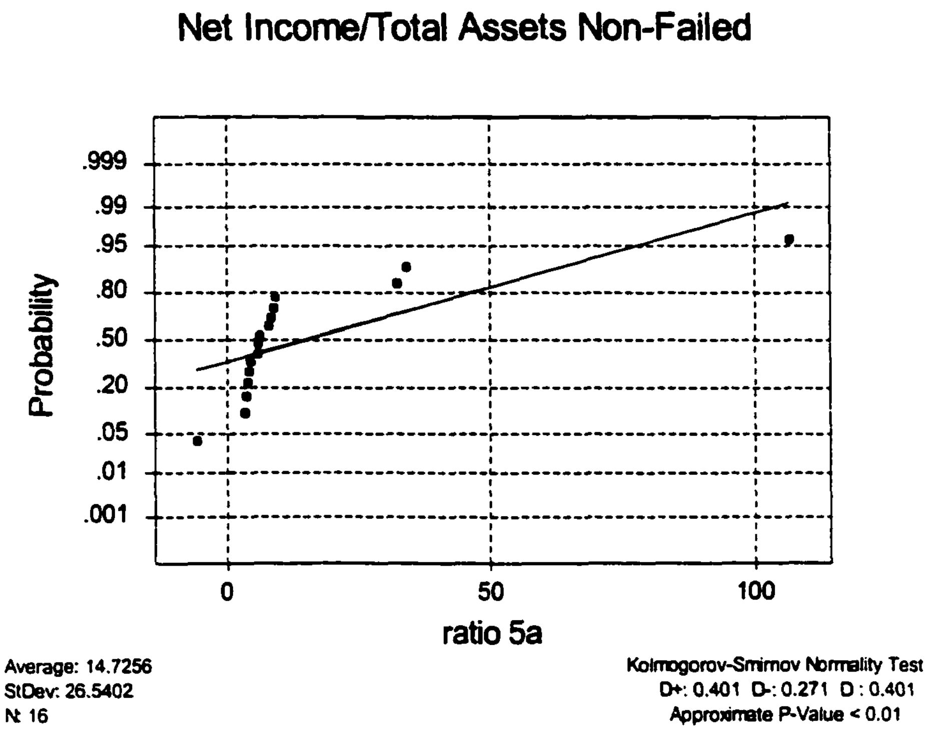


Figure A21

Test for normality – Sales/Assets for non-failed casinos

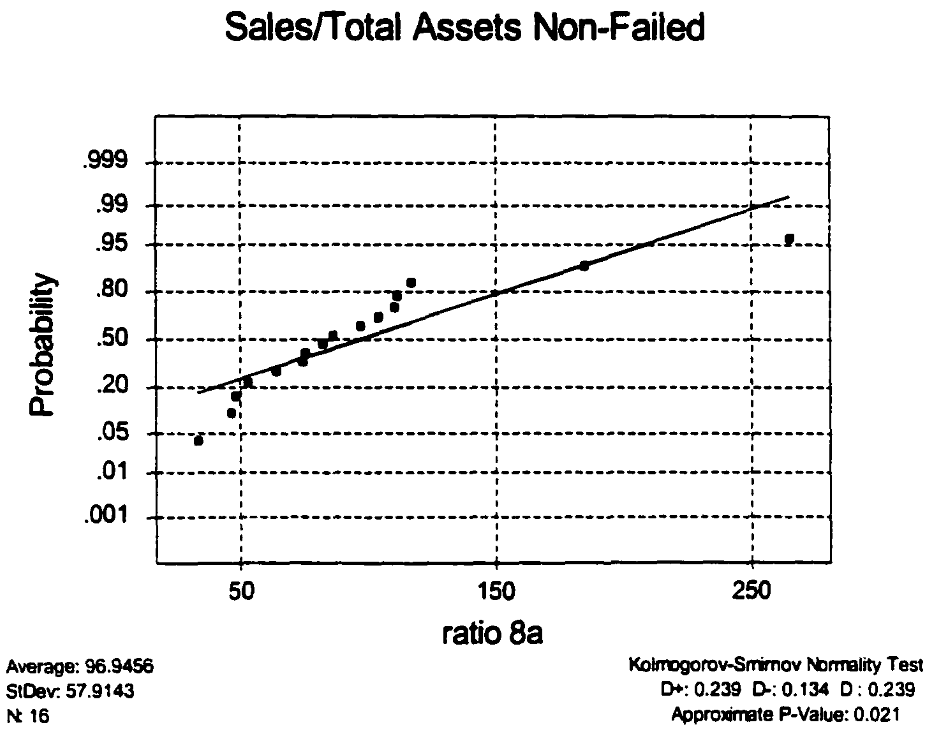


Figure A22

Test for normality – Operating Margin for non-failed casinos

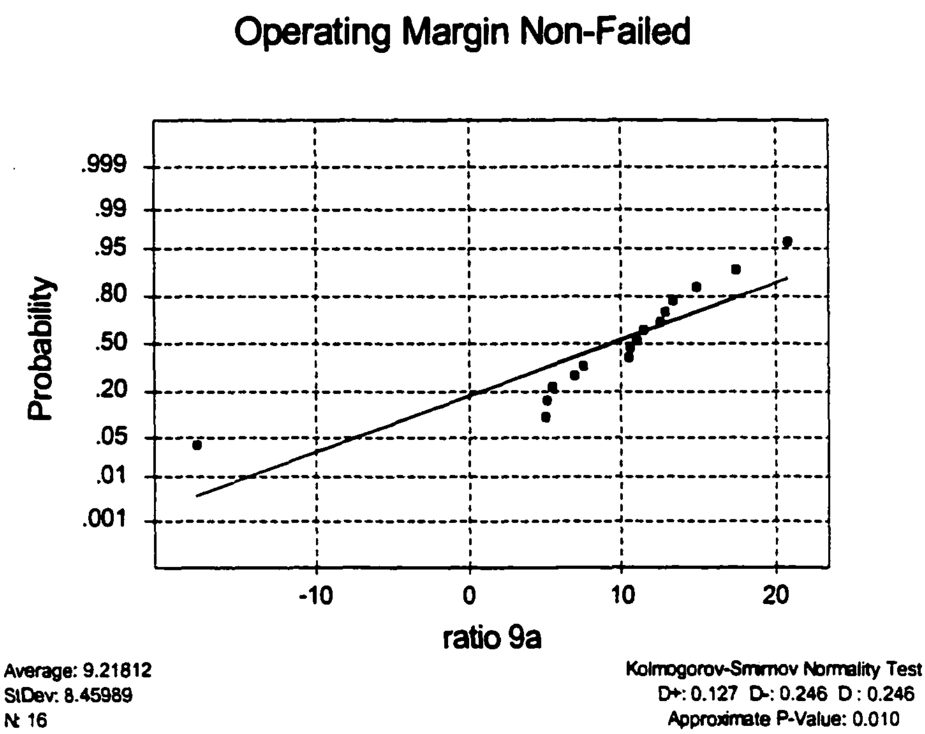


Figure A23

Test for normality – Payroll/Revenues for non-failed casinos

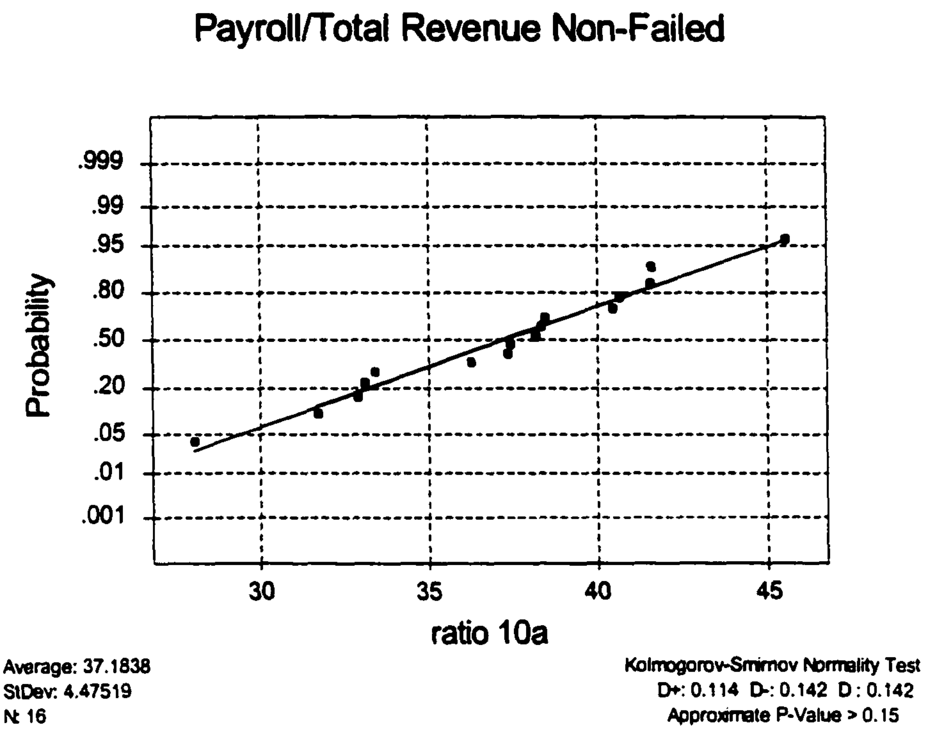


Figure A24

Test for normality – Payroll/Assets for non-failed casinos

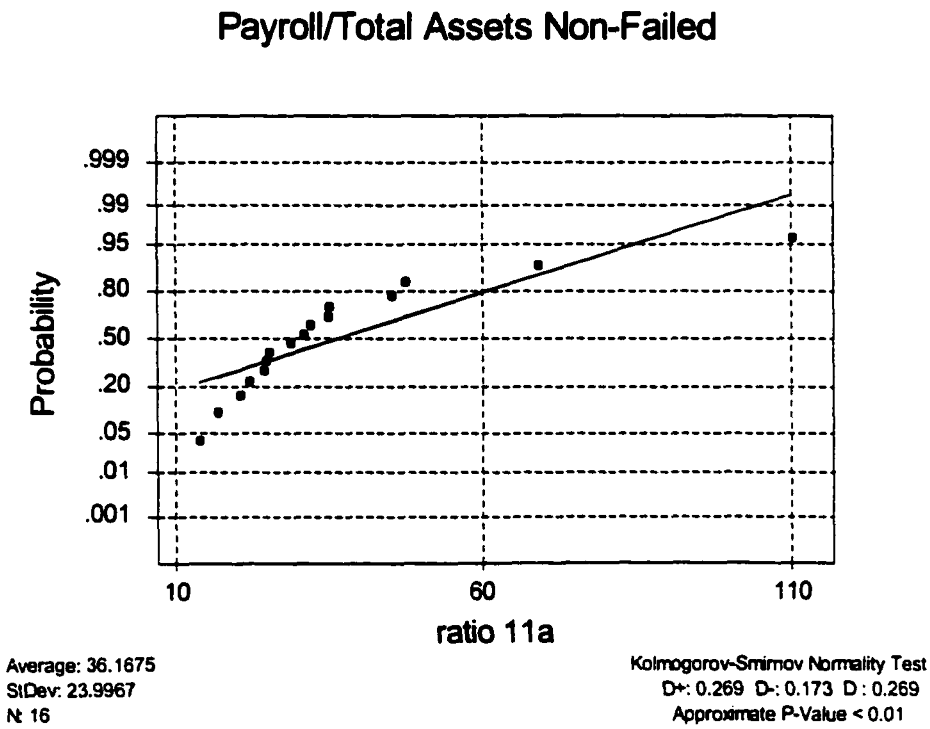


Figure A25

Test for normality – % Change in A&P/Total Revenue Ratio for non-failed casinos

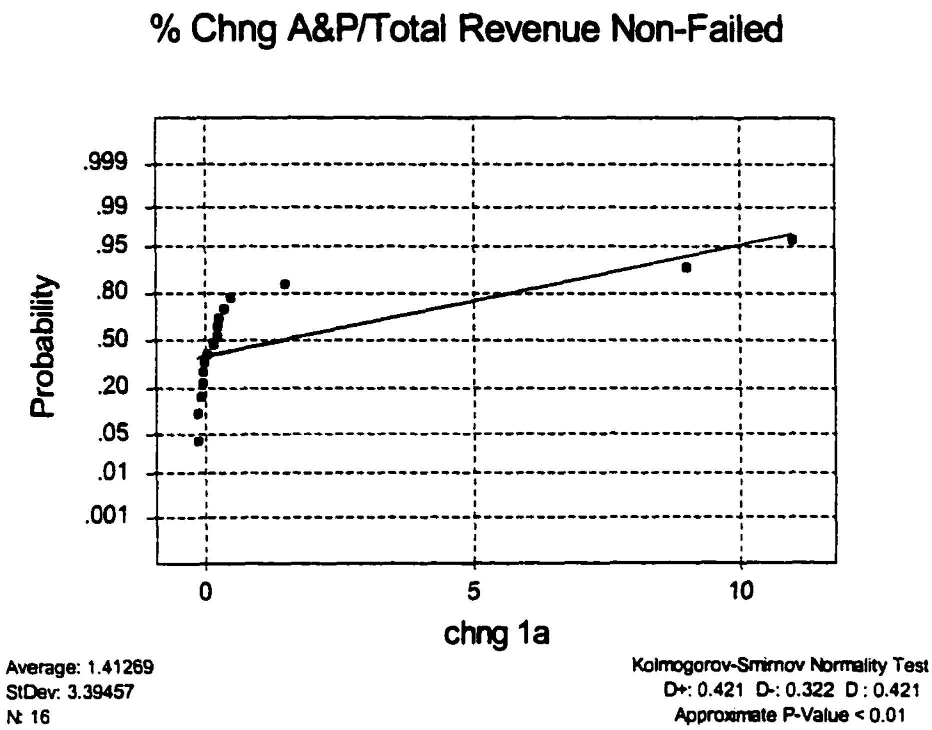


Figure A26

Test for normality -- % Change in Cash Flow/Liabilities Ratio for non-failed casinos

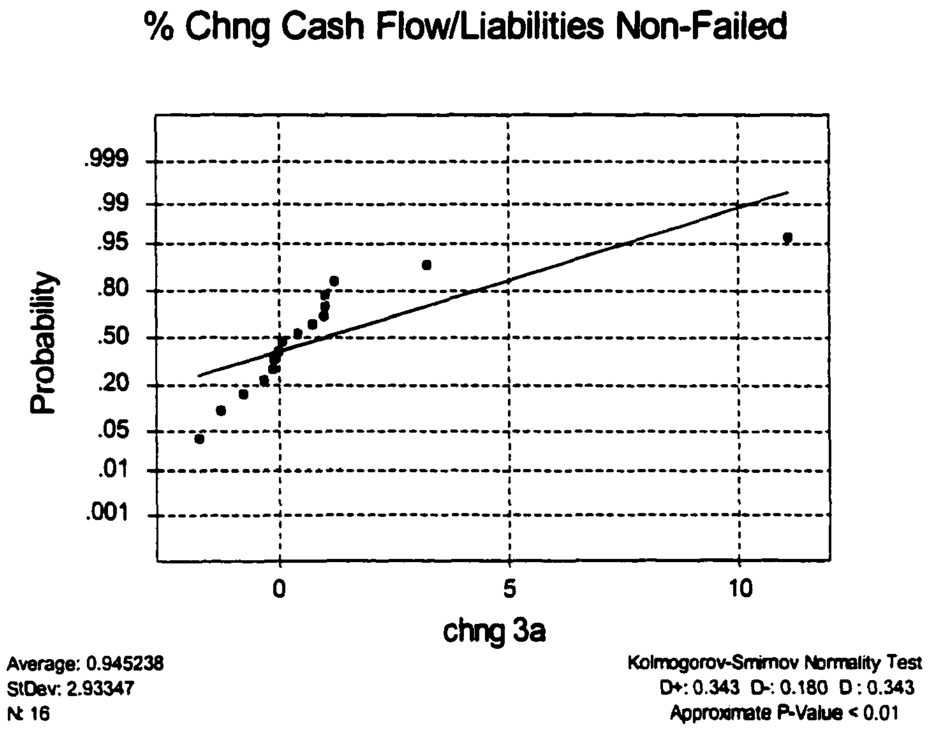


Figure A27

Test for normality -- % Change in Cash/Liabilities Ratio for non-failed casinos

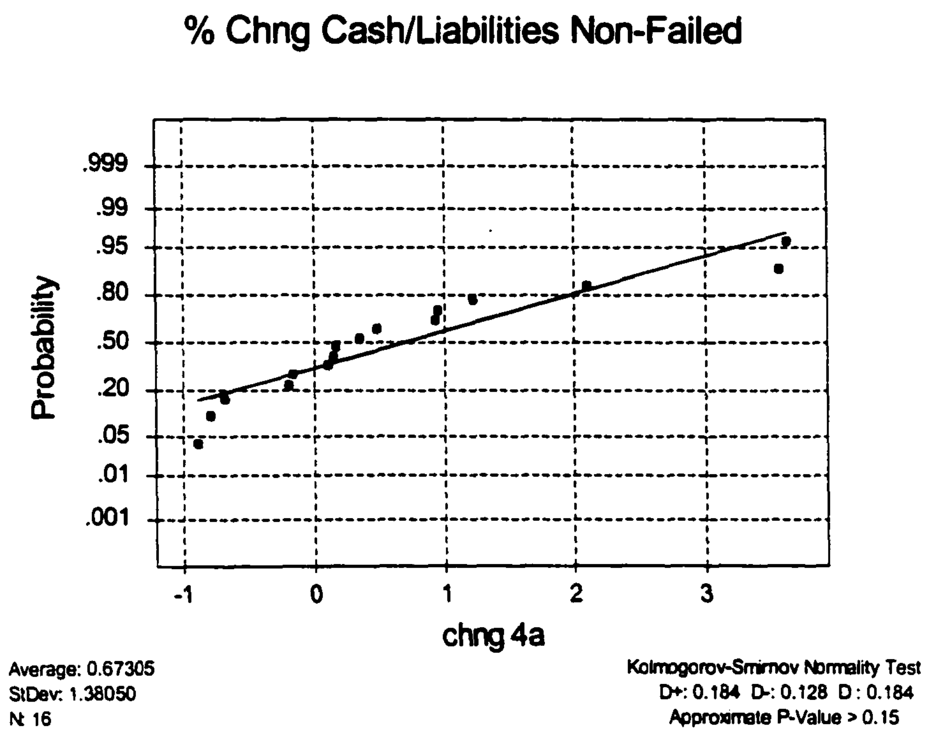


Figure A28

Test for normality -- % Change in Net Income/Assets Ratio for non-failed casinos

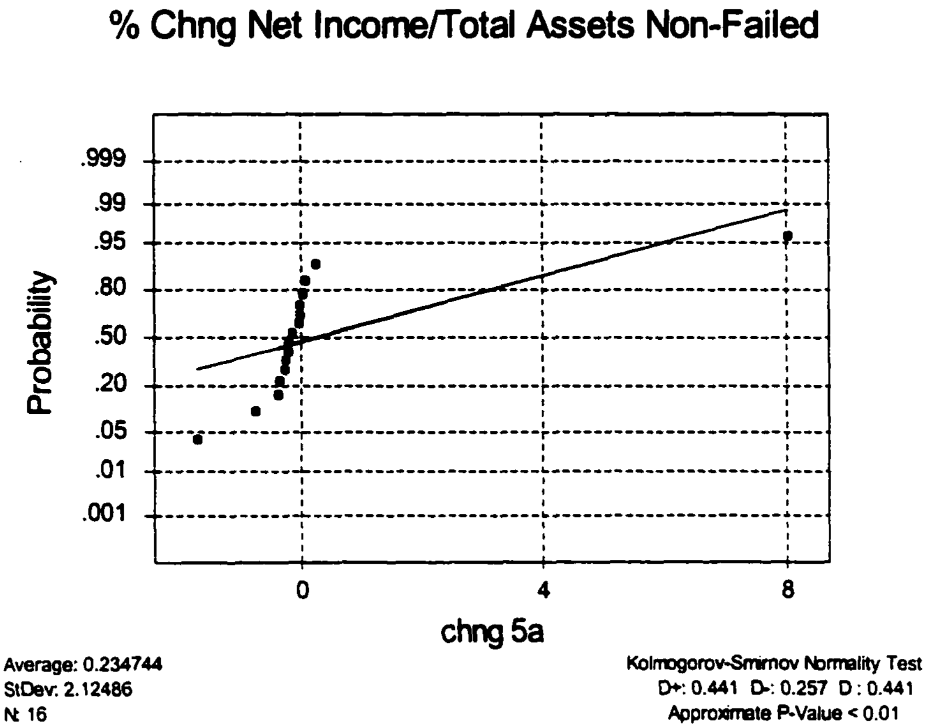


Figure A29

Test for normality -- % Change in Sales/Assets Ratio for non-failed casinos

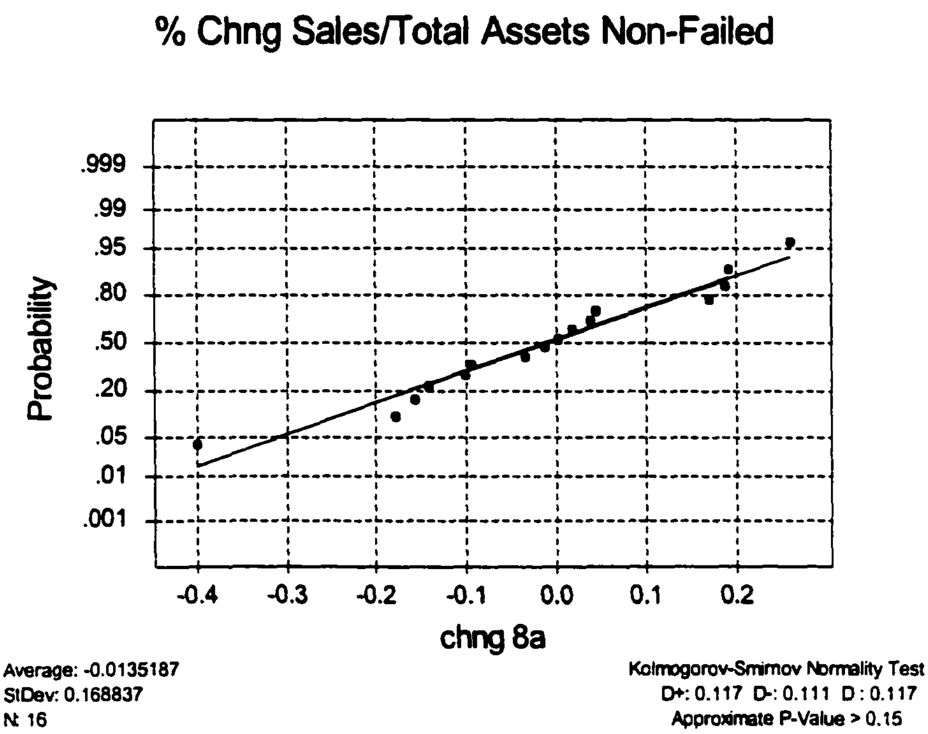


Figure A30

Test for normality -- % Change in Operating Margin Ratio for non-failed casinos

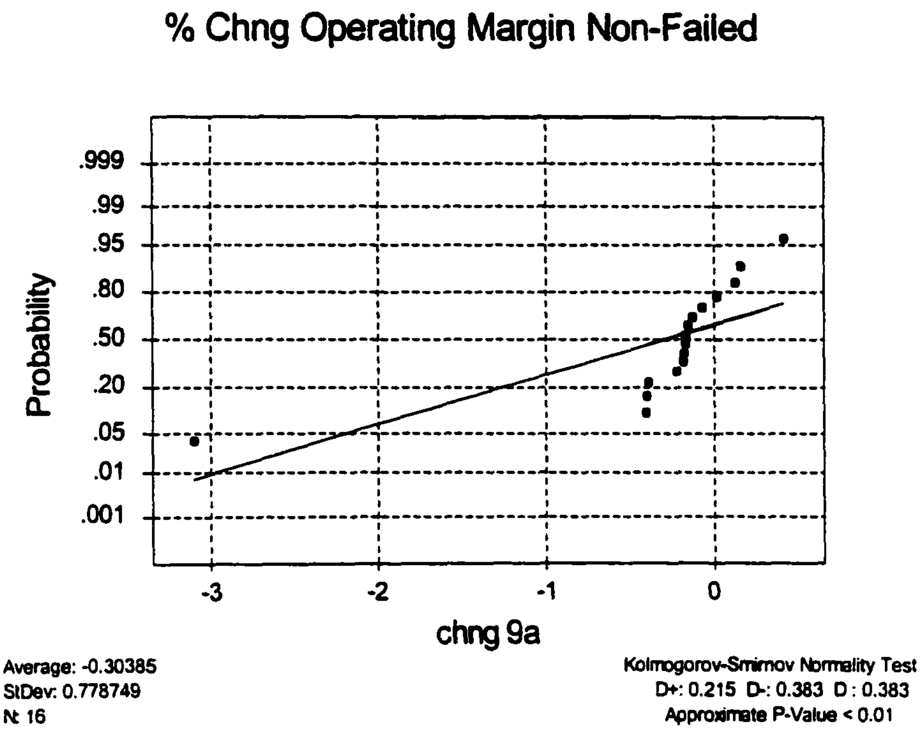


Figure A31

Test for normality -- % Change in Payroll/Revenues Ratio for non-failed casinos

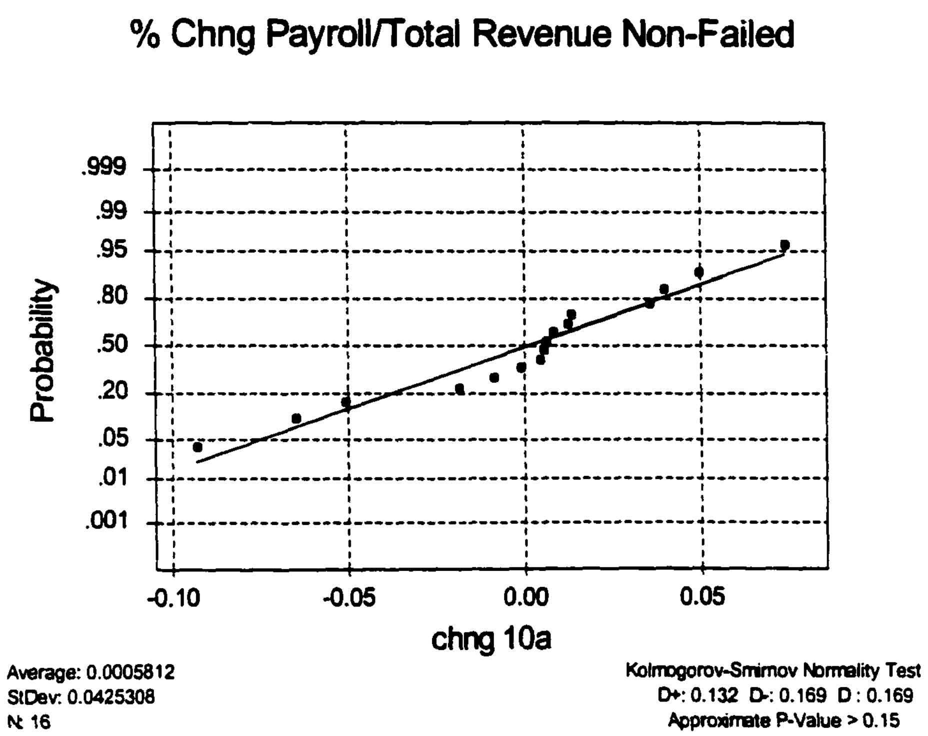
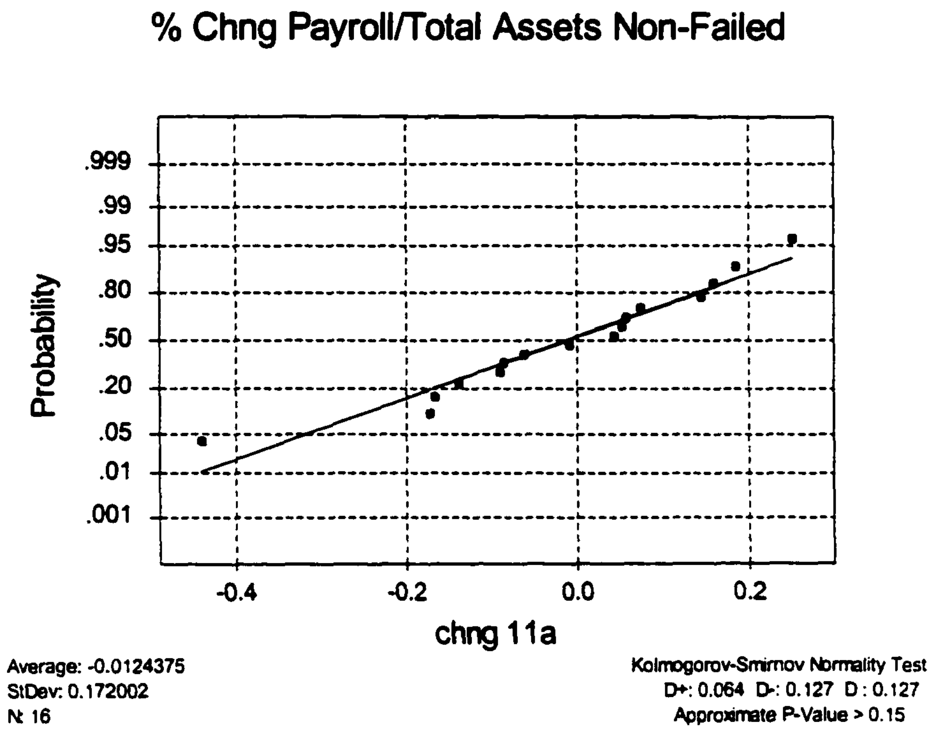


Figure A32

Test for normality -- % Change in Payroll/Assets Ratio for non-failed casinos



APPENDIX B

BOX PLOTS OF PREDICTOR VARIABLES

Figure B1

Within-Group Distribution – A&P/Revenue

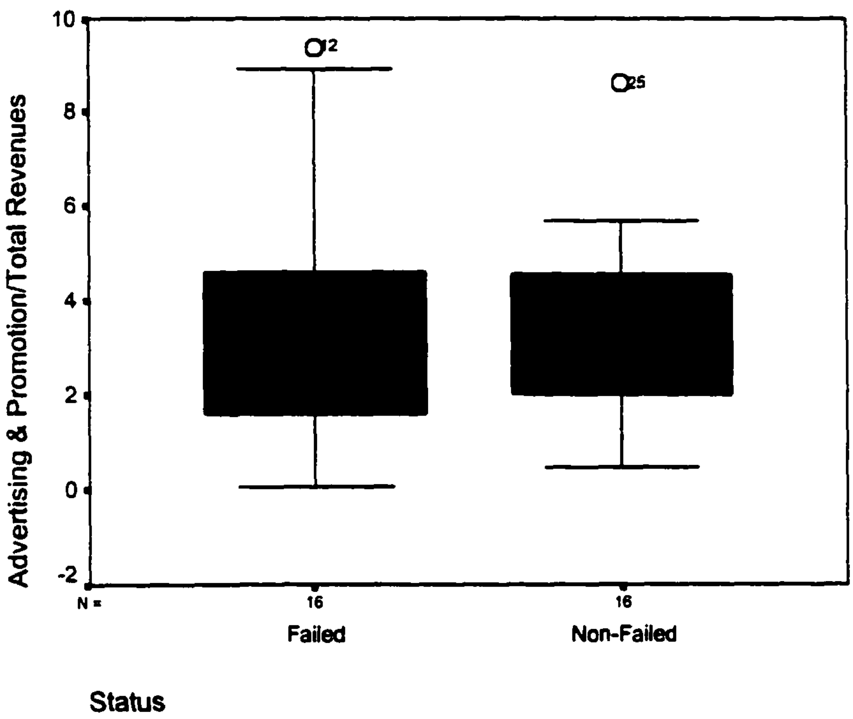


Figure B2

Within-Group Distribution – Cash Flow/Liabilities

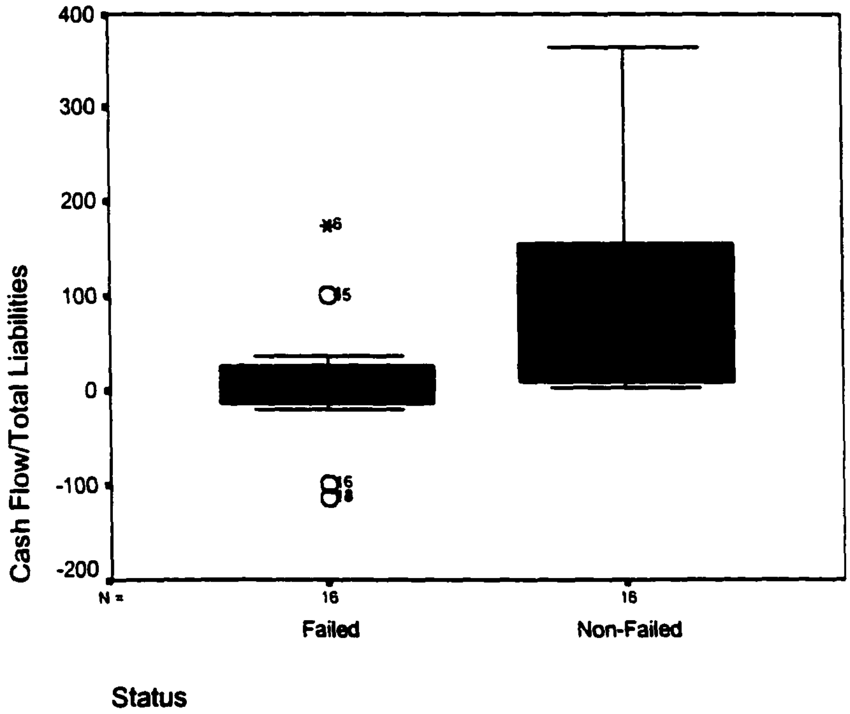


Figure B3

Within-Group Distribution – Net Income/Assets

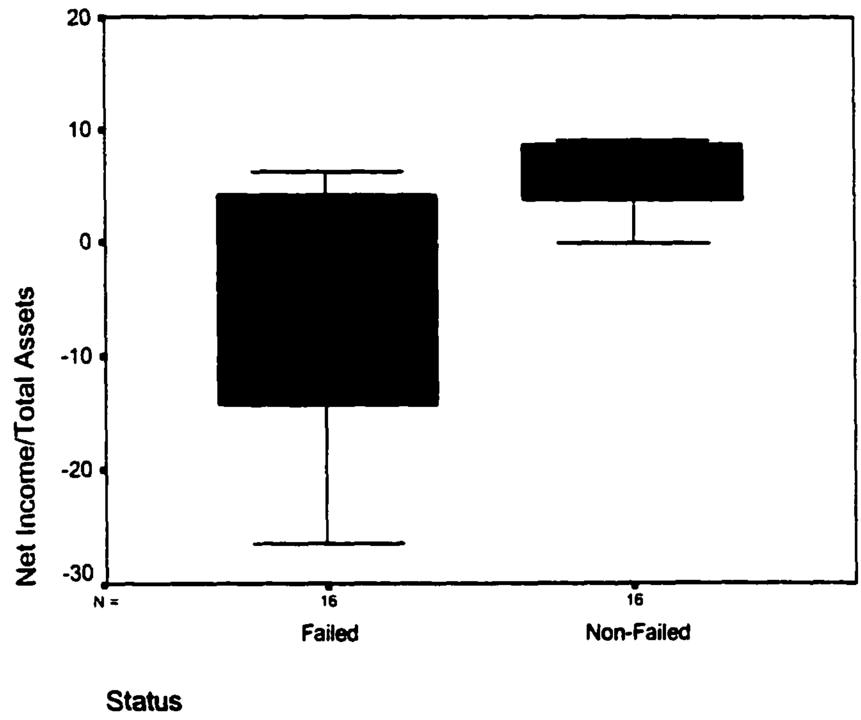


Figure B4

Within-Group Distribution – Sales/Assets

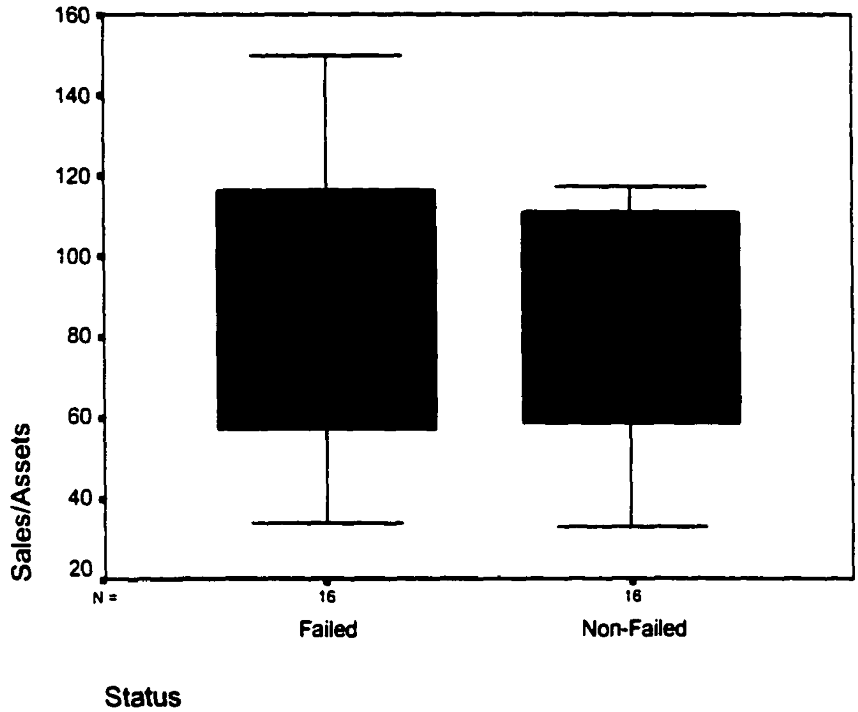


Figure B5

Within-Group Distribution – Operating Margin

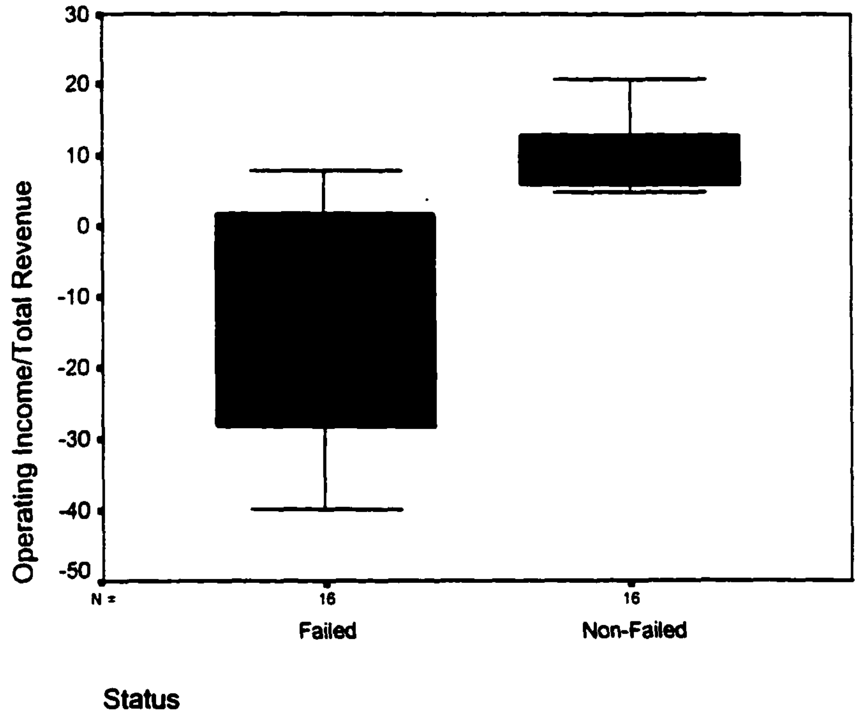


Figure B6

Within-Group Distribution – Payroll/Revenues

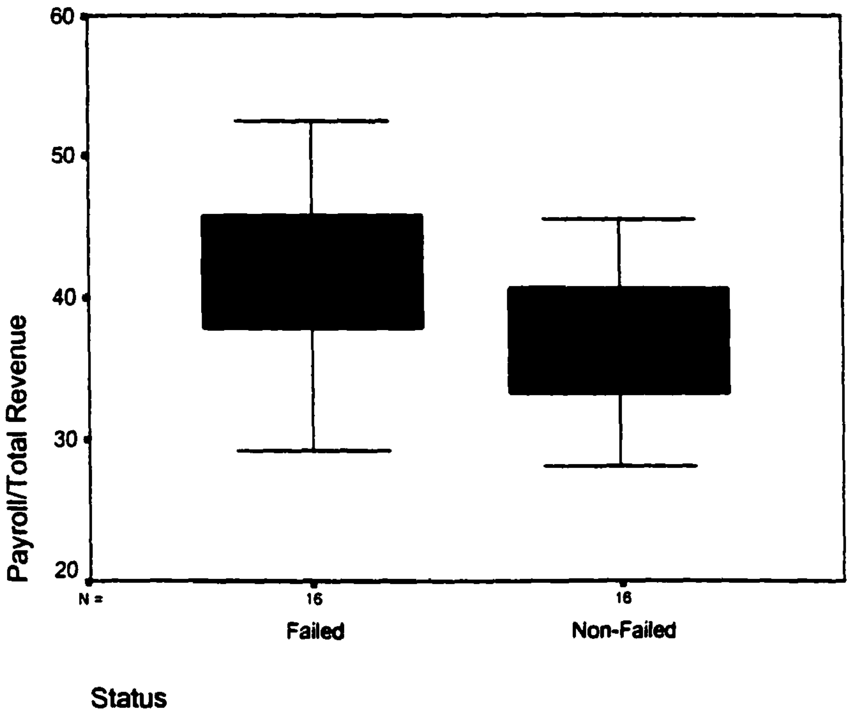


Figure B7

Within-Group Distribution – Payroll/Assets

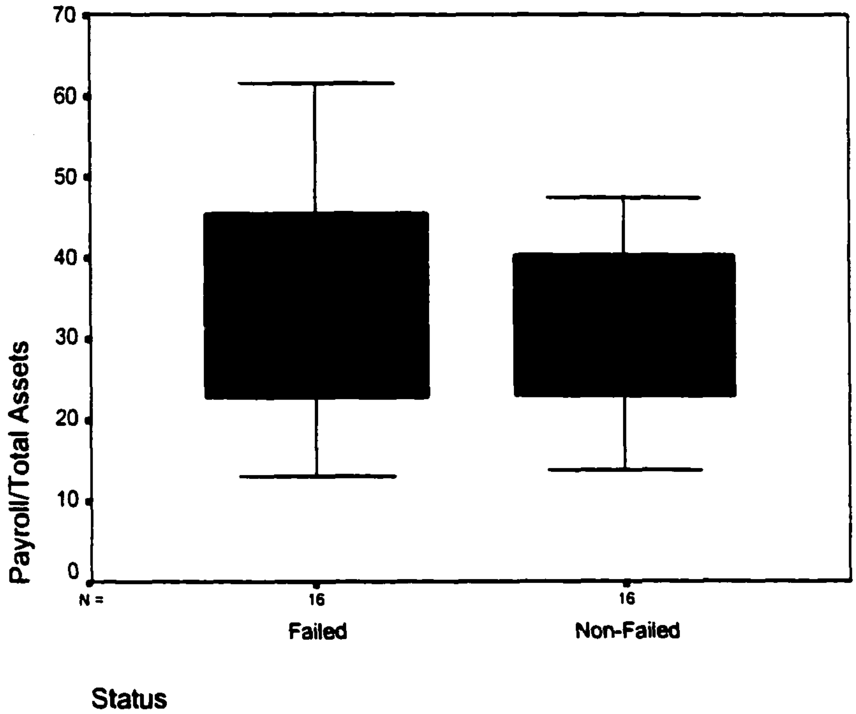


Figure B8

Within-Group Distribution -- % Change in A&P/Total Revenue Ratio

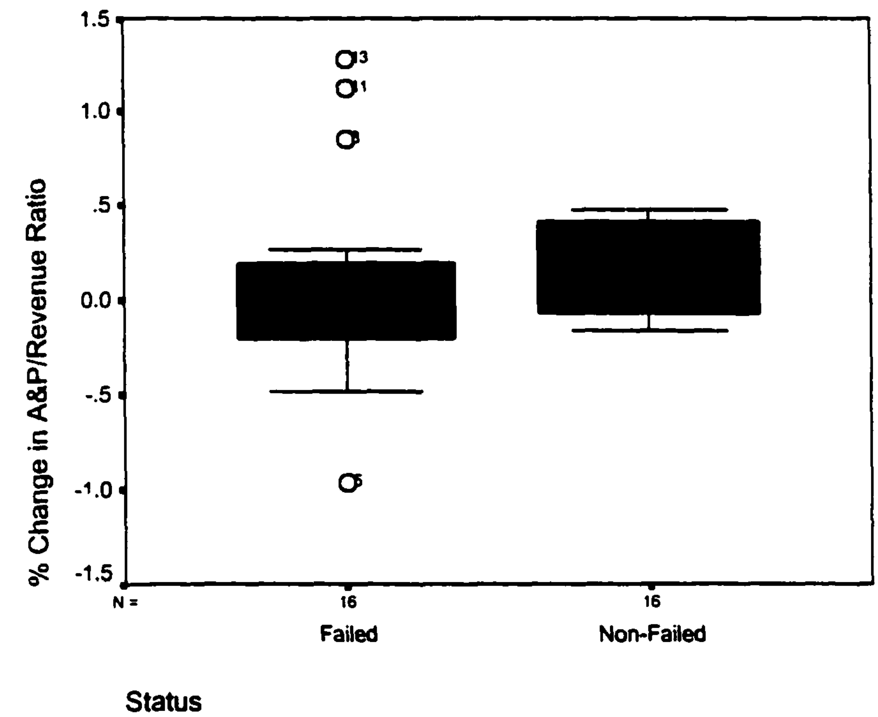


Figure B9

Within-Group Distribution -- % Change in Cash/Liabilities Ratio

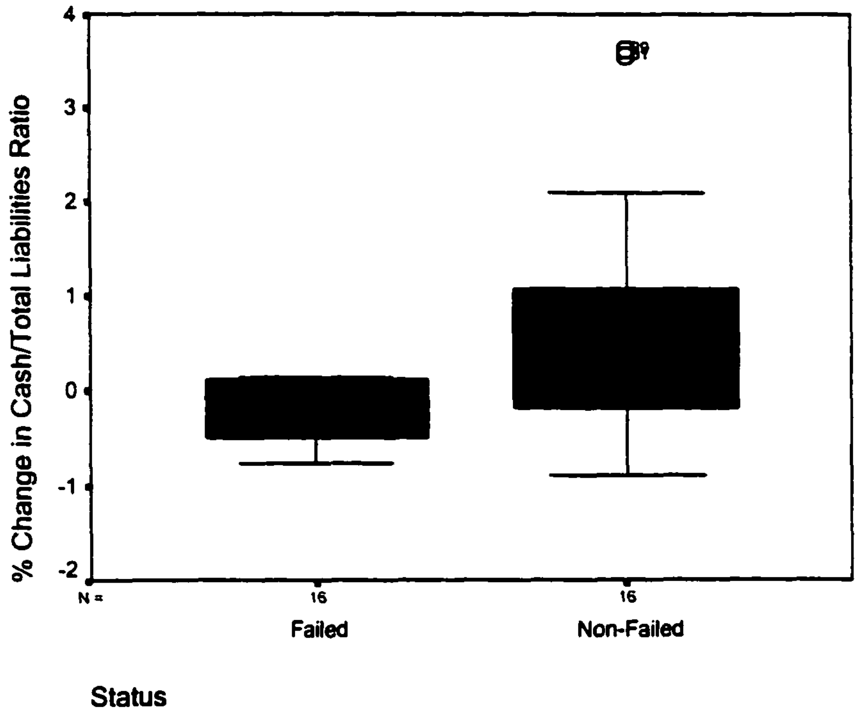


Figure B10
Within-Group Distribution -- % Change in Sales/Assets Ratio

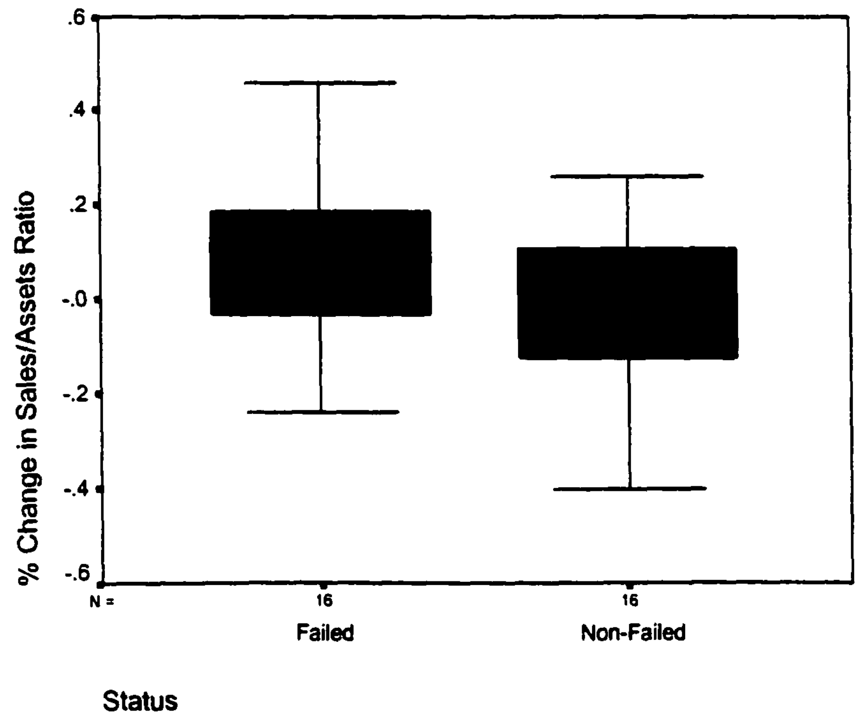


Figure B11

Within-Group Distribution -- % Change in Operating Margin Ratio

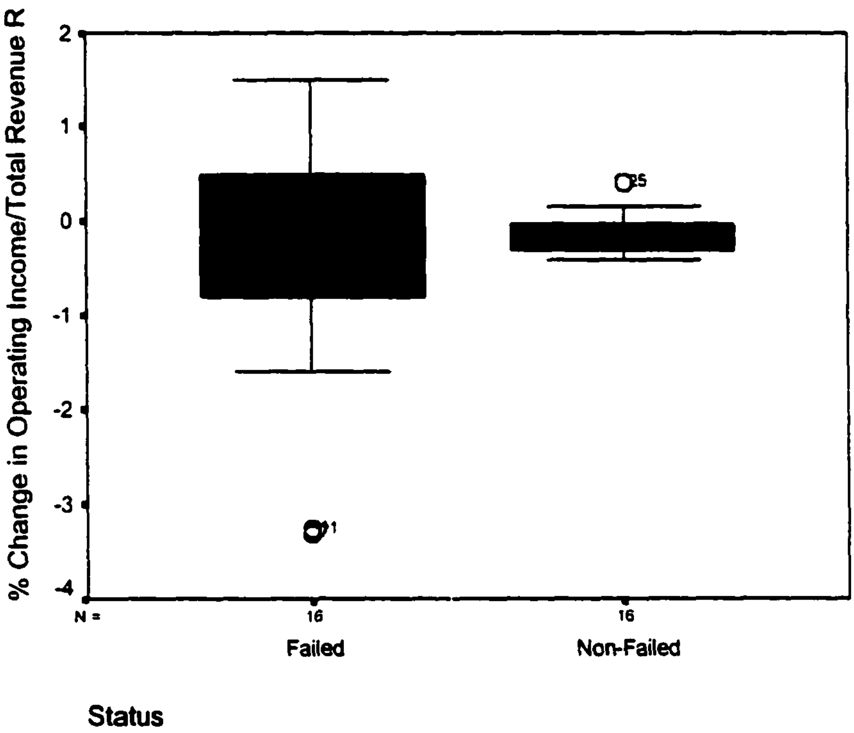


Figure B12

Within-Group Distribution -- % Change in Payroll/Revenues Ratio

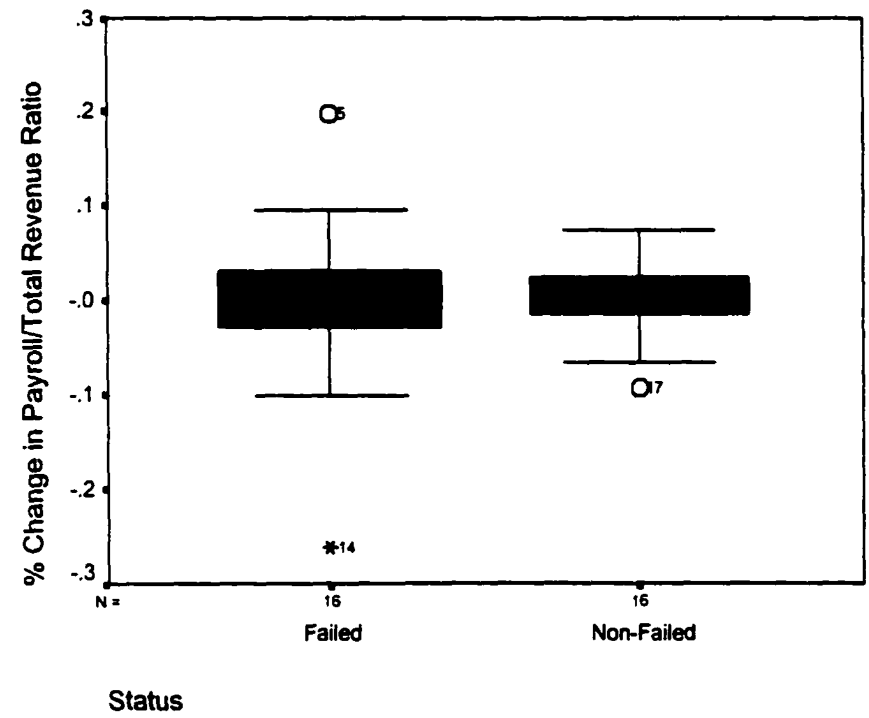
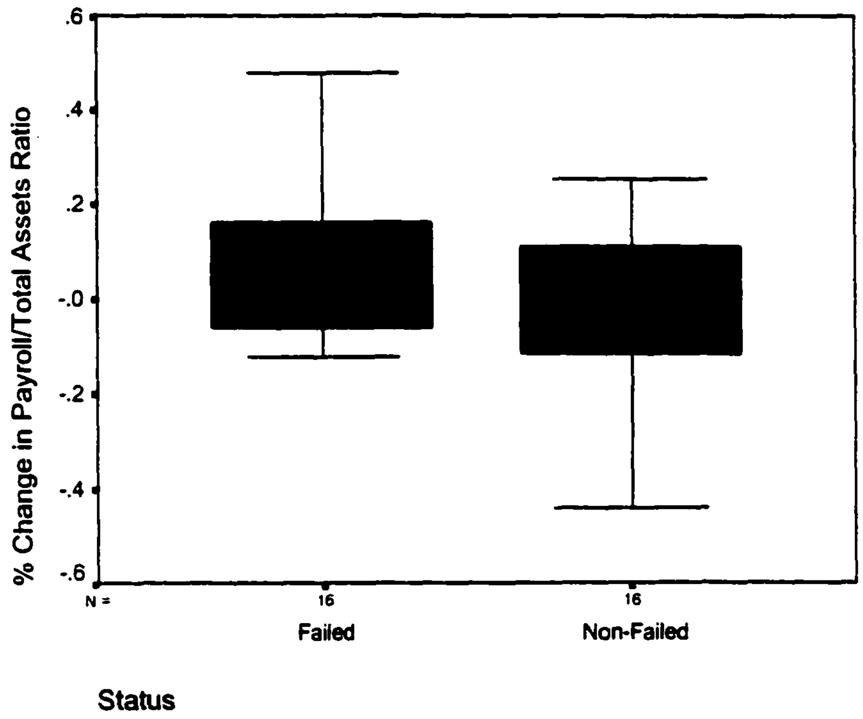


Figure B13

Within-Group Distribution -- % Change in Payroll/Assets Ratio



APPENDIX C

SCATTERPLOTS OF PREDICTOR VARIABLES

Figure C1

Scatterplot of A&P/Total Revenue

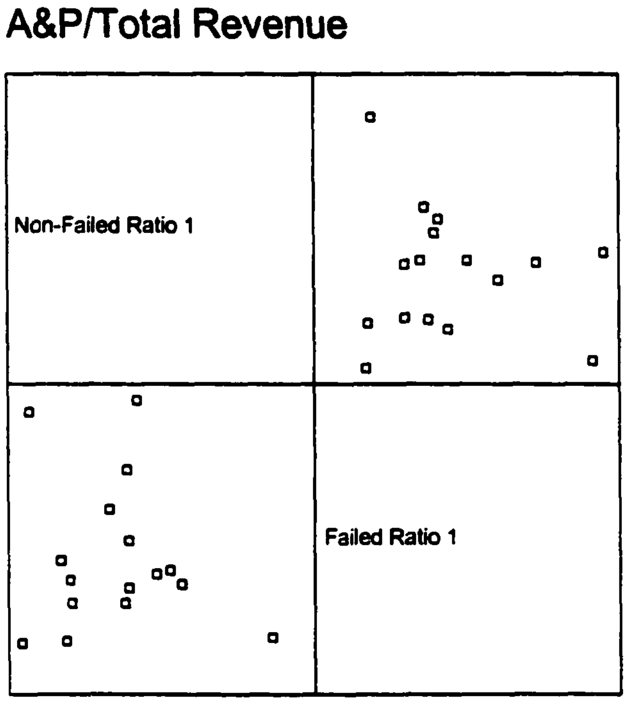


Figure C2

Scatterplot of Cash Flow/Liabilities

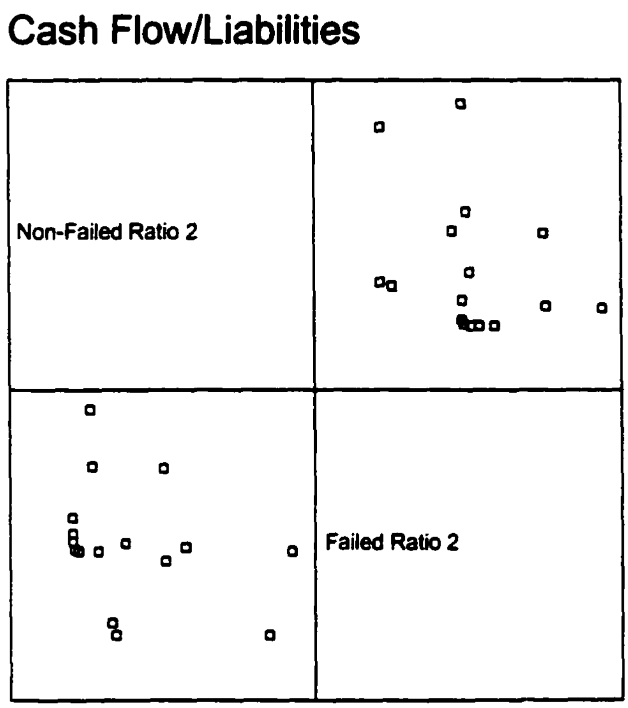


Figure C3

Scatterplot of Net Income/Assets

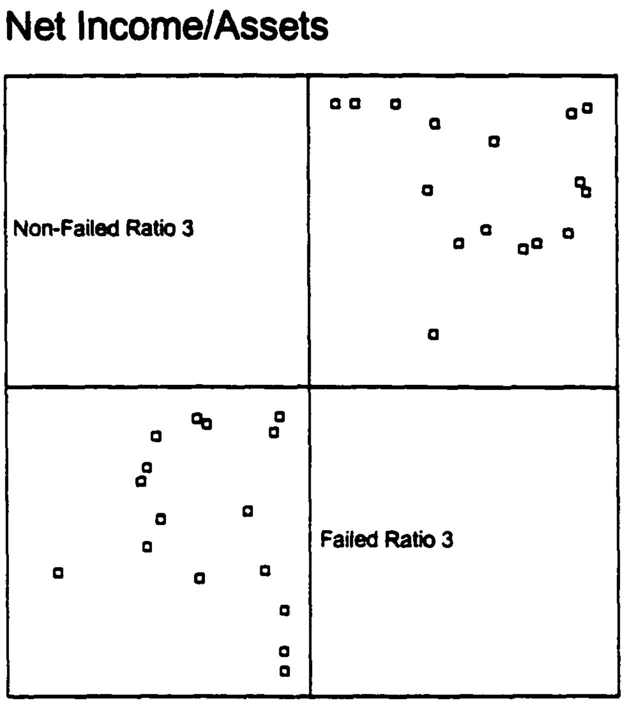


Figure C4

Scatterplot of Sales/Assets

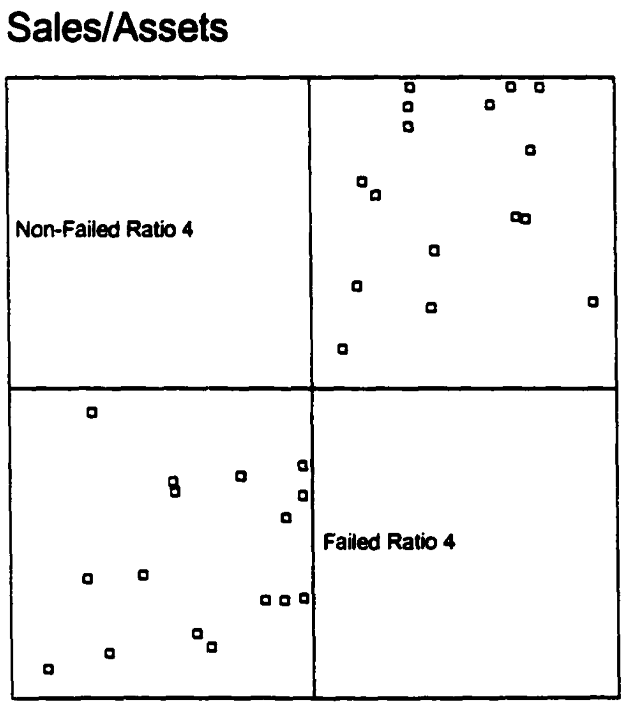


Figure C5

Scatterplot of Operating Margin

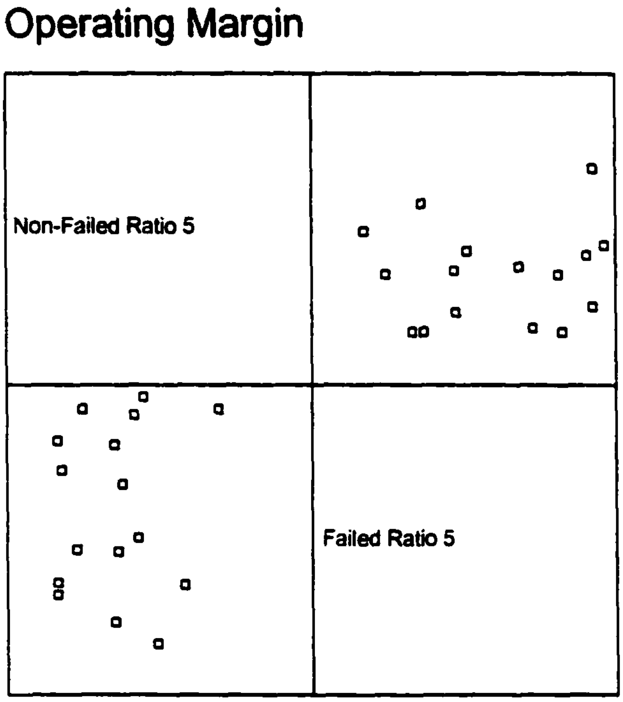


Figure C6

Scatterplot of Payroll/Revenues

Payroll/Revenues

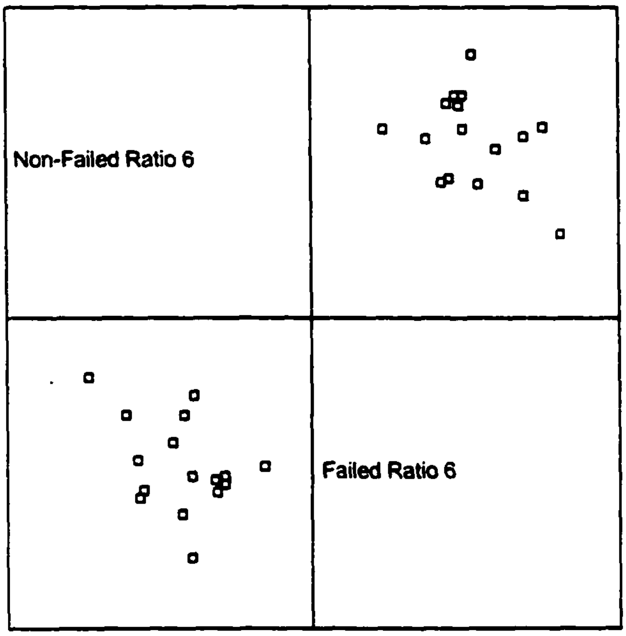


Figure C7

Scatterplot of Payroll/Assets

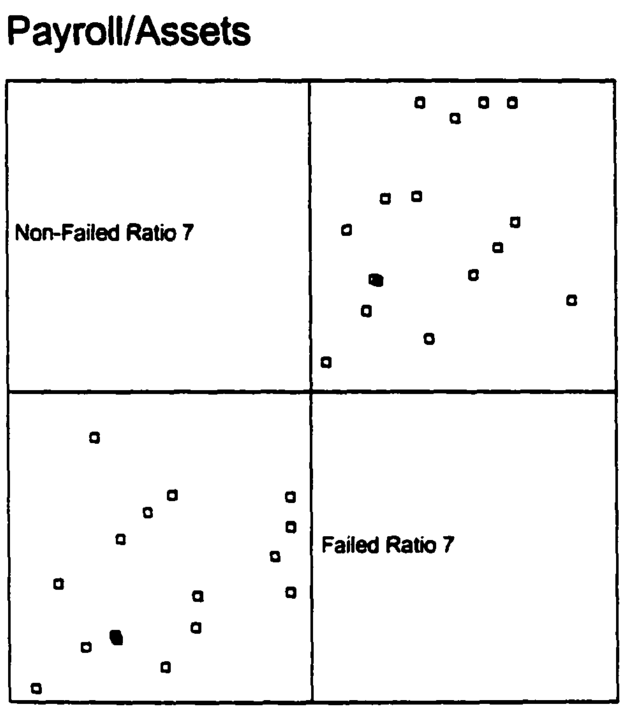


Figure C8

Scatterplot of % Change in A&P/Total Revenues Ratio

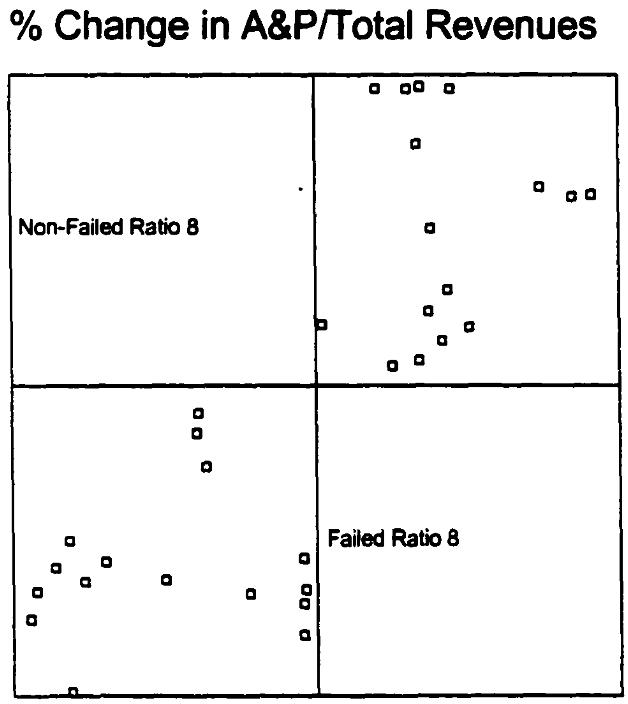


Figure C9

Scatterplot of % Change in Cash/Liabilities Ratio

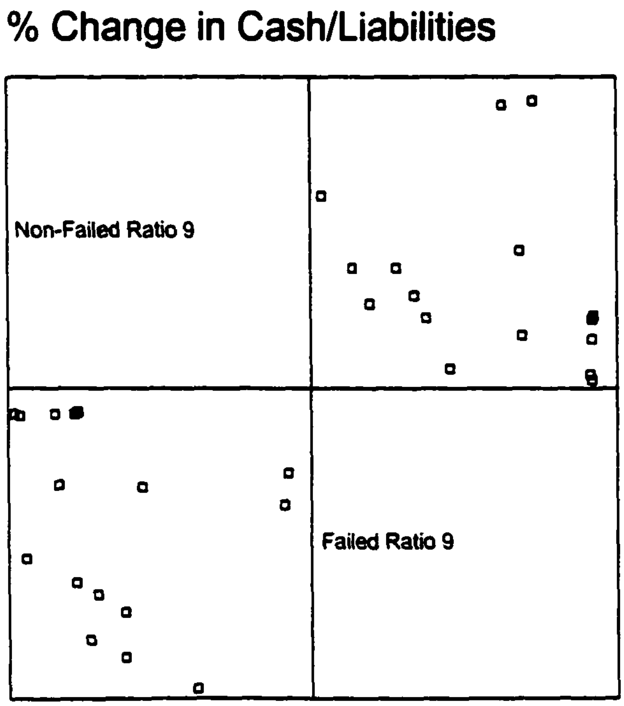


Figure C10

Scatterplot of % Change in Sales/Assets Ratio

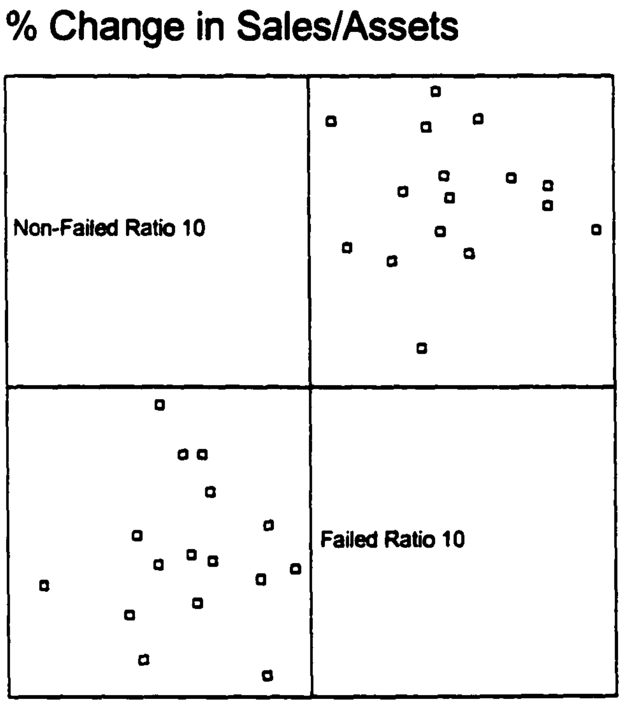


Figure C11

Scatterplot of % Change in Operating Margin

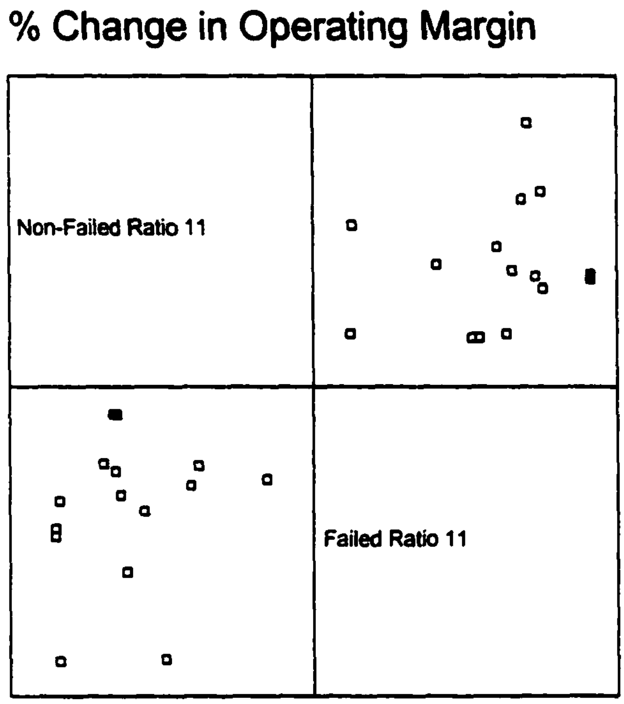


Figure C12

Scatterplot of % Change in Payroll/Revenue Ratio

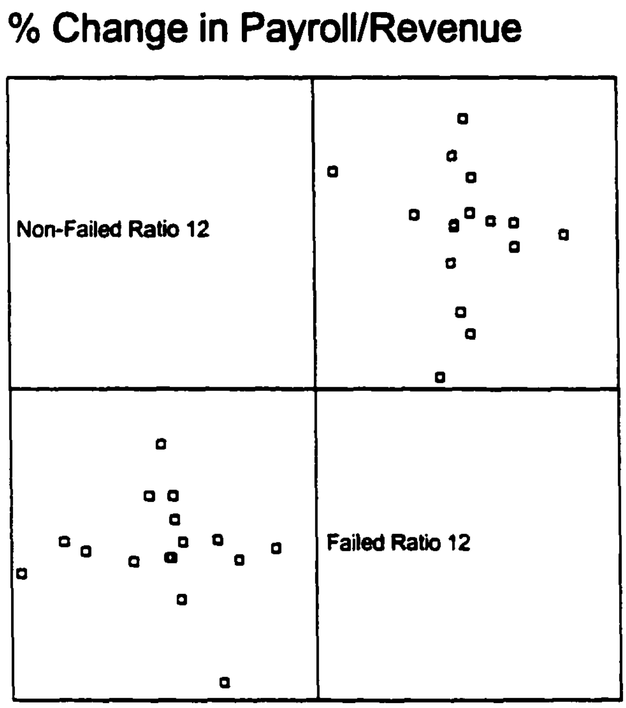
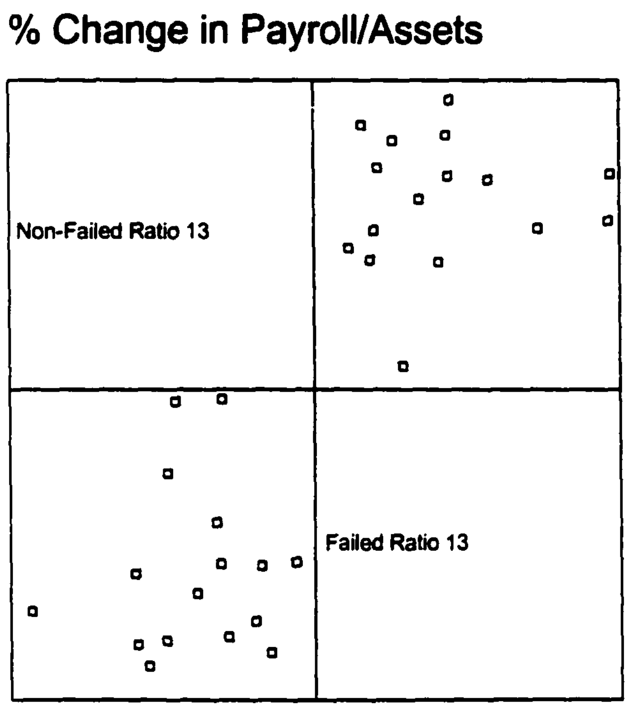


Figure C13

Scatterplot of % Change in Payroll/Assets Ratio



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