Predicting airline corporate bankruptcies using a modified Altman Z-score model

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PREDICTING AIRLINE CORPORATE BANKRUPTCIES

USING A MODIFIED ALTMAN Z-SCORE MODEL

by

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ABSTRACT

Predicting Airline Corporate Bankruptcies
Using a Modified Altman Z-Score Model

by

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Since 1979, 150 airlines have filed for bankruptcy. The airline industry was officially deregulated in October 1978, which brought about many changes including the strengthening of hub and spoke operations, fare-cutting, and the entry of new competitors into the industry. However, following deregulation, the airline industry has suffered financially from various problems: the economic recession of the early 1980s; rising jet fuel costs; rising labor costs; maintenance and interest costs; rising insurance costs; and intensified competition. The transition, from a regulated to a deregulated environment, increased the instability of the carriers’ operating profits. In 1998, airlines earned record profits, but by 2002, only two of the major carriers turned a profit. Since 1998, six major or national North American airlines filed for bankruptcy.
The objective of this study was to analyze bankrupt and non-bankrupt airlines using a traditional bankruptcy prediction model, the Altman Z-score model, in order to evaluate its ability to predict financial distress in the airline industry. The four financial ratios used in the model represented liquidity, cumulative profitability, productivity, and solvency. A second objective of this study was to develop and test a new statistical model that would better differentiate between bankrupt and non-bankrupt airlines.

The new model used only three variables, predicted membership to only one of two groups, and used a simple zero as a cut-off to distinguish whether a firm belonged to the bankrupt group or the non-bankrupt group. Furthermore, the new model’s predictions were accurate up to four years in advance of a bankruptcy filing. The Z” model, on the other hand, used four variables, did not always give a classification to one of two groups, and used two cut-offs. Furthermore, it performed no better than a naïve prediction in determining whether an airline firm should be classified as bankrupt or non-bankrupt.
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CHAPTER ONE

INTRODUCTION

In 1998, airlines earned record profits, but by 2002, only two of the major carriers turned a profit. What happened? Over capacity, higher fuel prices, recession, terrorism, war, SARS (Severe Acute Respiratory Syndrome), high competition, declining traffic, and bad management have contributed to a six-year financial roller-coaster ride for the airline industry (Airline Industry Survey, 2003).

Since 1979, 150 airlines have filed for bankruptcy (United Airlines Annual Report, 2003). The airline industry was officially deregulated in October 1978, which brought about many changes including the strengthening of hub and spoke operations, fare-cutting, and the entry of new competitors into the industry. However, following deregulation, the airline industry has suffered financially from various problems: the economic recession of the early 1980s; rising jet fuel costs; rising labor costs; maintenance and interest costs; foreign exchange risk; rising insurance costs; and, intensified competition. The transition, from a regulated to a deregulated environment, increased the instability of the carriers’ operating profits. Total risk (i.e., the volatility of net profits over time) increased dramatically in the airline industry.
There have been a number of studies using the Altman Z-Score Model to predict airline bankruptcy and financial distress; such studies were completed in 1974, 1982, 1986, 1992, 1996, and 2000. In 1986, Altman’s Z-Score model was tested to see if it could accurately predict airline bankruptcy in the late 1970s and early 1980s. In 2003, a doctoral dissertation was completed using the 1993 revised Altman Z”-Score model to determine the level of predictive accuracy between bankrupt and non-bankrupt publicly traded firms in the service industry (Hanson, 2003). Altman’s 1993 model correctly classified bankrupt service companies 92 percent, 69 percent, and 54 percent for years one, two, and three respectively. Thus, it is reasonable to continue to use this model for the current analysis of airlines, with the addition of several cash flow variables.

However, given the severe industry conditions and unpredictable events of the last six years, it is uncertain whether the Altman Model is still valid in assessing airline financial fitness. Furthermore, the Altman Z-Score model was revised in 1993 to a 4-variable model for nonmanufacturing firms, and this 4-variable model has not been tested on the airline industry. It may be the case that this 1993 model provides a better prediction than the 1968 model for predicting airline bankruptcies.

In late 2001, The United States (US) Congress formed the Air Transport Stabilization Board (ATSB), whose job was to dole out as much as $10 billion in loan guarantees to airlines unable to borrow in traditional credit markets after the September 11 terrorist hijackings (Airlines Industry Survey, 2003). America West Airlines was the first to apply for and receive the guarantees. US Airways Chief Executive David N. Siegel said in his letter to employees, “we will file an application with the ATSB for a loan guarantee since we have no other access to additional funding while we restructure the airline.”
The ATSB approved $900 million in backing for $1 billion in private loans to US Airways, provided that the airline obtain significant cuts. US Airways later filed for bankruptcy. United Airlines, the nation’s second-largest carrier, applied for $1.8 billion in ATSB loan guarantees, but had already racked up $678 million in losses before the terrorist attacks. United’s application was not approved. It later filed for Chapter 11 bankruptcy protection (Maynard, 2004).

Other major or national airlines that have either received the federal loan bailout, filed for bankruptcy, or both, include ATA, Frontier, TWA, Hawaiian Air, and Air Canada. TWA is no longer operating; it flew its last official flight on December 1, 2001.

The airline industry is a cyclical industry. It is very vulnerable to economic downturns. The airline industry is characterized by both high capital costs and high labor costs. Labor costs account for about 36 percent to 40 percent of total operating expenses (Airlines Industry Survey, 2003). Airlines are also energy-intensive operations. Fuel expenses are apt to remain near historical highs for the foreseeable future. Airline companies typically carry a significant amount of debt, contributing to their high fixed cost capital structures. When business drops off and costs are not covered, the result can be reorganization in bankruptcy, liquidation, or in recent cases of airline financial distress, the use of government loan bail-outs. The big airlines have been reeling since 2001, together posting more than $24 billion of dollars of losses due in part to constricted demand and high costs (Maynard, 2004).

The industry is highly volatile and is known for its propensity for financial distress. Stockholders, bondholders, other creditors, financial analysts, government regulatory bodies, and the traveling public need the ability to assess the level of financial distress that
prevails in the industry (Davalos, Gritta, and Chow, 1999). For this reason, models that can forecast financial distress are useful. Financial distress can be predicted one, two, and sometimes three years ahead of its occurrence using traditional financial ratios with statistical analysis (Altman, 1993).

If there were a means of predicting the combinations of characteristics 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 (Patterson, 2001). One method of predicting financial distress that has been widely used for over 35 years is the statistical bankruptcy prediction model, first presented by Altman (1968). Altman’s model (Altman Z-Score Model) is a popular approach for not only forecasting bankruptcy in advance of the event, but also for gauging the overall financial condition of a firm.

The Altman Z-Score Model uses five financial ratios to represent the elements of failure prediction. These elements are liquidity, cumulative profitability, productivity, solvency, and activity. Multiple discriminant analysis, a statistical technique, is applied to the financial ratios. The primary objectives of multiple discriminate analyses are to understand group differences and to predict the likelihood than an entity (individual or object) will belong to a particular class or group based on several metric variables (Hair, Tatham, Anderson, & Black, 1998). In this case, the two groups are financially distressed and non-financially distressed airlines, and the metric variables are the airlines’ financial ratios. Altman (1993) revised the model to a four-variable multiple discriminate model for nonmanufacturing firms, which is called the Z’-Score Model. The four
financial ratios used in the model represent liquidity, cumulative profitability, productivity, and solvency.

This dissertation tests the Altman Z’-Score Model to see if it could have accurately predicted airline bankruptcy/financial distress over a recent six-year period. Additionally, this dissertation seeks to revise the Altman Z’-Score Model so that it may be successfully applied to the evolving landscape of the airline industry.

Statement of Objectives

The objective of this study to analyze bankrupt and non-bankrupt airlines using a traditional bankruptcy prediction model in order to evaluate its ability to predict bankruptcy in the airline industry. The second objective was to develop and test a revised bankruptcy prediction model that would better differentiate between airlines that are likely to fail and those that are not likely to fail, by comparing the new model’s classification rate with the rate from the existing Z’-score model.

Hypotheses

The hypotheses to be tested in this dissertation are as follows:

H1₀: There is no relationship between the Altman Z’-score model and the likelihood of bankruptcy for an airline firm.

H1ₐ: There is a relationship between the Altman Z’-score model and the likelihood of bankruptcy for an airline firm.

H2ₐ: A revised bankruptcy prediction model is no better than the Altman Z’-score model in predicting the likelihood of bankruptcy for an airline firm.
H2A: A revised bankruptcy prediction model is better than the Altman Z’-Score model in predicting the likelihood of bankruptcy for an airline firm.

Justifications of the Study

Several different statistical techniques have been used in the past to assess airline financial performance: multiple discriminant analysis (Gritta, 1974 and 1982; Scaggs, 1986 Golaszewski, 1992; Chung and Szenberg, 1996); logistic regression (Gudmundsson, 1999; Gudmundsson, 2002); and, a neural network approach (Davalos, Gritta, and Chow, 1999; Gritta, Wang, Davalos, and Chow, 2000). Although the neural network approach predicted bankruptcy risk well, it is unlikely that individual investors, passengers, airport authorities, or airline management will be using artificial intelligence in the near future for this purpose.

Therefore, it was suggested that a revised model be developed and tested on existing airline businesses. A revised model can include one or more ratios that were not included in the earlier models, especially cash flow related ratios. From a practical standpoint, it makes good sense to include information about cash flows and total debt in a bankruptcy prediction. When a company lacks sufficient cash flow to make its debt payments, it is in default and must either reorganize or liquidate.

All public corporations are required to submit a Statement of Cash Flow (SCF) in their Securities and Exchange Commission (SEC) filings. The SCF can yield some very valuable information, and it is possible that some of that information could be used to improve the results of the Altman Z’-Score Model. In fact, one bankruptcy prediction model developed by Beaver (1966) states that the cash flow to debt ratio was the best
single ratio predictor. Altman did not include this ratio because of the lack of consistent and precise depreciation data available from public firms. Among companies in the same industry, however, it may be possible to obtain sufficient information that will allow a revised Altman model to also include cash flow ratios. Thus, an up-to-date analysis of airlines can help to predict the next major or national airline failure.

There has not been a study applying the 1993 Altman Z’-Score model to the airline industry. Additionally, there has not been a prediction model for airlines that included cash flow variables, which are relevant factors in bankruptcy/financial distress. The goal of this dissertation was to develop a model that identifies the key elements of airline bankruptcy/financial distress. Such a model should be valuable to industry practitioners and academics alike. Thus, this research will add useful knowledge to both the transportation and financial literature.

Limitations of the Study

There are a number of limitations involved in this study. First, this analysis was limited by the availability of financial data on airlines. Only publicly traded corporations are required to make their financial statements available to everyone. Therefore, only publicly traded airlines were part of this study. The data used in this study was limited to that which is available in filings with the SEC.

A second limitation is the consistency of the data that is available. For example, some of the airlines rely on leasing arrangements to obtain jets, which are the most important assets for an airline. Other airlines have purchased their jets, using long-term debt
financing. This leasing versus ownership difference may have an impact on the presentation of an airline’s balance sheet accounts.

A third limitation was the use of ratio analysis. Ratios are extremely useful to owners, creditors, and management in evaluating the financial condition of airlines. Ratios, however, are only indicators. Ratios do not reveal exactly what the problem is. Ratios only indicate that there may be a problem; in this case, much more investigation and analysis are required.

Delimitations of the Study

There were also several delimitations involved in this dissertation. First, the sample used in this study consisted of the Department of Transportation (DOT) classification known as major and national air carriers in North America. DOT defines major carriers as those airline firms that earn revenues of more than $1 billion per year, whereas national carriers include airline firms that earn revenues of $100 million to $1 billion per year. Second was the use of traditional financial ratios to analyze the airline firms’ financial performance. This study does not use load factors, or other airline industry specific ratios, as used by Chow, Gritta, and Leung (1991). Third, there were delimitations associated with the choice of multiple discriminant analysis, which will be discussed in Chapter 3 of this dissertation. Several kinds of statistical analysis have been used in bankruptcy prediction models, including univariate analysis (Beaver, 1967), multiple discriminate analysis (Altman, 1968; Deakin, 1972; Edmister, 1972), logit analysis (Ohlson, 1980; Zavgren, 1985; Gentry, Newbold and Whitford, 1985; Gudmundsson, 2002), probit analysis (Grablewsky and Talley, 1981), and neural network
Only multiple discriminant analysis was used in this study, in spite of its limitations as a statistical technique, including sensitivity to outliers, linearity, normality, and homogeneity of variances. This method has been used in more studies than any other method and 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 a case, chosen at random, being classified into the correct group, is 50 percent.

Bankrupt -- A debtor that, upon voluntary petition or one invoked by the debtor's creditors, is judged legally insolvent.

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

Collinearity -- Expression of the relationship between two (collinearity) or more independent variables (multicollinearity). Collinearity exists when there is a statistical relationship between two independent variables.

Default -- Failure to make required debt payments on a timely basis or to comply with other conditions of an obligation or agreement.

Failure -- A firm that has been a subject of bankruptcy proceedings, either voluntary or involuntary.
Liquidation -- The sale of a firm’s assets, payment of outstanding debts, distribution of the remainder to shareholders, and going out of business; Chapter 7 bankruptcy.

Multiple Discriminant Analysis -- A statistical analysis technique for distinguishing among defined groups by developing a linear combination of discriminating independent variables. The goal of multiple discriminant analysis is to predict group membership from a set of predictors.

Non-bankrupt -- A debtor that has not been the subject of bankruptcy proceedings.

Reorganization -- The action that may allow a company to emerge from Chapter 11 bankruptcy. Reorganization may consist of a series of agreements between the firm, its creditors, and the court which allow for the company to repay its debts and alter its structure to prevent the same event from arising again.

Revenue Passenger Miles -- A measure of an airline’s traffic. It refers to how many of an airline’s available seats were actually sold.

Univariate Analysis -- A statistical technique to determine, on the basis of one dependent measure, whether samples are from populations with equal means.

Organization of the Dissertation

This study is organized into five chapters. Chapter 1 includes background for the problem statement, the problem statement, hypotheses to be tested, delimitations of the study, and definitions of certain terms. Chapter 2 reviews the literature that is relevant to the study. Chapter 3 describes the data 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, the results of the prediction, and the tests of the research hypotheses. Tests of airlines that are not included in the development of the
model are used to validate the model. Chapter 5 summarizes the results of the test and offers conclusions, implications, and recommendations for further research.
CHAPTER TWO

LITERATURE REVIEW

Introduction

The literature review contained in this Chapter will provide a brief history and background of the airline industry, information on airline industry economics, background on the Altman Z-score bankruptcy prediction model, the Z-score model, a review of studies on airline bankruptcy prediction which used the Z-Score model, and other bankruptcy prediction models.

The U.S. Airline Industry—A Historical Perspective

In 1903, the Wright brothers’ first successful flight in Kitty Hawk, North Carolina marked the beginning of the aviation industry. The industry became more developed with the United States’ participation in World War I. In 1927, Charles Lindberg’s solo flight across that Atlantic Ocean created massive public interest in flying (Boyd, 1999).

After this, air transport companies were started, including American Airways, which later became American Airlines, as well as Boeing, and United Aircraft and Transportation Corporation, which later became United Airlines.

The US Postal Service provided the opportunity for private aircraft to function as mail carriers. This proved to be one of the biggest factors in the growth of the air transportation industry. Passenger service was also initiated as a way to augment the
incomes of the firms providing airmail services. Passenger volume grew, and the number of start-up airlines multiplied (Boyd, 1999).

During these early years of the aviation industry, as air traffic became more and more disorganized, it became apparent that air traffic rules were needed. In 1938, the Civil Aeronautics Authority, an independent regulatory bureau, was developed. By that date, many air transport companies were flying the new DC-3s, which were created to carry both mail and passengers. They could seat 21 passengers (Boyd, 1999).

In World War II, the U.S. sent commercial planes and pilots to Europe to participate in the war. The war generated support for development of new aircraft, which would also benefit post-war commercial aviation. By the 1950s, there were dramatic improvements in capacity and comfort on commercial planes. Jet service was introduced in 1959, which made for the fastest cross-country service available. Following some serious mid-air collisions, the Federal Aviation Administration (FAA) was created to develop an air traffic control system.

During the 1970s, fuel prices escalated. This was the time of the worldwide oil embargo. By then, Boeing had developed the first widebodied jet, the 747 jumbo, which had 385 seats compared with only 119 for the Boeing 707s that they replaced (Banks, 1982). However, the most dramatic event to change the industry, up to that point, occurred in 1978: deregulation.

The Airline Deregulation Act eased the entry of new airline companies into the business and gave them the freedom to set their own fares and fly the routes they chose. Deregulation resulted in the growth of smaller, low-cost carriers and the mergers of larger carriers. Costs were reduced by using nonunion labor, smaller used planes, and shorter
routes (Scaggs & Crawford, 1986). Air fares plummeted, and new routes opened. More cities than ever were serviced. Increased competition, lower fares, and expanded routes led to an increased demand for airline travel. In the mid-1970s, the major North American carriers flew 130 billion revenue passenger miles. By 1988, after a decade of deregulation, the number of revenue passenger miles had reached 330 billion ("The Airline Industry," 2000).

The airline industry was also affected by rising jet fuel costs, labor costs, and maintenance and interest costs associated with maintaining and/or replacing an aging fleet (Scaggs & Crawford, 1986). The airline industry experienced its first drop in passenger numbers in a decade in 1989. Between 1989 and 1992, the industry lost about $10 billion. The Gulf War of 1991 and an economic recession had a devastating impact on the number of passengers flying and on airline revenues. High debt levels plagued the industry (Chow, Gritta, & Hockstein, 1988). Pan American and Eastern went bankrupt and were liquidated. Trans World Airlines (TWA) and Continental filed for bankruptcy under Chapter 11 and reorganized.

After the economic recession of the early 1990s, new firms continued to enter the market. Most of these airlines competed with limited route structures and lower fares than the major carriers. Expansion and health returned to the industry by 1995. In 1997 and 1998, virtually all U.S. and Canadian carriers hit record profit levels.

By the beginning of 2001, the eight major U.S. airlines were feeling the effects of another economic recession. The terrorist attacks of September 11, 2001 on the World Trade Center in New York City and the Pentagon in Washington, DC had a terrible impact on the U.S. domestic and global airline industries. U.S. Airlines were grounded
for several days and many people cancelled their travel plans. Many airlines went bankrupt; others were forced to seek government-backed loans through the Federal Stabilization Act (Maynard & Atlas, 2002).

In late 2001, the U.S. Congress formed the Air Transport Stabilization Board (ATSB), whose job was to dole out as much as $10 billion in loan guarantees to airlines unable to borrow in traditional credit markets after the September 11, 2001 terrorist hijackings. America West Airlines was the first to apply for and receive the guarantees. US Airways Chief Executive David N. Siegel said in his letter to employees, "We will file an application with the A.T.S.B. for a loan guarantee since we have no other access to additional funding while we restructure the airline." The ATSB approved $900 million in backing for $1 billion in private loans to US Airways, provided that they obtain significant cost cuts. However, US Airways later filed for bankruptcy. United Airlines, the nation’s second-largest carrier, applied for $1.8 billion in A.T.S.B. loan guarantees, but had already racked up $678 million in losses before the terrorist attacks. United’s application was not approved, and it later filed for Chapter 11 bankruptcy protection (Maynard, 2004). Other major or national airlines that have filed for bankruptcy include: TWA, Hawaiian Air, and Air Canada. TWA is no longer operating; it flew its last official flight on December 1, 2001.

The larger, high-cost airlines were faced with increasing competition from domestic low-cost airlines. The domestic low-cost airlines, together with consumer expectations for lower fares, drove down revenues. In addition, the bursting of the technology industry bubble in 2000 caused a substantial decline in premium business travel.
Conditions at Air Canada typified the struggles in the industry, post-September 11, 2001. Their revenues were decreasing, but they were prevented from significantly reducing labor costs. According to Air Canada management, the declining economy, the September 11, 2001 terrorist attacks, the war in Iraq, and the 2003 SARS outbreak all combined to cause a significant reduction in consumer demand and in passenger revenues. Management stated that most airlines have limited ability to reduce labor costs and have relatively fixed aircraft fleet costs ("Air Canada," 2004). This means that the high-cost carriers were unable to bring down their costs structures to a level necessary to respond to the decline in traffic, or to the evolving landscape of the airline industry.

Air Canada suffered a net loss of (in Canadian dollars) $1.3 billion in 2001, a net loss of $828 million in 2002, and a net loss of $1.9 billion in 2003. Restated in U.S. dollars, these losses were approximately $950 million in 2001, $604 million in 2002, and $1.4 billion in 2003. In the first quarter of 2003, alternative sources of funding were not available. Air Canada elected to restructure its operations, debt, and capitalization under creditor protection. It also made a concurrent petition under the U.S. bankruptcy code.

In the years 1998-2004, several major and national carriers did not file for bankruptcy. These included AirTran (formerly ValuJet, which was in bankruptcy after a crash in 1996 killed 110 passengers), America West, Continental (which had filed for bankruptcy in 1993), newcomer JetBlue, Alaska, American, Delta, Northwest, Frontier, and industry star performer Southwest. However, not all of these airlines are operating at a profit today. Most recently, ATA filed for Chapter 11 bankruptcy protection on October 26, 2004.
The smaller, discount operators in this group, Southwest and JetBlue, spend six cents or less to fly a seat a mile, excluding fuel costs. The bigger airlines, however, have higher costs of operations. US Airways says it costs ten cents to fly a seat a mile, excluding fuel, and American and United spend more than 8 cents per mile. That gap is killing the bigger carriers (McCartney, 2004).

Having reviewed a historical perspective of the airline industry, the next section of the chapter discusses the current economics of the airline industry.

Industry Economics

Most analysts consider the airline industry to have a very high business risk (Gritta, Freed, & Chow, 1998). Fixed costs are relatively high, and comprise about 25 to 30 percent of operating revenues (Gritta, Chow, & Freed, 2003). Operating costs of a flight depend mostly on the distance traveled, and not on the number of passengers on board the flight itself. Fuel expenses, a highly volatile cost factor, account for about 30 percent of airline total costs. Labor costs also make up a significant portion of operating costs, absorbing about 40 percent of operating revenues (Airlines Industry Survey, 2003). Labor costs for both the crew and ground staff are determined largely by the type of aircraft, not by the number of passengers. The only true variable costs in the industry are travel agency commissions, food costs, and ticketing fees. Finally, the demand for air travel is very cyclical, and is also subject to seasonal fluctuations. Winter weather can reduce demand. The events of September 11, 2001, the recession in the U.S. economy, and the U.S. war with Iraq in 2003 have all disrupted the typical seasonality. For all these reasons, the airline industry is considered to have high business risk.
Airlines also have high levels of financial risk. Financial risk is defined as the added variability in earnings to stockholders that results from using long-term debt to finance the firm’s capital assets (Gritta, Freed, & Chow, 1998). It is caused by interest and principal payments on debt service. This risk is the result of managerial decisions, rather than the business environment. Interest represents a fixed charge and thereby reduces reported profit. Also, the likelihood of financial distress increases as a firm uses more debt in its capital structure. The airline business is very capital intensive. It requires significant amounts of capital to fund the acquisition of assets, especially aircraft. Airlines have often funded the acquisition of aircraft by issuing debt, which is often needed in capital intensive businesses.

The airline industry’s debt load greatly exceeds U.S. industry averages. Aircraft are the airlines’ only money making equipment, and are among the most expensive machines in the world. For example, a Boeing 777 costs more than $130 million per aircraft (Chung, 1996). The general aging of the aircraft used means higher maintenance costs and eventual aircraft replacement. Stricter government regulations for older planes place further burdens on those carriers who use them.

Labor costs are the highest single cost for United (“United Airlines,” 2003). Many of the major airlines’ restrictive union agreements limit their flexibility in reducing labor costs. Even Southwest has begun to experience labor problems, as employees have begun to demand higher pay levels. Southwest’s flight attendants spent over two years in negotiations with the airline to achieve their objectives of improved pay and quality of life (“Airlines Brief,” 2004).
As a result of the September 11, 2001 terrorist attacks, airline insurance premiums have increased significantly. Commercial insurers cancelled airlines’ liability insurance for losses resulting from what was considered acts of war (i.e., terrorism, sabotage, hijacking, and other similar acts), but airlines have obtained replacement coverage through the FAA (“United Airlines,” 2003). There is no guarantee that the FAA will continue this coverage. Passenger security costs are also expected to rise.

Most of the major airlines maintain their operations around a “hub-and-spoke” system. The spokes feed passengers from outlying points into a central airport, called the ‘hub’, where passengers travel to additional hubs or to their final destination. Establishing a major hub in a city like Chicago or Atlanta is very expensive. It can cost as much as $150 million for real estate and staffing. Some low-cost airlines, however, have been operating differently. Unlike other major airlines, Southwest, a low-cost carrier, provides no fancy terminals, no costly hub-and-spoke operations, and no amenities (Chung, 1996). The low-cost airlines together now control over a quarter of domestic air capacity, they fly in the highest-demand markets, and their low fares are easy to find and book on the Internet (“America West,” 2003).

The airline industry is highly competitive. Most of the regional carriers have lower costs structures than the major hub-and-spoke carriers. Both business and leisure travelers have become increasing price sensitive. The low-cost carriers continue to target and make inroads into markets that had been the domain of the network carriers, while network carriers have little flexibility to respond. The discount carriers have been able to thwart price hikes by the network carriers (“Airlines Rescinding,” 2004).
In general, the airline industry is in a dire condition. It is dealing with the industry’s worst downturn in history. The airline industry has yet to fully recover. Ongoing fare cuts, declining traffic, and softness in the economy have kept the industry in a weakened condition. Having reviewed the economics of the airline industry, the next section of this chapter examines the Altman Z-Score bankruptcy prediction model.

Altman Z-Score Model

The first study using financial ratios and multiple discriminant analysis to predict business failure was completed by Altman in his doctoral dissertation. The model that he developed correctly predicted 95 percent of manufacturing firm bankruptcies one year prior to failure. The model also correctly predicted 72 percent of manufacturing firm bankruptcies two years prior to failure (Altman, 1968).

According to Altman (1993), the detection of company operating and financial difficulties is a subject which has been particularly amenable to analysis with financial ratios. Studies dating back to the 1930s concluded that failing firms exhibit significantly different ratio measures than do continuing entities. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators in these studies (Altman, 1968). Knowing which ratios to use in detecting bankruptcy potential, and what weights should be attached to those ratios, is a question that Altman and others have tried to answer. It is a central question that this study also investigates.

Altman used Multiple Discriminant Analysis (MDA), a statistical technique that identifies the differentiating characteristics of pre-determined groups. MDA is used to derive a discriminant function. The discriminant function is a linear equation using a
combination of independent variables. The independent variables, in Altman’s study, were financial ratios. This equation was used to differentiate the firms studied into one of two groups: either bankrupt or non-bankrupt. This analytical method has also been applied successfully in consumer credit evaluation, in which a discriminant function, using financial data as independent variables, classifies individuals into two groups—credit-worthy or non-credit-worthy (Wagner, Reichert, & Cho, 1983).

Altman started with a list of 22 potentially useful ratios for evaluation. The variables were classified into five traditional ratio categories: liquidity, cumulative profitability over time, productivity, solvency, and activity. The ratios were chosen on the basis of their popularity in the literature and their potential relevancy. Using the financial statements of 33 bankrupt corporations and 33 non-bankrupt corporations, Altman used step-wise multiple discriminant analysis to establish which ratios would contribute the most to an equation that would differentiate between the two groups. The analysis yielded a formula that used five of the original 22 ratios as independent variables: 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 liabilities ($X_4$); and, sales/total assets ($X_5$). Collectively, these five ratios were considered “best” in the prediction of corporate bankruptcy. This function, shown in Table 1, did the best job among the alternatives, which included numerous computer runs analyzing different ratio profiles.

The dependent variable, the Z-score, maximizes the difference between the bankrupt group and the non-bankrupt group. Altman found that firms with a Z-score of greater than 2.99 are classified into the non-bankrupt category, while firms with a Z-score below
1.81 are classified as bankrupt. The area between 1.81 and 2.99 was considered a “gray area” because of the tendency for error classification. If a single cutoff is desired, Altman suggested using a Z-score of 2.67 to classify a firm as either bankrupt or non-bankrupt.

The final discriminant function was as follows in Altman’s original model (Altman, 1968).

Table 1

*Altman Z-Score Multiple Discriminant Analysis Model*

\[
Z = 0.12X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 + \varepsilon
\]

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 of equity/book value of total liabilities;
- \(X_5\) = sales/total assets;
- \(\varepsilon\) = error term; and,

\[Z\] = overall index.

Each of the ratios included in the model is explained below. For each ratio, a larger Z-score correlates to non-bankruptcy; a smaller Z-score correlates to bankruptcy.
The working capital/total assets ratio ($X_1$) is a measure of the net liquid assets of the firm relative to its total capitalization. A firm that has experienced consistent operating losses will have shrinking current assets relative to its total assets.

Retained earnings are thought of as earned surplus. According to Altman (1968), this measure of cumulative profitability over time implicitly considers the age of a firm. A relatively young firm will probably show a low retained earnings/total assets ratio ($X_2$) because it has not had time to build up its cumulative profits. The incidence of failure is much higher in a firm's early years.

The ratio of earnings before interest and taxes to total assets ($X_3$) is a measure of the productivity of the firm's assets. This ratio is the same as the traditional return on assets (using earnings before interest and taxes) ratio, which is an overall performance/profitability measure. Market value of equity to book value of liabilities ($X_4$) is a measure that shows how much the firm's assets can drop before its liabilities exceed its assets and the firm becomes insolvent. Sales to total assets ($X_5$) measures the sales generating ability of the firm's assets, which is an activity ratio.

The model was considered to be very accurate in classifying 95 percent of the total sample correctly one year prior to bankruptcy. The model correctly classified 72 percent of the total sample two years prior to the event. In some cases, bankruptcy was correctly predicted five years before the event. In addition to the general manufacturing, publicly held firm Z-score model, Altman later developed a variation of the model for privately held firms (the $Z'$-score model) and for nonmanufacturing industrials (the $Z''$-score model).

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In 1993, Altman revised this five-variable model to the four-variable model shown below as Table 2 (Z"-score model). In revising the original model, he changed the $X_4$ variable to net worth (book value) divided by total liabilities. He also dropped the last variable, $X_5$, and altered the coefficients of the dependent variables.

The $Z''$-Score Model follows (Altman, 1993).

Table 2

*Altman Z''-Score Model*

\[
Z'' = 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05 X_4 + \epsilon
\]

Where:

$X_1 = \text{working capital/total assets}$;

$X_2 = \text{retained earnings/total assets}$;

$X_3 = \text{earnings before interest and taxes/total assets}$;

$X_4 = \text{book value of equity/book value of total liabilities}$;

$\epsilon = \text{error term}$; and,

$Z'' = \text{overall index}$.

This newer model uses new cutoffs for classifying a firm as bankrupt or non-bankrupt. A firm with a $Z''$-score of more than 2.6 would be considered non-bankrupt; a firm with a score below 1.1 would be considered bankrupt. The firms that score between 1.1 and 2.6 fall into the gray area, where classification is difficult (Altman, 1993).
Both the Altman Z-Score and Z"-Score models do not include cash flow ratios. Altman stated the cash flow to debt ratio was not considered because of the lack of consistent and precise depreciation data. However, Beaver (1967) found that the cash flow to debt ratio was the best single ratio predictor of bankruptcy. Beaver stated that the larger a firm’s net cash flow from operations, the smaller the probability of failure. Thus, it seems practical that a model that predicts financial distress/bankruptcy should also include cash flow ratios to test their predictive ability.

Since 1988, publicly traded firms have been required to issue a Statement of Cash Flows (SCF) with other financial statements released to external users (Schmidgall, 2002). Investors and creditors use the SCF to assess the firm’s: (1) ability to pay its bills as they come due; (2) ability to pay dividends; and, (3) need for additional financing, including borrowing debt and selling capital stock. Since the SCF may contain information relevant to a prediction of failure or non-failure, it seems appropriate to include cash flow ratios in a new bankruptcy prediction model.

In their tests of the generalizability of the Z-score model, Grice and Ingram (2001) point out that researchers assume that the model is stable across economic conditions that change over time. However, as discussed earlier in Chapter 2, airline industry conditions have changed dramatically in recent years. Changing economic conditions can affect the accuracy, magnitude, and significance of the Z-Score coefficients (Mensah, 1984). Therefore, it is not likely that the Z-score model would perform equally well in all financial periods. These reasons suggest that a revised bankruptcy prediction model should be developed. Before doing so, however, this study will next discuss other bankruptcy prediction research in the airline industry.
Studies of Airline Bankruptcies using the Altman Z-Score Model

In 1981, Gritta (1982) accurately predicted that both Braniff and Continental would file for bankruptcy, using the Z-score model. Gritta, Davalos, and Chow (1996) used the Altman Z-Score Model to make airline Z-score comparisons over a very long time horizon. The carriers were divided into two groups: those which remained solvent over the period of the study, or which were solvent when merged; and, those which had failed one or more times. They found that the model separated the two groups fairly well.

Scaggs and Crawford (1986) revised the Altman Z-Score model, not on the dependent variable side, but on the independent variable side. They retained the single Z-score hurdle of 2.67, but changed the weighting of the independent variables (i.e., the financial ratios). Their study determined that the debt position of a firm was a significant factor in predicting U.S. airline failure. In fact, many airlines hold high debt positions in their capital structure, along with commensurate high interest payments. Their revised model accurately predicted Braniff, Continental, and Air Florida's bankruptcy three years prior to the event during the time period 1978-1982.

However, Golaszewski and Sanders (1992) contend that many U.S. carriers can continue to operate with lower than normal scores over the long haul. They state that when a Z-score falls below 1.0, the airline enters the range of concern. They also state that a score below 0.5 indicates financial distress and the need for financial restructuring. This cutoff is significantly lower than Altman's Z-Score cutoff.

Davalos, Gritta, and Chow (1999) used the variables from Altman's 1993 model, the Z''-Score model, but incorrectly used the cut-off scores from the 1968 Z-Score model in their research. Therefore, fourteen of their twenty-six classifications were incorrect.
The results of their study would have been the same, however, if the classifications had been correct; their neural network approach outperformed the Z''-Score model in predicting U.S. carrier bankruptcy.

Gritta, Davalos, and Chow (2000) built on prior studies to use the Z-score model to track the performance of the major air carriers over a 30-year period from 1966 to 1996. The purpose of their research was to assess the past and then-current health of the carriers. They stated that it also shed light on the importance of the debt burden in the industry, which has contributed to the industry’s instability over time. Next, the chapter turns to a discussion of other bankruptcy prediction models other than Altman’s models.

Other Bankruptcy Prediction Models

Five other researchers, Beaver (1967), Deakin (1972), Edmister (1972), Blum (1974), and Ohlson (1980), also investigated and expanded the topic of bankruptcy prediction in firms. Their individual studies are discussed below.

One of the classic studies in the area of ratio analysis and bankruptcy prediction was completed by Beaver (1967). Beaver used univariate analysis to examine the ability of financial ratios to predict business failure. This study set the stage for the multivariate attempts, by Altman and others, which followed (Altman, 1993). Beaver found that a number of indicators could discriminate between matched samples of failed and nonfailed firms for as long as five years prior to firm failure.

It is remarkable to note that some researchers found that cash flow data added very little incremental value to a traditional accrual-based prediction model (Altman, 1993). Altman felt that information from accrual statements provided adequate information.
However, Beaver found that the best performing ratio was cash flow to total debt. It thus seems appropriate to include a variety of ratios, including several cash flow ratios, to gauge the recent performance of airlines, as many of the failed airlines applied for government-backed loans.

Beaver’s (1967) model was based on four propositions. First, the more net liquid assets a firm has, the smaller is the probability of its failure. Second, the larger the net cash flow from operations, the smaller the probability of its failure. Third, the larger the amount of debt a firm has, the greater the probability of its failure. Fourth, the larger the amount of liquid assets required to fund operating expenditures, the greater the probability of its failure.

For each of five years prior to its failure, Beaver calculated 30 ratios. The ratios were selected on the basis of three criteria: (1) popularity in the literature; (2) performance in previous studies; and, (3) definition of the ratio in terms of a “cash flow” concept. Based on the lowest prediction error for each group (failed and non-failed) over the five-year period, six variables performed “best” in Beaver’s (1967) study: (1) cash flow to total debt; (2) net income to total assets; (3) total liabilities to total assets; (4) working capital to total assets; (5) current ratio; and, (6) no-credit-interval.

Deakin’s (1972) study was developed to provide an alternative business failure model to the initial works of Beaver and Altman. Deakin’s results, like Beaver’s, favored the use of the cash flow to total debt ratio as the best predictor of bankruptcy. Another researcher, Edmister (1972), analyzed the financial ratios of small businesses to predict business failure. He defined a small business as one with a loan from the Small Business Administration (SBA). The ratios chosen were those previously used in studies by
Beaver (1967), Altman (1968), and Blum (1974). However, he used a zero-one regression technique, in which the variables were transformed into categorical variables. His method included dividing a firm’s ratio by its respective industry average, then converting the result into a zero-one variable, depending on an arbitrary predetermined cutoff point. The concept of transforming the data into categorical variables is an interesting contribution to the research. Edmister’s (1972) bankruptcy prediction model is presented below as Table 3.

In Edmister’s model, a Z-score of less than 0.47 was used to predict a firm’s failure and a Z score of greater than 0.53 was used was used to predict a firm’s nonfailure. Z-scores between 0.47 and 0.53 were considered a gray zone where classification was difficult. The function predicted small business failure for 93 percent of the cases studied one year prior to the event.

The purpose of Blum’s (1974) study was to aid the antitrust division of the Justice Department by developing a model to assess the probability of business failure. Blum did this by analyzing the financial and market data of failing firms. Like Beaver, he found that cash flow to total debt was the best predictor ratio. However, Blum did not publish his actual formulas.

Ohlson (1980) used a logit analysis technique to predict bankruptcy. He started with only nine ratios in his study, based on “simplicity.” Five of those ratios included total liabilities to total assets, working capital to total assets, current liabilities to current assets, net income to total assets, cash flow from operation to total liabilities. He also included data on net income and the size of the firm in terms of total assets. Ohlson (1980) found
that the size of the firm was the most important predictor in his model, and the firm’s financial structure was the second most important factor.
Table 3

*Edmister's Small Business Failure Discriminate Function*

\[ Z = 0.951 - 0.523X_1 - 0.293X_2 - 0.482X_3 + 0.277X_4 - 0.452X_5 - 0.352X_6 - 0.924X_7 + \varepsilon \]

Where: \( Z = \) Overall Index;

\( X_1 = 1 \) if annual funds flow/current liabilities < 0.05, or
\( = 0 \) otherwise;

\( X_2 = 1 \) if equity/sales < 0.07, or
\( = 0 \) otherwise;

\( X_3 = 1 \) if (net working capital/sales)/industry average ratio < -0.02, or
\( = 0 \) otherwise;

\( X_4 = 1 \) if (current liabilities/equity)/industry average ratio < 0.48, or
\( = 0 \) otherwise;

\( X_5 = 1 \) if (inventory/sales)/industry average ratio < 0.04 and has shown an upward trend, or
\( = 0 \) otherwise;

\( X_6 = 1 \) if quick ratio/industry average ratio < 0.34 and has shown a downward trend, or
\( = 0 \) otherwise;

\( X_7 = 1 \) if quick ratio/industry average ratio has shown an upward trend, or
\( = 0 \) otherwise; and,

\( \varepsilon = \) error term.
These six studies suggest that a new bankruptcy prediction model, using classic but previously uncombined ratios, could be developed to predict bankruptcy more accurately than in the past. This new model could be tested on bankrupt and non-bankrupt airlines, using financial data for the six-year period 1998-2003. The ratios that would be included in this new model will be discussed next.

New Bankruptcy Prediction Model

This section of Chapter 2 discusses five financial ratio categories and how they relate to financial conditions in the airline industry. The first four financial ratio categories were used in Altman's Z’-Score Model (1993) as predictors of financial distress. These ratio categories are liquidity, cumulative profitability over time, productivity, and solvency. The last financial ratio category, cash flow, was found by Beaver (1967) to be the most important predictor of financial distress.

Additionally, it may be appropriate to develop a new cut-off point for the airline industry. Few major carriers have maintained Z-score above 2.99 for extended periods. Many have operated for extended periods with Z-Scores close to 1.0 without entering bankruptcy (Golaszewski & Sanders, 1992). In part, developing a new Z-score cut-off point for airlines stems from the fact that the federal government has often intervened to bail out troubled air carriers in an effort to keep the industry afloat.

Liquidity

The ability of a firm to meet its current obligations is important in evaluating its financial position (Schmidgall, 2002). Liquidity ratios are crucial in any bankruptcy
analysis of the airline industry, especially as they relate to debt service obligations. For example, in 2003, American Airlines was spending over 10 percent of its revenue on debt service obligations alone; thus, it was very close to filing bankruptcy.

The ATSB's loan guarantees have helped provide assistance to US Airways, Frontier, and America West so that those airlines could meet their current financial obligations. United Airlines has been operating under bankruptcy protection since December 2002, after the ATSB rejected its original application for $1.8 billion in guarantees (Maynard, 2004).

United has said it was likely to terminate its four employee pension plans. It has said that it will not make required contributions while it is in bankruptcy. In short, United has been unable to meet its current financial obligations. The threat has raised the ire of United's unions (Maynard, 2004). United may shed some or all of its $13 billion in pension obligations as the only way to succeed in emerging from bankruptcy proceedings. However, the federal agency that insures pensions is facing a possible cascade of bankruptcies and pension defaults in the airline industry. Some experts fear that this could lead to a multi-billion dollar taxpayer bailout, similar to the savings and loan industry collapse and subsequent taxpayer bailout of the 1980's.

Meanwhile, the entire industry almost certainly faces the prospect of rising security-related costs above and beyond what it is already paying. Congress set aside an additional $100 million to compensate airlines for reinforcing airline cockpit doors. However, the industry continues to face ongoing costs related to heightened security. Airlines are now required either to screen all bags for explosives or to make sure each bag on a plane is matched up to a passenger seated on that flight. This is both time-
consuming and expensive. Therefore, liquidity ratios should be included in any new bankruptcy prediction model for the airline industry.

Solvency

Solvency ratios measure the degree of debt financing used by a firm. These ratios reveal the equity cushion that is available to absorb any operating losses. An airline is solvent when its assets exceed its liabilities. High solvency ratios generally suggest that an operation can weather financial storms. For example, Continental’s $5 billion in debt is equal to half its total assets (Bonne, 2003). By comparison, the ratio of debt to equity for the airline industry for the first quarter of 2004 was 1.147 (Airline Overview, 2004).

Many airlines are carrying extremely high debt levels, at a time when investors are increasingly worried about balance sheet stability after the collapse of such companies as Enron Corporation and MCI/WorldCom. For example, Delta ended the year 2002 with total debt of $10.0 billion and a debt to equity ratio of 92 percent, compared to 2001, when it had total debt of $9.4 billion and a debt to equity ratio of 71 percent. Before its bankruptcy filing in August 2002, US Airways Group’s debt to equity ratio was over 100 percent, indicating negative stockholders’ equity (Airlines Industry Survey, 2003).

A heavy debt burden contributes to the instability of the airline industry. As a result of their increased leverage and the increased volatility of earnings, People Express, Eastern, and Pan American were unable to compete, following the passage of the Airline Deregulation Act of 1978 (Chow, Gritta, & Hockstein, 1988). Airlines currently operating with high leverage are similarly threatened.
“The industry is burdened with a staggering load of debt and unable to obtain capital,” said Tony Velocci, editor-in-chief of Aviation Week & Space Technology, in his presentation “Air Safety: At What Cost?” (Stein, 2004). The network carriers have slashed capital spending in the past few years by about $8 billion (S&P’s CreditWeek, 2004). With the ability to save $40-$50 million upfront on a new 737 aircraft, it is not surprising that leasing has allowed a handful of low-fare carriers to quickly build new fleets without assuming long-term debt burdens (Bonne, 2003). “It gives you a tremendous amount of flexibility to manage through up and down markets,” says Bob Genise, president and CEO of Bouillioun Aviation Services. “Instead of making a 25-year decision, you can take it on for five years.” The only downside, analysts warn, is that leases have become a popular way for some carriers to hide debt off the balance sheet.

Carriers, however, facing their toughest market in years, simply cannot afford the lease payments as they exist in many of the current contracts. If an airline goes bankrupt or a lease is nearing the end of its term, lessors may have to renegotiate the contract or run the risk of planes parked in the desert (Bruch, 2003). Thus, it is clear that financial leverage (i.e., solvency) ratios should be incorporated in a bankruptcy prediction model for airlines.

Cumulative Profitability over Time

The airlines’ current business model is under pressure, and it will have to change to restore profitability (Bruch, 2003). From 2001 through the second quarter of 2004, the
industry will have lost more than $24 billion. When the business-travel boom ended in 2001, revenue plunged but costs remained high (Johnson, WSJ, 10/05/2004).

Low-cost airlines now account for 29 percent of the domestic airline business, up from 7 percent of U.S. domestic air passengers in 1991. The rapid growth of the market share of low-cost, low-fare carriers during the past few years is one of the most significant current trends in the industry, and is perceived as presenting a considerable threat to the viability of the network carriers. The largest low-fare carriers currently operating in the U.S. are Southwest, America West, ATA, JetBlue, AirTran, Spirit, and Frontier. The response of the network carriers to the growing low-fare challenge will be critical to determining the future structure of the U.S. airline industry ("The Airline Industry," 2003).

The network airlines, for their part, have acknowledged that their cost structure is too high in comparison to low-cost carriers. "Network" is used to describe airlines like United, Northwest, Delta, US Airways, and Continental that operate extensive hub and spoke systems (Jenkins, 2004). The big hubs are costly in terms of real estate, staffing, and flight delays (Carey, 2004).

Fuel expenses - the second largest financial drain on airlines' operating budgets - are apt to remain near historical highs for the foreseeable future. At the time of this writing, oil prices have reached an astronomical $50 per barrel. In just the past year, oil prices have risen 75 percent. The network carriers in the past few years have done a remarkable job of reining in operating costs, which are down by $13.4 billion, but runaway fuel prices have negated much of those savings.
With fuel at an all-time high, network airlines made over 12 attempts to boost airfares in the first quarter of 2004. However, most of these efforts have failed to stick. Increasingly, the spoiler has been one or more low-fare airlines, which see a chance to extend their market shares by not raising their prices. For travelers, this change in pricing power could affect everything from ticket prices to the financial viability of the big airlines they use, to whether they must continue to endure unpopular restrictions, such as Saturday-night-stayover requirements, to get low fares (Carey, 2004).

Behind the price erosion is a weak economy; business travelers have moved to cheaper, restricted tickets and the growth of Southwest and its imitators. US Airways said that 70 percent of its domestic flying in 2003 was unprofitable. David Siegel, the chief executive, said in a speech to employees, “If we could charge more money, we would, but passengers want low fares” (Carey, 2004). Therefore, it seems evident that cumulative firm profitability is an important factor to consider in an airline bankruptcy model.

Productivity

The measure of the productivity of an airline’s assets can be obtained by dividing earnings before interest and taxes by total assets. Since a firm’s ultimate existence is based on the earning power of its assets, this ratio is particularly appropriate for studies dealing with corporate failure. Furthermore, insolvency in a bankruptcy sense occurs when the total liabilities exceed a fair valuation of the firm’s assets with value determined by the earning power of the assets (Altman, 1968).
The largest single expense item for all airlines is labor, over 40 percent of total costs for some airlines (Baggaley, 2003). In 2002, Southwest had costs per employee of $59,100, according to industry consultant Vaughn Cordle. At the same time, the top five network carriers averaged in payroll costs $95,500 per employee (Jenkins, 2004). The network carriers also have senior work forces compensated at the top of union scale (Carey, 2004). To address these problems, the network carriers have sought substantial wage and productivity adjustments from their unions, with those that have filed for bankruptcy, or are teetering on the edge. They have generally won concessions from them, with the exception of US Airways, which filed for bankruptcy a second time on September 12, 2004 after failing to achieve desired wage concessions from their labor unions. In addition, the major carriers have cut tens of billions of dollars in expenses, have laid off over 110,000 employees, and have taken several hundred aircraft out of service since September 2001, according to ATA President and CEO James May (Maynard, 2004; Baggaley, 2003).

The difference in the cost structures between network airlines like United and low-fare carriers like Southwest reflect substantial differences in the productivity of both aircraft and employees. Low-fare carriers typically operate “point-to-point” networks in which they can minimize aircraft ground times, in contrast to the hub-and-spoke networks of most network airlines. Shorter ground times translate directly into higher aircraft utilization rates (“The Airline Industry,” 2003). At the same time, Southwest’s operating cost per available seat mile, for the quarter ended March 31, 2003, was 7.5 cents per available seat mile. United’s operating cost per available seat mile was 11.5
cents, and US Airways was 12 cents. These differences are dramatic in an industry where cost control is of paramount importance (Baggaley, 2003).

The Internet has had a profound effect on the way airlines price and distributing their product. By selling tickets online, airlines have dramatically cut distribution costs. On the other hand, the Internet has also led to more competitive pricing. The Internet’s appeal for airlines is apparent. A commercial Web site can be kept open for business 24 hours a day, seven days a week. Southwest Airlines reported in 2002 that their Internet bookings cost them about one dollar to make, while their cost to book with a travel agent is between $6 and $8. Tickets booked through Southwest’s own agents cost several dollars. On the down side, however, the Internet may ultimately hurt airline profitability by making travelers too price-sensitive. It is very simple for the traveler to go online and compare prices of competitors. This makes it difficult for airlines to try to raise their fares. Both business travelers, formerly high fare-paying, and budget travelers, can make low-price flight arrangements on line (Airlines Industry Survey, 2003). Thus, a bankruptcy prediction model for airlines should likely include a productivity measure.

Cash Flow

Cash flow relates to the actual cash generated and paid by the firm. Operating cash flow is the net of cash inflows related to revenues and cash outflows for operational cash expenditures, including payments for salaries, wages, taxes, supplies, and interest on debt. Operating cash flow is found in a firm’s SCF. The SCF helps people to assess a firm’s ability to meet its short-term financial obligations. The ratio of operating cash
flows to total liabilities should be relatively high; that is, the cash flow from operations should be high relative to the firm’s total liabilities (Schmidgall, 2002).

Accounting income is not the relevant source of value in a firm. Cash flow is the ultimate source of value for the firm, since only cash can be spent to cover expenses (Moyer, McGuigan & Kretlow, 2001). An airline needs sufficient cash on hand to cover interest payments and other liquidity needs. Delta’s chief executive, Gerald A. Grinstein, said, “We must not just have costs in line with our competitors, we must have cash flow.” (Maynard, 2004).

Given the high debt levels carried by many airlines, and the frequency of large operating losses due to industry cycles, it is important to look at operating cash flow to assess the strength of an airline to weather financial storms. During times of industry losses, it is important to determine how quickly an airline may be using its available cash, its cash burn rate. In 2001 and 2002, for example, many airlines were burning through millions of dollars in cash each day. In such cases, it is important to gauge how long an airline can withstand a downturn and remain solvent (Airlines Industry Survey, 2003).

With losses mounting following a sharp drop-off in travel in the months after September 2001, most of the carriers were forced to shoulder new debt, tapping their credit lines and/or issuing bonds to respond to the rapid depletion of their available cash. These actions were vital to help the carriers survive, as passenger levels declined dramatically, fares dropped, and losses increased sharply.

President Bush signed into law the Emergency Wartime Supplemental Appropriations Act on April 16, 2003, after fierce lobbying by the airline industry. The airlines contended that costs of the war in Iraq and government-mandated security measures were
harming the industry. Under the Act, the Transportation Security Administration (T.S.A.) disbursed pretax cash payments totaling $2.29 billion in May 2003. These payments were intended to reimburse the carriers for security fees they had paid to the T.S.A. since February 2002. As a result of the cash grants, most of the top ten carriers reported a profit in the second quarter of 2003. However, after stripping out the cash grants, most airlines would have reported sizable losses (Airlines Industry Survey, 2003). For example, US Airways, in the second quarter of 2003 (its first full quarter since emerging from bankruptcy), reported profits of $13 million, but this reported figure included $216 million in government aid. If this grant were omitted, the company would instead have lost $188 million for the quarter.

Without the grants, more of the major carriers might have been forced to file for bankruptcy protection, and United and US Airways would have filed sooner. In some cases, the direct cash grants may have only served to delay the inevitable bankruptcy filing. Thus, it seems clear that a bankruptcy model for airlines should include a cash flow measure. Next, this chapter concludes with a brief commentary on the future outlook for the airline industry.

Future Outlook

What will likely emerge in the airline industry over time is a domestic market with several large, low-cost/low-fare airlines and several large, hub-and-spoke airlines (or perhaps several alliances of such carriers) competing for passengers. Such an outcome implies ongoing costs pressures on the network carriers, but not their total extinction (Baggaley, 2003). In any case, it seems evident that the industry is at a turning point - it
could well be on the brink of a major industry restructuring that includes the bankruptcy, liquidation, and/or consolidation of several major network carriers ("The Airline Industry," 2003). Thus, the development of a new bankruptcy prediction model for the airline industry might be very timely and useful. If the model can truly be predictive in nature, it could provide guidance for the many parties who are interested in the industry’s survival.

Summary

This chapter developed the theoretical background for testing Altman’s Z”-score model on airlines, and for creating a new bankruptcy prediction model. The next chapter discusses the proposed methodology for utilizing multiple discriminate analysis in this dissertation, and for performing the remainder of the research that is proposed in this dissertation.
CHAPTER THREE

RESEARCH METHODOLOGY

Introduction

The primary purpose of this dissertation was to test an existing bankruptcy prediction model, the Altman Z''-score model (Z''-score model) on airline firms, using financial ratios for the period 1998-2003. A second objective of this study was to develop a new bankruptcy prediction model, using airline financial ratios derived from the financial statements for years 1998-2003. A new bankruptcy prediction model needed to differentiate between airlines that were likely to go bankrupt and those that were not likely to go bankrupt. For it to be effective, this new model needed to predict bankruptcy more accurately than the Z''-score model. The new model also required either a higher classification rate, or needed to predict bankruptcy earlier, than the existing Z''-score model.

A possible outcome of this study was that a new model did not predict bankruptcy more accurately than the Z''-score model. The Z''-score model might have offered a superior classification rate, and may have been able to predict bankruptcy earlier than the new model. If so, then this dissertation will have provided further support for the use of the existing Z''-score model.

This chapter discusses the methodology that will be used to test the models described above. It begins with a discussion of the research design, including the selection of firms
used in the sample. It continues by explaining the principal methodology employed herein to test the bankruptcy prediction models, which is Multiple Discriminant Analysis (MDA), and identifies the major issues involved in the application of MDA. Finally, the chapter concludes with a discussion on how to validate the results of MDA.

Research Design

Altman (1993) states that, ideally, one would like to develop a bankruptcy prediction model utilizing a homogeneous group of bankrupt companies and data as near to the present as possible. This dissertation seeks to do that, consistent with Altman’s guidelines. The analyses in this study used bankrupt and non-bankrupt airline firms’ 1998-2003 financial statements. The financial statements were retrieved from the Securities Exchange Commission (SEC) website, www.sec.gov, using the EDGAR database, and from airline firms’ annual reports which were available on-line from the individual companies’ websites. All publicly held U.S. companies are required to file their financial statements with the SEC.

Bankrupt companies, for the purposes of this study, were defined as those meeting one of the following conditions: (1) in Chapter 11 bankruptcy; or, (2) in Chapter 7 liquidation. Thus, those airline firms that were in one or more of these states at any time during the 1998-2004 time period were considered to be bankrupt.

Selection of Firms

Only publicly held airlines were selected for this study, as the financial reports of these firms are readily available. Privately held companies are not required to make their
financial statements available to the public. Their financial reports are more difficult to obtain; therefore, they were not included in this dissertation. This study used a census approach, rather than random sample.

Major and National Airline Carriers

Only major and national airlines were selected for this study. Major airlines, or majors, are a group of large, certified air carriers that have annual operating revenues over $1 billion. National airlines, or nationals, are a group of large, certified air carriers that have annual operating revenues of $100 million to $1 billion.

The major passenger airlines include Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United, and USAir. They are all publicly owned and were included in this study. Air Canada was also included in this study, as it has sufficiently large revenues, and uses Generally Accepted Accounting Principles (GAAP) in preparing its financial statements, like publicly owned U.S. firms. Also, Air Canada stock is sold on the American Stock Exchange. Non-passenger airlines (DHL, Federal Express, and United Parcel Service) were not included in this study. Publicly owned national passenger airlines included in this study were AirTran (formerly ValuJet), ATA (formerly Amtran), Frontier, Hawaiian, and JetBlue.

Network and Low-Cost Carriers

The Bureau of Transportation Statistics [BTS] (2004) listed the following airlines as network carriers in 2004: Alaska; American; Continental; Delta; Northwest; United; and US Airways. All of these carriers were included in this study. Trans World Airlines
(TWA), which flew its last official flight December 1, 2001, was also a network carrier. As TWA was still operating during part of the 1998-2004 time period, was also included in this study.

The BTS (2004) listed the following as low-cost carriers: AirTran; ATA; America West; Frontier; JetBlue; Southwest; and Spirit. Spirit Airlines is not publicly owned and its financial statements are difficult to obtain. Thus, it was not included in this study. The other low-cost carriers were included herein. Therefore, this dissertation included financial data from a total of 16 airline firms over a 6-year period.

Time Frame of the Study

The time frame selected for this study was the period 1998-2004. It was during this period that the airline industry had seen its most turbulent times in its history. In 1998, air carriers were earning record profits. However, since 2000, a soft economy, increased competition, and rising fuel and labor costs and increased security costs cut into airline profits. By 2002, only 2 of the major carriers, Southwest and JetBlue, earned a profit. Most of the largest carriers in the United States (US) suffered their third consecutive year of heavy losses in 2003. As of 2004, US airline industry had accumulated over $30 billion in losses since 2000 (McCartney, 2004).

As discussed in Chapter 2, US airlines found themselves in a struggle on several fronts. The airlines now face a true challenge from low-cost entrants who have molded a completely different, and profitable, way of doing business; further, they are not upstarts, but well-established and successful companies (Bonne, 2003). The airline industry has been changing rapidly. Six publicly owned US major and national airlines went bankrupt
during the time period of 1998-2004, as will be discussed in this chapter. At the time of this writing, 2004 financial statements were not yet publicly available. Therefore, the 1998-2003 period seemed to be an appropriate one to use for testing the Z-score model, which is a model developed specifically for the prediction of non-manufacturing corporate bankruptcies. In this dissertation, the same airline firms’ data set was used to formulate a revised model. This new model was also tested to determine its ability to predict airline firm bankruptcy. Altman (1993) stated that a bankruptcy prediction model should use a homogeneous group of bankrupt companies and data as near to the present time as possible. This dissertation did that, consistent with Altman’s guidelines.

Sample Selection and Size

During the period 1998-2004, the following six airline firms were liquidated or filed for Chapter 11 bankruptcy: Air Canada; ATA; Hawaiian; TWA; United; and, US Air. Of these firms, four are majors, and two are nationals. One of these six firms is a low-cost carrier. During the same time period, the following ten firms were not liquidated, nor did they file for Chapter 11 bankruptcy: Air Tran; Alaska; America West; American; Continental; Delta; Frontier; JetBlue; Northwest; and, Southwest. Of these 11 firms, seven are majors, and four are nationals. Five of these ten firms are also low-cost carriers.

In the period of this study, the above sixteen firms would have filed a total of 96 annual reports, which would have resulted in 96 individual observations. However, TWA stopped operating in December 2001, so there are fewer than three years of available financial data for TWA. Also, JetBlue did not become a publicly traded entity
until 2002, but three years of financial data are available for 2001 through 2003. Additionally, Air Canada’s 1998 financial reports are not publicly available. Therefore, a total of 90 observations were available as the data set for this study.

This sample size was adequate, given the statistical method chosen. MDA is quite sensitive to the ratio of sample size to the number of predictor variables. Hair et al. (1998) state that many studies suggest a ratio of 20 observations for each predictor variable. Altman’s (1993) model uses only four variables, which would have required at least 80 observations, so that ratio is achieved. Further, the specified 20 to one ratio could be nearly achieved for a new five-variable model, and would only fall ten observations short of the desired total of 100 in this case. Also, at a minimum, the sample size of the smaller group should exceed the number of predictor variables (Tabachnick & Fidell, 2001). The sample size of the smaller group was 33, which greatly exceeded the number of variables to be used in either the Altman (1993) model, or the new model. Therefore, the sample size and the group size were both adequate for purposes of this dissertation. The sample size of the larger group was 57. Multiple discriminant analysis is a one-way analysis and no special problems are posed by unequal sample sizes in groups. In the next section, assumptions of MDA are covered.

Assumptions of Multiple Discriminant Analysis

Hair et al. (1998) state that it is desirable to meet certain conditions for proper application of MDA. The key assumptions for deriving the discriminant function are multivariate normality of the independent variable and equal covariances. MDA is relatively robust to failures of normality, if skewness rather than outliers causes the
violation. Tabachnick & Fidell (2001) state that robustness is expected with 20 cases in
the smallest group if there are only five or fewer predictors. Therefore, in this case, with
27 cases in the smallest group and five or fewer predictors, robustness to any failures in
normality of the residuals should be expected.

However, MDA is highly sensitive to outliers. Therefore, a test for outliers in the
data set for each group was run. To check for outliers, Mahalanobis’ distance was
computed. Any outliers were then examined individually. Outliers were not expected
among the financial ratio values.

MDA assumes linear relationships among all pairs of predictors within each group.
Where a curvilinear relationship exists, it may be corrected by transforming some of the
predictors (Tabachnick & Fidell, 2001).

Unequal covariance matrices can have an adverse affect on the classification process.
This effect can be minimized by using an adequate sample size (Hair et al., 1998). A
Levene test determines whether the variances are approximately equal.

Multicollinearity can be expected among the variables, as all of the financial
ratios come from the same source, financial statements. This analysis did not use a
stepwise procedure, but a simultaneous variable entry, to examine the power of all of the
variables altogether (Hair et al., 1998).

In classification, a decision was required as to whether one wants the a priori
probabilities of assignment to groups to be influenced by sample size (Tabachnick &
Fidell, 2001). It was decided that the probability with which a case is assigned to a group
should reflect the sample sizes of the two groups. The larger group, the non-bankrupt
group, included ten firms. The smaller group, the bankrupt group, included six firms.
Therefore, a naïve prediction of the probability of airline bankruptcy was six out of sixteen, or 37.5 percent.

Statistical Methodology

An appropriate statistical technique was selected in order to analyze the financial ratios and develop the differentiation model required for bankruptcy prediction. In order to select an appropriate method, the model assumptions were examined, relative to the information to be analyzed. MDA is the quantitative method that was selected for the purposes of this dissertation. MDA is a sophisticated quantitative method of data analysis that predicts group membership (e.g., bankrupt or non-bankrupt) from a set of predictors (Tabachnick and Fidell, 2001). In this dissertation, the predictors were a set of financial ratios that measured a firm’s liquidity, cumulative profitability, productivity, solvency, and cash flow. Using MDA, the airlines included in this study were classified into either one of two groups, bankrupt or non-bankrupt. A significant difference between the two groups, bankrupt or non-bankrupt, implies that one can predict whether a firm will be bankrupt in one, two, or even three years, depending upon the score that the firm receives from the application of MDA. Thus, the primary statistical problem in this research was one of classifying an individual business as a member of one of two classes, bankrupt or non-bankrupt, based upon the ratio variables that were identified as being key to their ultimate success. As in the studies cited in Chapter 2, MDA is used to form a linear model that classifies individual firms based on their historical financial ratios.

MDA is principally used to classify and to make predictions in situations where the criterion variable is in categorical form, as was the case in this study (e.g., bankrupt
versus non-bankrupt). A categorical variable is one that uses values that serve as a label or means of identification (Hair et al., 1998). The statistical software used in this dissertation was SPSS-Version 12.0. SPSS offers statistics including: Wilks’ Lambda (only variables that are well below 1.0 reflect an ability to discriminate); statistical significance of each discriminator; and, univariate F-ratio for each predictor or financial ratio (Meidan & Chiu, 1995). This information is important in identifying which ratios do the best job of differentiating between a bankrupt airline company and a non-bankrupt airline firm.

To validate the model, a split (sometimes called “hold-out) sample approach is suggested when there are at least 100 in the total sample (Hair et al., 1998). However, according to Tabachnick and Fidell (2001), jackknifed (or “leave one out”) classification gives a more realistic estimate of the ability of the predictors to separate groups. In jackknifed classification, the data from the firm are left out when the coefficients used to assign it to a group are computed. This study adopted the approach recommended by Tabachnick & Fidell (2001) and uses jackknifed classification for the analysis.

Either a simultaneous or sequential computational approach can be used to derive a discriminant function (Hair et al, 1998). The simultaneous approach was utilized on the four variables used in the Altman Z’-score model and on the new model.

After the new discriminant function for the new model has been computed, a t-test was performed. This determined whether the two groups’ scores were significantly different

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Computation of Ratios

All three of the major financial statements were used in this study; namely, the balance sheet, the income statement, and the statement of cash flows. The balance sheet is a major financial statement that is prepared at the end of each accounting period. The relevant period of time, for purposes of this study, was one year. The balance sheet reflects the financial position of the firm—its assets, liabilities, and owners’ equity—at a given date (Schmidgall, 2002).

The income statement reports the success of the firm’s operations for period of time. In this study, the relevant period of time was one year. The income statement shows the amount of revenues that the firm earned and the amount of expenses that were incurred in earning those revenues (Schmidgall, 2002).

The statement of cash flows shows the effects on cash of a business’s operating, investing, and financing activities for the period. The relevant period of time, in this study, was one year. The statement of cash flows explains the change in cash from the beginning of the year to the end of the year (Schmidgall, 2002).

The liquidity ratio used in the Z*-score model was working capital divided by total assets. Working capital is defined as current assets minus current liabilities. This information can be obtained from each firm’s balance sheet. Cumulative profitability, in Altman’s (1993) model, was defined as retained earnings divided by total assets. This information can also be obtained from each firm’s balance sheet.

The productivity ratio used in Altman’s model (1993) was earnings before interest and taxes, divided by total assets. This ratio is also known as gross return on assets. The
earnings information is found on each firm’s income statements, and the total assets figure is found on each firm’s balance sheet.

The solvency ratio used by Altman was net worth, or owners’ equity, divided by total liabilities. This is the same as the inverse of the traditional debt-to-equity ratio. These figures are found on each firm’s balance sheet.

Lastly, cash flow ratios can be included in a new bankruptcy prediction model. Beaver (1967), Deakin (1972), and Blum found that the ratio of cash flow to total debt was significant in predicting bankruptcy. Cash flow from operations data can be obtained from each firm’s statement of cash flows. The net cash flow from operating activities figure, for each firm, for each year, was used. Total firm debt is found on the balance sheet.

Analysis of Results

Once the variables (financial ratios) were identified, as discussed above, the ratios for the Z”-score model and the new model were computed. Applying the formula(s) for each model to the ratios yielded the appropriate score, or Z”-score, for each firm.

The Z”-score model produces one score for each company for each year. In Altman’s 1993 study, he determined that firms with a score of less 1.10 were failed and that firms with a score of greater than 2.60 were not failed. Scores between 1.10 and 2.60 were not consistently failed or non-failed and required further investigation. These same cutoff values were used to accomplish the initial classification under the new model in this study.

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The firms were first grouped into two groups, either bankrupt or non-bankrupt, according to their actual status. The Z"-scores were then computed. Using the computed Z"-scores, each firm within each group was then put into a second group that indicated one of three possible results of the test: bankrupt, non-bankrupt, or unclassified (the grey area). The results were then presented in a "prediction accuracy matrix" format adapted from the classification matrix format used by Altman (1993) to evaluate his study. One must construct classification matrices to determine the predictive ability of a discriminant function.

An analysis of the predictive ability of the model was then completed; that is, an assessment was made as to whether the model correctly predicted the firm's status, failed to predict the firm's status, or was unable to predict the firm's status. The model's accuracy was determined based on the percentage of the firms that were correctly classified into these categories. Therefore, there were three separate measures for accuracy: the percentage of bankrupt firms classified as bankrupt; the percentage of non-bankrupt firms classified as non-bankrupt, and the percentage of all the firms that were properly classified. These results are reported in Chapter 4 of this study.

The frequency of non-classification also impacts the utility of the model. If the model is unable to predict bankruptcy or non-bankruptcy, further analysis is required. While additional analysis is always appropriate before making decisions, the model does not add any value to the analysis if it does not produce a classification (Patterson, 2001).

For each model involved in this dissertation (i.e., the Z"-score model, and the Kroeze model), a prediction accuracy matrix was created showing the number and percentage of correct classifications and incorrect classifications. An example of an accuracy matrix is
shown in Table 4 (Altman, 1993). For example, in the first row, one can see that 33 firms are actually bankrupt. The model correctly classified 30 of the firms as bankrupt. Therefore, the model was correct in predicting bankruptcy 90.9 percent of the time. The model was also correct in predicting non-bankruptcy 97 percent of the time.

Table 4

*Prediction Accuracy Matrix*

<table>
<thead>
<tr>
<th></th>
<th>Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bankrupt</td>
</tr>
<tr>
<td>Bankrupt</td>
<td>30 (90.9%)</td>
</tr>
<tr>
<td>Non-bankrupt</td>
<td>1 (3.0%)</td>
</tr>
<tr>
<td>Total</td>
<td>31 (100%)</td>
</tr>
</tbody>
</table>

Source: Altman, 1993

Since this study used six bankrupt and ten non-bankrupt firms, a simple random classification of a firm as bankrupt or would be accurate six-sixteenths or 37.5 percent of the time. This type of classification is called a naïve selection, and the added utility of the models being evaluated was determined by how much better they predict bankruptcy or non-bankruptcy than a naïve prediction. This was determined by performing a chi-square test on the classification matrix.
Once the accuracy of each model was determined, the overall results of each model were compared to determine which model was the better predictor of bankruptcy in the airline industry. The results of each model were also evaluated against a naïve model.

The new model, or Kroeze model, was considered to be better than the Altman Z"-score model if it correctly predicted airline firm bankruptcy by at least one firm more than the Altman Z"-score model. For example, given that five airline firms have gone bankrupt, if the Altman Z"-score model correctly predicted which three airline firms will go bankrupt three years before the event, the Kroeze model needed to correctly predict which four airlines would go bankrupt, three years before the event.

Thus, H1 was tested by performing a chi-square test on the classification matrix that compared the Altman Z"-score to a naïve model. H2 was tested by performing a chi-square test on the classification matrix that compared the Altman Z"-score model to the Kroeze model. The hypotheses are reviewed below.

Restatement of Research Hypotheses

The hypotheses tested in this dissertation are as follows:

H1₀: There is no relationship between the Altman Z"-score model and the likelihood of bankruptcy for an airline firm.

H1ₐ: There is a relationship between the Altman Z"-score model and the likelihood of bankruptcy for an airline firm.

H2₀: A revised bankruptcy prediction model is no better than the Altman Z"-score model in predicting the likelihood of bankruptcy for an airline firm.
H2: A revised bankruptcy prediction model is better than the Altman Z’-score model in predicting the likelihood of bankruptcy for an airline firm.

The Altman Z’-score model (1993) is shown below in Table 5.

Table 5

Altman Z’-Score Model

\[ Z' = 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05X_4 + \epsilon \]

Where:

\( X_1 \) = working capital/total assets;
\( X_2 \) = retained earnings/total assets;
\( X_3 \) = earnings before interest and taxes/total assets;
\( X_4 \) = book value of equity/book value of total liabilities;
\( \epsilon \) = error term; and,

\( Z' \) = overall index.

Reliability and Validity Issues

Reliability and validity were not directly at issue in this dissertation. Reliability involves the extent to which the set of variables is consistent in what the set is intended to measure (Hair et al., 1998). Validity encompasses the idea of how well the concept is defined by the measures (Hair et al., 1998). This study did not collect primary data by means of a survey instrument; instead, it used secondary data from public sources to test
the models that were under scrutiny herein. Thus, reliability and validity were not major issues that have to be considered during the conduct of this study.

Summary

This chapter presented the research methodology that is involved in this dissertation. The research process involved in testing a bankruptcy prediction model was discussed. Next, issues relating to sample selection and sample size were discussed. This was followed by a discussion of the methodology to be used in the study (MDA). Finally, the methods for conducting statistical analyses on the data were addressed. The results of the application of these methods are discussed in the succeeding chapter.
CHAPTER FOUR

ANALYSIS AND RESULTS

Introduction

This chapter discusses the results of the analysis and the hypothesis testing for the data that were collected as discussed in Chapter 3. The first section of the chapter examines the issues of prediction accuracy of the models that were tested in this dissertation. The next section uses chi-square analysis to test the models’ predictive ability. The last section discusses testing of the data set that was used in this study, including the treatment of unequal sample sizes and missing data, and an examination of possible normality, outlier variables, linearity, variance, and collinearity issues.

Prediction Accuracy

There were six bankrupt firms and ten non-bankrupt firms. The bankrupt firms were coded one. The non-bankrupt firms were coded two. There were a total of 90 cases used to calculate a discriminant function. The 90 cases were obtained from 1998 through 2003 financial reports, include five Air Canada cases (1999 through 2003), six Hawaiian Air cases (1998 through 2003), four TWA cases (1998 through 2001), six US Airways cases (1998 through 2003), six United cases (1998 through 2003), six America West cases (1998 through 2003), six Frontier cases (1998 through 2003), six Alaska cases (1998 through 2003), six American cases (1998 through 2003), six Continental cases

Consistent with the methodology described in Chapter 3, Altman Z”-Score model (Z” Model) scores were calculated. The discriminant function for the Z” model was used to calculate a Z” score for each case. For example, Air Canada’s Z” scores were -5.22 in 2003, -2.62 in 2002, -2.16 in 2001, -1.04 in 2000, and -.06 in 1999.

The airlines used in this study were then classified as bankrupt, non-bankrupt, or in the grey area, according to the Z” Model and using the appropriate cutoff values that were suggested by prior research, as discussed in Chapter 2. The cutoffs were: less than 1.1, classified as bankrupt; greater than 2.6, classified as non-bankrupt; and between 1.1 and 2.6, in the grey area. Air Canada filed for bankruptcy in 2003. Therefore, Air Canada would have been correctly classified as bankrupt in 2002, one year ahead of the event; in 2001, two years ahead of the event; in 2000, three years ahead of the event; and in 1999, four years ahead of the event. There were a total of 23 cases for which a classification could be made one year, two years, three years, and four years ahead of a bankruptcy filing. Therefore, four of the 23 cases corresponded to Air Canada.

There were a total of 39 cases from firms that did not file for bankruptcy. Southwest, for example, had Z” scores greater than 2.6 for every year in this study. Therefore, Southwest would have been correctly classified as non-bankrupt in 2003 (one year before the most recent financial period), 2002 (two years before the most recent financial period)
2001 (three years before the most recent financial period), and 2000 (four years before the most recent financial period). Four of the 39 cases corresponded to Southwest.

The table below (Table 6) lists the airlines, the financial statement dates (years inclusive) used for calculating the financial ratios and classification scores, and the number of cases that each airline contributed. There were a total of 62 cases.
Table 6

*Airlines, Financial Statement Dates, and Cases*

<table>
<thead>
<tr>
<th>Airline</th>
<th>Financial Statement Dates</th>
<th>Number of Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATA</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Air Canada</td>
<td>1999 to 2002</td>
<td>4</td>
</tr>
<tr>
<td>Air Tran</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>America West</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>American</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Alaska</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Continental</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Delta</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Frontier</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Hawaiian</td>
<td>1999 to 2002</td>
<td>4</td>
</tr>
<tr>
<td>JetBlue</td>
<td>2001 to 2003</td>
<td>3</td>
</tr>
<tr>
<td>Northwest</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>Southwest</td>
<td>2000 to 2003</td>
<td>4</td>
</tr>
<tr>
<td>TWA</td>
<td>1998 to 2000</td>
<td>3</td>
</tr>
<tr>
<td>US Airways</td>
<td>1998 to 2001</td>
<td>4</td>
</tr>
<tr>
<td>United</td>
<td>1998 to 2001</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 7 (and the subsequent tables 8 through 11) is interpreted by reading across each row. For example, in Table 7 the number of airline firms that were actually bankrupt and
the model correctly predicted their bankrupt status was 23. There were a total of 23 cases of actual bankruptcy. Therefore, 23 correct out of a total of 23 equals 100 percent correctly predicted. However, only 7 firms that were actually non-bankrupt were correctly classified as non-bankrupt. There were a total of 39 cases of non-bankruptcy. Therefore, 7 correct out of a total of 39 equals 17.9 percent correctly predicted. Overall accuracy is calculated by adding the number of correctly classified firms, 7 plus 23, and dividing that by the total number of cases, 23 plus 39. Overall accuracy, then, was 30 divided by 62, or 48.4 percent.

Table 7

*Altman Z'-Score Model: Prediction Accuracy Matrix*

<table>
<thead>
<tr>
<th>Actual</th>
<th>Classified</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bankrupt</td>
<td>Non-bankrupt</td>
<td>Grey Area</td>
<td>Total</td>
</tr>
<tr>
<td>Bankrupt</td>
<td>23</td>
<td>0</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(0%)</td>
<td>(0%)</td>
<td></td>
</tr>
<tr>
<td>Non-bankrupt</td>
<td>26</td>
<td>7</td>
<td>6</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>(66.7%)</td>
<td>(17.9%)</td>
<td>(15.4%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>49</td>
<td>7</td>
<td>6</td>
<td>62</td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(100%)</td>
<td>(100%)</td>
<td></td>
</tr>
</tbody>
</table>

Source: Altman, 1993
The Z''-score model, as shown in Table 7, had no errors in classifying the bankrupt firms. All of the bankrupt firms were correctly classified by the Z'' model as bankrupt. However, there were serious errors among the non-bankrupt firms using this model. Only 17.9 percent of the non-bankrupt firms were correctly classified as non-bankrupt. Furthermore, 15.4 percent of the cases fell into the grey area and could not be classified without further analysis. Thus, these cases represent serious flaws in using the Z'' model to predict bankruptcy.

A naïve approach would predict that 37.1 percent (23/62) of the cases should be classified as bankrupt. This is quite close to a naïve prediction of 37.5 percent, which is calculated by dividing 6, the number of bankrupt firms, by the total number of firms, 16. Thus, the Altman Z''-score model (Z'' model), although it appears to be superior to a naïve prediction, is not very accurate at predicting airline corporate bankruptcy for the years 1998-2004.

Next, Multiple Discriminant Analysis (MDA) was performed using the same four financial ratios as predictors of bankruptcy. MDA was performed using SPSS 12.0; all four predictors were simultaneously forced into the equation. The predictor variables used were \( x_1, x_2, x_3, \) and \( x_4 \), as in the Z'' model. The results of MDA were statistically significant, and the classification accuracy was considerably higher than that of the Z'' model. However, the coefficient for variable \( x_3 \) was a negative, indicating that collinearity was likely present in the data set among one or more of the predictor variables. Therefore, a new MDA analysis was run, in which the \( x_3 \) variable was eliminated. This equation had nearly identical classification accuracy and scoring as the four variable model, without any multicollinearity issues; thus, it was deemed to be
superior to the four variable model. New variable coefficients and a new cutoff were then established, compared to the Z" model, which created a new discriminant function equation. Using this equation, overall prediction accuracy of the new three variable model (the Kroeze model) was found to be 45/62, or 72.6 percent, which represents a dramatic improvement in prediction accuracy (Table 8).

Table 8

*Kroeze Model: Prediction Accuracy Matrix*

<table>
<thead>
<tr>
<th>Classified</th>
<th>Bankrupt</th>
<th>Non-bankrupt</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bankrupt</td>
<td>18</td>
<td>5</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>(78.3%)</td>
<td>(21.7%)</td>
<td></td>
</tr>
<tr>
<td>Non-bankrupt</td>
<td>12</td>
<td>27</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>(30.8%)</td>
<td>(69.2%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>30</td>
<td>32</td>
<td>62</td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(100%)</td>
<td></td>
</tr>
</tbody>
</table>

Adapted from Altman, 1993

As shown above, 78.3 percent of bankrupt airline firms were correctly classified as bankrupt using the Kroeze model. Further, 69.2 percent of non-bankrupt firms were correctly classified as non-bankrupt. This result represented a considerable improvement over the Z" model. The Z" model uses a grey area, where firms with Z" scores between 1.1 and 2.6 are not classified. The Kroeze model is simpler. It does not use a grey area;
instead, it classifies firms as either bankrupt, or non-bankrupt. Firms with a positive score are classified as non-bankrupt. Firms with a negative score are classified as bankrupt.

Finally, a second MDA was performed, this time using a fifth predictor variable \(X_5\). \(X_5\) represented cash flow, which is net cash flow from operations divided by total liabilities. \(X_5\) was added to the \(Z''\) model, and to the Kroeze model. Although the MDA results were statistically significant, the addition of a new variable did not improve the classification accuracy of the models. In fact, the cash flow ratio reduced the models' accuracy. Therefore, consistent with the objective of parsimony in academic research (Hair et al., 1998), fewer is better. The Kroeze model is preferable to the four and five variable models. Therefore, the models that included the cash flow variable were discarded for the remainder of this study.

When one compares the \(Z''\) model and the Kroeze model year by year, it is apparent that the Kroeze model outperformed the \(Z''\) model. First, the initial sample of sixteen airline firms, six bankrupt and ten non-bankrupt firms, was examined using data one financial statement prior to bankruptcy. The two models' prediction accuracy matrices, one year prior to bankruptcy, are displayed below (Table 9). The \(Z''\) model predicted only half of the airline firms' status correctly one year before a bankruptcy filing. The model classified only 50 percent of the sample correctly; that is, eight out of sixteen firms. The Kroeze model correctly classified thirteen out of sixteen airline firms for 81.25 percent accuracy. This result represented a considerable improvement over the \(Z''\) model's predictive accuracy. Therefore, the Kroeze model was more accurate than the \(Z''\) model one financial statement prior to bankruptcy.
Table 9

*Prediction Accuracy Matrix, One Year Prior to Bankruptcy*

| Actual          | **Z'' Model, Classified** | |                  | **Kroeze Model, Classified** | |                  |
|-----------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
|                 | Bankrupt | Non-Bankrupt | Grey Area | Non-Bankrupt | Bankrupt | Non-Bankrupt | Total |
| Bankrupt        | 6        | 0            | 0         | 5           | 1         | 6            |
| Non-Bankrupt    | 7        | 2            | 1         | 3           | 7         | 10           |

Adapted from Altman, 1993

A second test was made to observe the discriminating ability of the models, using data from financial statements produced two years prior to bankruptcy. This test showed that the Z'' model had a 43.75 percent correct assignment rate; that is, seven out of sixteen firms were correctly classified. A test was also performed to observe the discriminating ability of the new model using data from two years prior to bankruptcy. The results are shown in Table 10. The reduction in the accuracy of group classification is understandable as bankruptcy was more remote. Nonetheless, 68.75 percent correct assignment (that is, 11/16) is evidence that airline bankruptcy can be predicted two years prior to its actual occurrence by the Kroeze model.
Table 10

*Prediction Accuracy Matrix, Two Years Prior to Bankruptcy*

<table>
<thead>
<tr>
<th>Actual</th>
<th>Z&quot; Model, Classified</th>
<th>Kroeze Model, Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bankrupt</td>
<td>Non-Bankrupt</td>
</tr>
<tr>
<td>Bankrupt</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Non-Bankrupt</td>
<td>7</td>
<td>1</td>
</tr>
</tbody>
</table>

Adapted from Altman, 1993

A third test was made to observe the discriminating ability of the model, using data from financial statements released three years prior to bankruptcy (Table 11). The Z" model classified firms correctly for 50 percent of the sample; that is, for eight out of sixteen firms. Although this rate is slightly higher than the accuracy rate for a later period, one should not conclude that the Z" model improved with increased time. A third test was also made to assess the accuracy the Kroeze model in predicting bankruptcy three years prior to the event. Again, the new model produced 68.75 percent classification accuracy (11/16). This is evidence that airline bankruptcy can be predicted three years prior to the event using the Kroeze model.
Table 11

Prediction Accuracy Matrix, Three Years Prior to Bankruptcy

<table>
<thead>
<tr>
<th></th>
<th>Z&quot; Model, Classified</th>
<th>Kroeze Model, Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bankrupt</td>
<td>Non-Bankrupt</td>
</tr>
<tr>
<td>Bankrupt</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Non-Bankrupt</td>
<td>7</td>
<td>2</td>
</tr>
</tbody>
</table>

Adapted from Altman, 1993

Finally, a fourth test was made, using financial statements produced four years prior to bankruptcy (Table 12). The Z" model correctly assigned seven out of fourteen firms, for 50 percent accuracy. The classification accuracy for the Kroeze model was 71.4 percent; that is, ten out of fourteen airline firms were correctly classified. This matrix excluded two firms that would have required the use of 1997 financial statements, which is beyond the time range used in this study. However, it is apparent that the Kroeze model can be used to predict airline bankruptcy up to four years prior to the actual event.
Table 12

Predication Accuracy Matrix, Four Years Prior to Bankruptcy

<table>
<thead>
<tr>
<th></th>
<th>Z” Model, Classified</th>
<th>Kroeze Model, Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bankrupt</td>
<td>Non-Bankrupt</td>
</tr>
<tr>
<td>Bankrupt</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Non-Bankrupt</td>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

Adapted from Altman, 1993

In summary, the results of comparing the models showed that for each of the four years before a bankruptcy filing, the Kroeze model consistently outperformed the Z” model in terms of prediction accuracy. Second, the Kroeze model used fewer variables in striving for parsimony. Third, the single cut-off of zero made classification very simple. Therefore, the Kroeze model is preferable to the Z” model in predicting airline firm bankruptcy up to four years before the event. Next, the two models were tested for statistical significance.

Chi Square Analysis and Hypothesis Testing

To test hypotheses about data that use counts, one computes a chi-square statistic and compares its value to the chi-square distribution to see how unlikely the observed value is if the null hypothesis is true (Norusis, 2001). The assumptions needed to use the chi-square test are: 1) the categories of a variable don’t overlap, 2) most of the expected
counts must be greater than five; and, 3) none of the expected counts can be less than one. These assumptions have been met.

A total of 62 cases were classified above. The same 62 cases will be used to test the hypotheses.

The hypotheses tested in this dissertation are as follows:

\( H_{10} \): There is no relationship between the Altman Z''-score model and the likelihood of bankruptcy for an airline firm.

\( H_{1A} \): There is a relationship between the Altman Z''-score model and the likelihood of bankruptcy for an airline firm.

\( H_{20} \): A revised bankruptcy prediction model is no better than the Altman Z''-score model in predicting the likelihood of bankruptcy for an airline firm.

\( H_{2A} \): A revised bankruptcy prediction model is better than the Altman Z''-score model in predicting the likelihood of bankruptcy for an airline firm.

First, the Z'' model was tested to determine if it classified better than a naïve prediction. Hypothesis \( H_{10} \) states that there is no relationship between the Altman Z''-Score model and the likelihood of bankruptcy for an airline firm. As shown in Table 13, the critical chi-square value of 7.87944 (p=.005, df 1) was not met. The Z'' model failed, and hypothesis \( H_{10} \) is not rejected. There is no relationship between the Altman Z''-Score and the likelihood of bankruptcy for an airline firm. Hypothesis \( H_{1A} \) is rejected.
Next, the Kroeze model was tested. The second hypothesis states that a revised bankruptcy prediction model is no better than the Altman Z"-Score model in predicting the likelihood of bankruptcy for an airline firm. Therefore, the Kroeze model was compared to the Z" model. As shown in Table 14, the critical value of 7.87944 was reached (p=.005, df 1). Therefore, Hypothesis H2 is rejected, and Hypothesis H2_0 is accepted. The Kroeze model is better than the Altman Z"-Score model in predicting the likelihood of bankruptcy for an airline firm.

Table 13

*Chi-Square Analysis, Z" Model*

<table>
<thead>
<tr>
<th>Correct</th>
<th>Not Correct</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>32</td>
<td>62</td>
</tr>
<tr>
<td>23</td>
<td>39</td>
<td>62</td>
</tr>
</tbody>
</table>

\[ X^2 = \frac{(30-23)^2}{23} + \frac{(32-39)^2}{39} = 3.86 \]

Table 14

*Chi-Square Analysis, Kroeze Model versus Z" Model*

<table>
<thead>
<tr>
<th>Correct</th>
<th>Not Correct</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>45</td>
<td>17</td>
<td>62</td>
</tr>
<tr>
<td>30</td>
<td>32</td>
<td>62</td>
</tr>
</tbody>
</table>

\[ X^2 = \frac{(45-30)^2}{30} + \frac{(17-32)^2}{32} = 14.53 \]
The Kroeze model is also better than a naïve prediction model in predicting airline firm bankruptcy. See Table 15. The critical value of 7.87944 was reached (p=.005, df 1).

Table 15

*Chi-Square Analysis, Kroeze Model versus Naïve Prediction*

<table>
<thead>
<tr>
<th></th>
<th>Correct</th>
<th>Not Correct</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>45</td>
<td>17</td>
<td>62</td>
</tr>
<tr>
<td>Expected Count</td>
<td>23</td>
<td>39</td>
<td>62</td>
</tr>
</tbody>
</table>

\[ \chi^2 = \frac{(45-23)^2}{23} + \frac{(17-39)^2}{39} = 33.45 \]

The Kroeze model is shown in Table 16. The cutoff for this model is 0.0. Therefore, a firm with a negative K score is classified as bankrupt. A firm with a positive K score is classified as non-bankrupt.
Table 16

*Kroeze Model*

\[ K = 0.268X_1 + 0.838X_2 + 0.111X_3 + \epsilon \]

Where:

- \( X_1 = \) working capital/total assets;
- \( X_2 = \) retained earnings/total assets;
- \( X_3 = \) book value of equity/total liabilities;
- \( \epsilon = \) error term; and,
- \( K = \) overall index.

**Findings**

The Kroeze model calculates a score which, if negative, indicates a classification of bankruptcy. If the score is positive, a classification of non-bankruptcy is indicated.

In the Kroeze model, the most important predictor of bankruptcy is the variable that represents retained earnings divided by total assets. It makes intuitive sense that negative retained earnings would spell financial distress for an airline. A firm cannot sustain net losses for an extended amount of time without failing.

The Kroeze model predicted that Air Canada, Hawaiian, and US Airways would go bankrupt four years before the actual occurrence of their bankruptcies. The Kroeze model predicted that TWA would go bankrupt three years before it did. It also predicted that ATA would go bankrupt two years prior to the actual event, and that United would...
go bankrupt one year prior to its actual bankruptcy filing. This situation constitutes good prediction accuracy up to four years before the actual event occurs.

See Figures 1 through 16 below for each airline’s K-score graph. Graphs of the six major or national airlines that filed for bankruptcy between 1998 and 2004 are shown first, followed by graphs of the ten major or national airlines that did not file for bankruptcy during the same period. A score that falls below zero indicates a prediction of bankruptcy.

The Kroeze model made bankruptcy predictions for Air Canada using 1999, 2000, 2001, 2002 and 2003 financial statements. Air Canada did file for bankruptcy in 2003. Therefore, the model was accurate four years before the event, and consistently made accurate bankruptcy predictions. See Figure 1 below.
The Kroeze model also produced ATA negative K-scores, indicating a bankruptcy prediction, using financial statement data from 2002 and 2003. ATA filed for bankruptcy in 2004. Therefore, the model gave an accurate prediction two years before the actual bankruptcy filing. The model gave bankruptcy predictions in both 2002 and 2003. See figure 2 below.
Figure 2. ATA’s K-scores, 1998-2003

The Kroeze model predicted Hawaiian’s 2003 bankruptcy in 1999. The model was correct four years prior to the event. Additionally, the model accurately predicted Hawaiian’s bankruptcy, five years in a row. See figure 3 below.
According to the model, TWA’s scores indicated bankruptcy four years before the actual event in 2001. TWA flew their last official flight in December of 2001 and were subsequently liquidated under Chapter 7 of the bankruptcy code. See Figure 4 below.

Figure 3. Hawaiian’s K-scores, 1998-2003.

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United Airlines filed for bankruptcy in 2003. Its K-scores indicated bankruptcy in 2001. Their K scores were consistently negative for three years. As of the time of this writing, United is still operating under bankruptcy protection, and is still in financial distress. As discussed earlier, United applied for federal loan guarantees three times. They have been turned down all three times. See figure 5 below.
US Airways filed for Chapter 11 bankruptcy in 2002. They then applied for, and received, a $900 million federal loan guarantee (Maynard, 2004). However, they again declared bankruptcy in 2004. At the time of this writing, they are still reorganizing and operating under bankruptcy protection. Observe that their K-scores are negative for each year of this study. See Figure 6 below.
Figure 6. US Airway’s K-scores, 1998-2003.

ValuJet, now called AirTran, filed for bankruptcy following a devastating 1996 plane crash in the Florida Everglades. It is no surprise, therefore, that their K-scores were negative for several years after their bankruptcy. In 2003, they earned a positive K-score. AirTran did not declare bankruptcy during the period of this study. See Figure 7 below.
Alaska did not file for bankruptcy, nor did they apply for a federal loan guarantee. Alaska consistently earned positive K-scores during the period of this study. See Figure 8.
Figure 8. Alaska’s K-scores, 1998-2003.

Note that America West received positive K-scores for 1998 through 2001, but then received negative K-scores in 2002 and 2003. Therefore, according to the model, America will file for bankruptcy protection in the near future, as shown in Figure 9. Also, they did not earn a profit in 2004. America West managers, employees, and investors should be aware that America West is in financial distress.
As discussed earlier, American was very close to filing for bankruptcy recently. As shown in Figure 10, the K-score model predicts that American will declare bankruptcy in the near future. Their K-scores were positive until 2002, when the scores fell below zero. Additionally, American sustained negative earnings in 2004.
Continental has earned positive K-scores over the period of this study, as shown in Figure 11. However, they sustained negative earnings in 2004. Investors would be well advised to monitor Continental's financial performance.
Interestingly, much has been written recently about Delta’s financial problems. Some analysts stated that it was only hours away from a bankruptcy filing in 2004 (Maynard). However, its retained earnings were still positive at the end of 2003, and the new model does yet predict its bankruptcy. However, inspection of the graph of its K-scores in Figure 12 indicates that firm’s financial performance should be closely watched, since its K-score is very low. Furthermore, Delta suffered the worst losses in the history of the airline industry in 2004. An update that includes these 2004 results gives a prediction of bankruptcy. This study, however, was restricted to using 1998 to 2003 financial statements.
Figure 12. Delta’s K-scores, 1998-2003.

Frontier’s scores have been positive since 1999. Their K-scores dropped after the year 2001, as shown in Figure 13. Frontier applied, and received, federal loan guarantees, as discussed earlier. They did not earn a bankruptcy prediction.
JetBlue, a low-cost carrier, has been a publicly owned entity only since 2001. Their score, in 2001, was negative, which is expected for a new firm, as shown in Figure 14. They, and Southwest, have been the only airlines to earn profits in recent years.
Northwest has not earned a profit in years, and as such, is predicted to file for bankruptcy in the near future. As shown in Figure 15, their K-scores are negative over the entire length of this study. Poor financial performance like this cannot be sustained indefinitely.
Figure 15. Northwest’s K-scores, 1998-2003.

Southwest has been the airline industry’s star performer. As shown below in Figure 16, their K-scores have been positive over the length of this study. It is interesting to note that their score dips a little in the year 2001, the year of the terrorist attacks on the World Trade Center and the Pentagon.
Figure 16. Southwest’s K-scores, 1998-2003.

General Implications

The Kroeze model predicted that America West will file for bankruptcy, as well as American and Northwest. As of the date of this writing, these airlines have not filed for bankruptcy. However, none of these airlines produced a profit in 2004. Further, America West had negative retained earnings in 2002 and 2003. Also, American had negative retained earnings in 2002 and 2003. Finally, Northwest has had negative retained earnings for the entire period of the study, 1998-2003. These facts suggest that America West, American, and Northwest are in financial distress and, according to the Kroeze model, will file for Chapter 11 bankruptcy protection in the near future. Inspection of the
graphs indicate that Delta, Northwest, America West, and American all appear to be in financial distress. Their K-scores are below, or very close to, zero. One would ideally want to use the 2004 financial report for up-to-date predictions.

The issue arises that the Kroeze model may only work for the time since the events of September 11, 2001. With this in mind, it is known that TWA filed for bankruptcy in 1995, which is, of course, a time well before 2001. TWA’s K-score for the year 1994 was calculated as -.33. This K-score is well below zero, and would have generated a bankruptcy prediction for TWA. Thus, the model’s strength is supported by this analysis.

Financial ratios appear to work well to help predict bankruptcy up to four years ahead of the event. Further studies, however, should be undertaken on other industries over a recent period.

The statistical significance of each predictor variable is shown below in Figures 17 and 18. All four variables had F values that were statistically significant (p<.005, df 88). Additionally, the tolerance levels were all over 0.1, which indicates that multicollinearity is not a problem.

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>Correlations</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
<td>Zero-order</td>
<td>Partial</td>
</tr>
<tr>
<td>1 (Constant)</td>
<td>5.832E-08</td>
<td>.000</td>
<td>-1.323</td>
<td>.189</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X1</td>
<td>.268</td>
<td>.000</td>
<td>.127</td>
<td>1112464.275</td>
<td>.000</td>
<td>.406</td>
</tr>
<tr>
<td>X2</td>
<td>.838</td>
<td>.000</td>
<td>.821</td>
<td>4746810.342</td>
<td>.000</td>
<td>.983</td>
</tr>
<tr>
<td>X3</td>
<td>.111</td>
<td>.000</td>
<td>.162</td>
<td>890559.531</td>
<td>.000</td>
<td>.866</td>
</tr>
</tbody>
</table>

Figure 17. Predictor variables and significance.
<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>Between Groups</td>
<td>.095</td>
<td>1</td>
<td>.095</td>
<td>7.256</td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>1.154</td>
<td>88</td>
<td>.013</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1.249</td>
<td>89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X2</td>
<td>Between Groups</td>
<td>1.605</td>
<td>1</td>
<td>1.605</td>
<td>38.189</td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>3.697</td>
<td>88</td>
<td>.042</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>5.302</td>
<td>89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X3</td>
<td>Between Groups</td>
<td>2.764</td>
<td>1</td>
<td>2.764</td>
<td>26.923</td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>9.034</td>
<td>88</td>
<td>.103</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>11.798</td>
<td>89</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 18. Analysis of variance.

Jackknifed (leave-one-out) Classification

SPSS provides a jackknifed or leave-one-out classification. In this classification, the data from the firm are left out when the coefficients used to assign it to a group are computed. This is a method of cross-validation to ensure validity and generalizability of the results. When the original and cross-validated proportions are the same or similar, the results are consistent and classification is valid (Tabachnick & Fidell, 2001). As seen in Figure 19, the results are 75.6 percent of original groups correctly classified and 74.4 percent of cross-validated groups correctly classified. These proportions are similar. Therefore, the results are consistent and the classification is valid.
Figure 19. Classification table.

Unequal Sample Size and Missing Data

There were 90 cases. The 90 cases, obtained from 1998 through 2003 financial reports, included five Air Canada cases, six Hawaiian Air cases, four TWA cases, six US Airways cases, six United cases, six America West cases, six Frontier cases, six Alaska cases, six American cases, six Continental cases, six Northwest cases, six Southwest cases, three JetBlue cases, six Delta cases, six ATA cases, and six Air Tran cases.

Tabachnick and Fidell (2001) state that there are no special problems posed by unequal sample sizes using MDA. There were 33 cases in the bankrupt group and 57 cases in the non-bankrupt group that were used to create the discriminant function. The sample size of the smallest group, 33, exceeded the number of predictor variables, five. During classification, unequal sample sizes of the two groups, bankrupt and non-bankrupt, were used to modify the probabilities with which cases are classified into
groups. Had this not been done, the MDA program would have used a default probability of 50 percent chance of bankruptcy and 50 percent chance of non-bankruptcy.

**Linearity**

The independent variables were linearly related to the dependent variable in the new model, as shown below in the scatterplots in Figure 20. By inspection, it appears that the independent variables have a roughly linear relationship to the dependent variable. Therefore, the assumption of linearity was met and data transformation was not necessary.

![Figure 20. Linearity.](image-url)
Equality of Variances

A Levene test for equality of variances was performed on the two groups, bankrupt and non-bankrupt (Figure 21). The statistical significance was such that one can accept the hypothesis that the two population variances are equal (Norusis, 2001). Therefore, the assumption of equal variances was met.

<table>
<thead>
<tr>
<th></th>
<th>Levene's Test for Equality of Variances</th>
<th>t-test for Equality of Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>Sig.</td>
</tr>
<tr>
<td>New var</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equal variances assumed</td>
<td>2.80</td>
<td>.098</td>
</tr>
<tr>
<td>Equal variances not assumed</td>
<td>6.095</td>
<td>56.645</td>
</tr>
</tbody>
</table>

Figure 21. Levene’s test for equality of variances.

Multicollinearity and Singularity

SPSS 12 was used for the major analysis, which protects against multicollinearity through checks of tolerance. The tolerances were all higher than 0.1. Therefore, multicollinearity did not appear to be a problem (Figure 22).
Discriminant analysis is sensitive to the inclusion of outliers (Tabachnick & Fidell, 2001). Therefore, a test was run for univariate and multivariate outliers for each group separately, both bankrupt and non-bankrupt. A very conservative criterion for multivariate outliers is Mahalanobis distance at a significance level \( p < .001 \). There were four variables in the Z" model; therefore, the critical value of \( \chi^2(4) = 18.467 \). Thus, any case with a Mahalanobis distance greater than 18.467 was treated as a multivariate outlier. Using SPSS 12.0, the Mahalanobis distance was obtained by running a dummy regression and saving it as a new variable in the data set. See Appendix, Figures 23 and 24.

A dummy regression was run using the three variables \( X_1 \), \( X_2 \), and \( X_4 \) as independent variables and the K scores as the dependent variable in order to obtain Mahalanobis distances. There were no outliers among the K scores. However, there were a few extreme variable values found among the independent variables. All of the values were verified and were found to be correct.

Figure 22. Collinearity tolerance.

Outliers

Table: Collinearity Tolerance

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (Constant)</td>
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<td>-1.323</td>
<td>.189</td>
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<tr>
<td>X1</td>
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<td>.127</td>
<td>1112464.275</td>
<td>.000</td>
</tr>
<tr>
<td>X2</td>
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<td>.000</td>
<td>.821</td>
<td>4748610.342</td>
<td>.000</td>
</tr>
<tr>
<td>X4</td>
<td>.111</td>
<td>.000</td>
<td>.162</td>
<td>890559.531</td>
<td>.000</td>
</tr>
</tbody>
</table>

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Box plots of the predictor variables and independent variable were run (Appendix, Figures 25, 26, 27, and 28). Three cases had unusual values for $X_1$, the working capital to total asset ratio. One case corresponded to Hawaiian Air, which in 2002, had large, negative working capital. Another case represented Frontier, which also had large, negative working capital. The last case corresponded to Air Tran, which had large, positive working capital. The cases were verified, found to be correct, and were kept in the analysis. Incidentally, it is not unusual for airlines to show a negative working capital amount, as passengers pay for seats on flights before the flights are actually taken.

Among the $X_2$ variable values, one case had an unusual value; Air Tran’s 1999 retained earnings to total assets ratio was very low. The data was verified and found to be correct.

Among the $X_4$ variable values, was one extreme value found: Hawaiian Air, 1998. The value was checked and verified. Hawaiian, classified as bankrupt, had had a relatively healthy owners’ equity to total liabilities ratio in 1998. All of these extreme values were found to be correct, and they were also retained in the analysis.

Normality

The sample sizes used in this study were large enough (i.e., more than 20) to suggest normality of the sampling distributions of means. No tests are currently feasible for testing the normality of all linear combinations of the sampling distributions of means of predictors. However, Q-Q plots (Appendix, Figures 29 30, 31, 32) of the three predictor variables and the dependent variable scores suggest univariate normality. The points cluster around a straight line which suggests that the data were from a normal distribution (Norusis, 2001).
Summary

This chapter showed that the Kroeze model for predicting airline firm bankruptcy was far superior to the $Z''$ model. The Kroeze model used only three variables, predicted membership to only one of two groups, and used a simple zero as a cut-off to distinguish whether a firm belonged to the bankrupt group or the non-bankrupt group. Furthermore, the Kroeze model’s predictions were accurate up to four years in advance of a bankruptcy filing. Additionally, its results were statistically significant. All of the assumptions of MDA were tested and met. The $Z''$ model, on the other hand, used four variables, did not always give a classification to one of two groups, and used two cut-offs. Furthermore, it performed no better than a naïve prediction in determining whether an airline firm should have been classified as bankrupt or non-bankrupt.

The final chapter of this work summarizes the study and discusses the status of each airline firm. The implications of the test of the hypotheses are discussed, as well as possibilities for future research.
CHAPTER FIVE

SUMMARY AND RECOMMENDATIONS

Introduction

This chapter summarizes and discusses the findings of this dissertation, and reviews the implications that stem from those findings. In the first section of the chapter, a summary of the study and a discussion of the findings are presented. Then, some general implications arising from the study are discussed. This is followed by a discussion of the study's limitations. The chapter concludes with suggestions for future research.

Summary of the Study

This dissertation discussed the state of the airline industry and corporate bankruptcy prediction models. The Altman Z"-Score model (Z" model) was tested for its capacity to predict airline firm bankruptcy, using financial statements from the period 1998-2003. A new model was created, using MDA and three of the four Z" model's predictor variables. Both of these models were compared against the results of a naïve prediction. The Z" model performed no better than a naïve prediction in predicting airline firm bankruptcy. The new three variable model, however, was able to predict airline firm bankruptcy quite accurately up to four years before the actual event.
Findings

The Kroeze model calculates a score which, if negative, indicates a classification of bankruptcy. If the score is positive, a classification of non-bankruptcy is indicated.

In the Kroeze model, the most important predictor of bankruptcy is the variable that represents retained earnings divided by total assets. It makes intuitive sense that negative retained earnings would spell financial distress for an airline. A firm can not sustain net losses for an extended amount of time without failing.

The Kroeze model predicted that Air Canada, Hawaiian, and US Airways would go bankrupt four years before the actual occurrence of their bankruptcies. The Kroeze model predicted that TWA would go bankrupt three years before it did. It also predicted that ATA would go bankrupt two years prior to the actual event, and that United would go bankrupt one year prior to its actual bankruptcy filing. This situation constitutes good prediction accuracy up to four years before the actual event occurs.

The Kroeze model predicted that America West will file bankruptcy, as well as American and Northwest. As of the date of this writing, these airlines have not filed for bankruptcy. However, none of these airlines produced a profit in 2004. Further, America West had negative retained earnings in 2002 and 2003. Also, American had negative retained earnings in 2002 and 2003. Finally, Northwest has had negative retained earnings for the entire period of the study, 1998-2003. These facts suggest that America West, American, and Northwest are in financial distress and could file for Chapter 11 bankruptcy protection in the near future. See Figures 6 through 21 below for each airline’s K-score graph. Graphs of the six major or national airlines that filed for bankruptcy between 1998 and 2004 are shown first, followed by graphs of the ten major
or national airlines that did not file for bankruptcy during the same period. Scores below zero indicate a prediction of bankruptcy.

Interestingly, much has been written recently about Delta’s financial problems. Some analysts stated that it was only hours away from a bankruptcy filing in 2004 (Maynard, 2004). However, its retained earnings were still positive at the end of 2003, and the new model does not yet predict its bankruptcy. However, inspection of the graph of its K-scores in Figure 17 indicates that firm’s financial performance should be closely watched, since its K-score is very low.

General Implications

Inspection of the graphs indicate that Delta, Northwest, America West, and American all appear to be in financial distress. Their K-scores are below, or very close to, zero. One would ideally want the 2004 financial report for an up-to-date prediction.

Financial ratios appear to work well to help predict bankruptcy up to four years ahead of the event. Further studies, however, should be undertaken on other industries over a recent period.

The transportation industry is critical to the economy to the United States. Hospitality and tourism, for example, rely on the movement of consumers as a crucial part of their business. Reliable, affordable air transport allows people to conduct business effectively and enjoy leisure activities away from home. The airline industry employs millions of people, directly and indirectly. There are many stakeholders in the future of the airline industry including travelers, employees, and investors.
Key Limitations

This study did not include financial ratios from 2004 annual reports. The 2004 financial statements were not yet available at the time of this writing. This study cannot be generalized to all airlines. Only publicly owned airlines were analyzed in this study. This study cannot be generalized to other service industry firms. Further studies should be done to test the new model on relatively homogenous industries, using recent data, especially restaurants.

Financial statement data is based on historical costs and accrual accounting. As such, assets are not shown at current value or replacement value. Net income is not the same as cash flow. Depreciation uses estimates of the expected life of a long-term asset. Airlines, for example, use the historical costs of their purchased jets, rather than current value or replacement value. Therefore, accounting data must be used with these weaknesses in mind.

Some firms have conducted off-balance sheet transactions. Although US Airways, for example, stated in its financial statements that there were no off-balance sheet transactions, there is the possibility that firms can effectively hide debt. This study did not seek to discover hidden debt.

There are weaknesses associated with the use of MDA to predict corporate bankruptcy. The variances of the two groups, bankrupt and non-bankrupt, must be the same. This condition was met in this study; however, this may not always be the case. Additionally, the predictor ratios must be normally distributed. Again, this may not always be true, as it was in this study. Different researchers have used between one and seven ratios in their discriminant functions: Deakin (1972); Edmister (1972); and Beaver
(1967). Some researchers developed bankruptcy prediction models using the logit technique (Ohlson, 1980) because they felt that violating MDA’s assumptions was unimportant.

Suggestions for Future Research

The results of this study should be studied to determine if the K-score is a measure of the overall financial health of the airline. It may be possible that the K-score’s magnitude is meaningful.

Additional data needs to be analyzed. When 2004 financial reports for the same sixteen airlines become available, the airlines’ new scores should be calculated and revised predictions should be made.

Other statistical techniques might be tested. As mentioned above, in cases where some of the assumptions of MDA may not be met, it may be useful to employ logit analysis.

The Kroeze model should be tested on the restaurant business, using recent financial data. Whether or not this bankruptcy prediction model is suitable for other service businesses is unknown. Altman states that a bankruptcy prediction model that utilizes a homogeneous group of bankrupt companies and data as near to the present as possible is ideal.

The practical and theoretical applications of bankruptcy prediction models are many and varied. These include banking and credit analysis, and the assessment of an individual firm’s financial condition. Other suggestions for future research include: 1) perform a study of airline financial performance for the years before September 11, 2001,
and after September 11, 2001 to see if results are the same. This will help offset the notion that this study was flawed by the impact of the events of September 11, 2001. Not every airline filed for bankruptcy after that time. 2) Look at airline stock prices and compare to the Kroeze model’s predictions to determine how well the market predicted bankruptcy; and, 3) develop a probit model that creates a dependent variable to be defined as the probability of bankruptcy.

Summary

This study has shown that financial ratios can be used to predict airline firm bankruptcy. The accuracy of a traditional model was tested. The traditional model did not predict airline firm bankruptcy accurately. A new, simpler model was developed, the Kroeze model. This new model was quite accurate in predicting airline firm bankruptcy up to four years ahead of the actual event.
## APPENDIX

### STATISTICAL ANALYSIS

<table>
<thead>
<tr>
<th>Predicted Value</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
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<tbody>
<tr>
<td></td>
<td>-.6927</td>
<td>.1186</td>
<td>-.1871</td>
<td>.23267</td>
<td>33</td>
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<tr>
<td>Std. Predicted Value</td>
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<td>.000</td>
<td>.000</td>
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<tr>
<td>Adjusted Predicted Value</td>
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<td>.1186</td>
<td>-.1871</td>
<td>.23267</td>
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<td>.952</td>
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<td>1.693</td>
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<td>1.026</td>
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<td>.00000</td>
<td>.00000</td>
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<tr>
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<td>.091</td>
<td>.097</td>
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</table>

| a Dependent Variable: K-Score |

Figure 23. Mahalanobis Distance, Kroeze Model.

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<tr>
<th>Predicted Value</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>N</th>
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<td>.4636</td>
<td>.1039</td>
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<td>Standard Error of Predicted Value</td>
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<td>.000</td>
<td>.000</td>
<td>57</td>
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<tr>
<td>Adjusted Predicted Value</td>
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<td>.1066</td>
<td>.19094</td>
<td>56</td>
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<td>.00000</td>
<td>.00000</td>
<td>.00000</td>
<td>57</td>
</tr>
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<td>Std. Residual</td>
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<td>.00000</td>
<td>56</td>
</tr>
<tr>
<td>Stud. Deleted Residual</td>
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<tr>
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<td>.113</td>
<td>.020</td>
<td>.024</td>
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<tr>
<td>Centered Leverage Value</td>
<td>.007</td>
<td>.194</td>
<td>.053</td>
<td>.042</td>
<td>57</td>
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</table>

| a Dependent Variable: K-Score |

Figure 24. Mahalanobis Distance, Kroeze Model, Non-Bankrupt Group.
Figure 25. Predictor Variable Box Plots, Bankrupt and Non-Bankrupt Groups.
Figure 26. Predictor Variable Box Plots, Bankrupt and Non-Bankrupt Groups.
Figure 27. Predictor Variable Box Plots, Bankrupt and Non-Bankrupt Groups.
Figure 28. Dependent Variable Box Plots, Bankrupt and Non-Bankrupt Groups.
Normal Q-Q Plot of $X_1$

Figure 29. Test for Normality of Predictor $X_1$. 

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Figure 30. Test for Normality of Predictor $X_2$. 

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Figure 31. Test for Normality of Predictor $X_3$. 

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Figure 32. Test for Normality for K-Scores.
### Analysis Case Processing Summary

<table>
<thead>
<tr>
<th>Unweighted Cases</th>
<th>N</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valid</td>
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<td>100.0</td>
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<tr>
<td>Excluded Missing or out-of-range group codes</td>
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<td>0.0</td>
</tr>
<tr>
<td>At least one missing discriminating variable</td>
<td>0</td>
<td>0.0</td>
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<td>Both missing or out-of-range group codes and at least one missing discriminating variable</td>
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<td>0.0</td>
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<tr>
<td>Total</td>
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### Group Statistics

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### Tests of Equality of Group Means

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</tbody>
</table>
Pooled Within-Groups Matrices(a)

<table>
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<th></th>
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</thead>
<tbody>
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<tr>
<td>X4</td>
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</table>

a The covariance matrix has 88 degrees of freedom.

Covariance Matrices(a)

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<td>X2</td>
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<td>X4</td>
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a The total covariance matrix has 89 degrees of freedom.

Log Determinants

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<td>2.00</td>
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<td>Pooled within-groups</td>
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The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Test Results

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</tr>
<tr>
<td>Sig.</td>
<td>.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tests null hypothesis of equal population covariance matrices.
### Eigenvalues

<table>
<thead>
<tr>
<th>Function</th>
<th>Eigenvalue</th>
<th>% of Variance</th>
<th>Cumulative %</th>
<th>Canonical Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.477(a)</td>
<td>100.0</td>
<td>100.0</td>
<td>.568</td>
</tr>
</tbody>
</table>

a  First 1 canonical discriminant functions were used in the analysis.

### Wilks' Lambda

<table>
<thead>
<tr>
<th>Test of Function(s)</th>
<th>Wilks' Lambda</th>
<th>Chi-square</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.677</td>
<td>33.712</td>
<td>3</td>
<td>.000</td>
</tr>
</tbody>
</table>

### Standardized Canonical Discriminant Function Coefficients

<table>
<thead>
<tr>
<th>Function</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>.268</td>
</tr>
<tr>
<td>X2</td>
<td>.838</td>
</tr>
<tr>
<td>X4</td>
<td>.111</td>
</tr>
</tbody>
</table>

### Structure Matrix

<table>
<thead>
<tr>
<th>Function</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>X2</td>
<td>.954</td>
</tr>
<tr>
<td>X4</td>
<td>.801</td>
</tr>
<tr>
<td>X1</td>
<td>.416</td>
</tr>
</tbody>
</table>

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.

### Functions at Group Centroids

<table>
<thead>
<tr>
<th>B1N2</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>-.897</td>
</tr>
<tr>
<td>2.00</td>
<td>.519</td>
</tr>
</tbody>
</table>

Unstandardized canonical discriminant functions evaluated at group means.
### Classification Processing Summary

<table>
<thead>
<tr>
<th>Processed</th>
<th>Excluded</th>
<th>Used in Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>90</td>
<td>0</td>
<td>90</td>
</tr>
</tbody>
</table>

- **Missed or out-of-range group codes**: 0
- **At least one missing discriminating variable**: 0

### Prior Probabilities for Groups

<table>
<thead>
<tr>
<th>B1N2</th>
<th>Prior</th>
<th>Cases Used in Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Unweighted</td>
</tr>
<tr>
<td>1.00</td>
<td>.367</td>
<td>33</td>
</tr>
<tr>
<td>2.00</td>
<td>.633</td>
<td>57</td>
</tr>
<tr>
<td>Total</td>
<td>1.000</td>
<td>90</td>
</tr>
</tbody>
</table>

### Classification Results (b,c)

<table>
<thead>
<tr>
<th>Original</th>
<th>Count</th>
<th>Predicted Group Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>B1N2</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.00</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.00</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>1.00</td>
<td>48.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.00</td>
<td>8.8</td>
</tr>
<tr>
<td>Cross-validated(a)</td>
<td>Count</td>
<td>1.00</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.00</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>1.00</td>
<td>45.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.00</td>
<td>8.8</td>
</tr>
</tbody>
</table>

- a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
- b 75.6% of original grouped cases correctly classified.
- c 74.4% of cross-validated grouped cases correctly classified.
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Lions Club Scholarship, Washington State University, 1989
Jesse Pepper Padelford Scholarships, University of Washington, 1981 and 1982

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Committee Member, Dr. Collin Ramdeen, Ph.D.
Graduate Faculty Representative, Dr. Thomas Carroll, Ph.D.