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Improving Airline Bankruptcy Prediction

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ABSTRACT
The airline industry plays an important role in the global economy but faces financial challenges. Numerous firms have filed for bankruptcy protection or have liquidated completely, each instance having a devastating effect on the company's stakeholders. The objective of this study is to compare a traditional bankruptcy prediction model with a proposed alternative model, with the goal of identifying a means of predicting the combinations of characteristics that are present when an airline is likely to fail. The alternate model proved to be more accurate than the traditional model in predicting bankruptcy, providing improved forecasting up to four years prior to the bankruptcy filing date. Airlines can use this model to deploy corrective measures to alter the firm's underlying problems, redefine strategies, and avoid bankruptcy, while investors can use this model to avoid or reduce investments in questionable firms that cannot be salvaged.

Keywords: *airline industry, Altman Z-Score model, bankruptcy prediction, multiple discriminant analysis, ratio analysis*

Introduction

Between 2001 and 2011, the U.S. airline business suffered $10 billion in losses (Neuman, 2011). The industry in aggregate lost over $60 billion in the 32 years following deregulation in 1978. Legacy airlines have had a particularly hard time. Since 1998, 10 large North American airlines have filed for bankruptcy: Air Canada; American; ATA (American Trans Air); Delta; Frontier; Hawaiian; Northwest; TWA (Trans World Airlines); US Airways; and United. TWA is no longer operating; it flew its last official flight on December 1, 2001. ATA ceased operations in 2008. America West acquired US Airways, which then merged with American Airlines; Continental merged with United; Northwest merged with Delta; Southwest acquired AirTran; and Alaska Airlines acquired Virgin America (Denning, 2011). By 2015, four mega-carriers made up a combined 80% of all U.S. flights (Groden, 2015).

Warren Buffett, chairman of Berkshire Hathaway and probably one of the most successful investors in the world, called the airline industry a "death trap for investors" in 2013 (La Monica, 2017). What happened? Volatile fuel prices, overcapacity, the economic recessions, terrorism, war, increased security costs, rising insurance premiums, high competition, and poor management have all contributed to the adverse financial impact on the airline industry (Federal Aviation Administration, 2014). 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. Before airline deregulation, no major airline filed for Chapter 11 bankruptcy (Cheng & McDonald, 1996). Following deregulation, the airline industry has suffered financially from various problems: the economic recessions of the early 1980s and 2008–2013, rising jet fuel prices, 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'

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operating profits. Total risk, defined as the volatility of net profits and cash flows over time, has increased dramatically in the airline industry. Oil prices have been, at times, over $100 per barrel. Consequently, jet fuel prices have skyrocketed, devastating the airlines' bottom lines.

If there were a means of predicting the combinations of characteristics of an airline that is likely to fail, corrective measures could be taken to alter the firm's underlying problems as well as redefine strategies and procedures. This could also be useful to investors by helping them 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 nearly 50 years is the statistical bankruptcy prediction model, first presented by Altman (1968). This model, the Altman Z-Score model, is a popular approach for not only forecasting bankruptcy in advance of the event but also gauging the overall financial condition of a firm.

The objective of this study is to analyze financially distressed and non-financially distressed airlines using a traditional bankruptcy prediction model, in order to evaluate its ability to predict bankruptcy in the airline industry. This study will add to bankruptcy research, addressing Altman and Hotchkiss's (2006) recommendations to enhance previous models by introducing an alternative statistical model that may better predict which airlines are likely to fail and which are not likely to fail. The new model's classification rate is compared to the rate generated using the Altman Z″-Score model, a variant of the original Altman Z-Score model.

Literature Review

Numerous models for predicting bankruptcy have been proposed. This paper will first examine general-purpose models, focusing on the Altman Z-Score model. Next, an overview of bankruptcy prediction research in the hospitality industry is presented, followed by a focus on past work predicting airline bankruptcy.

Common Bankruptcy Prediction Models

Numerous studies have used the Altman Z-Score (Z-Score) model and its variants to predict firm bankruptcies and financial distress for manufacturing firms. One method of predicting financial distress that has been widely used for over 50 years is the statistical bankruptcy prediction model, first presented by Altman (1968). The Altman Z-Score model uses five financial ratios to represent the elements that predict failure. These elements are liquidity, cumulative profitability, productivity, solvency, and activity. Multiple discriminant analysis (MDA) is applied to the financial ratios 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, Black, Babin, & Anderson, 2009).

In response to requests for a measure to predict the likelihood of bankruptcy for non-manufacturing firms, Altman developed the Z″ model (i.e., the "Z-prime-prime"), a four-variable multiple discriminant model (Altman & Hotchkiss, 2006). The four financial ratios used in the Z″-Score model represent liquidity, cumulative profitability, productivity, and solvency.

The Altman Z″-Score model is shown below:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + \acute{\varepsilon} \quad (1)$$

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,
$\acute{\varepsilon}$ = error term, and,
Z'' = overall index.

While the newer Z″-Score model provides greater accuracy for non-manufacturing and emerging markets (non-U.S.) firms, Altman and Hotchkiss (2006) do suggest that further developing of bankruptcy prediction models for specific industries would be desirable.

Bankruptcy Prediction Models for the Hospitality Industry

There have been few studies devoted to bankruptcy prediction in hospitality and travel. Gu and Gao

(2000) used an MDA model to predict bankruptcy for hospitality firms including restaurant, hotel, and casino firms. Their model used five variables (total liabilities to total assets, EBIT to current liabilities, gross profit margin, long-term debt to total assets, and sales to fixed assets). This model could correctly predict bankruptcy in 93% of the sample firms one year in advance of the actual bankruptcy. Gu (2002) focused on bankruptcy prediction in the restaurant industry using the same MDA methodology. His MDA model predicted bankruptcy in 92% of the sample firms one year in advance of the actual bankruptcy. A limitation of these two studies was the short-term predictive ability of their MDA models. Both models predicted bankruptcy only one year in advance.

Kim and Gu (2006a) first developed a logistic regression (logit) model to improve the prediction accuracy over the traditional MDA model. In this instance, they developed the model for use in the restaurant industry and found that while both logit and MDA performed about the same, the underlying soundness of the results was stronger when using logit. These models predicted restaurant bankruptcy approximately one year prior to the bankruptcy.

Kim and Gu (2006b) next revisited the logit approach to predict hospitality firm bankruptcy two years in advance. This logit model could correctly predict 91% of hospitality bankruptcies one year in advance of the actual event, and 84% of bankruptcies two years in advance of the event. The sample in this study included hotel, restaurant, and gaming companies. This improved model was proposed to help provide an "early distant warning" to hospitality industry operators to allow adequate time to correct deficiencies and head off the bankruptcy.

Youn and Gu (2010) used a combination of logistic regression and an artificial neural networking (ANN) model to predict Korean lodging firm failures. The addition of the ANN process improved the accuracy of the prediction rate over using only logistic regression. However, the use of an ANN requires a great deal of interpretation of "black box" processes. The ANN approach also does not provide prescriptive results, which has the disadvantage of not providing actionable data for the firm to use to improve its areas of weak performance.

Kim (2011) compared four different methods—MDA, logit, ANN, and support vector machine (SVM) models—to determine which provided the greatest accuracy and which minimized the incidences of Type 1 and Type 2 errors. The author concluded that the ANN technique provided the best accuracy of the four models.

Airline Bankruptcy Prediction Models

Several different statistical techniques have been used in the past to assess airline financial performance, including MDA, logit, and ANN.

MDA. The first approach, MDA, attempts to classify airlines as financially distressed or not distressed (Gritta, 1974; Gritta, 1982; Scaggs & Crawford, 1986; Golaszewski & Sanders, 1992; Chung & Szenberg, 1996; Gritta, Adrangi, Adams, & Tatyanina, 2008). Gritta (1974) looked at "the significance of the effects of capitalization on the 'perceived' amounts of long-term debt in an airline firm's capital structure, and therefore, on the debt-to-equity measures" (p. 47). Gritta (1982) applied a generally accepted model to air transportation in an effort to appraise air carriers' financial strength and to predict likely bankruptcy candidates. The analysis was designed to aid in pinpointing the causes of the air carriers' financial difficulties and was intended to be of interest to airline management, creditors, and regulators. Scaggs and Crawford (1986) revisited Altman's bankruptcy model to determine if airline bankruptcy could be predicted. Their model predicted bankruptcy well but did not predict non-bankruptcy well.

Golaszewski and Sanders (1992) stated that their object was "not to predict bankruptcy performance *per se;* rather, it is to examine the status of a carrier's finances prior to bankruptcy and then identify other carriers which, while not bankrupt, are under significant financial distress" (p. 313). Chung and Szenberg (1996) employed Altman's Z-Score as a measure of the airline industry's financial stability in the 1980s, following the industry's deregulation. They identified increased volatility throughout the industry, classifying the industry's "health" as either healthy or unhealthy. However, the authors did not use the model to predict bankruptcy.

Gritta et al. (2008) assessed the financial condition of the major U.S. air carriers from 2000 to 2006 and compared their financial strength to the 1995–1999 period when the carriers earned record profits.

They found an increasing trend in negative equity and increased leverage, predicting future bankruptcies if the low interest rates available from 2000–2006 were to rise.

Kroeze and Mayer (2006) developed a variant of the MDA approach and found improved predictive capabilities, and recommended retesting the model in the future to include a larger sample of companies that had undergone either Chapter 7 or 11 bankruptcy.

Logistic regression. Other researchers used a different approach by developing logistic regression (logit) models, which predict the odds-ratio of an event occurring. For example, Gudmundsson (1999; 2002) constructed a logistic regression model of airline distress prediction using three years of worldwide airline data (1996–1998) including non-financial operating data and proxy variables for governmental influence and quality of economic environment. The findings demonstrated a fairly good model, having 90.3% overall prediction accuracy. These findings, in conjunction with other research in this field, supported that models based on non-financial variables showed good prediction traits comparable to financial based models, yet provided more explanatory power.

Neural networks. Next, a few researchers have employed a neural network approach to predict airline bankruptcy. Davalos, Gritta, and Chow (1999) and Gritta, Wang, Davalos, and Chow (2000) developed airline bankruptcy prediction models using this approach. Studies were conducted on both major and regional air carriers using the neural network. Twenty-one pieces of financial information from carrier balance sheets and income statements were entered into the model. The study successfully classified all the major carriers that filed for receivership and most of the regional carriers. The use of neural networks may provide an interesting supplement to the analyst in appraising financial health.

Finally, some researchers are exploring bankruptcy from different perspectives. For example, Jayanti and Jayanti (2011) examined the effect of one airline company's bankruptcy on its competitors, finding that when a major airline announces it is going into Chapter 11 restructuring, its competitors realize abnormally high returns, although these returns drop precipitously when the bankrupt carrier emerges from bankruptcy.

Purpose of the Study

The purpose of this study is to test Altman's Z″-Score model in the context of the airline industry, and then to compare it against a new, proposed model. It seeks to update and extend these earlier studies of airline bankruptcy prediction. The goals are to add to theory and practice by identifying a model that is easy to use (unlike ANN modeling), accurate, and one that provides the greatest advance notice of the risk of bankruptcy proceedings. Such a model will help airline operators to take corrective action as soon as possible and help investors with decision-making. To do this, the study tests the following hypotheses:

$H1_0$: There is no relationship between the Altman Z″-Score model and the likelihood of bankruptcy for an airline firm.

$H1_A$: There is a relationship between the Altman Z″-Score model and the likelihood of bankruptcy for an airline firm.

$H2_0$: The proposed bankruptcy prediction model is no better than the Altman Z″-Score model in predicting the likelihood of bankruptcy for an airline firm.

$H2_A$: The proposed bankruptcy prediction model is better than the Altman Z″-Score model in predicting the likelihood of bankruptcy for an airline firm.

Methods

Altman (1968) stated 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. Following Altman's guidelines, this study used bankrupt and non-bankrupt airline firms' 1998–2005 financial statements. The financial statements were retrieved from the Securities Exchange Commission's *EDGAR* database (Securities Exchange Commission, 2018) and from airline firms' annual reports, which are available online 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 protection; or, (2) in Chapter 7 liquidation. Thus, those airline firms that were in one or more of these states at any time during the 1998–2005 period were considered to be bankrupt, leading to a dichotomous variable representing bankruptcy filing between 1998 and 2005.

This study used a census approach rather than a random sample. 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 financial data of publicly held *major* passenger airlines included Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United, and US Air. Air Canada was also included in this study, as it has sufficiently large revenues and used Generally Accepted Accounting Principles (GAAP) in preparing its financial statements, similar to publicly owned U.S. firms. Air Canada's stock was traded on the American Stock Exchange. The publicly owned *national* passenger airlines (not including regional airlines) included AirTran (formerly ValuJet), ATA (formerly Amtran), Frontier, Hawaiian, and JetBlue. Non-passenger airlines (DHL, Federal Express, and United Parcel Service) were not included in this study.

During the period 1998–2005, the following nine airline firms were liquidated or filed for Chapter 11 bankruptcy protection: Air Canada, ATA, America West, Delta, Hawaiian, Northwest, TWA, United, and US Airways. During the same period, the following seven firms were not liquidated, nor did they file for Chapter 11 bankruptcy protection: Air Tran, Alaska, American, Continental, Frontier, JetBlue, and Southwest.

This study utilized a holdout sample to evaluate the model. Holdout samples are useful when the period of the model is different from the period of evaluation. With this technique of model evaluation, the in-sample data ends at a point in time, and the remaining data are held out as a non-overlapping period of evaluation. The holdout sample is used to compare the forecasting accuracy of models fit to past data (SAS Institute, 2017). The in-sample size of 62 data points and the holdout sample size of 22 data points were adequate, given the statistical method chosen and the two classification groups (Hair et al., 2009).

Analysis and Results

The data were analyzed using multiple discriminant analysis (MDA) to predict group membership (Tabachnick & Fidell, 2012). MDA is principally used to classify and to make predictions in situations where the criterion variable is in categorical form (Hair et al., 2009), as was the case in this study (e.g., bankrupt versus 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. The predictors were a set of financial ratios that measured a firm's liquidity, cumulative profitability, productivity, solvency, and cash flow (Beaver, 1966).

Assumptions of MDA

The key assumptions for deriving the discriminant function are multivariate normality of the independent variable and equal covariances (Hair et al., 2009). MDA is relatively robust to failures of normality if skewness, rather than outliers, causes the violation. Robustness is expected with 20 cases in the smallest group if there are only five or fewer predictors (Tabachnick & Fidell, 2012). Therefore, in this case, robustness to any failures in normality of the residuals should be expected.

Results

Altman's Z″-Score model. Using the Altman Z″-Score model, a firm with a score under 1.1 is classified as bankrupt. A firm with a score over 2.6 is classified as non-bankrupt. A firm whose score is between 1.1 and 2.6 is classified as belonging to the "grey area." Using 1998–2003 data, this model did an unsatisfactory job of predicting airline bankruptcy. Overall accuracy was only 57.5% over the entire time period, which is little better than a coin toss.

Alternate model. An alternate three-variable model for predicting airline firm bankruptcy was created, using 1998–2003 data for an in-sample analysis. Of the financial ratios tested, it was found that only three variables were statistically significant as predictors and did not have a collinearity issue. Data from 2004–2005 was used as a holdout sample and to verify the prediction accuracy of the original model.

The alternate model is as follows:

$$Y_a = 0.268X_1 + 0.838X_2 + 0.111X_3 + \acute{\varepsilon} \qquad (2)$$

where

X_1 = working capital/total assets,
X_2 = retained earnings/total assets,
X_3 = book value of equity/total liabilities,
$\acute{\varepsilon}$ = error term, and,
Y_a = overall index.

Using 1998–2003 in-sample data, 82.5% of the bankrupt airline firms were correctly classified as bankrupt, and 73.9% of the non-bankrupt firms were correctly classified as non-bankrupt. Overall, the accuracy was 80.9%. This result represented a considerable improvement over the Z″-Score model's 57.5%. The alternate model was then tested using the holdout sample of 2004–2005 data. The model correctly predicted bankruptcy 93% of the time one year ahead of the event, 87% of the time two years ahead of the event, and 73% of the time for three years ahead. The prediction accuracy, using the holdout sample, was even better than that of the in-sample data. This implies that the alternate model could do a respectable job in predicting future bankruptcy and could be a useful management tool. Table 1 displays the number of years, in advance, that each airline received a bankruptcy classification. A negative score indicates that the airline was classified as bankrupt.

The scores for each non-bankrupt airline during the model development and testing period are displayed in Table 2. A positive score indicates that the airline was classified as non-bankrupt, according to the alternate model. Please note that although American Airlines received negative scores for 2004–2005, it did not file for bankruptcy until 2011.

Testing the Alternate Model with Recent Data

The financial data for four mega-carriers and two large national carriers were entered into the model to test its robustness over time. Table 3 displays the 2015 and 2016 scores using the most recent financial data available for American, Delta, Southwest, United, Alaska, and JetBlue. A positive score indicates that the airline was classified as non-bankrupt, according to the alternate model.

Please note that American Airlines a received negative score in 2015. It had large net losses each year from 2009–2013. It declared bankruptcy in 2011 and merged with US Airways in 2013. Although the company turned a profit in 2014 and 2015, its retained earnings were still negative in 2015. This resulted in a negative alternate model score for 2015. Its retained earnings became positive in 2016, and it achieved a positive score.

Frontier has been owned by an affiliate of Indigo Partners, LLC, a private equity firm, since

Table 1. Alternate Model Results for Bankrupt Firms

Airline	Year Bankruptcy Declared	Number of Years in Advance that Bankruptcy Was Correctly Predicted	Score, Year Bankruptcy Was Declared	Score, One Year before Bankruptcy	Score, Two Years before Bankruptcy	Score, Three Years before Bankruptcy	Score, Four Years before Bankruptcy
Air Canada	2003	4	−0.07	−0.45	−0.03	−0.09	−0.08
America West	2005	3	−0.01	−0.01	−0.05	−0.12	0.05
ATA	2004	2	−1.3	−0.16	−0.16	0.02	0.05
Delta	2005	2	−0.43	−0.23	−0.07	0.03	0.09
Hawaiian	2003	4	−0.36	−0.5	−0.2	−0.27	−0.08
Northwest	2005	4	−0.37	−0.16	−0.08	−0.11	−0.04
TWA	2001	3	−0.6	−0.5	−0.41	−0.2	N.A.
United	2002	1	−0.14	−0.02	0.08	0.09	0.03
US Airways	2004	4	−0.05	−0.03	−0.67	−0.39	−0.09

Table 2. Alternate Model Results for Non-Bankrupt Firms

Airline	Score, 2005	Score, 2004
Air Tran	0.14	0.30
Alaska	0.20	0.20
American	−0.04	−0.01
Continental	0.07	0.06
Frontier	0.20	0.23
JetBlue	0.06	0.09
Southwest	0.42	0.44

Table 3. Recent Alternate Model Results for the Largest Remaining Airlines

Airline	Score, 2016	Score, 2015
Alaska	0.33	0.43
American	0.02	−0.03
Delta	0.12	0.07
Hawaiian	0.16	0.24
JetBlue	0.28	0.20
Southwest	0.20	0.23
United	0.06	0.09

December 2, 2013 (Drum, 2013); its financial statements are no longer publicly available. Frontier has a small market share, less than 3% (Bureau of Transportation Statistics, 2017). Air Canada is now ACE Aviation. The company's financial statements are no longer available on the Securities Exchange Commission's website and the stock is no longer publicly available for sale in the United States. Therefore, Air Canada and Frontier no longer meet the study's requirements and have been dropped from the analysis.

Chi-Square Analysis and Hypothesis Testing

Next, the two models were tested for statistical significance. The data results were tested using chi-square analysis to see how unlikely the observed value is if the null hypothesis is true. The chi-square test's assumptions are: 1) the categories of a variable do not overlap; 2) most of the expected counts must be greater than five; and 3) none of the expected counts can be fewer than one. These assumptions were met.

First, the Altman Z″-Score model was tested to determine if it classified the companies' bankruptcy status better than a naïve prediction. Hypothesis $H1_0$ states that there is no relationship between the Altman Z″-Score model and the likelihood of bankruptcy for an airline firm. The critical chi-square value ($p<0.05$, df 1) was not met. The Altman Z″-Score model failed, and hypothesis $H1_0$ is not rejected. There is no relationship between the Altman Z″-Score and the likelihood of bankruptcy for an airline firm, therefore the alternate hypothesis is rejected.

Next, the alternate 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. The critical chi-square value of 7.87944 was achieved ($p<0.005$, df 1), thus rejecting $H2_{0.}$ Therefore, the alternate hypothesis is accepted, since the alternate model is better than the Altman Z″-Score model in predicting the likelihood of bankruptcy for an airline firm.

Key Variables

The alternate model calculates a score, which, if negative, indicates a classification of bankruptcy and, if positive, the classification is non-bankruptcy. In the alternate model, the most important predictor of bankruptcy is the variable that represents retained earnings divided by total assets. This variable corresponds with the largest coefficient, 0.838, making it the most important predictor of bankruptcy. 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.

As shown in Table 1, the alternate model predicted that Air Canada, Hawaiian, Northwest, and US Airways would go bankrupt four years in advance, that America West and TWA would go bankrupt three years before they did, that Delta and 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. These results constitute good prediction accuracy for up to four years before the actual event occurs.

Discussion

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.

Some airlines have responded to their financial troubles by merging. America West acquired US Airways, which then merged with American Airlines; Continental merged with United; Northwest merged with Delta; Southwest acquired AirTran; and Alaska Airlines acquired Virgin America (Denning, 2011). By 2015, four mega-carriers made up a combined 80% of all U.S. flights (Groden, 2015). The industry's financial health has improved to the point where, in 2016, Warren Buffett (who called the airline industry a financial investment death trap in 2013) invested in the four mega-carriers: American, United, Delta, and Southwest (La Monica, 2017).

There is also a not-so-subtle irony about bankruptcy: it costs money. And the bigger the company, the more it costs. Filing for Chapter 11 cost AMR hundreds of millions of dollars in attorney and other professional fees. There is also the stigma that is attached to bankruptcy. Nobody wants to work for a bankrupt company, and few CEOs want to be in charge of a bankrupt company (Neuman, 2011).

This study tested two corporate bankruptcy prediction models. The Altman Z″-Score 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 three of the four Altman Z″-Score model's predictor variables. Both of these models were compared against the results of a naïve prediction.

The three financial ratios used in the new model represent liquidity, cumulative profitability, and solvency. According to Schmidgall (2011), liquidity ratios reveal the ability of a firm to meet its current obligations. This study uses the working capital/total assets ratio, which is particularly useful for analyzing airline companies because they are capital-intensive and service significant amounts of debt, requiring liquidity to meet these obligations.

Cumulative profitability (Retained Earnings/Total Assets) indicates profits a company earns on its assets over time. According to Altman (1968), the age of a firm is implicitly incorporated in this ratio. The younger the firm is, the lower the ratio will be. On the other hand, since airline companies own very substantial assets, even a relatively low value may represent sizable profits.

Solvency ratios measure a firm's capability to meet long-term debt (Schmidgall, 2011). This study uses a solvency ratio that compares the firm's total equity to its total liabilities. This financial metric measures a firm's ability to withstand adversity.

The Altman Z″-Score model performed no better than a naïve prediction in predicting airline firm bankruptcy. The new three-variable model, however, could predict airline firm bankruptcy up to four years before the actual event. The alternate model not only performed better than the Z″-Score model but also was simpler, since it used fewer variables. Further, it predicted membership in one of only two groups (rather than three under the Z″-Score model), and used a single score (of zero) as a cut-off to distinguish whether a firm belonged to the bankrupt group or the non-bankrupt group. Therefore, the alternate model emerges as a more sophisticated and practical model at the same time, having major implications as a bankruptcy alert tool for the airline industry and any other industry that wishes to adapt it. Furthermore, this study responds to Altman and Hotchkiss's (2006) suggestion that there is a need for further development of bankruptcy prediction models for specific industries.

Limitations of the Study and Suggestions for Future Research

There are several limitations to this study. First, this analysis is limited by the availability of financial data on airlines. Only publicly traded corporations are required to make their financial statements available to everyone, via filings with the Securities Exchange Commission. Therefore, only publicly traded airlines were part of this study. The data used in this study was limited to financial statements that are available in filings with the SEC; the relatively small number of publicly traded airlines does not permit examination of a larger sample size.

A second limitation is the variation in operating models among the sample's airlines. For example, some airlines lease their jets, which are the most important assets for an airline. Other airlines purchase their jets, using long-term debt financing. This lease versus ownership difference may have an impact on the presentation of an airline's balance sheet accounts.

A third limitation is the use of ratio analysis. Ratios are extremely useful to owners, creditors, and management in evaluating the financial condition of airlines, and appear to work well to help predict bankruptcy up to four years ahead of the event. Ratios, however, are only indicators. They do not reveal a problem's source, just indicate that there may be a problem (Beaver, 1966). Future models should develop a solution to not only detect a problem but also pinpoint the source of the problem to permit companies to take corrective action. For example, a future study could use ratios and overlay trend data on other influencers, such as jet fuel costs or "black swan" events that strongly affect airline travel (e.g., pandemic outbreaks or major volcanic eruptions). Future studies could also use this study's model to predict bankruptcy in other types of businesses.

In 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 alternate model was developed, which could predict airline firm bankruptcy up to four years ahead of the actual event.

References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23,* 589–609.

Altman, E. I., & Hotchkiss, E. (2006). *Corporate financial distress and bankruptcy: Predicting and avoiding bankruptcy, analyze and invest in distressed debt.* Hoboken, NJ: John Wiley and Sons, Inc.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4 (Supplement),* 71–111.

Bureau of Transportation Statistics. (2017). *Air carrier financial reports.* Retrieved from https://www.transtats.bts.gov/Tables.asp?DB_ID=135&DB_Name=Air%20Carrier%20Financial%20Reports%20%28Form%2041%20Financial%20Data%29&DB_Short_Name=Air%20Carrier%20Financial.

Cheng, L. T. W., & McDonald, J. E. (1996). Industry structure and ripple effects of bankruptcy announcements. *Financial Review, 31,* 783–807.

Chung, C. C., & Szenberg, M. (1996). The effects of deregulation on the U.S. airline industry. *Journal of Applied Business Research, 12*(3), 133–140.

Davalos, S., Gritta, R. D., & Chow, G. (1999). The application of a neural network approach to predicting bankruptcy risks facing the major US air carriers: 1979–1996. *Journal of Air Transport Management, 5,* 81–86.

Denning, L. (2011, November 30). American Airlines takes evasive action. *Wall Street Journal.* Retrieved from https://www.wsj.com/articles/SB10001424052970203441704577068422381677392.

Drum, B. (2013, December 4). Frontier Airlines is now owned by Indigo Partners. [*World Airline News*]. Retrieved from https://worldairlinenews.com/category/frontier-airlines-2nd/page/8/.

Federal Aviation Administration. (2014). *FAA aerospace forecast: Fiscal years 2015–2035.* Retrieved from https://www.faa.gov/data_research/aviation/.

Golaszewski, R., & Saunders, M. (1992). Financial stress in the U.S. airline industry. *Journal of the Transportation Research Forum, 32,* 313–319.

Gritta, R. D. (1974). The impact of capitalization of leases on financial analysis: A case study in air transport. *Financial Analysts Journal, 30,* 47–52.

Gritta, R. D. (1982). Bankruptcy risks facing the major US airlines. *Journal of Air Law and Commerce, 48,* 89–108.

Gritta, R. D., Adrangi, B., Adams, B., & Tatyanina, N. (2008). An update on airline financial condition and insolvency prospects using the Altman Z″ score model. *Transportation Research Forum, 47,* 133–138.

Gritta, R. D., Wang, M., Davalos, S., & Chow, G. (2000). Forecasting small air carrier bankruptcies using a neural network approach. *Journal of Financial Management and Analysis, 13,* 44–49.

Groden, C. (2015, July 23). These cities have lost the most flights. *Fortune.* Retrieved from http://fortune.com/2015/07/23/fewer-flights-airline-consolidation/.

Gudmundsson, S. (1999). Airline failure and distress prediction: a comparison of quantitative and qualitative models. *Transportation Research, Part E, 35,* 155–182.

Gudmundsson, S. (2002). Airline distress prediction using non-financial indicators. *Journal of Air Transportation, 7,* 3–24.

Gu, Z. (2002). Analyzing bankruptcy in the restaurant industry: A multiple discriminant model. *Hospitality Management, 21,* 25–42.

Gu, Z., & Gao, L. (2000). A multivariate model for predicting business failures of hospitality firms. *Tourism and Hospitality Research, 2,* 37–49.

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis (7th* ed.*).* Englewood Cliffs, NJ: Pearson.

Jayanti, R. K., & Jayanti, S. V. (2011). Effects of airline bankruptcies: An event study. *Journal of Services Marketing, 25,* 399–409.

Kim, H., & Gu, Z. (2006a). Predicting restaurant bankruptcy: A logit model in comparison with a discriminant model. *Journal of Hospitality and Tourism Research, 30,* 474–493.

Kim, H., & Gu, Z. (2006b). A logistic regression analysis for predicting bankruptcy in the hospitality industry. *Journal of Hospitality Financial Management, 14,* 17–34.

Kim, S. Y. (2011). Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis. *Service Industries Journal, 31,* 441–468.

Kroeze, C., & Mayer, K. (2006, October). *Predicting airline corporate bankruptcies using a modified Altman z-score model.* Paper presented at the EuroCHRIE Conference, Thessaloniki, Greece.

La Monica, P. (2017, January 5). Warren Buffett's big bet on airlines flies high. *CNN.* Retrieved from http://money.cnn.com/2017/01/05/investing/airlines-warren-buffett/index.html.

Neuman, S. (2011, November 29). Is bankruptcy "business as usual" for airlines? *NPR.* Retrieved from http://www.npr.org/2011/11/29/142909836/is-bankruptcy-business-as-usual-for-airlines.

Patterson, D. W. (2001). *Bankruptcy prediction: A model for the casino industry* (Doctoral dissertation), University of Nevada, Las Vegas.

SAS Institute, Inc. (2017). *Using Holdout Samples.* Retrieved from http://support.sas.com.

Scaggs, M., & Crawford, P. (1986). Altman's corporate bankruptcy model revisited: Can airline bankruptcy be predicted? *Review of Regional Economics and Business, 11,* 11–17.

Schmidgall, R. S. (2011). *Hospitality industry managerial accounting* (*7th ed.*). Washington, DC: American Hotel and Lodging Educational Institute.

Securities Exchange Commission. (2018). *Edgar company filings database.* Retrieved from https://www.sec.gov/edgar/searchedgar/companysearch.html

Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics* (*6th ed.*). Upper Saddle River, NJ: Pearson.

United Airlines. (2003). *2002 annual report.* Retrieved from www.united.com/ual/en/us/.

Youn, H., & Gu, Z. (2010). Predicting Korean lodging failures: An artificial neural network model along with a logistic regression model. *International Journal of Hospitality Management, 29,* 120–127.