2012

Nonstatistical Factors Influencing Predictions of Financial Distress and Managerial Implications in the All-Cargo Airline Industry

Robert O. Walton
Embry-Riddle Aeronautical University, waltonr@erau.edu

Nonstatistical Factors Influencing Predictions of Financial Distress and Managerial Implications in the All-Cargo Airline Industry

Dissertation

Submitted to Northcentral University

Graduate Faculty of the School of Business
in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY IN BUSINESS ADMINISTRATION

by

ROBERT O. WALTON

Prescott Valley, Arizona
March 2012

APPROVAL PAGE

Nonstatistical Factors Influencing Predictions of Financial Distress and Managerial Implications in the All-Cargo Airline Industry

by

Robert O. Walton

Approved by:

3/20/12

Chair: Lawrence Ness, Ph.D. Date

Member: Steven Munkeby, D.M.

Member: Thomas Schaefer, D.B.A.

Certified by:

3/29/12

School Dean: Arthur Lee Smith, Ph.D. Date

Abstract

All-cargo airlines carry over 50% of global airfreight, yet they are prone to bankruptcy. Many financial models are designed to predict a firms' financial health, but they do not assess many nonstatistical factors that influence the prediction capability of these models. In this study, qualitative grounded theory design was used to identify nonstatistical factors and explore how they influence bankruptcy prediction models in the all-cargo airline industry. In the first phase of the study, financial data from 2005 to 2009 for 17 all-cargo U.S. airlines were used to determine the bankruptcy prediction ability of the Kroeze financial bankruptcy model. A sample of six all-cargo airlines (ABX Air, Arrow Air, Atlas Air, Cargo 360, Gemini Air Cargo, and Kitty Hawk Air Cargo) were selected containing a mixture of airlines for which the Kroeze model correctly and incorrectly predicted bankruptcy. The sample was used as the starting point to explore the nonstatistical factors using grounded theory. Data were obtained on the six airlines from company annual reports, SEC 10K annual reports, reports from professional journals such as Air Transport Intelligence and Traffic World, news reports and company press releases. The data were coded and grouped into conceptual categories, which were used in theory generation to support the emerging theory. Six categories (management, risk, operations, competitive advantage, financial, and external factors) that relate to the financial stability of an all-cargo airline emerged during the research. Three themes emerged that may improve current quantitative bankruptcy prediction models. The three themes are airline fleet type, type of aircraft flown, and aircraft utilization. The three themes relate to the type, use, and make up of an airline’s fleet. These themes influence bankruptcy prediction model and should be incorporated into failure prediction models to

improve their overall accuracy. Future research should be conducted to verify these findings on a larger population, such as all-cargo airlines that operate outside the United States. These airlines operate under different financial regimes that may affect the prediction models differently.

Acknowledgments

There are many people who have helped me along my path to the completion of this pinnacle moment. I wish to thank my wife, Petra, and daughter, Kinga, for their support over the last 5 years while I completed my doctoral studies and the lost family time while I spent many nights and weekends closed up in my office studying. I wish to also thank my parents for giving me the bug for higher education, and last but not least to my son Reese. I wish to give thanks to Dr. Mike Politano, mentor and friend, and Dr. Indra Sinka who guided me thorough the methodology pit falls. Drs. Schaefer and Munkeby, my dissertation committee, both of whom held me to a high standard and provided great advice for this successful journey; my initial chair, Dr. Phil Bos, who took my frustrated phone calls and kept me moving in the right direction, and Dr. Lonny Ness, who shepherded me through to completion.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Within the air-cargo industry, two main types of firms carry air cargo: passenger airlines that carry cargo in the lower cargo hold of passenger aircraft and dedicated cargo-only airlines that operate freighter aircraft. Examples of all-cargo airlines include Arrow Air, Lynden Air Cargo Airlines, and Northern Air Cargo. Such airlines carry over 50% of the global airfreight. The demand for the carriage of air cargo can fluctuate by 15% to 20% within a year (Hellermann, 2006). This fluctuation is driven by the global economy, which drives world trade and the amount of cargo that needs to be carried (Boeing, 2009). The fast, secure transport provided by the air-cargo industry is important to just-in-time production operations and the transportation of perishable goods throughout the world and; therefore, the world economy (Becker & Dill, 2007; Hellermann, 2006). Like most of the aviation industry, the all-cargo airline industry operates on low margins and is prone to bankruptcy (Boeing, 2009; Kroeze, 2005; Ribbink, Hofer, & Dresner, 2009). Bankruptcy within the all-cargo airlines can reduce available capacity and affect the global economy.

Many financial models found in the literature can be used to predict the financial health of a firm, and several have been used on the passenger airline industry (Altman & Hotchkiss, 2006; Chung & Szenberg, 1996; Kroeze, 2005; Ribbink et al., 2009). The various bankruptcy prediction models typically use a combination of weighted financial ratios that provide a score used to predict bankruptcy (Kroeze, 2005); however, these statistical models do not consider nonstatistical factors that may influence their prediction capabilities (Gudmundsson, 2002). This research was used to explore the nonstatistical factors, which may include management, cultural factors, aircraft type, route selection, and market themes. All of these may influence the accuracy of the Kroeze K-Score, a published bankruptcy prediction model. The following sections include an outline of the problem to be addressed in this study, the goal for the study, the theoretical framework, the research questions, and finally an overview of the significance of the study.

Background

The all-cargo airline industry comprises a small group of airline companies that do not carry passengers, but instead, move cargo only. Air transport, highway, rail, maritime, and pipeline are the five modes of global transportation for goods. While all modes except pipeline can transport the same commodities, maritime and air are the only two that can support transoceanic freight transport. Maritime transport is typically used for the low-cost transport of goods, whereas airfreight has the benefit of speed, reliability, and security (Boeing, 2009; Button, 2010). Changes in world air-cargo traffic are linked to changes in the world gross domestic product (GDP); therefore, as the world economy expands, so does the demand for air transport (Boeing, 2009; Hellermann, 2006; International Air Transport Association [IATA], 2010a). Between 1987 and 1997, worldwide demand for the transport of air cargo grew at an average rate of 7.1% annually; however, this growth slowed after September 11, 2001, to an annual growth rate of 4.1% (Boeing, 2009; IATA, 2010a). After the terrorist attacks in the United States on September 11, 2001, the price of fuel increased, increasing the cost of air shipments and causing companies to migrate toward less expensive road, rail, and maritime transport (Boeing, 2009; IATA, 2010). The high costs of providing air transport and the weak economy have pushed many all-cargo airlines to the brink of bankruptcy (Hofer, Dresner, & Windle, 2009; IATA, 2010b).

Of the many financial modeling techniques used to predict bankruptcy, no agreement exists within academia or the financial industry on which is best (Hensher & Jones, 2007; Ribbink et al., 2009; Ward, 2007). Certain bankruptcy prediction models tend to work better than other models in certain industries, and most models need to be calibrated to specific industry groups (Kroeze, 2005). The Altman Z-score model has been used in bankruptcy prediction research since the late 1960s (McKee, 2007). Altman's Z-score model uses multiple discriminant analysis to determine bankruptcy potential and has been tested on numerous industries with positive results (Altman & Hotchkiss, 2006; Chung & Szenberg, 1996; Kroeze, 2005; Ribbink et al., 2009; Scaggs & Crawford, 1986). The Altman Z-score model was updated in 2006 as the Altman Z"-score to improve its prediction capability; however, the model must be adjusted to specific industries (Altman & Hotchkiss, 2006).

The Kroeze (2005) model (K-score) modified the Altman Z"-score model to improve the bankruptcy prediction performance for the passenger airline industry; however, the performance results of most statistical techniques used in failure prediction modeling provide similar results, and since there appears to be little "difference in the predictive abilities of statistical models, it is important to analyze the problems related to their use" (Ooghe, Spaenjers, & Vandermoere, 2009, p. 8). Youn and Gu (2010) supported Ooghe et al.'s (2009) assertion, indicating that future research on statistical financial modeling should explore nonstatistical variables (e.g., qualitative factors) to improve prediction accuracy. The Kroeze model has been used to predict bankruptcy in the passenger airline industry (Kroeze, 2005), but no literature was found to indicate that the Kroeze model has been used for bankruptcy prediction on the all-cargo airline industry nor, like other models, have qualitative factors been explored. This study attempted to explore qualitative factors influencing the effectiveness of the Kroeze K-Score bankruptcy prediction model for the all-cargo airline industry.

Problem Statement

The problem addressed in this study was the inability of published financial prediction models to account for the nonstatistical factors that negatively influence bankruptcy prediction in the all-cargo airline industry (Kroeze, 2005; Ooghe et al., 2009; Ribbink et al., 2009; Wetter & Wennberg, 2009; Youn & Gu, 2010). Although financial measurements are used to calculate the health of a company, there are many nonstatistical factors influencing the fiscal viability of the company. Most, if not all, of the prediction models fail to account for these factors. This research was used to identify and enumerate some of the nonstatistical factors influencing the reliability and validity of the Kroeze model (Kroeze, 2005).

The all-cargo airline industry is critical to the world economy because it provides fast, secure trade over long distances for shippers of high value and perishable goods and carries over 50% of global airfreight (Boeing, 2009; Hellermann, 2006; Jones & Hensher, 2005). The importance of air cargo and the impact of its loss were witnessed in April 2010 when a volcanic ash cloud shut most European airspace to flights; within days, companies started running out of parts and had to stop production lines (IATA, 2010b). Between 2005 and 2009, two of the 17 all-cargo airlines in the United States declared bankruptcy and liquidated, thus removing over 10% of the firms from the market (TranStats, 2010). In addition, bankruptcies can inflict major social and economic cost on the world economy (Jones & Hensher, 2005). Because of the significant economic and social cost associated with bankruptcies, the development of accurate financial distress forecasting techniques is important to financial institutions, users of the services, suppliers, employees, and governments (Jones & Hensher, 2005). A better understanding of the nonstatistical factors that lead to bankruptcy may provide airline management with the tools needed to make better management choices. A sizeable body of literature on financial distress prediction exists, but there is no agreement as to which modeling technique is best, and most existing models do not consider nonstatistical variables, which are needed to improve bankruptcy prediction (Hensher & Jones, 2007; Jones & Hensher, 2005; Ribbink et al., 2009; Ward, 2007). Of the sizeable body of financial distress literature, only a small portion focuses on the airline industry and even less specifically on the all-cargo industry (Hofer et al., 2009; Jones & Hensher, 2005).

Purpose

The purpose of this qualitative grounded theory research was to explore the nonstatistical factors influencing the accuracy of the Kroeze K-Score bankruptcy prediction model for the all-cargo airline industry. Understanding the health of the all-cargo industry is essential to government, lenders to the industry, academics, and investors in air-cargo companies (Jones & Hensher, 2005). A grounded theory research strategy was used to explore nonstatistical factors that confound the Kroeze model and consequently make the model unreliable. The total population of all-cargo airlines in the United States between 2005 and 2009 was 17 carriers (TranStats, 2010); however, grounded theory design does not start with a specific sample, but instead, draws on concepts and their properties and differences (Corbin & Strauss, 1990). With the application of emergent theory, the research identified some of the factors necessary to predict potential bankruptcy in the all-cargo industry more accurately.

Theoretical Framework

The theoretical framework for this research is based on both theoretical and applied material. The prediction of bankruptcy using financial ratios was first developed in the United States at the turn of the 20th century (Altman, 1967). Aided by the development of computers, Altman (1967) was one of the earliest researchers to use multiple discriminant analysis (MDA) to examine corporate bankruptcy (McKee, 2007). Since Altman's 1967 seminal work, a number of other researchers (Chung & Szenberg, 1996; Hofer at al., 2009; Kroeze, 2005; Ribbink et al., 2009; Scaggs & Crawford, 1986) have examined the use of MDA in bankruptcy prediction specifically in the passenger airline industry. Most recently, Kroeze (2005) altered the Altman Z-score model to improve the prediction ability specifically for the passenger airline industry. Most of the researchers reported a positive relationship between the various models' bankruptcy prediction and actual bankruptcy events.

The neural networks (NN) approach may also be used to assess airline financial performance. While some research has shown a positive outcome for NN (Gritta, Wang, Davalos, & Chow, 2000), the complexity of the statistical methodology involved in an NN approach limits its utility to individual investors, airline management, and other stakeholders (Kroeze, 2005). Overall, past airline bankruptcy prediction models have "not improved the understanding of failure processes much, but rather improved the statistical methodology" (Gudmundsson, 2002, p. 21). The next step in the improvement of a statistically based approach is to understand the nonstatistical variables that affect the existing models (Ooghe et al., 2009; Youn & Gu, 2010).

The use of nonstatistical variables in bankruptcy prediction has been marginally examined (Gudmundsson, 2002, Kim & Han, 2003, Ooghe et al., 2009, Sun & Li, 2007, Youn & Gu, 2010). Past research on nonstatistical variables have primarily focused on attempting to quantify qualitative variables and force them into a prediction model (Gudmundsson, 2002, Ooghe et al., 2009). However, past research has not attempted to develop a comprehensive list of the nonstatistical variables that affect bankruptcy prediction models (Gudmundsson, 2002). This research extended Kroeze's (2005) work and provided a better understanding of the nonstatistical factors as advocated by Ooghe at al. (2009) and Young and Gu (2010).

The grounded theory method was selected as the most appropriate research methodology to explore the qualitative factors that may influence quantitative bankruptcy protection models. Grounded theory attempts to generate new theory directly from the data, as opposed to testing an existing theory (Birks & Mills, 2011). The use of grounded theory is rooted in social and behavioral science research; however, it is increasingly being used to conduct research in other fields (Birks & Mills, 2011). Grounded theory merges positivism and pragmatism into a systematic research approach in which constant comparative analysis is used to build categories that are then used to explain processes associated with the phenomena (Birks & Mills, 2011, Charmaz, 2006). Grounded theory enables the researcher to take a fresh look at a problem and not be bound by preconceived notions and past research (Birks & Mills, 2011).

Research Questions

Using grounded theory design the objective of this research was to discover and specify the nonstatistical influences that affect the accuracy of the Kroeze prediction model in predicting bankruptcy of all-cargo airlines. The intent of grounded theory is to explain the phenomenon in the research question using constant comparative analysis (Glaser & Strauss, 1967). Grounded theory is used to generate new theory directly from data, not test existing theory (Birks & Mills, 2011). To address the purpose of the study, the following research question was explored:

Q1. What nonstatistical factors influence the K-Score bankruptcy prediction models in the all-cargo airline industry?

Nature of the Study

The research design was a qualitative grounded theory study on nonstatistical factors that influence the prediction accuracy of bankruptcy prediction models in the all-cargo airlines. In this study, the researcher examined the Kroeze K-Score bankruptcy prediction model and the qualitative factors that influence the model. The grounded theory approach revealed nonstatistical factors affecting the bankruptcy prediction accuracy of the Kroeze model in U.S.-based all-cargo airlines. This research builds on the work of Scaggs and Crawford (1986), Kroeze (2005), Hofer et al. (2009), and others to improve bankruptcy prediction, specifically to the all-cargo airlines bankruptcy prediction, which is lacking in the literature.

The findings and conclusions reached by this researcher provide a better understanding of the Kroeze K-Score bankruptcy prediction model and the model's use within the all-cargo airline industry. Historical financial data from all-cargo companies was used as the input data for the Kroeze model to determine the model's accuracy. The financial data were obtained via data mining of specific financial data from the U.S. Department of Transportation (DOT), U.S. Bureau of Transportation Statistics, and Research and Innovative Technology Administration (RITA) database, also known as TranStats. Data from the period of 2005 to 2009 were inserted into the Kroeze K-score model and the results compared to actual bankruptcy events within the industry. The starting year for the data of 2005 was chosen to avoid the turmoil in the aviation industry after the terrorist attacks of September 2001, and 2009 was the most current data available at the start of this research. The results provided a baseline from which to explore issues and features that influence the accuracy of the model. The data for the grounded theory research were obtained from a multitude of sources, such as scholarly articles, industry related magazines, technical papers, books, government publications, company and industry literature, and websites (Birks & Mills, 2011; Corbin & Strauss, 1990).

Significance of the Study

Understanding the health of the all-cargo industry is important to governments, lenders to the industry, academics, and investors in air-cargo companies (Boeing, 2009). Additionally, auditors require a bankruptcy risk model as part of their due diligence responsibilities (McKee, 2007). The transport of cargo by air is an important part of the global supply chain. Air cargo provides the ability to transport finished and unfinished goods quickly to factories dispersed around the globe and to satisfy market demand for goods produced great distances from their markets (IATA, 2010a). Additionally, the transport by air of perishable goods allows producers to supply flowers and fresh fruit out of season throughout the world (Becker & Dill, 2007; Hellermann, 2006). The health of the air-cargo industry can have a direct impact on the ability to transport goods by air effectively and; therefore, can directly affect the supply chain and the world economy (Boeing, 2009; IATA, 2010a).

This study examined the nonstatistical factors that influenced the Kroeze K-score bankruptcy prediction model, which is a variation of the Altman Z-score, a widely used bankruptcy prediction model (Wetter & Wennberg, 2009). The Kroeze K-score model has an advantage over the Altman model because it has been specifically calibrated to the aviation industry (Kroeze, 2005). This research provides insight into the nonstatistical factors that influence not only the Kroeze model, but could also affect any model based on the Altman Z-score. This grounded theory research adds to the body of literature in two ways. First, the research extends the literature on the financial modeling of firms and provides another tool to determine the financial health of a company. Second, this research adds to the body of airline-specific papers and provides all-cargo airline management with a tool to help identify nonstatistical issues affecting the financial health of the company, which may allow management to alter decisions to improve a firm's financial situation.

Definitions

Below is a list of terms germane to this study.

All-cargo airlines. All-cargo airlines are airlines that specialize in transporting only freight (Wensveen, 2007).

Altman Z"-score. The Altman Z"-score is an updated Altman Z-score bankruptcy prediction model of the form Z" = 6.56(X1) + 3.26(X2) + 6.72(X3) +

1.05(X4) + 3.25. In the Z"-score model, X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = operating income/total assets, and X4 = book value of equity/total liabilities (Altman & Hotchkiss, 2006).

Bankruptcy. Bankruptcy occurs with a firm's declaration of bankruptcy to a judicial organization, normally when a firm's total liabilities exceed the value of its total assets (Altman & Hotchkiss, 2006).

Book value of equity. Book value of equity is total assets over total liabilities, sometimes referred to as net assets (Stickney & Weil, 2000).

Cargo aircraft. Cargo aircraft are aircraft built or converted to carry only freight (Wensveen, 2007).

Cargo revenue ton-miles. Cargo revenue ton-mile is a measure of efficiency in the air-cargo industry calculated as revenue-generating cargo times the miles transported, which can also be shown as revenue ton-kilometers (RTKs) (Wensveen, 2007).

Default. Default occurs when a firm violates a condition of an agreement with a creditor, such as missing a scheduled loan or bond payment (Altman & Hotchkiss, 2006).

Distressed. Distressed firms are firms that have had consecutive financial losses, but are not necessarily bankrupt (Ward, 2007). Most bankruptcy models predict financial distress in a firm (Altman & Hotchkiss, 2006; Gritta & Lippman, 2010).

Failure. Failure occurs when the realized rate of return on capital is lower than prevailing rates on similar investments (Altman & Hotchkiss, 2006).

Freight tonnes-kilometers (FTKs). Freight tonnes-kilometer is an efficiency measurement in the air-cargo industry calculated as total freight tonnes carried times the total number of kilometers flown (e.g., one tonne of cargo carried one kilometer)(Boeing, 2010).

Insolvency. Insolvency occurs when a firm cannot meet its current obligations, possibly leading to bankruptcy if the obligations cannot be covered in the short term (Altman & Hotchkiss, 2006).

Kroeze K-score. The Kroeze K-Score bankruptcy prediction model is based on the Altman Z”-score model, altered to improve the bankruptcy prediction capability in the passenger airline industry. The Kroeze K-Score model is of the form $K = .268(X1) + .838(X2) + .111(X3) + \acute{\varepsilon}$, where X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = book value of equity/total liabilities, $\acute{\varepsilon}$ = error term, and K = overall index (Kroeze, 2005).

Operating income. Operating income is the profit realized from a business operation, excluding operating expenses and depreciation from gross income (“Operating Income,” 2010). Operating income is also known as *operating profit* and is calculated as gross income minus operating expenses minus depreciation (“Operating Income,” 2010).

Retained earnings. Retained earnings score is calculated as the net income over the life of a firm, less all dividends. Retained earnings can also be stated as the owners’ equity less capital invested (Stickney & Weil, 2000).

Total assets. Total assets are the total items a firm owns, normally identified as current or fixed, current being items that will be consumed within 1 year. Fixed assets are expected to provide benefits for more than 1 year, such as buildings or airplanes (“Total Assets,” 2010).

Total liabilities. Total liabilities of a firm are the total debts or obligations, such as accounts payable, accrued liabilities, and other debts ("Total Liabilities," 2010).

Working capital. Working capital is calculated as the current assets minus current liabilities. Working capital is also called net working capital or net current assets (Stickney & Weil, 2000).

Summary

All-cargo airlines are an integral part of the global supply chain, and their financial health is important to maintaining an efficient supply chain (Boeing, 2009; Hellermann, 2006). Cargo airlines tend to operate on low margins and are affected by economic cycles, so they are prone to bankruptcy (Boeing, 2009; Hofer et al., 2009; Kroeze, 2005). Because of the significant economic cost associated with bankruptcies and the loss of air-cargo carrying capacity, the development of an accurate financial distress forecasting model is important to financial institutions, users of the services, suppliers, employees, and governments (Jones & Hensher, 2005).

Using grounded theory, this research was used to explore a popular bankruptcy prediction model to determine external factors that may influence the model's prediction ability in all-cargo airlines. This research expands on the work of Altman and Hotchkiss (2006), Kroeze (2005), Hofer et al. (2009), Scaggs and Crawford (1986), and others in relation to the financial modeling of firms and specifically to the all-cargo airline industry.

Chapter 2: Literature Review

A review of the literature reveals the need for modifications to existing bankruptcy prediction models for the all-cargo airline industry that explore nonstatistical factors. The use of multiple discriminant analysis (MDA) and neural networks (NN) for predicting financial distress in firms dominates the literature (Altman, 1968; Altman & Hotchkiss, 2006; Gritta et al., 2000; Kroeze, 2005; Scaggs & Crawford, 1986); however, statistical models have major limitations because they do not consider nonstatistical factors influencing the financial health of a company (Ooghe et al., 2009; Wetter & Wennberg, 2009). Examples of some of these nonstatistical factors may include airline management, cultural themes, and the type of aircraft and route structure the airline uses.

This literature review is organized by the following themes. In the first section, the nature of bankruptcy is discussed and a baseline understanding of bankruptcy is provided. In the second section, the air-cargo industry, industry economics, fleet management, air-cargo revenue management, and the difficulties related to revenue management within the industry are discussed. In the third section, an overview of the current state of predicting financial distress is provided as well as a review of Hofer et al.'s study (2009) that examined the extent to which an airline's financial distress affects pricing behavior is discussed. The fourth and most extensive section is a detailed description of some of the financial models found in the literature, which is needed to understand how the models work and how qualitative factors may affect the models. Altman's (1968) seminal research using MDA to predict financial distress was explored as well as the adjusted Kroeze K-Score model. In addition, the use of NN by Gritta, Adrangi, Adams, and Tatyanina (2008) for predicting financial distress in firms is reviewed. The use of statistical methods are limited in bankruptcy prediction so the fifth section contains a discussion of nonstatistical factors that may affect a model's prediction capability, which may include management, cultural factors, and choices in aircraft and routes (Gudmundsson, 2002; Ooghe et al., 2009). The final section provides an overview of the development of grounded theory from Glaser and Strauss (1967) to current literature on the use of grounded theory by Charmaz (2006) and Birks and Mills (2011).

Nature of Bankruptcy

The word *bankruptcy* originated from the Latin, meaning *broken bench* (Beraho, 2010). In Latin, *bancus*is a tradesman's bench where Roman moneylenders conducted their trade, and *ruptus* means *rotten* or *broken;* thus, these two words combined mean a place of business that is rotten or broken (Beraho, 2010). While bankruptcy as a legal recourse has been in place for over 2,000 years, the first authoritative bankruptcy laws were developed in 16th century England (Beraho, 2010). At that time, bankruptcy was considered a criminal offense, but today bankruptcy is based on prevention or corporate reorganizations (Beraho, 2010).

Legal bankruptcy results from a legal judgment in which a creditor has filed a petition against a debtor, or a debtor has voluntarily filed a petition of insolvency (Beraho, 2010). Jones and Hensher (2005) noted that bankruptcy could inflict a major economic and social cost on the economy. Ward (2007) echoed Jones and Hensher stating that "bankruptcy is a legal event and not an economic event" (p. 95). Bankruptcy usually occurs when a company declares a state of bankruptcy to a judicial organization, normally when a company's total liabilities exceed the value of its total assets (Altman & Hotchkiss, 2006); therefore, the total net worth of the company is negative and often leads to an attempt to reorganize the company under the legal protection of the court system or the total liquidation of the remaining assets (Altman & Hotchkiss, 2006). While liquidation may occur after a formal declaration of bankruptcy, the intent of modern bankruptcy laws is for the rehabilitation of the firm. In a bankruptcy, the firm is given the opportunity, under protection of the courts from debtors, to reorganize, remain viable, preserve employment opportunities, and retain whatever goodwill it still possesses (Altman & Hotchkiss, 2006; Beraho, 2010). A firm having an economic value greater than its liquidation value is a candidate for reorganization, but if the firm's economic value is less than its liquidation value, then liquidation is generally the best alternative (Altman & Hotchkiss, 2006).

Formal bankruptcy protection helps the economy by protecting businesses from devastating financial adversity (Beraho, 2010); however, Hofer et al. (2009) stated that current U.S. bankruptcy laws are intended for the dumbest competitor and undermines responsible management and calls for bankruptcy laws that are aimed at rewarding success and punishing failure. “Financially distressed and bankrupt firms sell at lower prices than their healthier competitors” (Hofer et al., 2009, p. 239) and; therefore, cause a negative economic impact on the industry.

Before a firm enters formal bankruptcy protection or moves straight to the liquidation process, the firm typically moves through a continuum of financial distress that may change from day to day (Ward, 2007). According to Ward, financial distress occurs when a company has had consecutive losses, but is not necessarily bankrupt; therefore, financial distress is an economic situation, but not necessarily a legal event; the legal recognition of bankruptcy can occur whether or not a firm is economically insolvent

(Ward, 2007). While the terms *failure*, *insolvency*, and *bankruptcy* are all terms of financial distress, they are often used interchangeably in the literature; however, they are distinct (Altman & Hotchkiss, 2006).

Goldratt and Cox (2004) noted that the goal of a business is to make money. Financial failure occurs when the realized rate of return on capital is lower than prevailing rates on similar investments, so again, like financial distress, failure is an economic event (Altman & Hotchkiss, 2006). Failure only occurs with a formal declaration of bankruptcy before the courts. Since failure is an economic situation, it may not lead to discontinuance of the firm; in fact, some firms may be in a status of failure for many years without failing because the firm meets its current obligations (Altman & Hotchkiss, 2006). Normally, in the case of a failure in which the company sustains for some extended period, the decision to stay operational is based on the expected future returns (Altman & Hotchkiss, 2006). The aviation industry is a classic example of an industry that operates in a constant state of failure (Hofer et al., 2009). As a whole, the aviation industry often operates close to the realm of failure and often slips in and out of bankruptcy protection (Hofer et al., 2009; Ribbink et al., 2009; Vasigh, Fleming, & Tacker, 2008).

Insolvency occurs when a firm cannot meet its current obligations, normally due to a lack of liquidity (Altman & Hotchkiss, 2006). Insolvency can be a temporary condition, but can also possibly, though not necessarily, lead to bankruptcy if obligations cannot be covered (Altman & Hotchkiss, 2006). Insolvency is often the cause of a formal bankruptcy filing (Altman & Hotchkiss, 2006).

There are many reasons why a firm may fail, but it normally comes down to negative cash flow. While management failure is normally the core reason firms fail, there are often several contributing factors (Altman & Hotchkiss, 2006; Hofer et al., 2009). Altman and Hotchkiss listed reasons that firms fail that are germane to the aviation industry. The first reason is that the aviation industry is considered a chronically sick industry; that is, the industry operates on low margins and is in a constant state of failure (Guzhva, 2008; Hofer et al., 2009; Vasigh et al., 2008). The second reason is that the deregulation of the aviation industry in the late 1970s removed the protective cover of government regulation and its artificial price controls (Altman & Hotchkiss, 2006; Chung & Szenberg, 1996; Vasigh et al., 2008). The third reason is overcapacity. During the 1990s, rising demand for air-cargo transport due to the expanding economy resulted in air-cargo carriers' adding capacity (Hellermann, 2006); however, since the events of September 11, 2001, and the economic downturn in the second half of the first decade of 2000, the aviation industry has been forced to reduce capacity to the determent of passenger service and availability of cargo space for cargo operators (Becker & Dill, 2007; Bisignani, 2006; Guzhva, 2008; Hellermann, 2006; Hofer et al., 2009; Vasigh et al., 2008). Capacity; however, is difficult to alter because it must be adjusted in relatively large increments (Hellermann, 2006). For example, adding one freighter to a cargo company’s fleet could increase the total capacity by 5%-20%, depending on the size of the existing fleet (Hellermann, 2006). Lastly, a reason for aviation's high rate of failure is that the aviation industry is highly leveraged with high fixed and labor costs (Bisignani, 2006; Vasigh et al., 2008).

Air-Cargo Industry

Sir Richard Branson, founder of Virgin Atlantic Airways, summed up the aviation business: “If you want to be a millionaire, start with a billion dollars and open an airline. Soon enough you will be a millionaire” (Vasigh et al., 2008, p. 1).

Three types of aviation companies that deal with the transport of air cargo exist: (a) the integrators, also known as express carriers; (b) combination carriers, which are passenger airlines that offer lower deck or belly cargo space for the transport of cargo; and (c) the pure all-cargo air carriers (Hellermann, 2006; Wensveen, 2007). The integrators, such as UPS, Federal Express, and DHL provide door-to-door transport as a packaged or integrated service (Hellermann, 2006; Wensveen, 2007). Integrators typically own or control the entire supply chain from the pickup and delivery trucks, sorting facility, and air assets and focus on the transportation of small packages, normally less than 100 pounds (Hellermann, 2006). The combination carriers are passenger airlines that offer belly cargo space for the transport of cargo. Combination carriers typically offer point-to-point air transportation for cargo and rely on freight forwarders for pickup and delivery service (Wensveen, 2007). About half of all air cargo moved is via belly space on passenger airlines, where a large majority of this supply is driven by unrelated market demand, the demand for air passenger transport in this case (Hellermann, 2006). Belly cargo is a co-product of passenger service, so the combination carriers have a lower marginal cost and; therefore, can offer the service more cheaply than the integrators (Wensveen, 2007). The third type of air-cargo carrier is the pure all-cargo carrier. All-cargo carriers operate dedicated freighter aircraft and do not service the passenger market. All-cargo carriers tend to deal with a small client base with most of the client base comprising freight forwarders that normally make large bookings (Becker & Dill, 2007, Hellermann, 2006). Freight forwarders or *intermediaries* consolidate multiple smaller shipments from various clients into larger shipments, effectively buying cargo slots on aircraft wholesale and reselling retail to smaller shippers (Hellermann, 2006). Freight forwarders conclude long-term contacts with all-cargo carriers to gain lower purchasing prices, guarantee slots, and hedge against price fluctuation (Hellermann, 2006). Except for the express carriers, the extensive use of freight forwards essentially makes the air-cargo market a business-to-business (B2B) service (Hellermann, 2006). Figure 1 depicts the typical air-cargo supply chain.

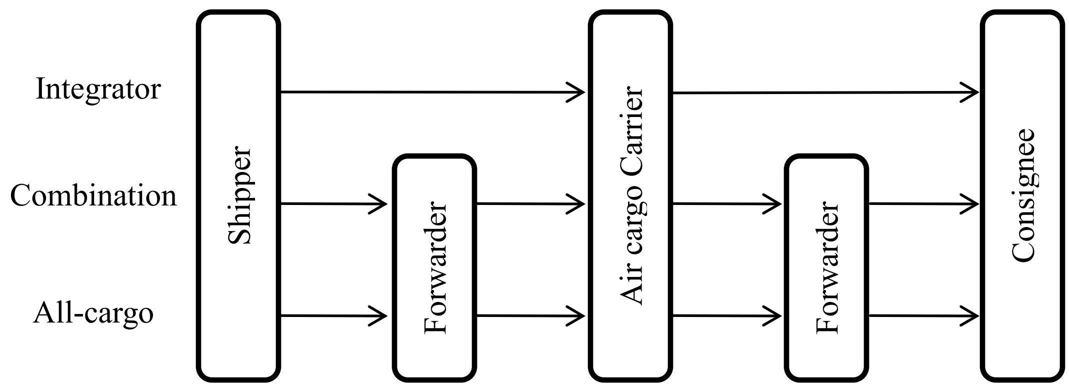

Figure 1. Simplified diagram of the air-cargo supply chain. Adapted from "Capacity Options for Revenue Management: Theory and Applications in the Air Cargo Industry," by R. Hellermann, 2006, p. 6. Copyright 2006 by Springer-Verlag Heidelberg, Germany. Used with permission.

A number of small operators owning only a few aircraft dominate the air-cargo industry. No definitive list of all of the world's all-cargo airlines from any source was available. The most definitive list of U.S.-active, all-cargo airlines was adapted from the U.S. Department of Transportation, Research and Innovative Technology Administration (RITA) TranStats database (see Appendix A).

According to Wensveen (2007), senior management of passenger airlines considers freighter aircraft as unprofitable and a poor investment, especially when compared to the cargo carried in the belly of passenger aircraft (Wensveen, 2007). Part of the senior airline managers may be due to the passenger-centric focus of the passenger airlines (Becker & Dill, 2007); however, some of the combination carriers make one third to one-half of their gross revenues from belly cargo (Wensveen, 2007). The problem with the shipment of cargo by passenger aircraft is that capacity is uncertain until near departure time because capacity is dependent on the number of passengers and the volume and weight of their baggage (Becker & Dill, 2007; Hellermann, 2006). Additionally, since one of the advantages of transportation by air is speed, urgent or perishable cargo dominates the market (Becker & Dill, 2007). This need for speed means that often the demand for air-cargo carriage is generated on short notice (Becker & Dill, 2007). The delay in booking hinders the air-cargo industry from maximizing its revenue management system. More details on revenue management will be discussed in the air-cargo revenue management section later in this chapter.

Table 1 provides a ranking of the top 10 cargo airlines by freight tonne-kilometers (FTK). *Freight tonne-kilometers* is an efficiency measure in the air-cargo industry and is calculated as total freight tonnes carried times the total number of kilometers flown (e.g., one tonne of cargo carried one kilometer; Boeing, 2010). Table 1 lists two of the integrator airlines (Federal Express and UPS), but only one all-cargo carrier, Cargolux, in the top ten airlines by FTKs. The remaining operators are passenger airlines that supply belly space and, counter to Wensveen's (2007) assertion that airline management does not consider freighter profitable, they all also operate dedicated freighter aircraft. The table also confirms that the all-cargo industry comprises many smaller all-cargo carriers with no dominant players, since only one all-cargo airline, Cargolux, is in the top 10, and none of the U.S. all-cargo airlines is present on the list (see Appendix A).

Table 1

Top 10 Scheduled Airlines Ranked by Freight Tonne-Kilometers Carried for year 2010

Rank	Airline	Millions of FTKs	Industry sector
1	Korean Air	8,225	Combination and freighters
2	Cathay Pacific Airways	7,722	Combination and freighters
3	Lufthansa	6,660	Combination and freighters
4	Singapore Airlines	6,455	Combination and freighters
5	Emirates	6,369	Combination and freighters
6	Federal Express	5,808	Integrator
7	China Airlines	4,903	Combination and freighter
8	Air France	4,672	Combination and freighter
9	Cargolux	4,652	All-cargo
10	UPS Airlines	4,652	Integrator

Note. Data obtained from "Top 50 Airlines,"*AirCargoWorld.com*, September 2010 and "World Air Transport Statistics," IATA 2010b.

According to Boeing (2010), in 2009 there were 1,755 freighter aircraft in operation worldwide. Of these, 37% were standard-body aircraft with a carrying capacity of less than 45 tonnes (e.g., DC-9, A320) while 36% of the fleet were medium wide-body aircraft that carry between 40 and 80 tonnes (e.g., B777, A330, IL-76), and the remaining 27% were large wide-body aircraft that carry in excess of 80 tonnes (e.g., B747, MD-11, AN-124) (Boeing, 2009, 2010). The freighter aircraft fleet is projected to grow to almost

3,000 aircraft by 2029 with a shift to a larger percentage of wide-body aircraft according to the Boeing report (2010). Table 2 lists the most common freighters grouped into size categories used by cargo airlines.

Table 2

Freighter Fleet Grouped Into Size Categories

Standard-body (<45 tonnes)	Medium wide-body (40-80 tonnes)	Large (>80 tonnes)
BAe 146	B767	MD-11
DC-9	A300	B747
B737	A310	B777
B727	L-1011SF	A340-600SF
TU-204	DC-10	A350
B-707	B787	A380 (cargo version not in production)
DC-8	A330	IL-96T
B757-200	A340-300SF	AN-124
A320	B777-A SF	-
-	IL-76 TD	-

Note. Adapted from "World Air Cargo Forecast 2008-2009," by Boeing, 2009. Copyright 2009 by Boeing. Used with permission.

Of all of the freighter aircraft, the quintessential aircraft is the Boeing B747. Developed as the world's first jumbo jet, the Boeing B747 entered into commercial service in 1970; today, the freighter version provides over half of the world's total freighter capacity (Boeing, n.d., 2010; Wensveen, 2007). The newest version of the Boeing B747 freighter is the -8F model, which has a range of 4,390 nautical miles and can carry 140 tonnes of cargo (Boeing, n.d.). The retail price in 2008 of a Boeing B747-8 freighter was just over $300 million (Boeing, n.d.). After several years of production delays, Cargolux is slated to receive the first B747-8 freighter in late 2011 (Boeing, n.d.).

Company background. This section provides further background information for the six airlines that were selected as the sample for this study for analysis using grounded theory. In grounded theory, theoretical sampling provides direction for subsequent data collection in a process of constant comparative analysis. This study started with initial purposeful sampling of 17 U.S. all-cargo airlines, and from the 17 airlines, six were selected based on the results of the K-Score model. Data from the six selected all-cargo carriers were collected, analyzed, and compared using grounded theory methodology. This section provides an overview of each of the six all-cargo carriers that were selected.

ABX Air, Inc. Between 2005 and 2009, ABX Air, Inc. (ABX) provided scheduled and ad hoc charter air-cargo transportation along with package handling, warehousing, and line-haul trucking service to its main customer DHL Express (DHL) (ABX Air, 2006). In 2005, ABX operated a network of 19 logistical hubs for DHL in the United States. On a smaller scale, ABX offered aircraft, crew, maintenance, and insurance (ACMI) services, also known as wet leasing, for which ABX provided the aircraft, crew, maintenance, and insurance to a customer as well as selling aircraft parts, providing maintenance and repair services, and flight-training services (ABX Air, 2006). ABX was originally founded in 1980 as part of Airborne, Inc. and became an independent publicly traded company in August of 2003 as part of the breakup of Airborne and the subsequent merger between Airborne and DHL (ABX Air, 2006).

The ACMI and hub service agreement with DHL, their main customer in 2005, provided for a cost-plus pricing structure with a mark-up of 1.75%. In 2005, ABX operated a mixed fleet of 112 aircraft (Boeing 767, DC-8 and DC-9 aircraft) all manufactured prior to 1990, and some over 35 years old (ABX Air, 2006). Older aircraft have a higher operating cost due to limited parts inventories, higher fuel burn rates, and higher maintenance cost. On December 31, 2007, ABX merged with Capital Cargo

International Airlines and Air Transport International, and all three airlines became subsidiaries to the newly formed holding company Air Transport Services Group, Inc. (ATSG), a publicly traded holding company on the NASDAQ Stock Market (SEC, 2010). In 2008, DHL, ABX's main customer began to restructure its operations in the United States because of substantial financial losses and closed its U.S. operations in 2009 (SEC, 2010). ABX continued to operate international delivery services to the U.S. for DHL and entered into a lease of 13 Boeing 767 aircraft to DHL through 2017. At the end of 2009, ABX operated 62 aircraft (Boeing 767, Boeing 757, and DC-8s). This represents about a 45% reduction in the number of aircraft over the 2005 fleet size. For the five years included in this study, ABX Air had a negative K-score, indicating that the company was in financial distress during the entire study timeframe.

Arrow Air, Inc. Arrow Air was originally established in 1947 in California, and the company moved to Florida in 1964. Arrow Air is most famous for the December 1985 crash of Arrow Air Flight 1285 in Gander Newfoundland, killing 248 members of the U.S. Army's 101st Airborne Division, and 8 crewmembers. In January 2004, just prior to the 2005-2009 sample window of this study, Arrow Air Inc, (dba Arrow Cargo) filed for Chapter 11 bankruptcy protection, but emerged 6 months later in June 2004 after court approved restructuring (*South Florida Sun–Sentinel*, 2005). In 2004, Arrow operated the industry's largest fleet of DC-8 freighter aircraft, older aircraft with high fuel burn rates and more costly to maintain, and had 520 employees (*South Florida Sun–Sentinel*, 2005). By the next year, 2005, Arrow employed 750 people (*South Florida Sun–Sentinel*, 2005). After the 2004 restructuring, Arrow began to acquire larger, more fuel efficient DC-10 freighter aircraft and started to phase out the DC-8 fleet.

In 2008, MatlinPatterson Global Advisers acquired an 85% stake in Arrow Air and intended to increase the fleet of DC-10 freighter aircraft and finish the phase out of DC-8s (“MatlinPatterson Global Opportunities Partners,” 2008). MatlinPatterson specialized in distressed debt ownership of firms (Stempal, 2010). In 2008, Arrow operated 10 cargo aircraft (six DC-10s and four DC-8s) and served more than 3,500 customers, mainly in the United States, Central and South America, and the Caribbean (“MatlinPatterson Global Opportunities Partners,” 2008). By Midyear 2010; however, Arrow again entered Chapter 11, and the company was liquidated after failing to find a buyer, laying off its workforce of 540 employees (Stempal, 2010). Arrow Air emerged from Chapter 11 the year before this study’s period (2005-2009) and reentered Chapter 11 the year after this study window. During the five years that this researcher examined financial data, Arrow retained a negative K-score for the entire period, indicating ongoing financial distress.

Atlas Air Inc. Atlas Air was founded in 1992 and was a wholly owned subsidiary of Atlas Air Worldwide Holdings (AAWW), which also owns Polar Air Cargo. Atlas mainly operates in the ACMI cargo aircraft leasing market. Atlas typically provides an aircraft with crew, maintenance, and insurance and is paid a fixed hourly rate with other operating expenses such as fuel, landing fees, and ground handling being paid for by the customer; this type of arrangement is called a dry lease (Atlas Air, 2006). Atlas also operated in the Air Mobility Command (AMC) charter market, flying cargo under contract to the U.S. Military, although within AAWW, the majority of this business was flown by Polar Air. In January 2004, Atlas, along with its holding company and other subsidiaries, entered Chapter 11 bankruptcy protection, reorganized, and reemerged 6 months later in July 2004 (Atlas Air, 2006). This bankruptcy coincided with the bankruptcy and reemergence of Arrow Air. In 2005 Atlas was the sole service provider of the Boeing 747-400 freighter aircraft, so it had no direct competition in this market; however, Atlas also leased older, less fuel-efficient Boeing 747-200 freighters, which had more market competition (Atlas Air, 2006). The Boeing 747-400 had the best operating performance in the intercontinental airfreighter market at that time. As of 2005, Atlas operated a common fleet of 15 Boeing 747-400 freighters, which increased to 22 B747-400s by 2009 (Atlas Air, 2010). In 2009, the average age of Atlas's B747-400 aircraft was less than 20. Atlas emerged from Chapter 11 the year before this study's window, but retained a positive K-score value throughout the five years covered by this research.

Cargo 360, Inc and Southern Air Inc. Cargo 360 was established in 2006 and was based in Seattle, Washington. Oak Hill Capital Partners owned a majority of Cargo 360 from the beginning and acquired Southern Air in 2008. Oak Hill merged Cargo 360 into Southern Air in 2008 and established operations in Norwalk, Conn, operating a fleet of 13 Boeing 747-200s (Santiago, 2007). Cargo 360 provided ACMI services to the Pacific Rim mainly under contract with Korean Air Cargo. Southern Air offered ACMI and charter cargo services including AMC charter flights supporting the U.S. military. Cargo 360 operated for two years (2006-2007) during the years of this study before merging with Southern Air. For both of these years, Cargo 360 had a negative K-score value, indicating financial distress, which could be expected for a startup company. From 2005 to 2007 at the time of the merger, Southern had a positive K-score, which indicates no financial distress; however, from 2008 to the end of this study in 2009 (after the merger) Southern had a negative K-score, indicating financial distress possibly caused by the merger of the weaker Cargo 360.

Gemini Air Cargo Airways. Gemini Air Cargo was founded in 1995 and provided ACMI using DC-10 freighter aircraft and was based out of Dulles, Virginia. Gemini also provided international and domestic scheduled service to international air carriers, airfreight forwarders, and AMC. In 2006, Gemini operated seven DC-10 and four MD-11 freighter aircraft, servicing customers that included DHL, Air Canada, and FedEx (Boyd, 2006). As with many airlines, after the terrorist attacks on September 11, 2001, Gemini saw a downturn in business and went through an out of court financial restructuring in 2003 as Gemini started to receive increased business from AMC cargo: however, Gemini entered the formal Chapter 11 process in March 2006 after failing to comply with several financial covenants (Boyd, 2006). Gemini emerged four months later with fresh capital from Bayside Holdings (Boyd, 2006); however, this fresh capital did not help, and Gemini entered Chapter 11 in 2008 and ceased operations. For both years of data available during this study period (2005 and 2006), Gemini had a negative K-score, indicating financial distress, which proved to be true because Gemini entered Chapter 11 twice during the studies time period.

Kitty Hawk Air Cargo. Kitty Hawk Air Cargo was a cargo airline that was originally founded in 1989 and was based in Grapevine Texas. Kitty Hawk Air Cargo was a wholly-owned subsidiary of Kitty Hawk, Inc. Kitty Hawk Air Cargo mainly provided airfreight services, ACMI, and ad-hoc charter to a variety of customers (SEC, 2006). As of 2005, Kitty Hawk Air Cargo operated seven Boeing 737 freighter aircraft and 10 Boeing 727 freighters (SEC, 2006). Kitty Hawk Air Cargo serviced over 550 freight forwarders and logistic company customers in 2005, with the top 25 customers accounting for more than 65% of their scheduled freight revenue (SEC, 2006). Kitty Hawk employed 618 full and part-time employees in 2005. Kitty Hawk Air Cargo, along with its parent company Kitty Hawk, Inc. was under Chapter 11 bankruptcy protection from 2000 to 2002 when it emerged after reorganization; however, the firm slipped back into bankruptcy and liquidation in 2008. Kitty Hawk stated the reason for the failure was significant losses due to high fuel prices and weakness in demand for airfreight services. During the research window from 2005 to 2009, Kitty Hawk showed a positive K-score for the years 2005, 2006, and 2007, which incorrectly indicated a firm not in financial distress.

This section contained an outline of the air-cargo industry, the types of air carriers, key firms in the industry, and type of aircraft typically used and included some of the challenges faced by the air-cargo industry. Also included was background information of the six airlines that made-up the sample in this study. The next section will delve into the economics of air-cargo operations.

Industry Economics

“The aviation industry is capital intensive and highly leveraged” (Chung & Szenberg, 1996, p. 135), and the need to buy and operate expensive aircraft requires extensive financing (Boeing, n.d.). The airline industry’s debt load exceeds most industry averages. In fact, the ratio of long-term debt to total capitalization has been estimated at more than 50% (Boeing, n.d.; Chung & Szenberg, 1996; Hellermann, 2006; Kroeze, 2005). Because of the high capitalization of the aviation industry, the financial health of the industry is highly correlated with the global economy (Vasigh et al., 2008).

As debt loads increase from the purchase of expensive aircraft and high operating expenses, so does the likelihood of financial distress (Kroeze, 2005). Vasigh et al. (2008) noted that this financial distress was not surprising, as the aviation industry is highly related to economic growth; thus, the industry suffers when the economy stalls. Hellermann (2006) supported Vasigh et al. by stating that economic fluctuation affects air-cargo carriers in an amplified way. As the world's economy expands, so does the demand for the movement of air cargo. In 2009, fuel prices increased, putting additional financial pressure on the aviation industry (Boeing, 2009).

The air-cargo industry, like the passenger airline industry, is reactive to national and world economies (Chung & Szenberg, 1996). An expanding economy leads to increased production, which results in an increase in demand for air cargo. Table 3 shows the U.S. real gross domestic product (GDP) for the Years 2003-2009 and the growth of air-cargo traffic based on freight tonnes. World air-cargo demand tends to drop off quickly as the world economy begins to stall, but also tends to be an early indicator of economic recovery, as demand increases early in the economic upturn. This trend is evident in Table 3 in that the growth in air-cargo traffic peaked in 2006, whereas real GCP lags behind air-cargo traffic and starts to level in 2007 and decrease in 2009.

An economic downturn can quickly result in an overcapacity in the cargo airlines, and an upturning economy can quickly leave the industry with too little capacity. Obtaining a new aircraft requires a long lead-time, so airline companies attempt to time the purchase of aircraft to coincide with a predicted future upturn in the economy (Hellermann, 2006). If management gets it right, then the new aircraft arrive in time to meet the increase in demand as the economy heats up, but getting the timing wrong means that management is left with an expensive asset that cannot be fully utilized (Hellermann, 2006). For example, Cargolux was to receive their first new Boeing 747-8 freighter aircraft in 2009. At that time, there was overcapacity in the industry, not a good time to be adding capacity; however, due to production delays, Cargolux is currently not scheduled to receive their first B747-8F until the fall of 2011 (Boeing, n.d.). Because of under capacity in the industry in 2010, Cargolux had to lease two older aircraft that were more costly to operate aircraft to meet demand (Cargolux, 2010).

Table 3

U.S. Real Gross Domestic Product (GCP) From 2003-2009

Year	Change from preceding period in real GDP (%)	Real GDP (%) (Index 2005=100)	Growth in air-cargo traffic (%) (based on freight tonnes)
2003	2.5	93.69	-6.67
2004	3.6	97.04	9.95
2005	3.1	100.00	2.26
2006	2.7	102.67	5.85
2007	1.9	104.67	5.03
2008	0.0	104.67	-3.11
2009	-2.6	101.92	-8.89

Note. Source for GDP, Bureau of Economic Analysis, U.S. Department of Commerce. National Income and Product Account (NIPA) historical tables. Accessed 19 Jan 2011; Source for growth in air traffic was IATA Financial Forecast, December 2010.

One of the reasons why the aviation industry has financial difficulties and low profit margins is that demand fluctuates constantly, but supply is relatively fixed. This is true for both passenger and cargo airlines (Vasigh et al., 2008). This fluctuation in demand makes it hard to optimize the use of available capacity (Vasigh et al., 2008).

Yield or revenue management is the process the aviation industry uses in an attempt to level out the demand fluctuations (Hellermann, 2006; Vasigh et al., 2008). The next section of this chapter includes the fleet management procedures used by airlines when deciding what type of aircraft to use, a potentially important nonstatistical aspect influencing the accuracy of bankruptcy prediction.

Fleet Management

To achieve economies of scale, airlines prefer to operate a limited number of different types of aircraft (Fleming & Tacker, 2008; Vasigh et al., 2008). For example, Southwest Airlines only operates a common fleet of Boeing 737s, and Cargolux operates Boeing 747s (Cargolux, 2010; Vasigh et al., 2008). Fleet management is the planning process to determine the type and mix of aircraft to operate. Fleet planning is a cornerstone of airline operational efficiency and is essential for the medium- and long-term planning process and the long-term financial survivability of an airline (Flouris, 2010). Aircraft are an expensive asset, and because of the high change over cost (re-training of flight crews, maintenance crews, ground equipment, spare parts inventories), the introduction of a new fleet of aircraft takes times and is a strategic management decision (Flouris, 2010). Once purchased, a typical aircraft type may be used for 10-20 years by an airline (Flouris, 2010). Operating a common fleet has the advantage of increased operational flexibility, because it is easier to find replacement aircraft or flight crew in the event of irregular operations (Vasigh et al., 2008). Once the fleet mix is determined, strict air-cargo revenue management processes are needed.

Air-Cargo Revenue Management

The all-cargo airline business is capital intensive because of the need to own and maintain aircraft (Kroeze, 2005). The all-cargo airlines struggle for market share, operate on low margins, need high cash flow to stay solvent, and are heavily tied to economic cycles; thus, all-cargo airlines constantly live on the brink of bankruptcy (Boeing, 2009; Hofer et al., 2009; Kroeze, 2005).

The air-cargo industry differs from the passenger industry in that cargo is normally not booked round trip, so cargo flow is unpaired and often unbalanced. For example, there may be more demand for cargo moving in one direction than the other (Hellermann, 2006). This situation often requires cargo airlines to fly less-than-full aircraft on some routes. For example, an airline may have to fly a less-than-full aircraft to China and return with a full aircraft. Unlike passenger aircraft for which there is a fixed capacity (i.e., seats), cargo is multidimensional (volume and weight), so the load must be balanced and optimized by mixing cargo of different volumes and weights to maximize the load. Optimization of cargo loads requires in-depth planning, but some space can be sold twice ("e.g., to one customer with voluminous, light cargo and another with heavy-weight, high-density cargo"; Hellermann, 2006, p. 7). All-cargo airlines also differ from passenger airlines in routing possibilities. Cargo does not have to fly a direct route; the only constraint is the required delivery time (Hellermann, 2006).

Revenue management planning in the air-cargo business is much more difficult than in the passenger airline industry (Becker & Dill, 2007). Passenger airlines have a vast amount of historical booking data they use to determine demand and pricing on various routes, which the cargo airlines lack (Hellermann, 2006). Because of the differences between the supply and demand of the two airline industries, revenue management for cargo airlines is more complex than for passenger only airlines (Becker & Dill, 2007). The capacity supply issues include the following: (a) uncertainty of capacity offer, (b) multidimensional capacity, (c) heterogeneous production platforms, (d) large number of routing possibilities, and (e) restrictions, and multisegment flights (Becker & Dill, 2007). Meanwhile, market demand issues include stowage loss, unequal trade lanes, short booking periods, volatile business, continuous show-up rates, market structure, and data shortcomings (Becker & Dill, 2007). For cargo shipments, the capacity for cargo is unpredictable until close to the time of departure (Becker & Dill, 2007); that is, the weight or volume may fluctuate, taking up more or less room on the aircraft, unlike passenger airlines in which a seat is a seat. Another issue is market structure. Air-cargo airlines typically only provide capacity to a limited number of customers, such as freight forwarders, who make the most of the bookings (Hellermann, 2006); therefore, the loss of one booking can have a large impact on the revenue for that flight. Seasonal fluctuation can also affect air-cargo operations in the short term by leading to under capacity in the high season, such as the months leading up to the winter holidays, or overcapacity in the low season, such as after the holiday rush (Kroeze, 2005).

Thus far, this chapter has included the nature of bankruptcy in general and provided some background on the air-cargo industry, the economics factors that can affect the industry, and the use of revenue management within the industry. The next section of this chapter contains the use of various models to predict financial distress in a firm in general and specifically the use of these models in predicting financial distress in the aviation industry.

Predicting Financial Distress

Research on financial distress in a company has produced various models since the 1960s (McKee, 2007), but there is no agreement on the best methodology (Hensher & Jones, 2007; Ribbink et al., 2009; Ward, 2007). With the recent spate of highly publicized corporate failures, the need for management, investors, and other stakeholders to be able to predict impending financial distress has grown. As noted above, all-cargo airlines operate on low margins and need high cash flow to stay solvent (Boeing, 2009; Hofer et al., 2009; Kroeze, 2005). High fuel cost, high labor cost, and expensive fixed assets contribute to low-operating margins for air-cargo airlines and make them prone to bankruptcy (Boeing, 2009; Ribbink et al., 2009); however, the air-cargo industry is critical to the world economy because it provides fast, secure trade over long distances for shippers of high-value and perishable goods.

Financial distress is the circumstance in which the liquidation value of a firm's assets is less than the total face value of creditor claims (Chen, Weston, & Altman, 1995). During financial distress periods, airlines may file for Chapter 11 bankruptcy protection to obtain reductions in labor, leasing, and debt costs (Hofer et al., 2009). This move, in turn, may give the distressed firm a competitive edge. Because prior research had suggested distressed airlines lower their fares as they approached bankruptcy, Hofer et al. examined the extent to which an airline's financial distress affects pricing behavior. Hofer et al. used the Altman's Z"-score model to determine which airlines were in distress and then compared the level of financial distress to ticket prices. Hofer et al. found financially distressed firms tend to reduce prices. Airlines heading into Chapter 11 bankruptcy protection tended to reduce fares by an average of 5.6% within 90-180 days prior to filing for bankruptcy protection (Borenstein & Rose, 1995); however, even with reduced fares, firms that entered Chapter 11 tended to see a decline in market share on existing routes (Borenstein & Rose, 1995).

Financial Models

Bankruptcy financial models are used to predict the future financial health of a company. Many financial modeling techniques are available, but there is no agreement within academia or the financial industry on which model is best (Hensher & Jones, 2007; Ribbink et al., 2009; Ward, 2007). In fact, certain models tend to work better than others in certain industries, and most models need to be calibrated to specific industry groups (Kroeze, 2005). One of the more common financial bankruptcy models discussed in the literature is the Altman Z-score model developed by Altman in a 1967 dissertation and published in the *Journal of Finance* in 1968. This seminal work has been altered over the last 40 years by Altman (Altman & Hotchkiss, 2006) and others (Chung & Szenberg, 1996; Kroeze, 2005; Ribbink et al., 2009; Scaggs & Crawford, 1986) and tested on numerous companies.

Ward (2007) examined the construct validity of different financial models for predicting financial distress. Ward scrutinized three response variables, compared the stability of the results to determine their validity, and theorized that unstable response variables would indicate that they were measuring different constructs. Also posited was that previous studies had been dependent on the response variable used. A *financially distressed company* is defined as a firm that has consecutive losses, possibly indicating a cash flow problem, but not necessarily headed to bankruptcy (Altman & Hotchkiss, 2006). Ward (2007) observed that companies typically do not fall into a simple bankrupt or nonbankrupt status, but move through different degrees of financial distress that may vary from day to day, and bankruptcy is a legal event, not an economic matter. Even though bankruptcy may take on different degrees of distress, many of the current financial models provide only a black or white (bankrupt or not) result. The results of prior financial distress studies that used different measures of financial distress cannot be compared because they had different constructs (Ward, 2007).

Not all financial models need to be complicated. For example, Liu (2009) examined the link between an airline's financial condition and its probability of entering new markets. The model used for Liu's research focused on financially distressed airlines and not bankrupt firms, so only basic financial ratios were used instead of the bankruptcy models proposed by Altman (1968). Liu noted that a firm can be financially strong, but if faced with weak demand can quickly become economically distressed or can have strong demand, but be financially weak due to poor management. Liu's research also included nonfinancial variables, such as large hub and slot-controlled airports, which could be barriers for entry into new airport-pair markets. To limit congestion, slot-controlled airports ration the number of landings and take-offs an airline can do each day. Slot-controlled airports (i.e., in the United States, only Chicago O'Hare, Reagan National, New York LaGuardia, and New York Kennedy) tend to affect only passenger airlines; all-cargo airlines tend to stay away from these airports because of congestion and cost (Liu, 2009). Liu found that legacy carriers are less likely to enter new markets as the carriers leverage increases and postulated that a distressed airline acts more conservatively in the end, but has an aggressive pricing strategy in the short run. Liu's simplified model predicted short-term financial distress in the aviation industry;

however, an in-depth model is needed to predict bankruptcy accurately several years into the future.

The use of statistical models has been questioned by some authors because of their inability to take qualitative information into consideration (Fabozzi, Chen, Hu, & Pan, 2010; Liu, 2009). In some cases, quantitative models may classify a company as in financial distress, but the firm may never fail because of proactive action by management or other attributes that quantitative models cannot detect (Fabozzi et al., 2010). The results of most statistical techniques used in bankruptcy prediction modeling provide analogous results (Ooghe et al., 2009). As there appears to be little difference in the bankruptcy predictive abilities of most statistical failure models, it is important to explore nonstatistical factors, such as company management and economic and industry influences, which statistical methods cannot measure (Ooghe et al., 2009). Recent research has concluded that stand-alone traditional statistical models are limited in their bankruptcy prediction ability and nonstatistical factors should be investigated (Ooghe et al., 2009; Youn & Gu, 2010). Wetter and Wennberg (2009) supported Ooghe et al. (2009) and Youn and Gu's (2010) assertion that pure statistical methods have major limitations while nonstatistical factors should be explored. The following section will discuss the more widely used financial bankruptcy models and the advantages and disadvantages of each.

Altman Z-score model. Throughout the literature, the Altman Z-score is touted as one of the seminal works on bankruptcy prediction (Wetter & Wennberg, 2009). In Altman’s (1967) dissertation work, he developed a bankruptcy prediction model for manufacturing firms using multiple discriminant analysis (MDA). For predictive variables, the model used five independent financial ratios based on a company's liquidity, profitability, solvency, and capital turnover. The Altman Z-score model is of the form $Z = .012(X1) + .014(X2) + .033(X3) + .006(X4) + .999(X5)$, where X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = earnings before interest and taxes/total assets, X4 = market value equity/book value of total debt, X5 = sales/total assets, and Z = overall index. Altman tested the model on 66 manufacturing firms and derived a discriminant function (or Z-Score) for each of the companies using MDA (Altman, 1967). The dependent variable, the Z-score, was then used to classify companies as either bankrupt or nonbankrupt with some falling into a gray area when the model could not determine the bankruptcy potential of a firm (being too close to call or what Altman called the *zone of ignorance*) (Altman, 1967). The model developed by Altman correctly predicted corporate bankruptcies in 94% of the samples (66 manufacturing firms) 1 year in advance of failure (Altman, 1967). Altman found the most serious deterioration in these ratios occurred 2 to 3 years before financial failure (Altman, 1967). Additionally, the model was able to predict failure in 72% of the samples 2 years in advance and 48% 3 years in advance (Altman, 1967).

Traditional financial ratios are input into the Z-score failure prediction model, and then MDA is used to derive an overall credit score (Z-score). Firms with Z-scores above 3.0 are considered to be in the safe zone while firms with scores between 1.8 and 3.0 are in the gray zone, and firms having a Z-score less than 1.8 are in financial danger (Altman, 1967). As of 1983, about 10% of U.S. manufacturing firms had a Z-score below 1.8, though Altman (1983) indicated not all of those firms would end up in Chapter 11 proceedings. In fact, the stigma of official bankruptcy and the expected cost in declaring

Chapter 11 motivates most firms to avoid court-regulated reorganization (Altman & Hotchkiss, 2006). Altman provided background on the application of the Z-score to two manufacturing firms, Manville Corporation and International Harvester (IH). Both firms had downward trending scores between 1972 and 1980, and Altman projected that, at the speed of the declining rate, both Manville and IH had little chance of survival because firms with such low Z-scores rarely recover from such depths (Altman, 1983). Because of financial troubles, IH was sold to J.I. Case in 1984, and Manville Corporation filed for Chapter 11 bankruptcy protection in 1982. Kroeze (2005) stated that changing economic circumstances could affect the accuracy of the Z-score coefficients; therefore, the accuracy of the model will differ under various economic conditions. For these reasons, bankruptcy models that do not take into account changing economic conditions need to be regularly updated.

Furthermore, Scaggs and Crawford (1986) applied the Altman Z-score model to the passenger airline industry and found the Altman model accurately forecast airline failures one to five years in advance; however, for nonbankrupt passenger airlines, the Altman Z-score model failed to provide an accurate prediction. Multiple discriminant analysis is used in the Altman model to categorize a population into groups based on quantitative features (Scaggs & Crawford, 1986). To predict airline failures accurately, Scaggs and Crawford tested a revised Altman Z-score model in the form: $Z = 0.012(X1) + 0.014(X2) + 0.033(X3) + 0.01524(X4) + 0.075\,(X5)$, where $X1$ = liquidity (working capital/total assets), $X2$ = profitability (retained earnings/total assets), $X3$ = leverage (earnings before interest and taxes/total assets), $X4$ = solvency (market value of equity/book value of total debt), and X5 = interest expense (total operating income/interest expense).

The variable $X_5$is a revised ratio that replaced X_5 = activity (sales/total assets) in the Altman model. The new X_5—interest expense ratio—was selected to reflect the high debt positions many of the airlines carried during the 1970s and early 1980s. The updated model better predicted airline bankruptcy by accurately predicting failure at least three years in advance; thus, Scaggs and Crawford (1986) showed the Altman Z-score model could be calibrated to improve bankruptcy prediction capability. Scaggs and Crawford also indicated the Altman model does not include all of the factors that could forecast bankruptcy in the airline industry; however, the model can be adjusted to include the characteristics of a particular industry. This study (Scaggs & Crawford, 1986) spanned the airline deregulation period with the population drawn from the periods prior to and after deregulation. During this time, there was turmoil in the airline industry with many new entries into the airline market, including a number of low-cost carriers. The new entries forced some airlines to cut fares to stay competitive, putting pressure on airline revenue, while at the same time many airlines carried a high debt position (Scaggs & Crawford, 1986). Ribbink et al. (2009) found similar results.

Chung and Szenberg (1996) examined the effects of airline deregulation on the U.S. airline industry by calculating the Altman Z”-score for eight major airlines between 1982 and 1996 (projections only for 1992-1996). While the use of the Altman Z”-score is widely seen in the literature, this study was used to attempt to reduce the impact of the gross domestic product (GDP) on the data by examining the relationship between the Z-score and the GDP. The airline industry is capital-intensive and highly leveraged, so the state of the economy directly affects this capital structure. A growing economy tends to lead to increased demand for air travel, so the GDP should be taken into consideration to remove the economic influence on the model. To detect any relation between GDP and the Altman Z"-score, Chung and Szenberg (1996) used a linear regression technique. The financial data were first scrutinized using the Altman Z"-score and classified into one of three groups: healthy, failure, or gray zone. A linear regression was derived from the Z"-score and GDP data and showed that for every one percentage point of growth, the Z"-score increased by 0.18 with eight degrees of freedom and was significant at the 0.01 level. Additionally, the R^2 value was 0.648, indicating almost 65% of the variation could be explained by the variation in the growth of GDP. Chung and Szenberg found that the airline industry is dividing into two market segments. The two market segments are the low-cost short-haul carriers, and the long-range legacy carriers. In addition, the study found that a sustained growing economy of 2.5% of GDP over three or more years would bring the airline industry into financial profitability (Chung & Szenberg, 1996).

The Altman bankruptcy formula has gone through several changes since Altman created it in the late 1960s. The latest version of the Altman bankruptcy formula and its application were published in Altman and Hotchkiss (2006). The current Altman Z"-score model is as follows: Z" = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4) + 3.25. In the Z"-score model, X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = operating income/total assets, and X4 = book value of equity/total liabilities. In this model, all Z"-scores below zero signify financially distressed conditions in a company. In the updated Z"-score model, all of the coefficients for variables X_1 to X_4 have changed from the original Z-score model (Altman & Hotchkiss, 2006). Altman and Hotchkiss stated that the Z"-score model is better than the original Z-score model for nonmanufacturers. Altman and Hotchkiss also indicated that "models developed for specific industries (e.g., retailers, telecoms, airlines) are an even better method for assessing the distress potential of like-industry firms" (p. 249). The current version of the Z"-score model has also been used to determine the financial health of non-U.S. corporations with high accuracy and reliability (Altman & Hotchkiss, 2006).

Kroeze K-score model. More recently, Kroeze (2005) used the Altman Z"-score model to test for bankruptcies in the passenger airlines business between 1998 and 2003. The updated Z"-score model (renamed Kroeze K-score) used only three financial ratios instead of the original five present in the Altman Z"-score model and modified the coefficients of the dependent variables. Examining 16 passenger airlines between 1998 and 2003, six bankrupt and ten nonbankrupt firms, Kroeze found Altman's Z"-score model was 100% accurate at classifying bankrupt airlines, but correctly classified only 18% of the nonbankrupt passenger airlines (Kroeze, 2005). Kroeze then proposed a modified Altman's Z"-score model, called the K-score model, to improve the prediction capability of the model for nonbankrupt passenger airlines.

In the Kroeze model, scores below zero indicate a bankrupt condition, whereas a score above zero indicates that a firm is not in immediate danger of bankruptcy. Using MDA, Kroeze determined that the X_3 (productivity ratio) variable from the Altman Z"-score model was negative for the dataset and so eliminated the variable when developing the K-score model. Adjustments were also made to the coefficients to create a new discriminant function equation (Kroeze, 2005). The K-score is of the form $K = .268(X1) + .838(X2) + .111(X3) + έ$, where X1 = working capital/total assets, X2 = retained earnings/total assets, X3 = book value of equity/total liabilities, έ = error term, and K = overall index. The K-score proved to be better at predicting bankruptcies one year before failure than the Altman Z"-score model. The K-score model correctly classified 69% of nonbankrupt passenger airlines one year before failure. The Kroeze model is an improvement over the Z"-model and is simpler because it uses only three variables. Kroeze noted the K-score model might not be valid in light of the events of September 11, 2001. Nevertheless, Kroeze tested and provided ideas on improving Altman's Z"-score prediction model of financial failure as it applied to the passenger airline industry.

Numerous financial ratios used in examining a company's financial health exist. Kroeze used liquidity, profitability, and solvency ratios in the K-score model. Liquidity is calculated as a firm's working capital divided by total assets (Kroeze, 2005). Liquidity indicates a company's ability to meet its current financial obligations (Kroeze, 2005). Because airlines tend to operate on low margins, liquidity is a vital factor when evaluating a company's financial position (Kroeze, 2005). The profitability ratio is calculated as retained earnings divided by total assets (Kroeze, 2005). To attract investors and provide for the ability to obtain lower interest loans, management must show that the firm is profitable. A solvency ratio is calculated by using the book value of equity divided by total liabilities (Kroeze, 2005). The solvency ratio indicates how much debt financing the firm has used and is an indicator of how much a firm can absorb in operating losses (Kroeze, 2005). The higher the solvency ratio, the more likely a firm can slip into financial distress (Kroeze, 2005).

Individual	X_1	X_2	X_3	…	X_p	
1	X_{11}	X_{112}	X_{113}	…	X_{11p}	
2	X_{211}	X_{212}	X_{213}	…	X_{21p}	
“	“	“	“	“	“	Group 1
“	“	“	“	“	“	
n_1	Xn_{111}	Xn_{112}	Xn_{113}	…	Xn_{11p}	
1	X_{121}	X_{122}	X_{123}	…	X_{12P}	
2	X_{221}	X_{222}	X_{223}	…	X_{22P}	
“	“	“	“	“	“	Group 2
“	“	“	“	“	“	
n2	Xn_{11}	Xn_{112}	Xn_{113}	…	Xn_{11p}	
1	X_1m_1	X_1m_2	X_1m_3	…	X_1mp	
2	X_2m_1	X_2m_2	X_2m_3	…	X_2mp	
“	“	“	“	“	“	Group M
“	“	“	“	“	“	
nm	$XnmM_1$	$XnmM_2$	$XnmM_3$	…	xnmMp	

Figure 2. Form of data for a discriminant function analysis. *Note.* Adapted from “A Discriminant Analysis of Public Sector Financial Management Performance of the Economies of Sub-Saharan Africa,” by N.C. Nwezeaku, 2010, in *Interdisciplinary Journal of Contemporary Research in Business, 1*(11), 71-89. Used with permission.

Multiple discriminant analysis. Thus far in this literature review, the financial models have all been based on multiple discriminant analysis (MDA), a statistical data analysis that can be used to categorize an observation into one of several *a priori* groupings (Kroeze, 2005; Nwezeaku, 2010). Kroeze (2005) noted that MDA is used to form a linear model that classifies companies based on historical financial ratios.

Altman's (1967) Z"-score model uses MDA to categorize firms as either bankrupt or nonbankrupt as does the Kroeze K-score model (see Figure 2).

Figure 2 depicts the form of data for a discriminant function analysis. Chung and Szenberg (1996) used MDA to examine the effects of deregulation on the U.S. airline industry, but normalized the results by considering change in the GDP. So far, this section of the chapter has discussed the Altman Z-score model and various incarnations of the Altman model proposed by several authors using MDA. The following sections include the use of neural network and mixed logit models in bankruptcy prediction.

Neural network models and genetic programming. Alternate models to the Altman Z"-score model involve neural networks (NNs), mixed logit, and genetic programming methodology. NN models simulate the thinking of the human brain and act to provide qualitative relationships between variables by answering *if-then* questions (Slim, 2007). Gritta et al. (2000) used an NN model to predict small air carrier bankruptcies. Between 1982 and 2000, 134 U.S. air carriers filed for bankruptcy, and some carriers were still susceptible to financial distress because of heavy debt loads (Gritta et al., 2000). Gritta et al. believed current MDA and neural network models did not accurately predict bankruptcy in small air carriers, so they explored a model that could better predict such bankruptcies. Gritta et al. indicated the use of an NN would provide a better result than MDA because an NN has the ability to indicate relations among the data. In addition, an NN is better at spotting patterns in small data sets.

The NN model used in this study was found to predict bankruptcy accurately in 91% of the samples. An overall success rate of 88% was reported with only one Type II error and three Type I errors out of a sample of 28 correctly identified samples. A Type I error occurs when an airlines is forecast to remain solvent, but the airline failed. A Type II error is the reverse, and, in this case, occurs when insolvency was predicted, but did not occur (Gritta, Adrangi, Davalos, & Bright, 2006). Other models similar to NNs, such as fuzzy neural models and classical back-propagated neural networks, have been used to forecast corporate bankruptcy (Slim, 2007). The Gritta et al. study determined the NN has advantages over MDA because NNs can better tolerate noise and missing data and have the ability to identify relations among the data. Others have found; however, that when comparing NNs to discriminant analysis, the latter tends to perform slightly better (McKee, 2007).

Another artificial intelligence data analysis method is genetic programming. McKee examined the variables used in the Altman model to determine individual significant of each variable. Genetic programming is based on the concept of natural selection or survival of the fittest. McKee noted that genetic programming has the advantage of not requiring any distributional assumptions to be made about the data being analyzed. This study confirmed that some of the variables used in the Altman Z"-score model were not statistically valid and noted that some of the variables could be dropped and still maintain the same level of accuracy (McKee, 2007). Kroeze (2005) also found that all of the original Altman Z"-score variables were not needed and dropped two of the variables when developing the Kroeze K-Score model.

Mixed logit models. Jones and Hensher (2005) proposed using a mixed logit methodology to predict financial distress in a firm. Jones and Hensher argued that a mixed logit is better at predicting bankruptcy than MDA, binary logistic, or rudimentary multinomial logit (MNL) models because of "their restrictive statistical assumptions and their failure to incorporate firm-specific observed and unobserved heterogeneity" (p. 21). Fabozzi et al. (2010) supported Jones and Hensher by stating that mixed logit or logit regression analysis could overcome the flaws of multiple discriminant analysis related to some of the assumptions needed to run the model.

The mixed logit model is based on discrete choice theory, which attempts to understand the behavioral responses of customers to the actions of a business, government, or market. The results obtained from a mixed logit model are used to categorize firms into one of three states: solvent firms, insolvent firms, and firms that have filed for bankruptcy. For this study, a sample of firms representing about 3,000 firm years was used to test the mixed logit model. The data were also analyzed using MNL. Jones and Hensher found the mixed logit provided an overall goodness of fit and had 95% accuracy for up to three reporting periods prior to failure and 78% accuracy at predicting failure five reporting periods out. While the mixed logit model proved to be better than MNL at predicting insolvency and failure, the MNL proved to be better at predicting success of firms. The mixed logit model was not tested against MDA, but Jones and Hensher (2007) noted that MDA is a popular method used extensively in the literature.

Furthermore, another study by Hensher and Jones (2007) used a mixed logit model to explore its ability to predict bankruptcy across a broad number of industries. The purpose of the study was to consider the predictive performance of various mixed logit models using different distribution assumptions. The sample for the study included 5,209 firm years, which included 4,980 firm years for firms not yet failed, 119 for insolvent firms, and 110 for firms that had filed for bankruptcy protection or liquidation.

Of the five mixed logit models studied, the unconditional triangular distribution offered the best predictive performance. Hensher and Jones (2007) concluded the multinomial mixed logit models seemed to be sensitive to the type of sampling methodology used. Unlike many authors who asserted bankruptcy models must be firm specific and focused for each industry type, Hensher and Jones (2007) noted that because of the inherent difficulties in precisely predicting corporate failures at the firm type level, there is no need to focus on one particular firm type.

Comparison of Models

The use of MDA or NN for predicting financial distress in firms is most prevalent in the literature. Altman's MDA Z"-score model has been shown to predict bankruptcy accurately in a sample of manufacturing firms 94% of the time (Altman, 1968); moreover, Scaggs and Crawford (1986) found the Altman Z-score, with alterations, could be used to forecast passenger airline failures accurately 1 to 5 years in advance. In 1996, Chung and Szenberg furthered the work of Scaggs and Crawford by using the Altman Z-score model to examine eight major passenger airlines between 1982 and 1996. In addition, Chung and Szenberg used GDP data in an attempt to remove economic influences on the model.

In the most recent passenger airline study using the Altman Z"-score, Kroeze (2005) extended the work of Scaggs and Crawford and proposed an altered Altman's Z"-Score. This altered model was found to improve the prediction capability of the model for use in predicting passenger airline bankruptcies. Ribbink et al. (2009) also used the Altman Z"-score model to determine financially distressed airlines and customer satisfaction and made no alterations to the model. Airlines have increasingly started to lease more aircraft, which removes these assets from the balance sheet and shifts them to short-term debt (Gritta & Lippman, 2010). Because of this shifting around between assets and short-term debt, the Altman Z"-score and variations thereof are becoming less reliable (Gritta & Lippman, 2010). For smaller sample sizes, Gritta et al. (2000) suggested using an NN while predicting bankruptcy in smaller passenger air carriers 91% of the time. Both the MDA and NN models have been shown to predict bankruptcy accurately in various industries, but they must be focused for each particular industry. While the NN model may have advantages over MDA, such as better tolerance for noise and missing data as well as the ability to identify relations among the data, the data processing methodology is complicated and not realistic for use by an novice researcher.

Table 4 provides a sample list of published bankruptcy prediction studies conducted on the aviation industry over the last 30 years. The oldest study found was conducted in 1986, less than 10 years after U.S. airline deregulation. Prior to 1977 (1978 for the passenger airline industry), U.S. air-cargo airlines where heavily regulated by the Civil Aeronautics Board (CAB) (Chung & Szenberg, 1996; Kroeze, 2005; Scaggs & Crawford, 1986). Under regulation, the CAB controlled prices and limited the number of airlines that could operate on a particular route, essentially eliminating competition and therefore limiting the number of bankruptcies seen in the industry

Table 4

Summary of Bankruptcy Prediction Studies in the Aviation Industry

Researcher(s) (Year)	Title	Number of airlines used	Methodology
Ribbink, Hofer and Dresner (2009)	Airline financial distress and customer satisfaction	21 passenger airlines	MDA tied to on-time performance, mishandled baggage and ticket sales
Gritta, Adrangi, Adams, and Tatyanina (2008)	An update on airline financial condition and insolvency prospects using the Altman Z" score model	15 passenger airlines between 1997-2006	MDA
Davalos, Gritta, and Adrangi (2007)	Deriving rules for forecasting air carrier financial stress and insolvency: A genetic algorithm approach	19 passenger airlines	Neural Network with a genetic algorithm
Kroeze (2005)	Predicting airline corporate bankruptcies using a modified Altman Z-score model	11 passenger airlines	MDA
Gritta, Wang, Davalos and Chow (2000)	Forecasting small air carrier bankruptcies using a neural network approach	32 passenger airlines	Neural Network
Chung and Szenberg (1996)	The effects of deregulation on the U.S. airline industry	8 passenger airlines	MDA normalizing for GDP
Scaggs and Crawford (1986)	Altman's corporate bankruptcy model revisited: Can airline bankruptcy be predicted	12 passenger airlines	MDA

In the 15 years after deregulation, 80 new airlines were established (including passenger, cargo, and charter carriers) with over half of the airlines going into bankruptcy protection during that period (Chung & Szenberg, 1996; Scaggs & Crawford, 1986). Finally, the Altman Z”-score model has been shown to predict bankruptcy accurately in a number of different industries (Altman, 1968, 1983; Chung & Szenberg, 1996; Hofer et al., 2009; Kroeze, 2005; Ribbink et al., 2009; Scaggs & Crawford, 1986); however, the model must be calibrated to each particular industry group. The most recent study that calibrated the Altman Z”-score model was conducted by Kroeze in 2005. The Kroeze model simplified the Altman model while improving the model's prediction capability specifically for the airline industry.

No matter which statistical method is used to predict bankruptcy, all of these methods have limitations that pure statistical methods cannot take into account (Fabozzi et al., 2010; Ooghe et al., 2009; Wetter & Wennberg, 2009; Youn & Gu, 2010). Past research on airline bankruptcy prediction models have not enhanced the understanding of bankruptcy prediction, but instead just improved the statistical methodology (Gudmundsson, 2002). Wetter and Wennberg (2009) outlined limitations that statistical methods cannot account for, such as the following:

1. They use a dichotomous dependent variable, though business failure is not a well-defined dichotomy.
2. The sampling method has some problems as there is a risk of using nonrandom samples and, thereby, oversampling the failing firms.
3. Classical models can be criticized because of problems relating to nonstationary and data instability; in classical models, it is assumed that the relationships among the variables are stationary over time.

> 4. The use of accounting information can be questioned, especially with regard to small or new firms, as there are doubts that these statements give a fair view of the financial situation in the firm.
>
> 5. The selection of independent variables is problematic as there is a general lack of theory regarding independent variable selection in accounting, and a purely empirical selection of variables may lead to over-fitting and, thereby, an unstable model with little general applicability. (p. 30)

Fabozzi et al. (2010) stated that financial distress could be influenced by economic factors such as the deterioration of an industry, financial factors such as high debt loads, corporate fraud, mismanagement, and disasters such as natural catastrophes or terrorism.

Nonstatistical Factors

Some of the nonstatistical factors that may affect a bankruptcy model include management, cultural factors, and the type of aircraft and route structure the airline uses. First, management and airline leadership may be significant factors in the success or failure of an airline, though to what extent is unknown (McCabe, 1998). Human capital theory states that an investment in education and new knowledge will provide for better managers and owners (Wetter & Wennberg, 2009), indicating that the more educated an airline management is, the more likely the airline will prosper. Sun and Li (2007) used a factor of management and control when exploring early warning signed of financial distress, as did Kim and Han (2003). Therefore, human capital theory may provide some insight into a firms failure potential.

Culture can also play a role in the financial health of a company. Giapponi and Scheraga (2007) used Hofstede's five dimensions of culture to examine the airline industry, as did Roberts, Walton, and Muldoon (2011). Giapponi and Scheraga noted that organizations in an individualistic culture tend to be individualistic in nature, whereas organizations in a collectivist culture tend to bond together. Cultures with high power distance tend to have problems with the delegations of authority and; therefore, reduced transparency (Giapponi & Scheraga, 2007). In cultures that are considered feminine, discussion is favored over aggression and cooperation is favored over competition, (Giapponi & Scheraga, 2007), whereas in masculine cultures, fierce competition and basic mistrust is common. Hofstede's work related values for the United States as low power distance and uncertainty avoidance with high masculinity and high individualism (Giapponi & Scheraga, 2008). Roberts et al. (2011) noted that the speed of innovation acceptance is also influenced by culture. Cultures with higher uncertainty avoidance, masculinity, and power distance dimensions tend to have slower innovation acceptance rates (Roberts et al., 2011). Because of these reasons, company management must adopt its management style to the type of workforce employed to maximize revenues (Roberts et al., 2011).

Another factor that may affect the financial health of an airline is the type of aircraft and routes flown. The advantages of obtaining the proper fleet mix were discussed above, but an additional factor of efficiency for an airline is the average fleet age (Gudmundsson, 2002). Older aircraft cost more to maintain and typically have higher fuel consumption, making them more expensive to operate, which may be a trait of a poorer performing airline (Gudmundsson, 2002). The routes and frequency of an airline's services may also affect the financial health of an airline. Economies of density from a consolidation of routes in the passenger market come from the hub-and-spoke system in which airlines consolidate operations at a single airport, such as Delta Airlines' Atlanta hub (Gudmundsson, 2004; Vasigh et al., 2008). All-cargo airlines also often operate through consolidated terminals where cargo can be trans-loaded onto other aircraft and benefit from economies of density. Airline alliances are also used by both passenger and cargo airlines and so benefit from economies of scope by expanding locations serviced and optimization of their route structure (Vasigh et al., 2008).

Subject matter experts (SMEs) have been used in financial distress prediction studies to improve prediction accuracy (Kim & Han, 2003; Sun & Li, 2007). Sun and Li, (2007) stated that to improve financial distress prediction methods, SMEs and other nonfinancial data is needed. Quantitative bankruptcy prediction models use past data, whereas the use of SMEs can provide near term insight into companies (Kim & Li, 2007).

The last section includes the grounded theory research design for this study. While this study used grounded theory design based on the idea that theory is derived directly from the data as it emerges with no preconceived notions (Mello & Flint, 2009), an understanding of how the aviation industry and the current bankruptcy prediction models work is essential to the research.

Grounded Theory Design

The literature review has focused on cargo airlines, bankruptcy models, and the factors that may affect a bankruptcy model's prediction capability; therefore, the background knowledge provided in this literature review provides a basis for the conduct of this study's use of ground theory design. Grounded theory was originally developed by Glaser and Strauss (1967) in *Discovery of Grounded Theory* and expanded separately by Corbin and Strauss (1990), Charmaz (2006), and Allen (2010). Grounded theory is used to construct theory directly from field data such as interviews, observations, and document analysis (Mello & Flint, 2009), not just test existing theory (Birks & Mills, 2011).

Grounded theory is a systematic approach to research that assists the researcher to develop theoretical abstraction from field data through a course of constant comparative analysis (Mello & Flint, 2009). Data are collected and coded into emergent categories, refined, and used to capture relevant topics of the phenomena (Allen, 2010; Corbin & Strauss, 1990; Mello & Flint, 2009). These topics are then used to construct a verifiable theory, either quantitatively or qualitatively, that should be easily understandable for academics, students, and practitioners (Mello & Flint, 2009). The aim of grounded theory is to move the analytical process beyond simple description to exploration (Birks & Mills, 2011).

Grounded theory is based on the idea that theory is built directly from the data, and analysis begins as soon as data are collected (Luckerhoff & Guillemette, 2011). The use of emergence research requires a flexible and "rudimentary research design" (Luckerhoff & Guillemette, 2011, p. 402), because the researcher must avoid preconceived notions of where the data may lead (Corbin & Strauss, 1990). Charmaz (1995) summarized the research methods and design problems best by stating the following:

> The grounded theorist builds the research as it ensues rather than having it completely planned before beginning the data collection. Similarly, you shape and alter the data collection to pursue the most interesting and relevant material.

> This approach differs sharply from the traditional research design with its structured interments that are used in the same ways with each research subject. (pp. 47-48)

It is a basic tenet of grounded theory design not to have a fully developed research plan before starting, since it is unknown at the start of a study as to which data or analysis instrument is best to use (Luckerhoff & Guillemette, 2011). It is; however, important to plan the initial steps in the research and for the researcher to have a firm understanding of the process to ensure a successful and defendable research project. Grounded theory was first developed by Glaser and Strauss in 1967 and published in *The Discovery of Grounded Theory*. Glaser and Strauss's work was later refined by Corbin and Strauss in 1990 (Luckerhoff & Guillemette, 2011). Corbin ad Strauss (1990) outlined the canons and procedures for grounded theory. Current writers on grounded theory such as Charmaz (2006) and Birks and Mills (2011) generally accept these procedures as the best process to conduct a grounded study. The cannons outlined by Corbin and Strauss (1990) are:

1. Data collection and analysis are interrelated processes.
2. Concepts are the basic unit of analysis.
3. Categories must be developed and related.
4. Sampling in grounded theory proceeds on theoretical grounds.
5. Analysis makes use of constant comparisons.
6. Patterns and variations must be accounted for.
7. Process must be built into the theory.
8. Writing theoretical memos is an integral part of doing grounded theory.

9. Hypotheses about relationships among categories should be developed and verified.

10. The grounded theorist need not work alone.

11. Broader structural conditions must be analyzed, however microscopic the research.

Summary

Several authors (Chung & Szenberg 1996; Kroeze, 2005; Ribbink et al., 2009; Scaggs & Crawford, 1986) have used the Altman Z-score or the newer Z"-score to predict financial distress in the passenger airlines industry. Kroeze tested the Altman Z"-score model on the passenger airline industry and developed an updated model called the Kroeze K-score; however, the literature does not indicate whether the Kroeze model has been tested on the all-cargo airline industry. Other authors have argued that nonstatistical variables should be considered in financial models (Fabozzi et al., 2010; Gudmundsson, 2002; Ooghe et al., 2009; Wetter & Wennberg, 2009; Youn & Gu, 2010). Significant operational and economic differences exist between passenger and all-cargo airlines that may affect the financial stability of the two industries differently (e.g., demand, traffic patterns), and these differences along with other qualitative factors are explored in this study.

Chapter 3: Research Method

Introduction

The purpose of this study was to explore the nonstatistical factors influencing the accuracy of the Kroeze K-score bankruptcy prediction model for the all-cargo airline industry, using a grounded theory design. The first step in this study was to determine the effectiveness of the Kroeze K-score model in predicting bankruptcy by comparing the model's results to actual U.S. all-cargo airline bankruptcies between the Years 2005 and 2009. Once the prediction success rate was established, grounded theory was used to identify some of the nonstatistical influences that cause inaccurate predictions in the statistical model.

Recent research has indicated that stand-alone traditional statistical models are limited in their bankruptcy prediction ability, and nonstatistical factors should be explored to improve this (Ooghe et al., 2009; Wetter & Wennberg, 2009; Youn & Gu, 2010). For example, by incorporating management decisions regarding airline routes into the prediction model, the accuracy of the model may be increased. The model could then be used to avoid financial distress, in part by reconsidering routes. Such connections can be explored as the researcher discovers the data; thus, a grounded theory method was determined to be the best approach for this research. The project used financial data from U.S. all-cargo airlines from 2004 to 2009, applied a published financial bankruptcy model (Kroeze K-score), and compared the predicted results with the actual events.

The results of the K-score model provided a starting point for the grounded theory design to explore the external influences that may affect the prediction model. Grounded theory is one of discovery in which concepts are uncovered by systematically examining a multitude of data from many sources (Corbin & Strauss, 1990; Mello & Flint, 2009). For this study, data were obtained from numerous sources, including, but not limited to, scholarly articles, magazines, newspapers, technical papers, books, government publications, company and industry literature, and company and professional websites. The data were coded and grouped into categories to expose concepts that describe the factors that influence the K-score model's prediction inaccuracies. The research question for this study was as follows:

RQ: What nonstatistical factors influence the K-score bankruptcy prediction models in the all-cargo airline industry?

This chapter includes an overview of the research method and design for this grounded theory study. The chapter includes a discussion of the population, data collection methodology, and analysis. The chapter then contains the assumptions and limitations of the study and the process to ensure ethical research standards are met.

Research Methods and Design

Grounded theory is based on the idea that theory is built directly from the data and emergence research requires a flexible design. It is a basic tenet of grounded theory design not to have a fully developed research plan before starting; however, it is important to plan the initial steps in the research, and for the researcher to have a firm understanding of the process to ensure a successful and defendable research project. The rest of this chapter includes the steps used to conduct this grounded theory study.

This study was used to explore nonstatistical factors that affect a quantitative model’s prediction ability. The prediction ability of current quantitative bankruptcy prediction models has been honed to a point where little improvement can be made

(Gudmundsson, 2002), yet more accurate models are needed. A better understanding of the nonstatistical (i.e., qualitative factors) variables is needed to advance bankruptcy protection (Ooghe et al., 2009; Youn & Gu, 2010). Some of the nonstatistical data originated from human interactions such as the management practices and other processes germane to a real-life organization. These human interaction factors are best explored using qualitative methods as quantitative data would be missing, hard to obtain, or would not provide the data needed (Mello & Flint, 2009). Within the realm of qualitative methods, grounded theory can be used to gain insights into phenomena and to discover and understand the meanings and concepts surrounding the subject (Charmaz, 2006; Mello & Flint, 2009). Further, grounded theory is used to construct theory directly from field data (Mello & Flint, 2009). Grounded theory, while rooted in nursing research, has been used in other disciplines to open up new avenues of research (Mello & Flint, 2009). The literature review revealed one grounded theory airline bankruptcy study, conducted by McCabe in 1998. The need to understand the social system within the organization, the ease of obtaining data, and the advantage of constant comparative analysis has led to the conclusion that grounded theory will be the best method to conduct this research. Using grounded theory for a study of this type is to some extent uncharted territory; however, the need to explore the data, untainted, by connections and relationships suggested by previous approaches is paramount and allowed for exploration of the data in unconventional ways.

The process as outlined by Corbin and Strauss (1990) was used as the road map for the conduct of this research. Simplified, the three major phases of grounded theory research used in this study are as follows: (a) the discovery of categories and properties,

(b) the discovery of the relationship between the categories and properties, and (c) the discovery of theory as it emerges from the refinement of categories and properties (Birks & Mills, 2011; Charmaz, 2006; Corbin & Strauss, 1990; Mello & Flint, 2009; McCabe, 1998).

The first phase of the grounded theory research was the discovery of categories and properties that are likely to affect the bankruptcy prediction ability of the K-score. The data were coded and grouped into categories with similar properties. Categories are abstract concepts into which other concepts can be grouped; this grouping includes specific characteristics or attributes of a category, which allows a category to be defined, and given meaning (Mello & Flint, 2009).

The next phase of the research was the detection of the association and patterns between the categories and properties related to nonstatistical bankruptcy factors. This phase continued until theoretical saturation occurred. Saturation occurs when no new information is emerging from the data (Corbin & Strauss, 1990; Mello & Flint, 2009). Birks and Mills (2011) discussed the coding process as first fracturing the data then reconnecting "the data in ways that are conceptually much more abstract than would be produced by a thematic analysis" (p. 12).

The final phase of the research was the refinement of categories and properties to reveal the theory. Throughout all three phases of the research, constant comparative analysis of the data was ongoing, so as new categories are discovered, they were incorporated into the dataset and refined. The constant comparison is directed toward similarities and differences in order to develop concepts that helped interpret and explain behavior (Mello & Flint, 2009). Through this three-phase process, theory was constructed from the categories and their properties to result in a theory that provides categories and verifiable hypotheses (Mello & Flint, 2009). The next section of this chapter will discuss the population to be examined.

Participants

Grounded theory sampling progresses on theoretical grounds in which there are no “specific groups of individuals, units of time, and so on, but in terms of concepts, their properties, dimensions, and variations” (Corbin &Strauss, 1990, p. 8); therefore, in grounded theory design, there is no set sample size needed. Instead, the size may be as few as one, or many may be needed to reach saturation (Corbin & Strauss, 1990; Luckerhoff & Guillemette, 2011; Mello & Flint, 2009; Mello & Hunt, 2009). While grounded theory does not require a minimum sample size, the initial population for this study was all of the all-cargo airlines in operation in the United States between 2005 and 2009 with operating revenues of $20 million. The reason for this is that these companies must report financial data to the DOT quarterly in accordance with 14 Code of Federal Regulations (CFR) 241.

A search of such airlines was performed through the TranStats database and revealed there were17 all-cargo airlines in operation during the years 2005 to 2009 (see Appendix A). The TranStats database is maintained by the U.S. Department of Transportation (DOT), U.S. Bureau of Transportation Statistics, Research and Innovative Technology Administration (RITA); therefore, the starting sample of 17 all-cargo airlines and the population were the same. During the research process, six of the 17 all-cargo airlines were selected for detailed analysis.

Data Collection Method

The initial financial data for this study were obtained by data mining the U.S. Department of Transportation (DOT), U.S. Bureau of Transportation Statistics, and Research and Innovative Technology Administration (RITA) database (also known as TranStats). The TranStats financial data are stored in the Air Carrier Financial Reports (Form 41 Financial Data) database. All U.S. air carriers with annual operating revenues of $20 million or more must report financial data to the DOT quarterly in accordance with 14 Code of Federal Regulation (CFR) 241. Their data are made available for research by the DOT as part of the TranStats database. Failure to report financial information is an indication of cessation of operations. In these instances, bankruptcy was confirmed using a literature search. Gathering financial data using a survey is not a practical method to collect the detailed financial data necessary for this study, and because the financial data are publicly available, the survey method is unnecessary. Additionally, response rate to a survey from senior personnel who would have access to the required data from within the all-cargo industry was expected to be low.

An electronic search of the TranStats database was conducted to extract the data for input into the K-score model. The data extracted included working capital, total assets, retained earnings, book value of equity, current liabilities, and total liabilities. Using the financial information, the required financial ratios were calculated for input into the Kroeze K-score model. Financial data were obtained for the 5-year period from 2005 to 2009 for all U.S. all-cargo airlines with operating revenues of $20 million or more.

The results of the K-score model provided a starting point for the grounded theory design to explore the influences on the prediction model. An initial sample of six all-cargo airlines was chosen to provide a cross-section of airlines where the model correctly and incorrectly predicted bankruptcy. Documentary data about these airlines and the industry as a whole were collected from scholarly articles, magazines, newspapers, technical papers, books, government publications, company and industry literature, and company and professional websites. Both qualitative and quantitative data were used in this study, and data were collected from multiple sources. The collection of rich and substantial data, from multiple sources, gave the study more quality and credibility (Charmaz, 2006).

The literature, while downplayed by some grounded theorists, is an important starting point for the study. Review of published scholarly literature provided general knowledge of the subject and helped define the terms and processes used in other researchers work. Scholarly research is a source of data for the study and provides a context for this research in the field. Another source of data for this study entailed personal communication with SMEs. As with other sources of data, open-ended interviews with SMEs were used to provide data for this study. Transcripts from interviews were coded just as other documentary data. Coding of data was used to summarize and sort the data into general categories. According to Corbin and Strauss (1990), in grounded theory protocol, as data were collected, ongoing analysis was conducted on the data to uncover concepts and categorize the data into phenomena that may represent patterns. The direction of the research and further data collection events were determined as data emerged. Data collection continued until no new patterns in the data emerged and relationships among the categories were established.

Measurement/Assessments

A grounded theory design was used in this research on bankruptcy prediction with all-cargo airlines. The research was used to explore the factors that affect the bankruptcy prediction ability of the Kroeze K-score model in the all-cargo airline industry. For the study, a Kroeze K-score model was applied to 17 U.S. all-cargo airlines to determined which companies the model worked and in which it did not by comparing the prediction to actual bankruptcies. For this study, the raw data for use in the Kroeber K-score model were assumed reliable and valid, since the data were obtained from a government database. This study did not collect primary data by means of a survey instrument, but used only secondary data from the TranStats database and interview data from SMEs. Airline companies with operating revenues of $20 million or more are required to report certified financial data quarterly to the U.S. government for inclusion in the TranStats database.

The outcome of the Kroeze model was analyzed and six all-cargo airlines were chosen as the sample to explore the nonstatistical variables affecting the accuracy of the Kroeze model using grounded theory. Multiple sources of data were compared and grouped throughout the research until saturation of the data was observed. After concepts emerged from the data, unstructured interviews with SMEs were conducted to gain insight into bankruptcies and how the emergent concepts fit into existing theories.

The continual comparison and grouping process used in grounded theory guards against bias and achieves greater precision and consistency (Corbin & Strauss, 1990).

Additionally, triangulation of different data sources was used to add validity to the study (Guion, Diehl, & McDonald, 2011). To provide external validity and transferability to the study, a detailed description of the information was provided to present an accurate description of the methods used. Grounded theory requires the researcher to be open to all ideas and have no preconceived theories (Corbin & Strauss, 1990; Luckerhoff & Guillemette, 2011). This openness to ideas helps to avoid bias in the research (Luckerhoff & Guillemette, 2011). Strict grounded theorists reject any review of literature related to the research prior to starting data collection to avoid the temptation of the researcher to use *a priori* concepts during data analysis (Luckerhoff & Guillemette, 2011); however, in reality all professional researchers have some understanding of their disciplines, and therefore, some level of *a priori* concepts (Luckerhoff & Guillemette, 2011).

Data Analyses

The first step in the process was to run the Kroeze K-score model on the 17 U.S. all-cargo airlines in operation between the 2005 and 2009. The predicted results were compared to the actual bankruptcies of the firms during this period, but no attempts to alter the model were made. In the second phase of the research, cases in which the model failed to predict actual events and cases in which the model succeeded in predicting actual events accurately were explored using grounded theory. The data used in grounded theory research come from a range of sources, such as newspapers, books, government documents, and videos, indeed, any data that can provide any insight into the research question (Corbin & Strauss, 1990).

The underlying theme in grounded theory is the search for concepts and the ongoing analysis of data, and as new data is uncovered, the direction of the research must change to account for the data (Birks & Mills, 2011; Charmaz, 2006; Corbin & Strauss, 1990). Extensive use of coding was used to compare events and interactions for similarities and differences (Corbin & Strauss, 1990). Initial coding was used to fracture the data and once concepts emerged, categories of related ideas were organized and grouped together for further analysis (Birks & Mills, 2011; Charmaz, 2006; Corbin & Strauss, 1990).

Coding is the process of naming segments of data that summarizes and categorizes each piece of data. Codes are a synopsis of the essence of a segment of text and show action. During initial coding, segments of data to be coded were groups of words, a sentence, paragraph, or a section of text. Initial coding of data was provisional and provided an extensive list of codes. As themes developed, codes were grouped into similar ideas and used to summarize and sort the data into general categories. Focused coding, which identified and grouped the most significant data into conceptual categories, followed. Finally, the third round of coding, or theoretical coding, produced theoretical codes that suggest possible associations between categories and show links in the data. Theoretical coding reassembles the data that was fractured during initial coding to reveal new ways to view the data and expose the story the data is telling.

Throughout the coding process, memoing and sorting of the data identified incomplete categories and holes in the analysis that were further explored to assist in the theoretical integration of the categories. Memos are free flowing analytical notes that helped to refine, compare, and understand the data. Once the initial round of theoretical coding was completed and themes started to emerge, theoretical sampling was conducted to expand and refine the categories of the emerging theory. Unlike traditional quantitative research design, theoretical sampling in grounded theory research is used to obtain data to expand the categories that were identified during the theoretical coding process. The sampling is not meant to represent a population, but to focus on the theoretical and conceptual development of the emerging theory. This process continued until saturation of the data occurs and the phenomena explained.

The atlas.ti qualitative data analysis software package was used to record and conduct data analysis. The atlas.ti software allowed for the collection of text, audio, video, and image data. As data were input into the software, they were labeled as codes that were later grouped into categories. The software allowed for memo writing, whereby ongoing comparison between data was annotated and used to construct analytic notes. The software allowed for the data to be searched, filtered, and grouped into codes and categories in various ways to support theoretical integration of the categories. Additionally, the atlas.ti software provided high-level quantification of the data through tracking the frequency of codes and words in the dataset, database searching, and filters to determine links between the data. All data were input into the atlas.ti software and coded until categories emerge that were then used to determine patterns in the data that were related back to the failed financial model. Data were collected and analyzed until no new patterns in the data emerged and the relationships among the categories were well established.

After the data were collected and analyzed two SMEs were interviewed using open-ended questions relating to bankruptcy prediction. The interviews where held by phone, and the sessions taped and later transcribed. The two SMEs were Dr. Robert Tompkins, professor of finance at the Frankfurt School of Finance and Management and Dr. Richard Gritta, professor of finance at the University of Portland.

Methodological Assumptions, Limitations, and Delimitations

Validation of grounded theory has been the center of considerable debate (Luckerhoff & Guillemette, 2011; McCabe, 1998; Mello & Flint, 2009) because some do not view grounded theory as a valid research method due to the circularity of the research method, the lack of references to normal theoretical frameworks, and theoretical sampling (Luckerhoff & Guillemette, 2011). Grounded theory research is sometimes viewed as nonscientific, or is criticized for a lack of planning when compared to traditional scientific methods (Luckerhoff & Guillemette, 2011). The initial sampling plan outlined in this document provided a starting point, but could not and did not determine the direction the research took; however, a carefully designed and executed study using a systematic approach can provide verifiable results (Mello & Flint, 2009). In addition, the continual comparison and grouping process used in grounded theory guarded against bias and helped achieve greater precision and consistency (Corbin & Strauss, 1990).

Qualitative research is meant to provide an understanding of a particular social situation or interaction and is largely a process of comparing, contrasting, replicating, cataloguing, and classifying the subject (Creswell, 2009). Grounded theory is based largely on the judgment of the researcher to contrast, compare, catalog, and classify the data in the study, and; therefore, may have inherent bias (Luckerhoff & Guillemette, 2011). There is risk of researcher bias, but this was minimized by the researcher keeping an open mind and holding no preconceptions on the subject; however, there is more danger in bias from the actors involved than from the researcher (Luckerhoff & Guillemette, 2011).

Creswell (2009) stated that researcher bias could also be reduced through open discussion of the researcher's background. This bias cannot be completely removed since the researcher inherently has preconceived unselfconscious theories about the subject. Additionally, and in keeping with grounded theory design, to avoid *a priori* concepts, little literature review was conducted on the nonstatistical factors that may affect bankruptcy prediction models. The literature was not reviewed in depth for the following reasons: (a) to avoid *a priori* concepts and (b) the literature is largely lacking in studies on the use of nonstatistical qualitative information in bankruptcy prediction. An extensive literature review was conducted on statistical bankruptcy prediction methods and the use of grounded theory.

Internal validity was maintained through the triangulation of data in which data from multiple sources was used for cross-verification (Guion et al., 2011). Cross-verification is inherent in the research process of grounded theory with the expectation that data will appear in several forms before being considered in the theory. The use of data triangulation increased the confidence in the research data through verification from several sources including, SMEs (Guion et al., 2011). Additionally, detailed descriptions of the data were provided to give a thorough perspective of the data, adding validity to the research (Guion et al., 2011). *External validity threats* arise when incorrect inferences from the data is drawn and generalizations cannot be made to other persons, settings, and times (Guion et al., 2011). External validity threats were minimized using the circularity that is inherent in grounded theory. Ideas that emerge from one set of data were checked and *re-circulated* through other settings and different time frames to check for consistency of results (Luckerhoff & Guillemette, 2011). While steps were taken to reduce external validity threats, results of this study can only be applied to the sample in the study and cannot be generalized across all of the all-cargo carriers.

The initial financial data for this research were obtained from the TranStats database. Reporting financial information to this database is mandatory under U.S. federal law for airlines in the dataset; therefore, it is assumed that the data were properly reported. Financial data were collected from the TransStats database for all-cargo airlines for the Years 2005 to 2009. Qualitative data were obtained from numerous sources, including, scholarly articles, magazines, newspapers, technical papers, books, government publications, company and industry literature, and company and professional websites. A list of all of the sources used to obtain data is in Appendix B. All data were obtained from known professional sources, and since this information is in the public domain, it is assumed to be correct; however, the data were crossed-checked using triangulation methods to confirm validity.

Ethical Assurances

All ethical guidelines were stringently followed in the implementation of this study. Ethical rules and guidelines ensure that research is conducted to minimize risk to humans and that the potential benefits are balanced with the risk (Creswell, 2009). The proposed research obtained the required publicly available financial data by the process of data mining of the TranStats database. For the qualitative analysis, published materials, annual report, company websites, and other open sources of information were examined.

Names and backgrounds of some management personnel (e.g., education level, work experience, and management styles) used in this study were collected from previously published secondary sources (e.g., the Internet, company websites). Although some names and identifying features were found in the literature, none was used in the writing of this study.

Personal communication with SMEs was conducted as part of this study to provide background information on the subject. Personal communications with SMEs were in the form of open-ended interview questions, and interviews were conducted synchronously via personal interviews. The role of the SMEs was to provide information on the subject. Interview questions were not focused on them personally. Personal communications with SMEs are properly cited in this study and release forms were collected. Northcentral University's Institutional Review Board (IRB) approval was obtained prior to any data collection; however, because the data for this research were obtained from secondary, previously published sources, the research falls into the exempt research categories as outlined in 45 Code of Federal Regulations 46.101b, since this research did not expose humans to psychological, social, or physical risks.

Summary

A grounded theory method was used for this research. The research was used to examine the Kroeze K-score model, which uses various financial ratios to calculate a K-score. The K-score was then used to classify companies as being either bankrupt or nonbankrupt. Finally, external factors that influence the model were examined using grounded theory.

Using grounded theory, the research was used to explore nonstatistical factors that affected the Kroeze K-score model. The data for the proposed research were obtained from publicly available sources, such as published research, company annual reports, airline industry publications, and government publications and databases. The testing of the Kroeze K-score model on the all-cargo industry and determining the qualitative factors that affect the model provide new insight into the financial stability of the all-cargo airlines. This research also adds to the body of knowledge on the use of predictive modeling and qualitative, nonstatistical factors that may influence bankruptcy predictive modeling.

Chapter 4: Findings

Introduction

The goal of this qualitative study is to explain the nonstatistical factors that influence the Kroeze K-score qualitative bankruptcy prediction model. Through the analysis of 34 publicly available documents (i.e., scholarly articles, magazines, newspapers, government records, and company literature), 35 unique codes emerged during the coding process. After intermediate coding, six categories emerged that form the basis of the emergent theory. Two subject matter expert interviews were also conducted to provide data for the study, along with a re-review of the literature for additional data as theoretical sampling directed and for comparison of previously published with the findings of this study.

In the results section, a summary of the prediction accuracy of the Kroeze K-score model is provided followed by the open-coding and intermediate-coding process and results. Finally, in the Evaluation of Findings section, the results are analyzed in relationship to the emergent theory, and the results of this research within the context of the existing literature on financial distress and bankruptcy prediction are discussed.

Results

The results section begins with an analysis of the prediction accuracy of the Kroeze K-score model for 17 U.S. all-cargo airlines. Subsequently, the categories that emerged during the open-coding and intermediate-coding phases of this research are discussed in relation to the research question. The data analysis and findings to support the research question (What nonstatistical factors influence the case for bankruptcy prediction model in the all-cargo airline industry?) will be addressed in the following sections. Because of the nature of qualitative research, the results section includes illustrations and observations with interpretive components.

Prediction Accuracy

The sample of all-cargo airlines (*N* = 17) included two firms that went bankrupt during the study timeframe, 14 all-cargo airlines that did not, and one cargo airline (Cargo 360) that merged with Southern Air, Inc. Bankrupt airlines were coded as 1, and nonbankrupt airlines where coded as 2. The 76 discreet cases (one case per airline per year in operation), were used to calculate a K-score for each year for each airline in the sample. For example, ABX's K-scores were -0.54 in 2005, -0.44 in 2006, -0.26 in 2007, -0.12 in 2008, and -0.09 in 2009. The all-cargo airlines were then classified as bankrupt or nonbankrupt according to the K-score model, using the appropriate cutoff value of zero as suggested by Kroeze (2005). Table 5 indicates the airlines, financial statement dates, years data were available for the sample, and if the airline declared bankruptcy during the study.

Table 6 indicates a summary of the K-score for the 17 U.S. air-cargo airlines in operation from 2005 to 2009. A negative K-score indicates a company that is in financial distress and in potential risk of bankruptcy, whereas a positive K-score indicates a company that is not in financial distress. The raw financial data obtained from the RITA schedule B1 forms and used in the calculations of the K-scores can be found in Appendix C. The negative K-scores are marked by asterisk (*).

Table 5

List of All-Cargo Airlines, Financial Statement Dates, Years Active During the Study and Bankruptcy Declaration

Airline	Financial statement dates	Number of years	Bankrupt?
ABX Air, Inc.	2005 to 2009	5	No
Aloha Air Cargo	2005 to 2009	5	No
Amerijet International	2005 to 2009	5	No
Arrow Air Inc.	2005 to 2009	5	No
Astar USA, LLC	2005 to 2009	5	No
Atlas Air Inc.	2005 to 2009	5	No
Capital Cargo International	2005 to 2009	5	No
Cargo 360, Inc.	2006 to 2007	2	No
Centurion Cargo Inc.	2006 to 2009	4	No
Evergreen Int'l Inc.	2005 to 2009	5	No
Gemini Air Cargo Airways	2005 to 2006	2	Yes
Kalitta Air LLC	2005 to 2009	5	No
Kitty Hawk Air Cargo	2005 to 2007	3	Yes
Lynden Air Cargo Airlines	2005 to 2009	5	No
Northern Air Cargo Inc.	2005 to 2009	5	No
Polar Air Cargo Airways	2005 to 2009	5	No
Southern Air Inc.	2005 to 2009	5	No

Table 6

K-Scores for Air-Cargo Airlines Between 2005 and 2009

Company	2009	2008	2007	2006	2005
Abx Air, Inc.	-0.09*	-0.12*	-0.26*	-0.44*	-0.54*
Aloha Air Cargo	0.59	-0.69*	-0.49*	-0.86*	-1.14*
Amerijet International	0.07	0.06	0.15	0.06	0.09
Arrow Air Inc.	-0.68*	-0.50*	-0.18*	-0.13*	-0.05*
Astar USA, LLC	-0.55*	-0.33*	-0.28*	-0.39*	-0.32*
Atlas Air Inc.	0.29	0.28	0.30	0.15	0.05
Capital Cargo International	0.24	0.67	-0.49*	-1.82*	-0.58*
Cargo 360, Inc.		Merged	-0.02*	-0.41*	New
Centurion Cargo Inc.	-0.61*	-0.07*	-0.62*	-1.71*	New
Evergreen Int'l Inc.	0.29	0.33	0.31	0.31	0.26
Gemini Air Cargo Airways		Bankrupt	—	-1.34*	-2.65*
Kalitta Air LLC	0.75	0.87	1.47	1.27	1.32
Kitty Hawk Air Cargo		Bankrupt	0.50	0.45	0.65
Lynden Air Cargo Airlines	1.13	0.79	1.07	0.91	0.73
Northern Air Cargo Inc.	0.34	0.21	0.27	0.39	0.24
Polar Air Cargo Airways	-0.26*	0.00*	0.10	0.42	0.50
Southern Air Inc.	-0.58*	-0.04*	0.27	0.48	0.46

Note. * =K-scores = < 0.0. Company considered not in financial distress if K-score is > 0.0, and in financial distress if K-score is = < 0.0. Source of data RITA Schedule B1 data.
Note. — = no data.

Testing the Original Kroeze K-Score Model

The original K-score bankruptcy prediction model developed by Kroeze was based on the Altman Z-score and used multiple discriminate function analysis (MDA). Within the sample for this study, the K-score model correctly classified one of the two bankrupt firms (50.0% correctly classified) as bankrupt and seven of the nonbankrupt firms correctly (46.7% correctly classified). The K-score model did not perform as well on this sample as in the Kroeze (2005) study in which the K-score model correctly classified 69% of nonbankrupt passenger airlines 1 year before failure. Table 7 indicates the prediction accuracy matrix for the Kroeze K-score model.

Table 7

Kroeze K-Score Model: Prediction Accuracy Matrix

			Predicted group membership		
		Group	Bankrupt	Nonbankrupt	Total
Original	Count	Bankrupt	1	1	2
		Nonbankrupt	8	7	15
	%	Bankrupt	50.0	50.0	100.0
		Nonbankrupt	53.3	46.7	100.0

An initial sample of six all-cargo airlines was drawn from airlines for which the K-score model correctly and incorrectly predicted bankruptcy. The six airlines were ABX Air, Inc, Arrow Air Inc., Atlas Air Inc., Cargo 360, Inc., Gemini Air Cargo Airways, and Kitty Hawk Air Cargo. ABX Air and Arrow Air Inc. are both cargo airlines for which the K-score model predicted bankruptcy, but the airlines continued operations. Atlas Air was correctly predicted and remained solvent throughout the sample window. In the sample, two airlines entered Chapter 11 bankruptcy during this period and both were examined using grounded theory. One of the two, Gemini Air Cargo, was correctly predicted by the K-score to enter bankruptcy; however, Kitty Hawk Air Cargo entered bankruptcy in 2008, an event that the K-score model did not predict. The other firm that went out of operation during this study period was Cargo 360; however, Cargo 360 did not enter bankruptcy, but instead, merged with Southern Air. After the merger, Southern Air went from a positive K-score to a negative score. Table 8 indicates the 17 all-cargo firms in operation between 2005 and 2009 in a prediction accuracy matrix, and the six all-cargo airlines chosen as the initial sample for this study are marked with an asterisk.

Table 8

Kroeze K-Score Model: Prediction Accuracy Matrix With Airline Names

		Predicted group membership		
	Group	Bankrupt	Nonbankrupt	Total
Original	Bankrupt	Gemini Air Cargo*	Kitty Hawk*	2
	NonBankrupt	ABX Air*	Amerijet Int'l	16
		Aloha Air Cargo	Atlas Air*	
		Arrow Air*	Cargo 360*	
		Astar USA	Evergreen Int'l	
		Captal Cargo	Kalitta Air	
		Centurion Cargo	Lynden Air Cargo	
		Polar Air Cargo	Northern Air	
		Southern Air		

Note: Airlines marked with an asterisk were the initial sample of airlines for this study.

Table 9 indicates the K-scores for the all-cargo airlines that were part of the initial sample. Negative K-scores, which indicate financial distress, are marked with an asterisk. This sample of airlines was chosen to give a mix of cases for which the model correctly and incorrectly predicted bankruptcy. The next part of this chapter provides an overview of the six all-cargo carriers selected for this study.

Table 9

K-Scores for Air Cargo Airlines Between 2005 and 2009 for Sample Airlines

Company	2009	2008	2007	2006	2005
ABX Air	-0.09*	-0.12*	-0.26*	-0.44*	-0.54*
Arrow Air	-0.68*	-0.50*	-0.18*	-0.13*	-0.05*
Atlas Air	0.29	0.28	0.30	0.15	0.05
Cargo 360		Merged	-0.02*	-0.41*	New
Gemini Air Cargo Airways			Bankrupt	-1.34*	-2.65*
Kitty Hawk Air Cargo		Bankrupt	0.50	0.45	0.65

Note: K-Scores = < 0.0 are marked with an asterisk (*). Company considered not in financial distress if K-Score is > 0.0, and in financial distress if K-Score is = < 0.0. Source of data RITA Schedule B1 data.

Open-Coding Results

Once the six all-cargo airlines were selected for further examination, data were collected on the operation of these airlines. During the open-coding phase a total of 34 documents were reviewed which included company annual reports, SEC 10K annual and quarterly reports, reports from professional journals such as Air Transport Intelligence and Traffic World, news reports, and company press releases from the period 2005 to 2009. A list of all of the sources used for data is in Appendix B. The first phase of data collection included the uploading into Atlas.ti software and review of documents related to the six all-cargo airlines in the sample. The Atlas.ti software is a commercially available database program that was used to organize, code, memo, and visualize the data and is specifically programmed to assist in qualitative data collection research. The software also includes a search, filter, and query tool, which allows a researcher to interrogate the data in many ways. Documents were collected and reviewed, and codes were developed as they emerged from the text.

Coding was conducted on a sentence-by-sentence or theme-by-theme basis in which a code or group of codes were assigned to each sentence or group of sentences with the same theme. The codes that were assigned to the text was intended to identify the process being discussed, and was not limited by any particular theme or idea. As codes emerged, more documents were collected and coded until saturation in the data was observed. Saturation occurs when no new data is emerging from the documents. A total of 34 documents was examined before saturation was observed. After the initial coding round, there were 35 unique codes that emerged from the data (see Table 10). These codes are based on segments of the text and can be viewed as general concepts that summarize the text. Definitions for the codes can be found in Appendix D.

Table 10

The 35 Codes Developed During Initial Coding

Accidents	Environmental	Price
Antitrust	Fleet mix	Regulation
Bankruptcy	Flight_frequency	Reliability
Capacity	Fuel_efficiency	Revenue
Cash flow	Geographic location	Risk
Competition	Labor_Issues	Routes
Competitive Advantage	Maintenance	Security
Cost	Management	Service
Credit_markets	Market	Size
Customers	Merger	Tax
Earnings	Operations	Utilization
Economics	Ownership	

Since codes were established as they emerged, the entire set of 34 documents was re-reviewed a second time to ensure that all text was properly coded. In total, 2,593 segments of text were categorized into 35 unique codes. The code frequencies are shown in Table 11. These codes represent themes or ideas that emerged from the data; however not all of these codes may not be significant. During the intermediate-coding process, these codes were grouped to form several categories. Throughout the process, memos were kept that were used to develop the ideas on what the data were indicating and were later used to assist in theory development.

Table 11

*Code Frequencies (*N *=2593)*

Codes	Code frequency	
Accidents	43	
Antitrust	5	
Bankruptcy	92	
Capacity	103	
Cash flow	59	
Competition	24	
Competitive Advantage	27	
Cost	238	
Credit_markets	166	
Customers	393	
Earnings	129	
Economics	85	
Environment	90	
Fleet mix	124	
Flight_frequency	12	
Fuel_efficiency	30	
Geographic location	19	
Labor_Issues	43	
Maintenance	123	
Management	59	(*continued*)

Table 11
Code Frequency (*continued*)

Code	Code frequency
Market	8
Merger	21
Operations	35
Ownership	37
Price	9
Regulation	277
Reliability	42
Revenue	42
Risk	77
Routes	60
Security	100
Service	2
Size	15
Tax	1
Utilization	3
Total *N* (coded sections)	2593

Table 12 indicates the percentage each code rated for that airline at the end of the open-coding process. These percentages are based on the number of times the code was linked to a segment of text and may indicate the importance of the code to the company (reference, year). The percentages vary between the different airlines; however, the highest percentages, those above 10%, were connected to the codes bankruptcy, cost, customers, earnings, fleet mix, management, merger, ownership, and regulation. Of the codes with percentages above 10%, five (bankruptcy, cost, earnings, merger, and ownership) are associated with the financial factors category that will be discussed later in this chapter. The list is presented in alphabetical order and is not based on actual rankings because these differ between airlines.

Table 12

Percentage for Each Code Broken out by Airline

	Airline					
Code	Cargo 360	ABX Air	Atlas Air	Kitty Hawk	Arrow Air	Gemini
Accidents	0	0	1	4	0	0
Antitrust	0	0	1	0	0	0
Bankruptcy	1	0	4	2	20	30
Capacity	0	1	8	3	4	5
Cash flow	0	4	2	2	4	0
Competition	0	1	1	1	0	0
Competitive advantage	2	0	3	0	2	0
Cost	1	13	10	8	2	0
Credit_markets	0	6	7	7	4	9
Customers	9	8	17	21	4	7
Earnings	0	13	3	2	0	0
Economics	0	3	4	3	4	3
Environment	0	4	1	6	0	0
Fleet mix	16	4	6	2	18	9
Flight frequency	0	0	0	1	0	0
Fuel_efficiency	0	1	2	1	4	1
Geographic location	5	1	0	0	6	1
Labor_Issues	0	2	2	1	4	6
Maintenance	6	11	1	5	0	1
Management	14	2	2	1	8	7
Market	0	0	1	0	0	0
Merger	11	1	0	0	0	1
Operations	6	2	1	0	0	2
Ownership	7	1	1	0	8	13
Price	0	0	1	0	0	0
Regulation	11	10	7	17	0	0
Reliability	0	2	1	2	0	0
Revenue	2	3	1	1	0	2
Risk	0	2	5	3	0	0
Routes	2	2	3	2	6	1
Security	0	2	4	6	0	0
Service	0	0	0	0	0	0
Size	6	1	0	0	2	1
Tax	0	0	0	0	0	0
Utilization	0	0	0	0	2	0

Throughout the open-coding process, that is the initial data collecting and coding generated from the documents, codes were developed to fracture the data. Fractionation of the data during the open-coding process allows codes to be re-assembled into meaningful categories during the intermediate-coding phase of this research (Birks & Mills, 2011; Corbin & Strauss, 1990). Ongoing review of these codes was conducted in a process of constant comparative analysis in an attempt to start to link the codes and concepts and was followed by additional theoretical sampling. After theoretical saturation was observed in the data; that is, there were no new codes being identified, the next step in the process was intermediate coding. Intermediate coding is the process by which the data was regrouped to form intermediate codes.

Intermediate Coding

After the initial codes were developed and theoretical saturation occurred, the research moved into the intermediate-coding phase in which codes were compared to identify relationships that may exist in the data (Birks & Mills, 2011; Corbin & Strauss, 1990). The initial 35 codes were synthesized into six categories. The name of some of these categories came directly from code names (e.g., operations, competitive advantage) while the names of other categories were generated after grouping a set of codes together (e.g., financial factors, external factors). The six categories that emerged during the research were management, risk, operations, competitive advantage, financial factors, and external factors. Figure 3 graphically shows the six categories and the linkage of the code groups to these categories.

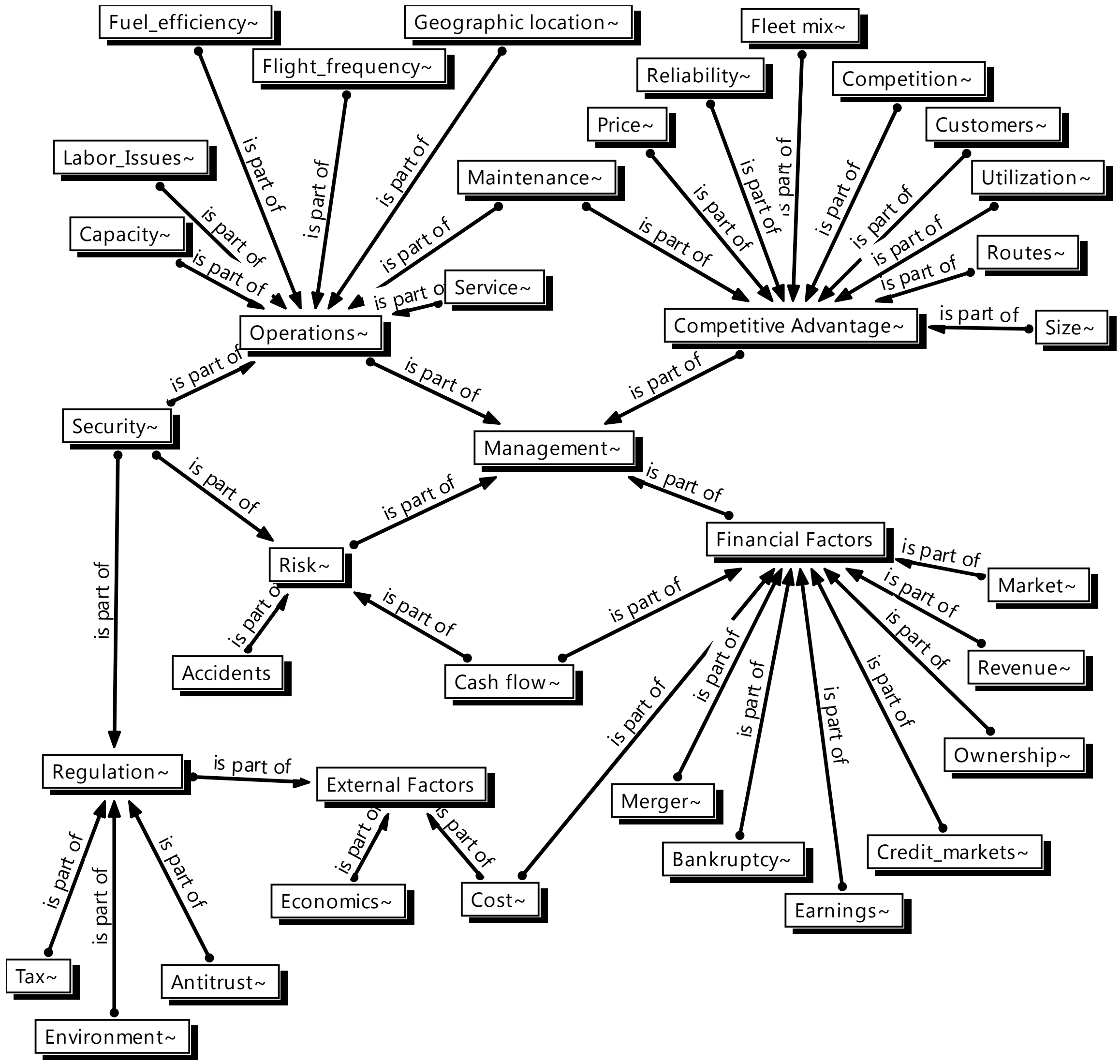

Figure 3. Graphic representation of codes and their linkage.

Part of grounded theory methodology is to ensure validity through a rich discussion of the data that emerges throughout the research (Birks & Mills, 2011). The data for this research is based on segments of text found in the documents that were reviewed. Throughout the remainder of this chapter, many quotations will be provided from the 34 documents reviewed to support the theory development. Table E1 in Appendix E provides a list of the six categories and examples of quotations and their link to individual codes. The detailed quotes that support each of the six categories are intended not only to provide examples of coded text, but also to provide a detailed description of the data so that a through perception of the data is presented, thus adding validity to the research (Birks & Mills, 2011). Further discussion of these codes and links are discussed found in Table E1 (see Appendix E).

The six qualitative categories that emerged from the intermediate-coding process that may influence bankruptcy prediction models are management, operations, financial factors, competitive advantage, risk, and external factors. While these are broad categories, they are all linked to specific codes or ideas found in the data and form the basis of the emergent theory. The following is a description of each of the six categories and their component codes.

Management

The main overarching code that emerged was management that was linked to categories such as operations, financial factors, competitive advantage, and risk. The management category is not linked to any codes directly, but is linked to four other categories because management directly influences all of the categories except possibly for the external factors of economics and regulations. As depicted in Figure 3, management is at the center of any organization and can be viewed as the hub around which all the other categories and codes revolve. Management has both a strategic and operational function.

Dr. Richard Gritta discussed management at length during the subject matter expert interview held on October 28, 2011. Dr. Gritta stated that management has oversight of both operating strategies and financial strategies.

> If it's operating strategies, one of the keys would be; do you have efficient routes, and are you flying aircraft that are matched to your route. Are you minimizing your fuel bill by having your pilots fly more intelligently, and are you managing your labor issues properly. Because that is part of your operating strategy. The financial strategy part of management is how much debt that you have on the balance sheet, and how much disguised debt that you have in the form of leases, because obviously the more debt you have, the higher the probability of a financial problem. That's the magic of the US system like with Southwest and Alaska as compared to the rest of the airlines, is they have low levels of debt. (Richard Gritta, personal communication, October 28, 2011)

One of the categories directly linked to management is operations that encompass the day-to-day management of the firm.

Operations

Operations, linked to management, included codes such as security, service, flight frequency, maintenance, geographic location, labor issues, capacity, and fuel efficiency. Security, while a part of operations, is also considered part of regulation, which is an external factor that will be discussed in the external factors section. Likewise, maintenance is also a part of competitive advantage and will be discussed in the competitive advantage section.

The cost of fuel typically makes up about one third of the operating expenses for an airline (Atlas Air, 2006). Arrow Air noted that “rising jet fuel prices outpaced its ability to boost prices for customers. This resulted in significant recurring operating losses and a large operating deficit” (Stempal, 2010, para. 5). Rising fuel prices had a significant impact on Arrow Air since it "operated one of the industry's largest fleet of DC-8 freighters, older planes that guzzle fuel and are costly to maintain" (*South Florida Sun–Sentinel,* 2005, para. 5). Because fuel is such a large portion of the operating expenses, the text associated with the code fuel is found throughout all of the documents reviewed with many of the airlines discussing the future plans for more fuel-efficient aircraft. For example, Atlas Air and their 2009 annual report stated the following:

> The relative operating cost efficiency of our current 747-400F aircraft and future 747-8F aircraft, including their superior fuel efficiency, capacity and loading capabilities, create a compelling value proposition for our customers and position us well to manage market conditions and for future growth. (Atlas Air, 2010, p. 28)

ABX Air stated that "the primary competitive factors in our industry are price, geographic coverage, flight frequency, reliability and capacity" (Atlas Air, 2006, p. 6). Kitty Hawk Air Cargo echoed these factors by stating that "the ability to compete effectively depends on price, frequency of service, cargo capacity, ability to track freight, extent of geographic coverage and reliability" (SEC, 2007b, p. 25). Of these competitive factors, three (i.e., capacity, flight frequency, and geographic coverage) are directly related to the category of operations; however, the others are also affected by the operations department in an airline.

Capacity can be viewed as the total lift capacity of the airline or the individual capacity of each of their aircraft. Atlas Air Cargo and Cargo 360 operated Boeing 747 freighters, which have the largest lift capacity compared to the smaller aircraft operated by the other four airlines, which were MD-11s, Boeing 737s, Boeing 767s, DC-8s, DC-

9s, and DC-10s. No matter how much lift capacity and airline may have, the most important aspect is the total utilization of that aircraft. Total utilization of an aircraft refers to the maximization of both volume and weight of cargo for every leg of the flight; however, fluctuating demand makes it difficult to optimize the use of available capacity (Walton, 2011).

Reliability can be viewed as the dependability of the aircraft or the optimization of flight operations to ensure reliable delivery. Kitty Hawk Air Cargo was so concerned with aircraft reliability that “to enhance the reliability of our service, it is generally our policy to have available at least one operational spare aircraft” (SEC, 2007c, p. 9). In the documents reviewed for this research, Kitty Hawk Air Cargo was the only airline that made a point of noting that they keep a spare aircraft in waiting. It can be hypothesized that the underutilization of this aircraft may have negatively affected Kitty Hawk's revenues and could possibly be connected to its bankruptcy filing.

The documents did not provide much detail on any of the airlines' flight frequencies. In general, all the airlines have a global reach and serve the major cargo airports of the world. During the timeframe of the study, ABX Air was the only exception to this in that it supported mostly U.S. domestic DHL cargo.

Financial Factors

Also linked to management was the category of financial factors, which was made up of the codes bankruptcy, market, credit markets, merger, earnings, ownership, revenue, costs, and cash flow. The code bankruptcy falls under the category of financial factors and is germane to the study. The data related to bankruptcy were mostly found in the documents for Gemini Air Cargo and Kitty Hawk Air Cargo, the two airlines in this sample that went bankrupt. References to bankruptcy were also found in the documents related to Arrow Air. Arrow Air exited Chapter 11 bankruptcy protection in June 2004 just before the sample window of this study started and then reentered Chapter 11 bankruptcy again in 2010 just after the sample window closed. Arrow Air carried a negative case score throughout the entire sample window 2005-2009, so never seemed to be financially healthy even after exiting Chapter 11 in 2004. Access to credit markets was also a recurrent theme throughout the documents, especially from the financially weaker firms such as Kitty Hawk Air Cargo; however, even financially sound firms such as ABX Air worried that “tight credit markets could impact [a] company's future access to liquidity” (ABX Air, 2010, p. 10). In the 2009 annual report for ABX Air, officials stated that “Given the current tight credit markets, the interest rates and other costs of a renegotiated or new facility, if one can be obtained, would be more expensive and may require more rapid amortization of principal than under the terms of the current credit agreement” (ABX Air, 2010, pp. 10-11).

During this sample, only one merger took place: Cargo 360 merged into Southern Air. Cargo 360 had shown two years of negative K-score values before merging with Southern Air. Up until the time of the merger, Southern Air had had a positive K-score, but at the merger, showed negative case score values for the years 2008 and 2009. While mergers may be viewed as positive within the aviation industry due to a reduction in capacity and the removal of a competitor (R. Gritta, personal communication, October 28, 2011), the Cargo 360 and Southern Air merger may have put Southern Air in financial peril. In the company's 2005 annual report, Atlas Air officials stated that “ACMI [Aircraft, Crew, Maintenance and Insurance] maximizes yield and traffic demand risk in the air-cargo business and provides a more predictable annual revenue and cost base" (Atlas Air, 2006, p. 3), which indicates that air carriers that operate only ACMI may have a more stable balance sheet. Revenue is directly tied to financial factors and is a important part of the financial management of the company.

For the firms in the sample, ABX in Kitty Hawk Air Cargo had a limited number of customers from which they received most of their revenues. ABX had almost all of its revenue tied to one customer, DHL, and officials recognized this dangerous position in their 2005 annual report where they stated, "We rely on a single customer for substantially all of our revenue and operating cash flows" (ABX Air, 2006, p. 10). The main competitors to DHL in the U.S. market were the established Federal Express Corporation (Fedx) and United Parcel Service (UPS), which had "significant resources, market penetration and brand recognition" (ABX Air, 2006, p. 10). Due to this competition and ABX's perilous position of only having a single substantial customer, DHL was able to place pressure on ABX to reduce costs and improve productivity. This pressure from DHL limited ABX's revenues and may have been the reason that the K-score model predicted ABX to go bankrupt throughout this sample. So while DHL, as the sole customer, could pressure ABX to reduce cost and; therefore, reduce revenues, officials of DHL could not afford for ABX to go bankrupt. Kitty Hawk Air Cargo also operated with a small client base, and officials of the company recognized the fact that they derived "a significant portion of [their] revenues from a limited number of customers, and the loss of their business or payment defaults by one or more of them could have a material adverse effect on results of operations" (SEC, 2006, p. 14). The statement by Kitty Hawk Air Cargo seems to be a recurring comment and adds credence to the idea that air-cargo airlines operate on tight margin, so much so, at least in this case, that even one nonpaying customer can jeopardize the entire company.

Cost was another concept that was prolific throughout the data. The costs code was associated with the idea operating cost and referred mostly to the cost of fuel, which is the largest portion of an airline's operating costs. For example Arrow Air operated DC 8-freighters that company officials stated “guzzle fuel and are costly to maintain” (*South Florida Sun–Sentinel*, 2005, para. 1), before switching to newer, more fuel-efficient DC-10s. Further officials of Arrow Air noted that “rising jet fuel prices outpaced its ability to boost prices for customers. This resulted in significant recurring operating losses and a large operating deficit” (Stempal, 2010, para. 6). The cost of jet fuel could also be considered an external factor.

Cash flow is the last code associated financial factors and is probably the most important, since a lack of cash flow is what ultimately drives companies into bankruptcy. Dr. Tompkins (personal communication, October 15, 2011) noted that cash flow is the most important element because “that's really what causes a company to go bankrupt.” Cash flow is a qualitative indicator that is used in many of the published financial distress models, so it is no surprise that it appears in the data. The next category to be explored is risk.

Risk

The category of risk with the code of accidents also was linked to the management category. Risk is a factor that management must deal with on a daily basis. Whether the risk to a firm is from accidents, related to business decisions, external factors, or related to government regulation, management must put in place processes to reduce the overall risk to the company. Anecdotally, aviation is viewed as inherently risky due to the extensive press coverage anytime there is an aviation accident, and while aircraft accidents occur, they are a rare event.

Although there was an indication of risk throughout the literature review, Kitty Hawk Air Cargo appeared to be more prominent in the discussion of risk and the articles reviewed than any other. In their annual report, officials of Kitty Hawk Air Cargo outlined in detail the various risks the airline faces. An indication that Kitty Hawk Air Cargo was in financial distress before going bankrupt in 2008 was a discussion in its 2006 SEC 10K annual report in which Kitty Hawk Air Cargo officials stated that an "aircraft or truck accidents and the resulting repercussions could have a material adverse effect on our business" (SEC, 2007a, p. 21). Although the loss of an aircraft for a small air-cargo company could be devastating, rarely do airlines go out of business because of the loss of an aircraft (R. Gritta, personal communication, October 28, 2011); however an indication of financial difficulty can be found in the statement by Kitty Hawk Air Cargo officials indicating that even the loss of a truck "could have a material adverse effect on [their] business" (SEC, 2007a, p. 21).

The rising cost of jet fuel was also seen as a risk factor for the all-cargo companies in the sample, which in some cases exceeded 30% of total operating expenses (Atlas Air, 2006). Even for the companies that have ACMI contracts, which require the customer to pay for aviation fuel, an increase in fuel costs is seen as a risk due to the fact that higher fuel payment may limit the viability of the ACMI business because of the inability of the customers to cover the cost of the increased aviation fuel (Atlas Air, 2006).

Security, which is one of the codes that is part of operations, can also be considered under the category of risk. The aviation industry is subject to extensive governmental regulations, and failure to comply with these regulations may have an adverse effect on the business (Atlas Air, 2006). After the terrorist attacks on September 11, 2001, the U.S. government adopted new rules and regulations to increase the security requirements in the aviation industry. In a 2005 annual report, officials of Atlas Air stated that “These new regulations and others that potentially might be adopted could have an adverse impact on our ability to efficiently process cargo or could increase our costs” (Atlas Air, 2006, p. 12).

Access to credit markets could also be considered a risk factor for the all-cargo industry. Atlas air officials stated that “We are highly leveraged and our substantial debt and other obligations could limit our financial resources and ability to compete and may make us more vulnerable to adverse economic events” (Atlas Air, 2006, p. 13). The officials of Atlas Air continued by stating that restricted access to credit markets would require “us to dedicate a substantial portion of our cash flow from operations for interest, principal and lease payments and reducing our ability to use our cash flow to fund working capital and other general corporate requirements” (Atlas Air, 2006, p. 13). If a company's cash flow is restricted it may be forced to restructure or refinance its debt, sell assets, delay capital expenditures, obtain additional financing, limit future business plans (Atlas Air, 2006), or ultimately file for bankruptcy protection.

Competitive Advantage

The category of competitive advantage was supported by codes such as price, reliability, fleet mix, routes, competition, size, customers, and utilization. Most business textbooks will have a large section on competitive advantage. Typically, after defining competitive advantage the author of these texts will go into a detailed discussion of how to determine a firm's strengths and weaknesses and how to minimize the weaknesses and take advantage of the firm's strengths to be more competitive in the marketplace. The codes related to competitive advantage were found in every document reviewed.

Officials of Atlas Air were probably more expansive in their discussion of competitive advantage than any of the other airlines in the sample. Atlas Air clearly holds a competitive advantage in the ACMI wide-body aircraft marketplace, since the company was the only ACMI provider of the Boeing 747–400 freighters during the timeframe of the study (Atlas Air, 2010). Not only does Atlas Air have a competitive advantage because the company is the only provider of Boeing 748-400 aircraft, but "By managing the largest fleet of 747 freighter aircraft, [they] achieve significant economies of scale in areas such as aircraft maintenance, crew training, crew efficiency, inventory management, and purchasing" (Atlas Air, 2010, p. 29). Additionally, officials of Atlas stated, "The most important elements for competition in the air-cargo business are the range, payload and cubic capacities of the aircraft and the price, flexibility, quality and reliability of the cargo transportation services provided" (Atlas Air, 2006, p. 13).

Reliability is one of the codes that support competitive advantage. Reliability within the cargo industry refers to on time delivery and no damage to the cargo. Officials of both ABX and Atlas Air in their annual reports stated that reliability is one of the key elements to their business model. ABX officials state that all of their aircraft have Category II or III landing equipment on all their aircraft, which gives them the ability to land in limited visibility weather conditions, increasing their reliability (ABX Air, 2006).

The number and type of customers can provide a competitive advantage to the company. ABX Air primarily sole sourced all of its cargo space to DHL, giving DHL more pricing power, whereas Atlas Air operated long-term ACMI contracts for five years, giving the company a more predictable cash flow (Atlas Air, 2006). Officials of Kitty Hawk Air Cargo in their 2005 annual report stated that the company had "over 550 active freight forwarders and logistics company customers…however [the company's] top 25 customers accounted for more than 65.0% of [its] schedule freight revenue" (SEC, 2006, p. 6). Kitty Hawk Air Cargo officials met regularly with their top customers "as part of [their] strategic planning activities for [their] schedule freight network" (SEC, 2006, p. 6). While Kitty Hawk Air Cargo had a much larger clientele base than ABX it did not save the company from bankruptcy in 2007.

Fleet mix is an important aspect of competitive advantage and plays a key role in the operation of an airline. Fleet mix refers to the type of aircraft that the company flies and the age of those aircraft. By operating a single aircraft type, an airline can achieve economies of scale and the strategy provides "increased operational flexibility, because it is easier to find a replacement aircraft for flight crew in the event of your regular operations" (Walton, 2011, p. 55). In addition to the operational flexibility, airlines that fly a single aircraft type have lower crew training, maintenance, parts, and equipment costs. Table 13 summarizes the type of aircraft fleet the airlines operated versus their actual and bankruptcy prediction membership as predicted by the K-Score. Of the six airlines in the sample, four flew mixed fleets and two operated with a single aircraft type fleet. The two airlines that operated a single type aircraft fleet, Atlas Air and Cargo 360, were the only two airlines that the K-score model correctly identified as nonbankrupt airlines during the timeframe of the study. Airlines for which the K–score incorrectly predicted bankruptcy, that is, Kitty Hawk Air Cargo, ABX Air, and Arrow Air, all operated a mixed fleet. Gemini Air Cargo, the only airline for which the model correctly predicted bankruptcy, operated a mixed fleet.

Table 13

Type of Aircraft Fleet Mix versus K-Score Predicted Group Membership

		Predicted group membership	
	Group	Bankrupt	Nonbankrupt
Original	Bankrupt	Gemini (mixed)	Kitty Hawk (mixed)
	Nonbankrupt	ABX Air (mixed)	Atlas Air (single)
		Arrow Air (mixed)	Cargo 360 (single)

Atlas Air, Cargo 360, and Gemini operated only wide-body aircraft, whereas the other three airlines operated a mixed fleet of both wide-body and narrow-body aircraft. Narrow body aircraft are defined as a single aisle aircraft having a cargo carrying capacity of less than 45 tonnes, whereas a wide-body aircraft has a carrying capacity of over 40 tonnes and twin aisles in the passenger versions (Walton, 2011). Table 14 summarizes the type of aircraft operated by the carrier versus the actual and K-Score prediction group. For the three cases in which the K-score model correctly predicted bankruptcy or nonbankruptcy, the airlines all flew wide-body aircraft, and in the cases for which the K-score did not provide an accurate prediction, these airlines all operated narrow body aircraft as part of their fleet.

Table 14

Type of Aircraft Versus K-Score Predicted Group Membership

		Predicted group membership	
	Group	Bankrupt	Nonbankrupt
Original	Bankrupt	Gemini (MD 11 & DC 10)	Kitty Hawk (B737 & B727)
	Nonbankrupt	ABX Air (DC-8, DC-9, B767)	Atlas Air (B747)
		Arrow Air (DC-10, DC-8, B767)	Cargo 360 (B747)

Changing or integrating different aircraft into a fleet adds a significant cost to an airline. In 2004 and 2005, officials of Kitty Hawk Air Cargo stated that it

> incurred significant one-time costs to integrate these Boeing 737-300SF cargo aircraft into our current fleet and operations, including, but not limited to, costs relating to pilot training, maintenance training, purchases of additional tooling and spare parts and costs to modify our operational manuals and maintenance program. (SEC, 2006, p. 7)

Two years later Kitty Hawk Air Cargo declared bankruptcy and liquidated.

Along with fleet mix and the age of aircraft, maintenance, while considered part of operations, can also affect an airlines competitive advantage by improving mechanical reliability. All of the firms in this study performed their own lower-level maintenance. The size of the company within any industry can also be a competitive advantage. With increased size comes an increase in economy of scale for airline operation. Officials of Kitty Hawk Air Cargo in their 2005 annual report noted that many of their "competitors have substantially larger freight networks, serve significantly more cities, and have considerably more freight system capacity, capital and financial resources than we do" (SEC, 2006, p. 6), whereas Atlas Air positions itself as "the world's leading provider of outsourced cargo aircraft, crew, maintenance and insurance service to major international airlines" ("Atlas Air Inc. Named Best Air Charter," 2007, para. 1).

Dr. Gritta stated that size is important because you have more staying power and carry more clout: "You're the big elephant in the room" (personal communication, October 28, 2011). Dr. Gritta also indicated that some financial bankruptcy prediction models use a log transformation variable for size. A successor model to the Altman Z-Score, called the Altman ZETA credit score model uses a variable of firm size in calculating bankruptcy potential (Gritta et al., 2006). The larger a company is, the more operational economies of scale the firm has, leading to potentially higher revenues and making the company less prone to bankruptcy. The next section discusses the categories related to external factors.

External Factors

Categorized as external factors were the codes economics and regulations; the codes of antitrust, environment, and taxation are listed under external factors. Cost is also a code that falls under external factors; although management does have some control over cost, managers are at the mercy of their suppliers. For example, the cost of fuel steadily increased during the timeframe of the study, interspersed with large price changes. In the 2009 annual report for Atlas Air, the impact of fuel prices on the air-cargo business and the difficulties of management to project future operating cost are discussed. While the cost of fuel is a variable cost that changes with utilization of an aircraft, it is the largest single operating expense for an airline and affects all airlines equally (Atlas Air, 2010).

The 2009 annual report stated the following:

> The average fuel price per gallon for the Scheduled Service and Commercial Charter businesses was approximately $3.35 for 2008, compared with approximately $2.24 for 2007, an increase of $1.11 or 49.6%. During 2008, aviation fuel prices rose steadily during the first seven months of the year peaking at an average of $4.33 per gallon in July before declining sharply from August through the end of the year to an average of $2.13 per gallon for the month of December. (Atlas Air, 2010, p. 41)

Under the external factor of regulation was environment. Environmental issues are a growing concern to the public and to companies that must comply with environmental regulations. Airlines and airports can affect the environment in a number of ways. In 2010, a U. S. Government Accountability Office report on aviation and the environment listed possible environmental impact factors from airlines as noise, emissions, water pollution, and environmental sustainability (U.S. Government Accountability Office, 2010). In the documents reviewed, all four types of impacts were discussed; however, noise and emissions seemed to be of greatest concern to the airlines. While quieter and lower emissions jets are being developed by the airline manufacturers, the short-term effects of the clean air act, Kyoto treaty, and local and federal noise compliance regulations are of greatest concern to the airlines (ABX Air, 2010). Cargo airlines that fly noisier aircraft may be limited in the number of airports that they can serve or their operation may be restricted to certain times of the day, affecting their revenue stream or limiting their route structure.

Under the category of regulation was the code antitrust, which refers to a criminal investigation conducted by the U.S. Department of Justice for price fixing related to a fuel surcharge charged by many cargo carriers between January 2000 and February 2006 (ABX Air, 2010). The investigation, started by the U.S. Department of Justice, has also triggered regulators from Australia, the European Union, Korea, New Zealand, and Switzerland to open price-fixing investigations (ABX Air, 2010). In addition to the antitrust investigation, other lawsuits and claims were also filed. None of the cargo airlines in this sample were a party to the investigation; however, Atlas Air's sister airline Polar LLC was a target of the investigation.

Industry economics is another external factor that affects all of the airlines. Officials of ABX stated in their 2005 annual report that "An economic downturn in the U.S. is likely to adversely affect demand for delivery services [and] during an economic slowdown, customers generally use ground-based delivery services instead of more expensive air delivery services" (ABX Air, 2006, p. 10). Officials of ABX also stated, "Cargo volumes within the U.S. are highly dependent on the economic conditions and the level of commercial activity [because] generally, time-critical delivery needs, such as just-in-time inventory management, increase the demand for air cargo delivery" (ABX Air, 2006, p. 6). In addition to being vulnerable to economic conditions, global trade flows are typically seasonal and unbalanced. The peak season for air cargo traditionally runs from September through mid-December to support the retail holiday season (Atlas

Air, 2010), and there is a far greater flow of goods out of Asia, which limits the full utilization of aircraft.

Co-Occurrence of Data

Co-occurrence can give an indication of related terms (Garcia, 2005). Co-occurrence is the idea that "concepts that co-occur more frequently tend to be related" (Garcia, 2005, para. 4). Whenever a segment of text is coded with more than one code, a co-occurrence of codes occurs (Garcia, 2005). Atlas.ti was used to produce a co-occurrence table that provided a co-occurrence coefficient for each code group. The co-occurrence coefficient ranges between zero (codes that do not co-occur) and one (codes co-occur whenever they are used) (Muhr, 2009). A higher coefficient would indicate more co-occurrence between codes and; therefore, a greater relationship. The co-occurrence data were used to extract a list of related codes generated by the study, and all codes with a co-occurrence index of 0.1 or above are shown in Table 15. A list of the co-occurrence coefficients for all of the codes can be found in Appendix F.

Table 15

Co-Occurrence of Codes with Index of 0.1 or above

Code	Flight frequency
Capacity	0.10
Price	0.11
Reliability	0.17
Revenue	0.10

All of the codes with the co-occurrence index of 0.10 or above were related to flight frequency, and no other codes reached this threshold. There was no interco-occurrence between the codes of capacity, price, reliability, and revenue. The lack of interco-occurrence indicates a high relationship between the code of flight frequency and the codes capacity, price, reliability, and revenue.

Subject Matter Expert Interviews

Following the intermediate-coding phase of the research, two SMEs were interviewed. The intent of the interviews was to provide data for the study in relation to the codes that were developed during the open-coding and intermediate-coding phase of the research. Using the data obtained during the initial- and intermediate-coding phase of the research, open-ended questions were developed for use in the interviews. An unstructured interview format was used in which the SMEs were asked open-ended questions dealing with qualitative factors that may influence bankruptcy prediction models and specifically about any insight into bankruptcies in the all-cargo airline industry. An unstructured interview format was selected to allow for the direction of the conversation to be dictated by the SME, thus allowing for the free flow of ideas (Birks & Mills, 2011).

The main question posed to the SMEs was as follows: What qualitative factors do you feel may influence quantitative bankruptcy prediction models such as the (K-score) in the all-cargo industry? Follow-up questions asked SMEs to provide any possible insight into the bankruptcy of Kitty Hawk Air Cargo or Gemini air cargo or of the merger of Cargo 360 with Southern Air in 2008. Further, the SMEs were asked if they had any thoughts on the operation of ABX Air, Arrow Air, or Atlas Air during the years 2005-2009. Finally, the SMEs were asked their thoughts on the 35 codes that were developed in the initial coding round of this research study. A list of all of the questions posed during the interview appear in Appendix G. These interviews were conducted by telephone and the interviews were recorded, and transcribed. The accuracy of the transcriptions was verified by reviewing the recordings.

The first interview was conducted with Dr. Robert Tompkins. Dr. Tompkins holds a doctorate from the University of Warwick and completed postdoctoral work at the University Technology in Vienna Austria. Dr. Tompkins's postdoctoral work is in the research area of financial management and option pricing. Dr. Tompkins is presently a professor of finance at the Frankfurt School of Finance and Management in Frankfurt, Germany, and an adjunct faculty member in the Business Department of Embry Riddle Aeronautical University Worldwide. Dr. Tompkins is the author of several books and many articles in peer-reviewed journals on finance and financial related subjects. The consent form to serve as an SME for Dr. Tompkins is in Appendix H.

During the interview, Dr. Tompkins mentioned several items that seem to be germane to this research project. Dr. Tompkins stated, "Well obviously the most important qualitative factor is perception of that particular firm in the industry by customers and suppliers" (R. Tompkins, personal communication, October 15, 2011). Because if customers or suppliers feel that a company is in financial difficulties, they may shy away from doing business with that particular firm potentially driving the firm further into financial difficulties (R. Tompkins, personal communication, October 15, 2011). Perception of a particular firm can possibly be linked to the following codes that were developed during the coding phase: service, management, customers, size, bankruptcy, and reliability (R. Tompkins, personal communication, October 15, 2011). Dr. Tompkins also noted that an increase in the flow of information on the Internet has been shown to be an important indicator of changes in a firm (R. Tompkins, personal communication, October 15, 2011). The indicator of change is due to the fact that as a firm has either positive or negative news to report, the *Google Factor*, that is the number of hits or the number reports on the Internet increases, popularizing the firm's news and influencing the company's customers and suppliers (R. Tompkins, personal communication, October 15, 2011).

Regulating the flow of information, either negative or positive, can be linked to the management code discovered during the initial round of coding (R. Tompkins, personal communication, October 15, 2011). When discussing the codes that were discovered in the first round of this research project, Dr. Tompkins noted that cash flow is the most important element because “That's really what causes a company to go bankrupt” (R. Tompkins, personal communication, October 15, 2011). Related to that, deferred maintenance may also be an indication that an airline is having cash flow problems (R. Tompkins, personal communication, October 15, 2011). While cash flow has been identified as one of the codes during the initial round of research and emphasized by Dr. Tompkins, cash flow is a quantitative factor and is often used in qualitative financial distress models.

The second interview was conducted with Dr. Richard Gritta. Dr. Gritta is a professor of finance at the University of Portland. He holds a master's of business administration (MBA) from Indiana University and a doctorate from the University of Maryland. Dr. Gritta teaches courses in financial management and investments and has research interests that include air carrier bankruptcy forecasting and risk/return in air transportation. Dr. Gritta has published over 90 refereed articles in such journals as the *Journal of the Transportation Research Forum*, *Transportation Journal*, *Financial*

Management, and others. He is currently an editor of air transportation for the *Journal of the Transportation Research Forum* and acts as an advisor to U.S. Sen. Ron Wyden on airline matters. Some of Dr. Gritta's research was outlined in the literature review section of this study. The consent form to serve as an SME for Dr. Gritta is in Appendix H.

Dr. Gritta felt that one of the biggest qualitative factors that may influence quantitative bankruptcy prediction models is the relationship between management, unions, pilots, and mechanics (R. Gritta, personal communication, October 28, 2011). In addition, the quality of the management team must be taken into account when exploring qualitative factors. As also noted by Dr. Tompkins, Dr. Gritta noted that "cash flow is highly correlated with bankruptcy" and "virtually all the models have some measure that directly or indirectly measures cash flow" (R. Gritta, personal communication, October 28, 2011). So cash flow while not a qualitative measure, "makes sense, the more cash flow you have the less probability you will go bankrupt and vice versa" (R. Gritta, personal communication, October 28, 2011).

Dr. Gritta indicated that customers are also a key qualitative theme (R. Gritta, personal communication, October 28, 2011). Also noted during the interview was the importance of fleet mix, flight frequency, and fuel efficiency to determine the financial health of a firm. In response to the code mergers, Dr. Gritta stated, "If there are mergers in the works for the carrier that would be advantageous, because you're going to lower the capacity of the industry and you're going to remove competition" (R. Gritta, personal communication, October 28, 2011). Dr. Gritta was asked the following question: To what extent do you think airline management or airline leadership plays and success or failure of an airline? In response, Dr. Gritta stated that it plays a

> huge role; it's like a football coach in American football, you know you have a team that doesn't do anything and they hire this new coach and before you know it they turned the program around. I don't think you can ever underestimate the quality of your management team. (R. Gritta, personal communication, October 28, 2011)

Before the final step of delineation of the theory, we return to the published literature. In grounded theory, scholarly literature is used not as a theoretical framework to guide your research based on past research, as in traditional research methodologies, but is data itself. Grounded theorists go to the literature when theoretical sampling directs them to do so. The purpose of going to the literature in this research project was to gather more data as ground theory requires, but also to review and compare how this emergent theory relates to the published literature. Additionally, by returning to the literature the data is triangulated, which gives the research more validity and allows for the findings of the study to be compared and contrasted to other studies in the published literature.

Evaluation of Findings

Through this grounded theory research process three ideas or themes have emerged. For the sample group of six all-cargo airlines there appears to be a relationship between aircraft fleet mix (single fleet versus mixed fleet) and the K-score predicted group membership versus actual events. The airlines that were predicted nonbankrupt and did not go bankrupt (Atlas Air and Cargo 360) both flew a single aircraft type, whereas the other four airlines in the sample flew a mixed fleet of different types of aircraft. The relationship between aircraft fleet mix is supported by Dr. Gritta who stated that he has "done some research that shows the fewer the types of aircraft you fly, the lower your cost per unit, and that's an advantage" (R. Gritta, personal communication, October 28, 2011).

Further, the research indicated there might be a relationship between the type of aircraft flown by the airline and financial status. The financial status of the three airlines that operated wide-body aircraft (Gemini, Atlas Air, and Cargo 360) was predicted correctly by the K-score model, and the three incorrect predictions made by the K-score model all involved airlines that flew narrow body aircraft (Kitty Hawk Air Cargo, ABX Air, and Arrow Air). The finding of a relationship between type of aircraft flown and financial status is closely related to the first finding on aircraft fleet mix.

The third idea that emerged during the research was there was a high co-occurrence of codes among flight frequency and capacity, price, reliability, and revenue. Many of the codes and themes that emerged throughout the research come as no surprise. The ideas of competitive advantage, operations, financial factors, risk, and many of the other codes that emerged are germane not only to the airline industry, but to most companies in general. The high co-occurrence of flight frequency with capacity, price, reliability, and revenue is supported by the statement made by Dr. Gritta, that if flight frequency

> resulted in higher hours of utilization per aircraft, it would be a good thing. The higher your average flight hours for each day of utilization of the aircraft, the

> lower cost that you have, so that would mean a lower probability of bankruptcy. (personal communication, October 28, 2011)

The dominate research methodologies found in the literature on bankruptcy prediction are "classical cross-sectional statistical methods and multivariate discriminant analysis (MDA)… however, these methods have some major limitations" (Wetter & Wennberg, 2009, p. 30). In addition, the performance of many of the failure prediction models based on statistical methods is similar, so other methods of failure prediction should be explored (Ooghe et al., 2009). Ooghe et al. (2009) suggested that to improve the statistically based models it is important to understand first the nonstatistical variables that may affect these existing models. This research has attempted to provide a better understanding of the nonstatistical themes that may affect traditional statistical based bankruptcy prediction models. One of the underlying tenets of grounded research is to look at the data with an open mind and not be influenced by previous research; however, once new theory has emerged, it is essential to explore the published literature to determine where the new theory stands in relation to previous research.

The literature on research into nonstatistical themes that affect bankruptcy prediction is limited; however, some research has been published. Sun and Li (2007) developed a methodological framework for group expert decision making for predicting financial distress using qualitative risk factors. The qualitative risk factors used by Sun and Li are listed in Table 16. The qualitative risk factors used by Sun and Li fit well with the categories developed in this study with the exception that several of the risk factors used by Sun and Li are divided into several subcategories. For example, the financial factors category, which emerged in this study, is divided into four categories by Sun and

Li (financial ability, investment risk, consciousness of debt risk, and corporate governance).

Kim and Han (2003) developed a bankruptcy prediction model using a genetic algorithm based model and qualitative decisions by expert testimony. The experts considered six qualitative risk factors (i.e., credibility, competitiveness, financial flexibility, industry risk, management risk, and operating risk). Table 16 includes a comparison of the qualitative factors used by Kim and Han with those of the current study. There appears to be a match between the six qualitative risk factors of Kim and Han in the categories developed in this study. With the exception, like Son and Li (2007), the financial factors category of the study is divided into several qualitative categories. The other deviation from Sun and Li (2007) and Kim and Han (2003) is that both studies considered all of the factors *risk,* whereas this study provides a separate category for *risk*. Both of these studies support the six categories that emerged in this research.

Table 16 *Comparison of Qualitative Factors Used in Other Studies*

Current study	Sun & Li (2007)	Kim & Han (2003)
Management	Management and control	Management risk
Risk	All a risk factor	All a risk factor
Operations	Management and control	Operating risk
Competitive advantage	Market information	Competitiveness
Financial factors	Financial ability	Credibility
	Investment risk	Financial flexibility
	Consciousness of debt risk	
	Corporate governance	
External factors	Outside risk	Industry risk

Kim and Han (2003) advocated for a combined approach of both qualitative and quantitative methods to improve bankruptcy prediction model performance. Kim and

Han noted that qualitative bankruptcy prediction models were limited because of the fact that they used historical data, whereas qualitative methods and the use of SMEs were able to provide better future predictions. While this research independently developed a similar list of qualitative factors to Kim and Han that should be explored, it used subject matter expert testimony to confirm and support the categories, whereas Kim and Han used SMEs to provide an opinion on specific airline bankruptcies.

Management was one of the categories that emerged during this research, and it is a central theme found in qualitative financial distress research. Dr. Gritta noted that management was one of the biggest qualitative factors that influence financial distress in a firm (R. Gritta, personal communication, October 28, 2011). Wetter and Wennberg (2009) developed a model that used variables for human capital and social capital of their management team, which performed better than the Altman Z-score model in a study of 1,735 Swedish firms. The variable for human capital took into consideration the company founder's years of education, years of industry experience, and years of entrepreneurial experience, and for social capital used years of residency in a country and a dummy variable for parents who were entrepreneurs. Using the variables human capital and social capital, Wetter and Wennberg (2009) had a prediction accuracy of 65.88% where as the Altman Z-score correctly classified only 52.56%. The findings in the study showed that a variable for management in a bankruptcy prediction model should be considered.

The first two themes that emerged in this research concerned aircraft fleet mix (single fleet versus mixed fleet) and type of aircraft flown by the airline (narrow-body versus wide-body aircraft). In addition, the third theme that emerged concerned the relationships among the following codes: flight frequency and capacity, price, reliability, and revenue. Gudmundsson (2002) used a regression analysis with independent variables that were related to the codes uncovered in this research in developing a bankruptcy prediction model. Unlike most financial prediction models, Gudmundsson's model incorporates operating or traffic statistics instead of the traditional financial data. Gudmundsson used an independent variable for different types of aircraft operated as one of 10 independent variables. Three other independent variables of load factor, number of passengers per departure, and number of departures per aircraft were used, all of which are related to capacity and flight frequency. Gudmundsson also used the variables of average age of aircraft fleet and annual inflation rate; both of these variables can be related to fleet mix and economic factors uncovered in this research; therefore, six of the 10 independent variables used by Gudmundsson were independently uncovered in this research. Of the 10 independent variables used by Gudmundsson, only two were significant in the model; average age of fleet and the number of employees per aircraft. The findings of Gudmundsson provide credence that issues surrounding the makeup of the fleet may be significant.

In another study by Gudmundsson (2004), productivity was positively related to financial distress in airlines. Productivity in the aviation industry does not just refer to labor issues. Economies of scale productivity increase related to the use, makeup, and deployment of the aircraft fleet as well (Gudmundsson, 2004).

Gudmundsson (2002) found that airlines that fly single fleet wide-body aircraft are less prone to bankruptcy; however, Gudmundsson (1999) indicated in previous research "that carriers operating smaller equipment fared better than those operating larger equipment" (p. 173). The difference in results may be attributed to the fact that Gudmundsson's findings were from a sample of passenger airlines between 1978 and 1992. This 5-year sample was immediately following airline deregulation in the United States, and 9 years before the terrorist attacks of September 11, 2001. Both events caused many changes and upheaval within the aviation industry (Walton, 2011).

The third theme that emerged concerned the relationships among flight frequency and capacity, price, reliability, and revenue. The third theme is related to the utilization of an aircraft in a process called revenue management. Revenue management is the plan for the maximization of the cargo scheduled to fly full aircraft and the optimization of the route structure to ensure full utilization of the aircraft (Walton, 2011). Airlines can only increase capacity in large increments, so optimization of the capacity of the aircraft is critical to the maximization of revenue (Hellermann, 2006). Airlines that are able to maximize the revenue are less prone to bankruptcy (Dr. Gritta, personal communication, October 28, 2011). In addition, airlines that are able to maximize their utilization have higher economy of scale and lower cost per unit (Hellermann, 2006), making them less prone to bankruptcy.

Emergent Theory and Theoretical Integration

Three themes have emerged from this grounded theory research process. There appears to be a relationship between aircraft fleet mix and the K-score prediction model; there appears to be a relationship between the type of aircraft flown by an airline and the K-score prediction model; and there is a high co-occurrence of codes among flight frequency and capacity, price, reliability, and revenue, which indicates the importance of flight related factors in qualitative financial distress prediction models.

While the literature is limited on qualitative financial distress prediction research, this study has confirmed the importance of considering fleet mix and type of aircraft flown as part of qualitative study. In addition, the high co-occurrence of flight frequency and capacity, price, reliability, and revenue are also qualitative indicators that have been explored in other research. Most published financial distress prediction models use a set of quantitative financial ratios; however, this research has shown that qualitative and traffic statistics should be considered in prediction models.

Summary

This research used grounded theory to explore the nonfinancial factors that may affect quantitative bankruptcy prediction models. The results of a published bankruptcy prediction model (K-score) accuracy on 17 U.S. all-cargo airlines between 2005 and 2009 were used as a starting point to draw a sample of six airlines. The K-score model was originally developed to predict bankruptcy in the passenger airline industry for the years 1999-2003. Uncalibrated, for the air-cargo airlines, the model was able to correctly to classify 1 of the 2 bankrupt firms (50.0% correctly classified) as bankrupt. For the nonbankrupt air-cargo airlines, the original Kroeze model predicted seven of the nonbankrupt firms correctly (46.7% correctly classified) for an overall accuracy of 47.1% of the original grouped cases correctly classified. In total, 34 documents were coded and 35 unique codes or ideas emerged from the documents. Two SME interviews were conducted to provide additional background on financial distress in the all-cargo airline industry.

Three relationships emerged from the data that provide insight into some of the qualitative factors that should be considered in financial prediction models. First, there is a relationship between aircraft fleet mix in the K-Score prediction model. Second, there is a relationship between the type of aircraft flown by an airline and the K-Score prediction model. Third, there is a relationship between traffic statistics relating to flight frequency and capacity, price, reliability, and revenue.

Chapter 5: Implications, Recommendations, and Conclusions

The problem addressed in this study was the inability of published financial prediction models to account for nonstatistical factors that may influence the models. Financial prediction models, typically quantitative in nature, are used to determine the financial stability of the company. These quantitative, statistical based models have been refined to a point where they provide similar results, so further improvement may be obtained through exploration of the nonstatistical variables that affect these models (Ooghe et al., 2009; Youn & Gu, 2010). The population for the study was the U.S. all-cargo airline industry between 2005 and 2009. There were 17 U.S. all-cargo airlines in operation during this period. Using grounded theory, the purpose of this research was to explore the nonstatistical factors influencing a published bankruptcy prediction model, the K-score. A basic grounded theory research processes was followed in this study as outlined by Corbin and Strauss (1990) in which constant comparison analysis was used throughout the data collection process.

Validation of grounded theory is questioned by some researchers; however, validity was maintained through the use of triangulation of data from multiple sources. Additionally, validity was added through the detailed description of the data that was provided in chapter 4. Publicly available data was used in this study and did not involve any human subjects so there was no risk to humans; however, Northcentral University's Institutional Review Board approval was obtained prior to any data collection.

In this chapter, the research question and the theory that emerged during the study will be summarized. The chapter includes the limitations of the study and where it fits with existing literature. The chapter will continue with a discussion of the managerial implications of this research and its findings; moreover, the chapter will end with a discussion of recommendations and conclusions.

Implications

This research uncovered six categories (management, risk, operations, competitive advantage, financial factors, and external factors) that relate to the financial stability of an all-cargo airline. The categories that emerged from the data are relevant not only to the all-cargo airline industry, but to most companies in general. Several studies (Kim & Han, 2003; Sun & Li, 2007) have used similar qualitative factors in bankruptcy prediction modeling. Figure 4 graphically displays the six categories that emerged during this research and their interrelations. Financial factors, operations, risk, and competitive advantage are all part of management, and management has direct control over these categories; however, all of these categories are influenced by external factors outside of the control of management and set the parameters in which the firm must operate. All of these factors influence the financial stability of the firm, and the long-term health of the company.

The research question that was explored in this study was as follows: What nonstatistical factors influence the K-score bankruptcy prediction model in the all-cargo airline industry? The findings of this research uncovered three themes that address the research question. For the six all-cargo airlines examined in this study the research found a relationship between aircraft fleet mix and the K-score predicted group membership. The two airlines (Atlas Air and Cargo 360) both operated single fleet type of aircraft and both were correctly predicted nonbankrupt, whereas all of the airlines, except one (Gemini), that flew a mixed fleet of different type aircraft were correctly predicted as either bankrupt or nonbankrupt by the K-score model. The second relationship uncovered in this research was between the type of aircraft flown by an airline and the K-score model. Of the six airlines in this sample, three flew only a single body type aircraft (Gemini, Atlas air, cargo 360). All three of these airlines were correctly classified by the K-score model. The other three airlines (Kitty Hawk, ABX Air, and Arrow Air) all flew at least some narrow-body aircraft, and all three were incorrectly classified by the K-score model. The fleet type and mix of aircraft that an airline flies is a strategic decision for all-cargo airlines. Although flying a mixed fleet may allow an airline to better size aircraft on certain routes, it increases the overall operational cost of an airline.

Although the literature on qualitative financial distress modeling is limited, most qualitative research attempts to account for the type of fleet that an airline flies. For example, Gudmundsson (2002) used an independent variable of different types of aircraft operated in a qualitative model that he developed. The independent emergence of this data separately from previously published research adds validity to this study and to the previous work of Gudmundsson and others and indicates that the type of aircraft fleet affects the financial success or failure of an airline. Airlines that operate older fleets tend to have higher fuel and maintenance costs and lower overall reliability, whereas airlines that fly newer aircraft have the advantage of fuel savings, reduced maintenance cost, and improved reliability.

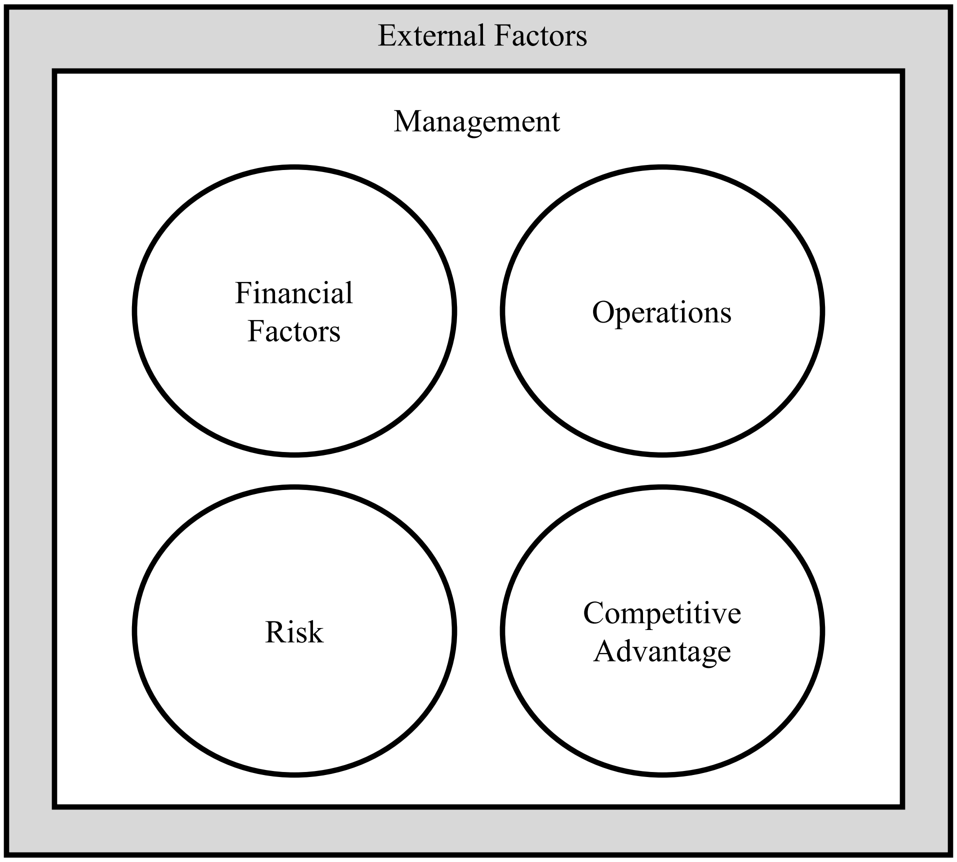

Figure 4. Six categories that affect financial distress in a firm.

The third theme that emerged in this research concerns the relationships between flight frequency and capacity, price, reliability, and revenue. These factors are related to the utilization of an aircraft. To maximize revenue an all-cargo carrier strives for full utilization of its aircraft on all legs of a flight. Full utilization of aircraft is difficult to manage because of the complexity of network planning and capacity allocation. Unlike passenger airlines where a passenger can be assigned to exactly one seat, cargo shipments have multiple dimensions (volume and weight) that must be taken into account in an attempt to maximize utilization of an aircraft. Additionally, cargo shipments typically are not round-trip, and imbalances in the trade lanes may require a cargo airline to operate a less than full aircraft in one direction (e.g., from China to the United States the aircraft is full, but on return to China the aircraft is not fully utilized). By maximizing revenue, an airline reduces its probability of bankruptcy. The importance of the theme of revenue maximization was confirmed by Dr. Gritta (personal communication, October 28, 2011) who stated that airlines that have a higher utilization of their aircraft have a lower probability of bankruptcy.

Figure 5 graphically illustrates the three themes that emerged during this research. These themes act as pillars to financial prediction models in the all-cargo airline industry. All three of these themes, fleet mix, type of aircraft, and aircraft utilization deal directly with the production unit of the firm, the aircraft. Just as with a manufacturing company with a factory, the production unit is where the firm's key competency must be focused to maximize revenue and control cost in an attempt to maximize profits for all of the shareholders. The three themes have emerged as the key factors that influence financial distress in all-cargo airlines and therefore affect financial distress models. Qualitative bankruptcy prediction models have been unable to account fully for qualitative factors that affect their prediction capability. The three pillars of fleet mix, type of aircraft flown, and aircraft utilization have not been taken into consideration by qualitative bankruptcy prediction models; however, this research has shown that these factors are important to improving bankruptcy predictions for the aviation industry.

This research explored the nonstatistical factors that influence the accuracy of the Kroeze K-score model. Using grounded theory, this research contributes to the body of literature. This study indicates the importance of qualitative factors in financial distress prediction and provides some of the factors that may be important in improving bankruptcy prediction accuracy; additionally, this research confirms the importance of the type of fleet, aircraft type mix, and maximizing aircraft utilization to profitable operation.

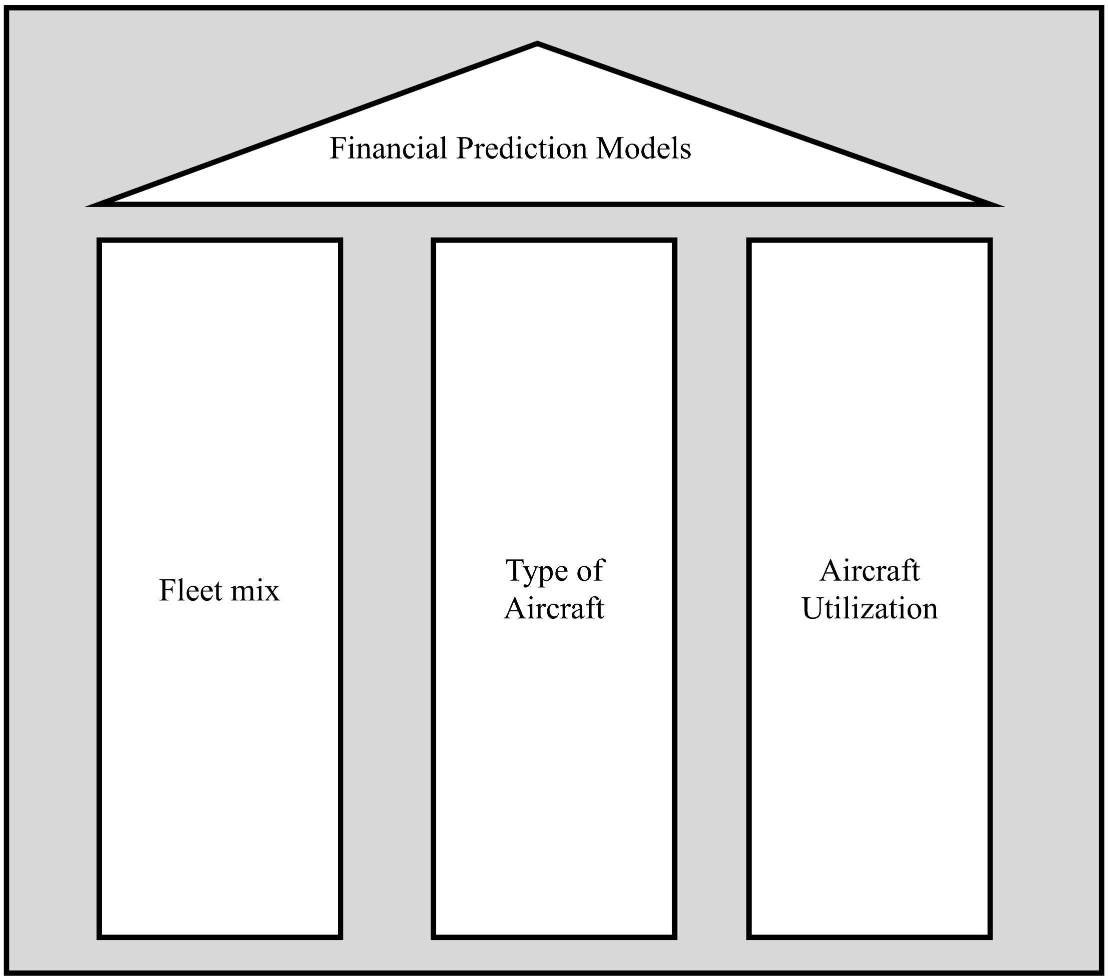

Figure 5. Factors that influence financial distress.

Recommendations

The qualitative factors uncovered in this research can be used to improve financial prediction models. These findings can be used to identify themes and relationships and provide a better understanding of the failure process. This research determined there are six themes (management, risk, operations, competitive advantage, financial factors, and external factors) that relate to the financial stability of an all-cargo airline. Previous research has used some of these same themes in financial distress prediction modeling, but not all of them (Kim & Han, 2003; Sun & Li, 2007). Future research should explore the incorporation of all six themes into all-cargo airline financial distress prediction models to verify their relevance. The six themes may be relevant to companies outside of the aviation industry, and their use in financial distress prediction of nonaviation-related firms should be explored to determine the transferability of the categories between industries.

Factors that influence financial distress models in the all-cargo airline industry were determined to be related to fleet mix, type of aircraft, and aircraft utilization. Previous qualitative financial distress research has attempted to account for some of these factors (Gudmundsson, 2002). These three factors make up the production unit of an airline and should be the focus of airline management to maximize revenue and minimize cost. Because of the importance of these three factors to airline profitability, additional research on the relationship of these factors to financial distress modeling should be conducted.

The main limitation of this study was the small population available, which precluded the possibility of testing the findings, which was, in any case, outside the scope of this research. Future research should be conducted to verify these findings on a larger population. The study researched U.S. all-cargo airlines, and used a sample of six of the 17 all-cargo carriers in operation from 2005 to 2009. Since the total population of U.S. all-cargo carriers is small, future research could be conducted on the entire population. Non-U.S. all-cargo airlines operate under a different financial reporting regime that may affect financial prediction models that are calibrated using U.S. company data, so future studies should be conducted which consider these factors in relation to airlines which operate outside the United States.

This research includes secondary data augmented by two interviews conducted with subject matter experts. The use of secondary data in the grounded theory process has many obstacles and limitations for its use in theoretical sampling (Birks & Mills, 2011). The limitations of using secondary data are that it removes the researcher from the generation and collection of data, which is counter to the idea of grounded theory that the researcher will have some influence over the nature of the data that is gathered. When generating theory using secondary data, the researcher's philosophical position may impact how the data is interpreted, and "gaps may subsequently exist in the theoretical constructions" (Birks & Mills, 2011, p. 84) that hinder the generation of a cohesive theory. Although the use of secondary data may hinder a comprehensive theory development, Birks and Mills (2011) noted that "attention to the application of essential grounded theory methods in your treatment of secondary data will minimize the potential disadvantages" (p. 85) and that the use of secondary data can provide a cost and time advantage in research.

Traditional quantitative bankruptcy prediction models that use past data are limited in predicting financial distress that might occur in the future, whereas the use of qualitative data and SMEs may provide improved predictions further into the future. The factors and the qualitative models; however, have not been fully developed. Future research focused on the use of qualitative data and SMEs may be able to improve prediction performance.

In addition to a theoretical or research interest, this research also provides a list of factors that should be considered by airline managers when making decisions. Most senior managers, no matter what industry, are trained to examine external factors that may affect their firm along with considerations of competitive advantage, financial factors, and risk factors. In addition, one of the primary functions of management is overseeing operations. These factors all emerged as part of six categories that may affect financial distress and a firm and confirms the importance to the company. Specific to the aviation industry are the factors of fleet mix, type of aircraft flying, and aircraft utilization, which influence financial distress in a company. Fleet decisions are strategic multimillion-dollar decisions that airline managers must make. If management makes the correct fleet decisions they may avoid future financial turmoil; get it wrong and management may set firm on a path to destruction. The third theme uncovered in this research in relation to flight frequency also impacts management's decisions. Managers must determine the price of providing air cargo services, and through fleet decisions determine the capacity and reliability of their aircraft. These factors will affect the final revenue stream of company and therefore the financial health firm.

Conclusions

"Firms which cannot recognize financial distress and take measures at an early stage will run into bankruptcy, which not only brings great lost stockholders, creditors, managers and other interested parts, but also affects the stability of social economy" (Sun & Li, 2007, p. 885). The findings in this study provide information that is important to both the theoretical academic community and the practical, managerial, day-to-day operations of an airline. The research on bankruptcy prediction modeling is extensive, and the findings from this research can be used to improve the financial distress modeling process. For airline managers, an understanding of the factors that may cause bankruptcy will help avoid financial distress in their company. The categories identified in this research that relate to the financial distress of a firm were management, risk, operations, competitive advantage, financial factors, and external factors. Company managers must deal with many issues on a daily basis; however, this research has indicated that these six categories are related to the financial health of the company, so an effort should be made by management to specifically focus on these factors.

The profit-making unit of an airline is its fleet. The fleet mix, type of aircraft, and utilization are key to operating a profitable airline. The findings showed that these three factors also influence the financial health of all-cargo airlines. The decision on what types of aircraft and the proper mix of aircraft to support the route structure of an airline is a multimillion-dollar decision and can affect the long-term financial health of an organization.

The theory that emerges from the data as discussed in this dissertation lead back to the fact that the qualitative themes uncovered in the course of this research have not been widely used in bankruptcy prediction models. These themes influence the financial well being of an airline and should improve the prediction capability of financial bankruptcy models if incorporated into future model.

This research has confirmed, but not quantified, there is a relationship between aircraft fleet mix, type of aircraft flown by airline, and a published prediction financial model. The findings of the study have also confirmed the importance of aircraft utilization and revenue management and provided a list of categories (management, risk, operations, competitive advantage, financial factors, and external factors) that influence the financial stability of an all-cargo airline industry. The all-cargo airline industry in the as a whole operates on tight margins and is prone to bankruptcy. The results of this research add to the body of knowledge on financial distress modeling and can be of benefit to governments, lenders, academics, and investors. Additional research is recommended to verify the results using a larger population of all-cargo airlines and on companies outside of the aviation industry.

References

Allen, L. M. (2010). A critique of four grounded theory texts. *The Qualitative Report, 16*, 1606-1620.

Altman, E. I. (1967). *The prediction of corporate bankruptcy: A discriminant analysis.* Unpublished doctoral dissertation, University of California, Los Angeles.

Altman, E. I. (1968). Financial ratios, discriminate analysis and the reduction of corporate bankruptcy. *The Journal of Finance*, *23*, 589-690.

Altman, E. I. (1983). Exploring the road to bankruptcy. *The Journal of Business Strategy, 4*(2), 36. Retrieved from ABI/INFORM Global. (Document ID: 7657885)

Altman, E. I., & Hotchkiss, E. (2006). *Corporate financial distress and bankruptcy* (3rd ed.). Hoboken, NJ: Wiley.

ABX Air. (2010). *ABX air 2009 Annual Report.*

Atlas Air. (2006). *Atlas Air Worldwide Holdings, Inc. Annual Report 2005*.

Atlas Air. (2010). *Atlas Air Worldwide Holdings 2009 Annual Report*.

Becker, B., & Dill, N. (2007). Managing the complexity of air cargo revenue management. *Journal of Revenue and Pricing Management, 6*(3),175-187.

Beraho, E. K. (2010). Influence of country culture on bankruptcy and insolvency legal reform management. *The Business Review, Cambridge, 16*(2), 78-83.

Birks, M., & Mills, J. (2011). *Grounded theory: A practical guide*. Thousand Oaks, CA: Sage.

Bisignani, G. (2006). Airlines. *Foreign Policy, 152,* 22-28.

Boeing. (n.d.). *Boeing*. Retrieved from http://www.boeing.com

Boeing. (2009). *World air cargo forecast 2008-2009*. Retrieved from http://www.boeing .com/commercial/cargo

Boeing. (2010). *World air cargo forecast 2010-2011*. Retrieved from http://www.boeing.com

Borenstein, S., & Rose, N. L.(1995). Bankruptcy and pricing behavior in US airline markets. *The American Economic Review, 85*, 397. Retrieved from ABI/INFORM Global. (Document ID:1458543)

Boyd, J. D. (2006, August 7). Gemini cleared for takeoff. *Traffic World.*

Button, K. (2010). *Transport economics* (3rd ed.). Northampton, MA: Edward Elgar.

Cargolux. (2010). *Annual report 2009*. Retrieved from http://www.cargolux.lu

Charmaz, K. (1995). Grounded theory. In J. A. Smith, R. Harre, & L. Van Langenhove (Eds.), *Rethinking methods in psychology* (pp. 27-49). London, UK: Sage

Charmaz, K. (2006). *Constructing grounded theory: A practical guide through qualitative analysis*. Thousand Oaks, CA: Sage.

Chen, Y., Weston, J. F., & Altman, E. I.(1995). Financial distress and restructuring models. *Financial Management, 24*(2), 57.

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

Corbin, J., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology, 13*(1), 3-21.

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd ed.). Thousand Oaks, CA: Sage.

Fabozzi, F. J., Chen, R. R., Hu, S. Y., & Pan, G. G. (2010). Tests of the performance of structural models in bankruptcy prediction. *The Journal of Credit Risk, 6*(2), 37-78.

Flouris, T. (2010). Rationalizing aircraft performance dynamic modeling in airline fleet planning decisions. *Enterprise Risk Management, 1*(1), 39-67.

Garcia, E. (2005). *Keywords co-occurrence and semantic connectivity*. Retrieved from http://www.miislita.com/semantics/c-index-1.html

Giapponi, C. C., & Scheraga, C. A. (2007). Cross-cultural factors and corporate governance transparency in global airline strategic alliances. *Journal of the Transportation Research Forum, 46*(2), 101-122.

Giapponi, C. C., & Scheraga, C. A. (2008). National culture and competitive strategy disclosure in global airline strategic alliances. *Journal of the Transportation Research Forum, 47*(1), 57-72.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Piscataway, NJ: Aldine Transaction.

Goldratt, G. M., & Cox, J. (2004). *The goal: A process of ongoing improvement* (3rd ed.). Great Barrington, MA: The North River Press.

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. *Journal of the Transportation Research Forum, 47*(2), 133-138.

Gritta, R. D., Adrangi, B., Davalos, S., & Bright, D. (2006). A review of air carrier bankruptcy forecasting methodologies and directions for future research. *The Credit and Financial Management Review, 12*(3), 11-29.

Gritta, R., & Lippman, E. (2010). Aircraft leasing and its effect on air carrier's debt burdens: A comparison over the past several decades. *Journal of the Transportation Research Forum, 49*(3), 101-110.

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*(1),44-49. Retrieved from ABI/INFORM Global. (Document ID:63689167)

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

Gudmundsson, S. V. (2002). Airline distress prediction using non-statistical indicators. *Journal of Air Transportation, 7*(2), 3-23.

Gudmundsson, S. V. (2004). Management emphasis and performance in the airline industy: An exploratory multilevel analysis. *Transportation Research Part E, 40,* 443-463. doi: 10.1016/j.tre.2004.08.004

Guion, L. A., Diehl, D. C., & McDonald, D. (2011). *Triangulation: Establishing the validity of qualitative studies.* Retrieved from: http://edis.ifas.ufl.edu/fy394

Guzhva, V. S. (2008). Applying intervention analysis to financial performance data: the case of US airlines and September 11th. *Journal of Economics and Finance, 32*, 243-259.

Hellermann, R. (2006). *Capacity options for revenue management: Theory and applications in the air cargo industry*. Heidelberg, Germany: Springer-Verlag.

Hensher, D. A., & Jones, S. (2007). Forecasting corporate bankruptcy: Optimizing the performance of the mixed logit model. *Abacus, 43*, 241-364. doi:10.1111/ j.1467-6281.2007.00228.x

Hofer, C., Dresner, M. E., & Windle, R. L. (2009). The impact of airline financial distress on US air fares: A contingency approach. *Transportation Research Part E: Logistics and Transportation Review, 45*, 238-249. doi:10.1016/ j.tre.2008.04.001

International Air Transport Association (IATA). (2010a). *World air transport statistics* (54th ed.). Montreal, Canada: International Air Transport Association.

International Air Transport Association (IATA). (2010b). *Annual report*. June 2010. Retrieved from http://www.iata.org

Jones, S., & Hensher, D. A. (2005). Advanced probability modeling and the prediction of corporate bankruptcy. *Journal of Applied Management Accounting Research, 3*(2), 21-35. Retrieved from Accounting & Tax Periodicals. (Document ID:1381615641)

Kim, M-J., & Han, I. (2003). The discovery of experts' decision rules from qualitative bankruptcy data using genetic algorithms. *Expert Systems and Applications, 25*, 637-646.

Kroeze, C. (2005). *Predicting airline corporate bankruptcies using a modified Altman Z-score model.* (Doctoral dissertation, University of Nevada, Las Vegas). Retrieved from http://books.google.com/books?id=mM4MKQEACAAJ &source=gbs_navlinks_s.

Liu, C. (2009). Entry behavior and financial distress: An empirical analysis of the US domestic airline industry. *Journal of Transport Economics and Policy, 43*, 237-256. Retrieved from ABI/INFORM Global. (Document ID: 1783148811)

Luckerhoff, J., & Guillemette, F. (2011). The conflicts between grounded theory requirements and institutional requirements for scientific research. *The Qualitative Report, 16*, 396-414.

MatlinPatterson Global Opportunities Partners III acquires controlling interest in Arrow Air Holdings Corporation. (2008, June 30). *PR Newswire Association LLC.*

McCabe, R. M. (1998). *Why airlines succeed or fail: A system dynamics synthesis*. Retrieved from http://en.scientificcommons.org/6047227

McKee, T. E. (2007). Altman's 1968 bankruptcy prediction model revisited via genetic programming: New wine from on old bottle or a better fermentation process? *Journal of Emerging Technologies in Accounting, 4,* 87-101.

Mello, J., & Flint, D. J. (2009). A refined view of grounded theory and its application to logistics research. *Journal of Business Logistics, 30*(1), 107-125.

Mello, J. E., & Hunt, C. S. (2009). Developing a theoretical framework for research into driver control practices in the trucking industry. *Transportation Journal, 48*(4), 20-39.

Muhr, T. (2009). *Some Cooc Table Explorer (CTE) mysteries unveiled*. Retrieved from http://forum.atlasti.com/showthread.php?t=4317

Nwezeaku, N. C. (2010). A discriminant analysis of public sector financial management performance of the economies of sub-Saharan Africa. *Interdisciplinary Journal of Contemporary Research in Business, 1*(11), 71-89.

Ooghe, H., Spaenjers, C., & Vandermoere, P. (2009). Business failure prediction: simple-intuitive models versus statistical models. *IUP Journal of Business Strategy, 6*(3/4), 7-44.

Operating income. (2010). *Investopedia*. Retrieved from http://www .investopedia.com/

Ribbink, D., Hofer, C., & Dresner, M. (2009). Airline financial distress and customer satisfaction. *Journal of the Transportation Research Forum, 48*(1), 89-104.

Roberts, D. L., Walton, R. O., & Muldoon, W. J. (2011). Airbus and the production of the A380: A consideration of multicultural differences in globally distributed operations. *Journal of Business and Behavioral Sciences, 23*(1), 191-197.

Santiago, A. (2007, August 6). Cargo 360, Southern Air merger chugging along. *Aviation Daily, 369*(25), 6.

Scaggs, M. B., & Crawford, P. J. (1986). Altman's corporate bankruptcy model revisited: Can airline bankruptcy be predicted? *Review of Regional Economics and Business, 11*(2), 11-16. Retrieved from ABI/INFORM Global. (Document ID: 1291432)

SEC. (2006). *Form 10-K for Kitty Hawk, Inc. fiscal year ending December 31, 2005.* Washington, DC: United States Securities and Exchange Commission.

SEC. (2007a). *Form 10-K for Kitty Hawk, Inc. fiscal year ending December 31, 2006.* Washington, DC: United States Securities and Exchange Commission.

SEC. (2007b). *Form 10-Q form for Kitty Hawk, Inc. ending 31 March 2007*. Washington, DC: United States Securities and Exchange Commission.

SEC. (2007c). *Form 10-Q for Kitty Hawk, Inc ending 30 June 2007*. Washington, DC: United States Securities and Exchange Commission.

SEC. (2010). *Form 10-K Air Transport Services Group, Inc fiscal year ending December 31, 2009.* Washington, DC: United States Securities and Exchange Commission.

Slim, C. S. (2007). Fuzzy neural model for bankruptcy prediction. *The Business Review, Cambridge, 8*(2), 117-122.

Stickney, C. P., & Weil, R. L. (2000). *Financial accounting: An introduction to concepts, methods, and uses* (9th ed.). Fort Worth, TX: Dryden Press.

South Florida Sun-Sentinel. (2005, February 16). Arrow Air is ready to ascend cargo carrier rebounds from bankruptcy. *South Florida Sun-Sentinel,* p. 2D.

Stempal, J. (2010, July 1). Cargo carrier Arrow Air bankrupt, to liquidate. *Thomson Reuters.*

Sun, J., & Li, H. (2007). Financial distress early warning based on group decision making. *Computers & Operations Research, 36*, 885-906. doi:10.1016/j.cor.2007.11.005

TranStats. (2010). *Air Carrier Financial Reports (Form 41 Financial Data) database*. US Department of Transportation (DOT), US Bureau of Transportation Statistics, Research and Innovative Technology Administration (RITA).

Top 50 airlines. (2010, September). *Air Cargo World,* 22.

Total assets. (2010). *Investopedia*. Retrieved from http://www .investopedia.com/

Total liabilities. (2010). *Investopedia*. Retrieved from http://www .investopedia.com/

U.S. Government Accountability Office, (2010). *Aviation and the environment: Systematically addressing environmental impacts and community concerns can help airport reduce project delays* (GAO-10-50). Washington, D.C: Government Printing Office.

Vasigh, B., Fleming, K., & Tacker, T. (2008). *Introduction to air transport economics*. Burlington, VT: Ashgate.

Walton, R. O. (2011). *Air cargo operations: A collection of papers and articles on current events in the air cargo industry*. Chicago, IL: Publisher Services.

Ward, T. J. (2007). The impact of the response measure used for financial distress on results concerning the predictive usefulness of accounting information. *Academy of Accounting and Financial Studies Journal, 11*(3), 85-107. Retrieved from Accounting & Tax Periodicals. (Document ID:1300255171)

Wensveen, J. G. (2007). *Air transportation: A management perspective* (6th ed.). Burlington, VT: Ashgate.

Wetter, E., & Wennberg, K. (2009). Improving business failure prediction for new firms: Benchmarking financial models with human and social capital. *The Journal of Private Equity, 12*(2), 30-37.

Youn, H., & Gu, Z. (2010). Predict U.S. restaurant firm failures: The artificial neural network model versus logistic regression model. *Tourism and Hospitality Research, 10*(3), 171-187

Appendixes

Appendix A

List of Cargo Airlines

List of all-cargo U.S. airlines in business 2005-2009

- Abx Air, Inc.
- Aloha Air Cargo
- Amerijet International
- Arrow Air Inc.
- Astar USA, LLC
- Atlas Air Inc.
- Capital Cargo International
- Cargo 360, Inc.
- Centurion Cargo Inc.
- Evergreen Int'l Inc.
- Gemini Air Cargo Airways
- Kalitta Air LLC
- Kitty Hawk Air Cargo
- Lynden Air Cargo Airlines
- Northern Air Cargo Inc.
- Polar Air Cargo Airways
- Southern Air Inc.

Source: RITA TranStats database

Appendix B

Documents Reviewed

Table B1

Title	Source	Published
Oak Hill to buy Southern Air and merge it with Cargo 360	Air Transport Intelligence	2007
Southern Air drops plans to add 747-400SF	Air Transport Intelligence	2008
Cargo 360, Southern Air merger chugging along	Aviation Daily	2007
Oak Hill Capital Partners to acquire Southern Air; Southern Air to be combined with Cargo 360 to create a leading global Air cargo company	PR Newswire	2007
US DOT grants Cargo 360 air operator’s certificate	Air Transport Intelligence	2006
Cargo 360: proving by selling	Traffic World	2006
Oak Hill Capital Partners to acquire Southern Air	Press release Oak Hill Capital Partners	2007
ABX Air 2005 Annual Report	ABX Air	2006
U.S. SEC form 10-K for Air Transport Services Group, Inc annual report 2009	U.S. Securities and Exchange Commission	2010
Atlas Air annual report 2005	Atlas Air	2006
Atlas Air annual report 2009	Atlas Air	2010
Atlas Air profits surge	Journal of Commerce	2009
Atlas Air, Inc. named best air charter/ACMI operator	Business Wire	2007
Atlas Air recovery aids B747-400F values	Aircraft Value News	2005
Panalpina, Atlas Air renew freighter pact	Journal of Commerce	2009
ABX air cargo says Florida-based rival offering buyout	Dayton Daily News	2007

Title	Source	Published
U.S. SEC form 10-K for Kitty Hawk, Inc. annual report 2005	U.S. Securities and Exchange commission	2006
U.S. SEC form 10-K for Kitty Hawk, Inc. annual report 2006	U.S. Securities and Exchange commission	2007
U.S. SEC form 10-K for Kitty Hawk, Inc. quarterly report ending June 2007	U.S. Securities and Exchange commission	2007
U.S. SEC form 10-K for Kitty Hawk, Inc. quarterly report ending March 2007	U.S. Securities and Exchange commission	2007
MatlinPatterson takes majority stake in Arrow Cargo parent	Air Transport Intelligence	2008
New appointments announced by Arrow Air	Airline Industry Information	2008
Cargo carrier Arrow Air bankrupt, to liquidate	Reuters	2010
Arrow air exits chapter 11 bankruptcy protection	Air Transport Intelligence	2004
Arrow Air expands DC-10 fleet, buys Miami facility	Air Transport Intelligence	205
MatlinPatterson Global Opportunities Partners III acquires controlling interest in Arrow Air Holdings Corporation	PR Newswire	2008
Arrow air is ready to ascend cargo carrier rebounds from bankruptcy	South florida Sun – Sentinel	2005
US cargo operator Gemini emerges from Ch 11 bankruptcy	Air Transport Intelligence	2006
Is outsourced air out?	Traffic World	2008
Gemini Air Cargo closes	Journal of Commerce	2008
Gemini Air reorganizes	Traffic World	2006
Gemini Air Cargo, Inc. announces emergence from Chapter 11; Bayside Capital takes majority stake; company eliminates approximately $50 million of Debt	Business Wire	2006

Title	Source	Published
Gemini cleared for takeoff	Traffic World	2006
Gemini files for Chapter 11 bankruptcy protection	Air Traffic Intelligence	2008

Appendix C

Financial Data

Financial data used to calculate the K-Score for each airline

ABX Air, Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	2,386,866	1,960,010	775,645	421,493	469,713
Total Assets	3,894,583	4,108,751	3,175,464	2,248,354	1,976,776
Total Current Liabilities	653,641	681,774	538,835	570,729	585,362
Total Noncurrent Liabilities	2,470,165	2,797,912	2,065,288	1,168,788	971,926
Retained Earnings	-1,103,466	-1,108,654	-1,161,636	-1,214,914	-1,298,537
Net Stockholders Equity	767,447	627,401	571,341	508,837	419,488
Kroeze K-score	-0.091	-0.123	-0.262	-0.438	-0.536

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Aloha Air Cargo					
	2009	2008	2007	2006	2005
Total Current Assets	36,605	98,282	290,345	346,820	412,782
Total Assets	90,282	259,315	891,046	691,650	646,287
Total Current Liabilities	16,444	274,364	840,468	617,645	834,060
Total Noncurrent Liabilities	176	35,250	126,563	383,513	472,606
Retained Earnings	3,904	-150,628	-334,973	-594,882	-704,271
Net Stockholders Equity	73,663	-51,595	-78,893	-310,215	-666,155
Kroeze K-score	0.588	-0.687	-0.490	-0.860	-1.144

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Amerijet International					
	2009	2008	2007	2006	2005
Total Current Assets	152,624	163,466	148,605	138,690	129,227
Total Assets	207,916	214,505	195,982	186,052	175,840
Total Current Liabilities	163,975	172,308	123,337	133,260	122,461
Total Noncurrent Liabilities	14,293	16,727	39,613	32,460	30,636
Retained Earnings	17,561	13,383	21,255	9,490	12,270
Net Stockholders Equity	29,648	25,470	33,031	20,332	22,743
Kroeze K-score	0.075	0.056	0.148	0.064	0.085

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Arrow Air Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	138,341	132,325	134,793	118,162	87,210
Total Assets	308,147	274,241	278,921	269,265	179,665
Total Current Liabilities	139,679	199,912	135,056	173,097	99,763
Total Noncurrent Liabilities	142,467	56,425	154,015	90,832	66,101
Retained Earnings	-255,170	-145,096	-58,154	-26,243	-9,009
Net Stockholders Equity	26,001	17,904	-10,150	5,336	13,801
Kroeze K-score	-0.685	-0.502	-0.179	-0.134	-0.052

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Astar USA, LLC					
	2009	2008	2007	2006	2005
Total Current Assets	219,810	296,731	360,424	248,677	227,898
Total Assets	645,512	860,859	895,120	717,032	599,642
Total Current Liabilities	458,151	500,552	496,590	453,189	353,973
Total Noncurrent Liabilities	360,974	478,246	501,556	465,472	359,326
Retained Earnings	-327,781	-264,753	-242,518	-246,609	-172,140
Net Stockholders Equity	-175,165	-118,715	-103,442	-206,609	-132,140
Kroeze K-score	-0.548	-0.335	-0.279	-0.390	-0.317

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Atlas Air Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	965,782	1,061,519	1,005,798	933,473	790,368
Total Assets	4,813,940	4,521,675	3,478,215	3,320,763	3,344,655
Total Current Liabilities	567,000	619,961	619,520	790,640	716,711
Total Noncurrent Liabilities	2,595,933	2,523,616	1,669,756	1,760,189	2,234,215
Retained Earnings	1,247,695	1,136,399	895,478	421,985	115,108
Net Stockholders Equity	1,386,432	1,265,478	1,167,960	713,965	308,473
Kroeze K-score	0.288	0.281	0.302	0.149	0.046

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Capital Cargo International					
	2009	2008	2007	2006	2005
Total Current Assets	10,407	8,616	15,281	14,942	19,280
Total Assets	120,488	116,660	59,972	60,917	70,163
Total Current Liabilities	19,185	12,359	9,256	17,078	22,286
Total Noncurrent Liabilities	3,755	2,431	3,867	17,977	27,183
Retained Earnings	-21,429	-7,657	-65,116	-137,651	-51,375
Net Stockholders Equity	83,736	97,511	46,567	25,789	20,675
Kroeze K-score	0.237	0.668	-0.489	-1.821	-0.579

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Cargo 360, Inc.					
	2009	2008	2007	2006	2005
Total Current Assets			56,056	46,269	
Total Assets			1,052,861	55,092	
Total Current Liabilities			73,055	15,113	
Total Noncurrent Liabilities			978,429	44,467	
Retained Earnings			-20,171	-36,215	
Net Stockholders Equity			927	-4,488	
Kroeze K-score			-0.020	-0.408	

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Centurion Cargo Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	112,258	324,809	156,338	15,971	
Total Assets	164,355	394,486	190,186	33,837	
Total Current Liabilities	113,372	287,995	171,236	27,361	
Total Noncurrent Liabilities	24,321	23,324	8,257	255	
Retained Earnings	-122,517	-60,601	-137,979	-66,437	
Net Stockholders Equity	25,162	81,995	7,996	6,220	
Kroeze K-score	-0.606	-0.074	-0.624	-1.711	

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Evergreen International Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	127,069	156,702	123,372	112,851	103,591
Total Assets	1,892,330	1,958,743	1,958,510	1,869,958	1,809,637
Total Current Liabilities	326,200	306,477	277,831	281,827	259,332
Total Noncurrent Liabilities	339,060	322,078	370,260	328,987	372,556
Retained Earnings	450,294	503,344	477,500	451,727	366,943
Net Stockholders Equity	739,897	792,947	767,103	741,330	656,547
Kroeze K-score	0.295	0.335	0.315	0.313	0.262

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Gemini Air Cargo Airways					
	2009	2008	2007	2006	2005
Total Current Assets				97,497	83,619
Total Assets				275,986	251,933
Total Current Liabilities				187,916	184,581
Total Noncurrent Liabilities				184,532	302,547
Retained Earnings				-401,878	-747,150
Net Stockholders Equity				-97,099	-235,194
Kroeze K-score				-1.337	-2.646

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Kalitta Air LLC					
	2009	2008	2007	2006	2005
Total Current Assets	704,687	483,413	603,640	468,565	357,869
Total Assets	1,921,402	1,766,426	1,414,689	1,193,751	976,391
Total Current Liabilities	462,234	274,243	212,636	225,123	174,575
Total Noncurrent Liabilities	304,829	302,389	0	0	0
Retained Earnings	1,249,259	1,277,617	1,288,904	1,052,830	885,582
Net Stockholders Equity	1,154,339	1,189,794	1,202,052	968,627	801,816
Kroeze K-score	0.746	0.867	1.465	1.271	1.320

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Kitty Hawk Aircargo					
	2009	2008	2007	2006	2005
Total Current Assets			12,056	12,517	36,742
Total Assets			22,833	12,443	29,228
Total Current Liabilities			12,021	8,031	16,218
Total Noncurrent Liabilities			0	0	0
Retained Earnings			10,812	4,412	13,010
Net Stockholders Equity			10,812	4,412	13,010
Kroeze K-score			0.497	0.455	0.650

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Lynden Air Cargo Airlines					
	2009	2008	2007	2006	2005
Total Current Assets	40,592	68,758	53,653	39,915	31,306
Total Assets	215,341	240,597	243,897	243,466	226,941
Total Current Liabilities	33,932	59,469	43,414	54,894	51,720
Total Noncurrent Liabilities	1,025	6,131	2,017	537	17,192
Retained Earnings	141,163	139,910	167,498	160,910	134,752
Net Stockholders Equity	180,460	175,019	198,496	188,144	157,924
Kroeze K-score	1.131	0.794	1.072	0.914	0.728

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Northern Air Cargo Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	19,413	20,904	22,401	25,186	27,916
Total Assets	126,506	129,161	141,000	99,983	73,734
Total Current Liabilities	46,292	49,735	39,478	29,848	41,737
Total Noncurrent Liabilities	331	0	0	0	9,726
Retained Earnings	31,781	14,529	3,640	16,810	21,471
Net Stockholders Equity	79,883	79,426	101,522	70,135	22,271
Kroeze K-score	0.344	0.212	0.275	0.389	0.242

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Polar Air Cargo Airways					
	2009	2008	2007	2006	2005
Total Current Assets	180,665	424,983	320,911	674,409	721,426
Total Assets	190,409	437,228	378,641	922,572	1,133,029
Total Current Liabilities	123,566	246,587	168,871	208,659	226,300
Total Noncurrent Liabilities	4,551	124,098	135,882	69,665	64,685
Retained Earnings	-89,483	-69,490	-14,316	30,075	83,346
Net Stockholders Equity	62,293	66,543	67,293	644,247	842,044
Kroeze K-score	-0.259	-0.004	0.100	0.420	0.500

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Southern Air Inc.					
	2009	2008	2007	2006	2005
Total Current Assets	74,888	216,801	37,976	29,945	23,574
Total Assets	1,338,371	1,974,298	211,149	164,409	142,284
Total Current Liabilities	123,980	163,837	107,731	42,497	23,310
Total Noncurrent Liabilities	1,157,932	1,123,473	14,989	35,182	47,400
Retained Earnings	-918,298	-251,643	70,292	74,731	59,574
Net Stockholders Equity	53,643	685,966	88,032	86,731	71,574
Kroeze K-score	-0.580	-0.040	0.270	0.484	0.464

Note. Company considered not in financial distress if K-Score is >0.0, and in financial distress if K-Score is =<0.0. Financial figures shown is Thousands of US$. Source of data RITA Schedule B1 data.

Appendix D: Definition of Codes

Accidents. This code denotes mention of aircraft accidents.

Antitrust. This code refers to the impact of the fuel surcharge antitrust lawsuits started in Feb 2006.

Bankruptcy. This code is used when the segment of text discussed bankruptcy or the discussion of any sort of restructuring that has taken place or is being considered.

Capacity. This code indicates capacity issues related to air-cargo operations. Capacity can be either the carrying capacity of the particular aircraft or the overall capacity of the airline.

Cash flow. This code represents cash flow issues within a firm.

Competition. This code is used to examine competition within the air-cargo industry

Competitive Advantage. This code indicates the competitive advantages a company may have over a competitor.

Cost. This code refers to cargo airline cost issues such as fuel and salaries.

Credit_markets. This code indicates when a carrier is looking to the credit markets for funding.

Customers. This code signifies issues related to customer service and customers in general.

Earnings. This code explores the earnings of an airline.

Economics. This code looks at the external economics that may affect an all-cargo operation (i.e. world GDP...).

Environment. This code is for all environment issues such as environmental protection agency (EPA), noise, or emissions regulations.

Fleet mix. This code is used to identify the fleet mix that the airline is operating in any issues with the current or future aircraft fleet.

Flight_frequency. This code represents flight frequency issues related to air-cargo operations.

Fuel_efficiency. This code signifies fuel efficiency issues related to air-cargo operation.

Geographic location. This code represents the physical location of a company's operations and the geographical reach or airports serviced and issues related to air-cargo operations.

Labor_Issues. This code indicates labor issues or union agreements/issues.

Maintenance. This code outlines aircraft maintenance issues.

Management. This code is used to identify managers, owners, and management issues.

Market. This code looks at market factors in the industry.

Merger. This code is used to identify issues related to a merger.

Operations. This code looks at issues in the day-to-day or short-term operations of the airline.

Ownership. This code indicates ownership and ownership issues.

Price. This code is for pricing issues related to air-cargo operations

Regulation. This code identifies issues with government regulations, both national and international.

Reliability. This code is for reliability issues related to air-cargo operations, such as on-time delivery.

Revenue. This code refers to the revenue, imcome, or financial issues in an airline.

Risk. This code signifies issues of potential or real risk for the company.

Routes. This code designates routes the airlines fly and location served.

Security. This code symbolizes cargo security cost and issues.

Service. This code refers to the level of service and airline provides.

Size. This code indicates the size of the airline within the industry.

Tax. This code relates to taxation issues.

Utilization. This code signifies the amount of time and aircraft is used.

Appendix E

Categories With Examples of Quotations

Table E1

Categories with Examples of Quotations Linked to Codes

Category	Examples of quotations (preceded by code name)
Management	Management - "We announced an operational excellence program focused on cost savings and revenue enhancement. This program, if successfully implemented, could benefit our operating performance by more than $100 million over the next several years." (Atlas Air, 2006, p. 4) Management –"Gemini will keep its current management team, and should quickly show further improvement because "if you take out all the debt service, Gemini has been performing very well for over a year." (Boyd, 2006, p. 2) Management – "In the course of its ongoing evaluation, our management has identified certain areas requiring improvement, which we are addressing." (SEC, 2006, p. 53) Management – "Our senior management team has extensive operating and leadership experience in the airfreight, airline…" (Atlas Air, 2010, p. 30) Management – "Our business depends on highly qualified management and flight crew personnel.: (Atlas Air, 2010, p. 30)
Operations	Operations - "Outsourcing provides a cost-effective and efficient alternative for passenger airlines to maintain and expand the air-cargo portion of their business." (Atlas Air, 2006, p. 2) Maintenance - "Maintenance is our third-largest operating expense…" (Atlas Air, 2006, p. 4) Security - "The TSA extensively regulates aviation security through rules, regulations and security directives." (Atlas Air, 2006, p. 6) Fuel_efficiency - "Aviation fuel is one of the most significant expenses for an airline." (Atlas Air, 2006, p. 8)
Financial factors	Earnings - "We reported strong earnings, and we made tremendous progress in our efforts to strengthen our business."(Atlas Air, 2006, p. 5)

Category	Examples of quotations (preceded by code name)
	Revenue - “ACMI minimizes yield and traffic demand risk in the air-cargo business and provides a more predictable annual revenue and cost base” (Atlas Air, 2006, p. 3) Bankruptcy - “Chapter 11 filing had also helped facilitate the issuance of the new equity securities required by certain of the restructuring agreements” (Atlas Air, 2006, p. 10) Cost - “In addition, if fuel costs increase significantly, our customers may reduce the volume and frequency of cargo shipments or find less costly alternatives for cargo delivery, such as land and sea carriers” (Atlas Air, 2006, p. 11) Merger – “increased competition, including the possible impact of any mergers, alliances or combinations of competitors” (SEC, 2007, p. 14)
Competitive advantage	Fleet Mix - “After all, our fleet consisted of 20 Boeing 747-400s and 23 Boeing 747 Classics” (Atlas Air, 2006, p. 4) Competitive Advantage - “The primary competitive factors in the Scheduled Service market are price, geographic coverage, flight frequency, reliability and capacity.” (Atlas Air, 2006, p. 8) Competitive Advantage - “With a sizeable fleet and sophisticated operations, we had a competitive advantage compared with smaller carriers.” (Atlas Air, 2006, p. 4) Fleet Mix - “renewing the fleet is at the heart of our multi-year strategy” (Atlas Air, 2006, p. 5) Competition - “The market for outsourcing cargo ACMI services is highly competitive.” (Atlas Air, 2006, p. 8) Competition - “We are the only service provider in the Boeing 747-400 ACMI market, as there are presently no direct competitors.” (Atlas Air, 2006, p. 8) Competitive Advantage – “We believe that the most important elements for competition in the air-cargo business are the range, payload and cubic capacities of the aircraft and the price, flexibility, quality and reliability of the cargo transportation services provided.” (Atlas Air, 2006, p. 13) Size – “Atlas Air, Inc., the world's leading provider of outsourced cargo aircraft, crew, maintenance and insurance service to major

Category	Examples of quotations (preceded by code name)
	international airlines” (Business Wire, 2007, para. 1) Customers – “In 2006, our top 25 customers accounted for more than 59.3% of our scheduled freight revenue, and our top five customers accounted for more than 27.4% of our scheduled freight revenue.” (SEC, 2007, p. 6)
Risk	Risk - “We rely on DHL for substantially all of ABX’s revenues and the majority of ABX’s net operating cash flows.” (ABX Air, 2006, p. 10) Accident – “We are vulnerable to potential losses that may be incurred in the event of an aircraft incident or accident including damage to the aircraft due to FOD.” (SEC, 2007, p. 13) Risk – “increased competition, including the possible impact of any mergers, alliances or combinations of competitors” (SEC, 2007, p. 14)
External factors	Economics - “An economic downturn in the U.S. is likely to adversely affect demand for delivery services…” (ABX Air, 2006, p. 10) Economics - “We depend on worldwide demand and any economic decrease in the demand for cargo transport could adversely affect our business and operations.” (Atlas Air, 2006, p. 11) Economics – “The as-needed nature of our scheduled freight business and the types of industries we serve subject our business to significant market fluctuations that are beyond our control, and a downward market fluctuation could have a material adverse effect on our results of operations.” (SEC, 2007, p. 15) Economics – “…overall demand for our freight services is primarily influenced by the health of the U.S. economy, which is cyclical in nature, the seasonality and economic health of the industries generating the freight we transport in our network and the availability, reliability and cost of alternative freight services…” (SEC, 2007, p. 15)

Appendix F
Co-Occurrence Table of All Codes

	Bankruptcy	Capacity	Cash flow	Competition	Competitive Advantage	Cost	Credit_ markets	Customers	Earnings	Economics	Environment	Fleet mix	Flight_ frequency	Fuel_ efficiency	Geographic location
Accidents	0	0	0	0	0	0	0	0.01	0	0	0	0.01	0	0	0
Antitrust	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0
Bankruptcy	0	0.02	0	0	0	0	0.02	0.01	0	0.02	0	0.01	0	0.01	0
Capacity	0.02	0	0.01	0.04	0.02	0	0	0.02	0	0.02	0	0.02	0.1	0.05	0
Cash flow	0	0.01	0	0.01	0	0.01	0.03	0.01	0.04	0.02	0	0.01	0	0	0
Competition	0	0.04	0.01	0	0.02	0	0	0	0	0.01	0	0	0.03	0	0
Competitive Advantag	0	0.02	0	0.02	0	0	0	0.02	0	0	0	0.03	0	0	0
Cost	0	0	0.01	0	0	0	0	0.02	0.01	0.01	0.02	0.01	0	0.03	0
Credit_markets	0.02	0	0.03	0	0	0	0	0	0	0.02	0	0	0	0	0
Customers	0.01	0.02	0.01	0	0.02	0.02	0	0	0.01	0.02	0	0.01	0	0.01	0
Earnings	0	0	0.04	0	0	0.01	0	0.01	0	0	0	0	0	0	0
Economics	0.02	0.02	0.02	0.01	0	0.01	0.02	0.02	0	0	0	0.01	0.01	0.03	0
Environment	0	0	0	0	0	0.02	0	0	0	0	0	0	0	0.01	0
Fleet mix	0.01	0.02	0.01	0	0.03	0.01	0	0.01	0	0.01	0	0	0	0.02	0
Flight_frequency	0	0.1	0	0.03	0	0	0	0	0	0.01	0	0	0	0.02	0
Fuel_efficiency	0.01	0.05	0	0	0	0.03	0	0.01	0	0.03	0.01	0.02	0.02	0	0
Geographic location	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Labor_Issues	0.01	0	0	0	0	0.02	0	0	0	0	0.01	0.01	0	0	0.02
Maintenance	0	0	0.01	0	0.01	0.03	0	0.02	0.01	0	0	0	0	0	0.02
Management	0.01	0.01	0.03	0	0.08	0	0.01	0.01	0.01	0.01	0	0	0	0	0
Market	0	0.03	0	0.03	0	0	0	0.01	0	0.03	0	0.01	0	0	0
Merger	0.01	0.01	0	0.05	0.02	0	0	0	0	0	0	0.01	0	0	0
Operations	0	0	0.01	0.02	0.02	0.02	0	0.01	0	0.01	0	0.01	0	0	0.02
Ownership	0.05	0	0	0	0	0	0	0	0.01	0	0	0.01	0	0	0
Price	0	0.02	0	0.03	0.03	0.01	0	0.01	0.01	0.02	0	0	0.11	0.08	0
Regulation	0	0	0	0	0	0.03	0	0	0	0.01	0.1	0	0	0	0
Reliability	0	0.07	0	0.02	0.03	0.01	0	0.01	0	0.06	0	0	0.17	0.04	0
Revenue	0.02	0	0.04	0	0.01	0.01	0	0.03	0	0.01	0	0.01	0	0	0
Risk	0	0.01	0.03	0	0	0.03	0	0.02	0	0.01	0.05	0.01	0	0.02	0.01
Routes	0	0.01	0	0.01	0.01	0	0	0	0	0.01	0	0	0.06	0.01	0.01
Security	0	0	0	0	0	0.02	0	0	0	0	0.02	0	0	0	0.01
Service	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0
Size	0.01	0	0	0	0.05	0	0	0.01	0	0	0	0.02	0	0	0.06

	Maintenance	Management	Market	Merger	Operations	Ownership	Price	Regulation	Reliability	Revenue	Risk	Routes	Security	Service	Size
Accidents	0.01	0	0	0	0	0	0	0	0	0	0.02	0	0	0	0
Antitrust	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0
Bankruptcy	0	0.01	0	0.01	0	0.05	0	0	0	0.02	0	0	0	0	0.01
Capacity	0	0.01	0.03	0.01	0	0	0.02	0	0.07	0	0.01	0.01	0	0	0
Cash flow	0.01	0.03	0	0	0.01	0	0	0	0	0.04	0.03	0	0	0.02	0
Competition	0	0	0.03	0.05	0.02	0	0.03	0	0.02	0	0	0.01	0	0	0
Competitive Advantag	0.01	0.08	0	0.02	0.02	0	0.03	0	0.03	0.01	0	0.01	0	0	0.05
Cost	0.03	0	0	0	0.02	0	0.01	0.03	0.01	0.01	0.03	0	0.02	0	0
Credit_markets	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0
Customers	0.02	0.01	0.01	0	0.01	0	0.01	0	0.01	0.03	0.02	0	0	0	0.01
Earnings	0.01	0.01	0	0	0	0.01	0.01	0	0	0	0	0	0	0	0
Economics	0	0.01	0.03	0	0.01	0	0.02	0.01	0.06	0.01	0.01	0.01	0	0	0
Environment	0	0	0	0	0	0	0	0.1	0	0	0.05	0	0.02	0	0
Fleet mix	0	0	0.01	0.01	0.01	0.01	0	0	0	0.01	0.01	0	0	0	0.02
Flight_frequency	0	0	0	0	0	0	0.11	0	0.17	0	0	0.06	0	0	0
Fuel_efficiency	0	0	0	0	0	0	0.08	0	0.04	0	0.02	0.01	0	0	0
Geographic location	0.02	0	0	0	0.02	0	0	0	0	0	0.01	0.01	0.01	0	0.06
Labor_Issues	0.01	0.01	0	0.02	0	0	0	0	0.01	0	0.01	0	0	0	0
Maintenance	0	0	0	0	0.04	0	0	0.01	0.03	0.02	0	0.01	0	0	0.01
Management	0	0	0	0.03	0.02	0.03	0	0	0.01	0.05	0	0.01	0	0	0.04
Market	0	0	0	0	0.02	0	0	0	0	0.02	0	0	0	0	0
Merger	0	0.03	0	0	0.02	0.05	0	0	0	0	0	0	0	0	0
Operations	0.04	0.02	0.02	0.02	0	0	0.02	0.01	0.01	0.1	0	0.01	0.04	0	0.02
Ownership	0	0.03	0	0.05	0	0	0	0	0	0	0	0	0	0	0.02
Price	0	0	0	0	0.02	0	0	0	0.09	0.02	0	0.03	0	0	0
Regulation	0.01	0	0	0	0.01	0	0	0	0	0	0	0	0.08	0	0
Reliability	0.03	0.01	0	0	0.01	0	0.09	0	0	0	0	0.03	0	0.02	0
Revenue	0.02	0.05	0.02	0	0.1	0	0.02	0	0	0	0.02	0	0	0	0.02
Risk	0	0	0	0	0	0	0	0	0	0.02	0	0	0.02	0	0
Routes	0.01	0.01	0	0	0.01	0	0.03	0	0.03	0	0	0	0.01	0	0.01
Security	0	0	0	0	0.04	0	0	0.08	0	0	0.02	0.01	0	0	0
Service	0	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0
Size	0.01	0.04	0	0	0.02	0.02	0	0	0	0.02	0	0.01	0	0	0

Appendix G

Subject Matter Expert Questions

What qualitative factors do you feel may influence quantitative bankruptcy prediction models such as the (K-score) in the all-cargo industry?

Do you have any insight into the bankruptcy of Kitty Hawk Air Cargo or Gemini air cargo or of the merger of Cargo 360 with Southern Air in 2008.

Do you have any insight into the operation of ABX Air, Arrow Air, or Atlas Air during the years 2005-2009.

What are your thoughts on the following terms as they relate to bankruptcy or financial distress in the all-cargo airline industry?
Accidents
Antitrust
Bankruptcy
Capacity
Cash flow
Competition
Competitive advantage
Cost
Credit_markets
Customers
Earnings
Economics
Environment
Fleet mix
Flight frequency
Fuel_efficiency
Geographic location
Labor_Issues
Maintenance
Management
Market
Merger
Operations
Ownership
Price
Regulation
Reliability
Revenue
Risk
Routes
Security

Service
Size
Tax
Utilization

Is there other insight you would like to provide in relationship to bankruptcy or financial distress?

Appendix H

Signed Consent Forms for Subject Matter Experts

Consent form for Dr. Robert G. Tompkins

Northcentral University

Informed Consent Form

Non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry

Purpose. You are invited to participate as a Subject Matter Expert (SME) in a research study being conducted for a dissertation at Northcentral University in Prescott, Arizona. The purpose of this study is to examine the non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry. I am interested in your opinions and research on financial distress issues in the all-cargo cargo airline industry.

Participation requirements. Phone, email, and/or personal interviews will be conducted using open-ended questions to learn of your opinions on financial distress issues in the all-cargo airline industry. These interviews may be recorded for later transcription.

Research Personnel. The following people are involved in this research project and may be contacted at any time: Robert Walton waltonr@erau.edu

Potential Risk/ Discomfort. Although there are no known risks in this study, you may withdraw at any time and you may choose not to answer any question that you feel uncomfortable in answering.

Potential Benefit. There are no direct benefits to you of participating in this research. No incentives are offered. The results will have scientific interest that may eventually have benefits in the field of prediction of financial distress in companies.

Anonymity/ Confidentiality. The data collected in this study is not confidential. As a SME your input may be used as a source of data in the research. Your comments will be properly cited in the report.

Right to Withdraw. You have the right to withdraw from the study at any time without penalty. You may omit questions if you do not want to answer them.

I would be happy to answer any question that may arise about the study. Please direct your questions or comments to me at: waltonr@erau.edu.

Signatures

I have read the above description of the Non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry study and understand the conditions of my participation. My signature indicates that I agree to participate as a subject matter expert for this research.

Participant's Name: Dr. Robert G. Tompkins

Researcher's Name: Robert O. Walton

Participant's Signature: Robert G. Tompkins, MS

Researcher's Signature: Robert O. Walton

Date: 15 Oct 11

Consent form for Dr. Richard Gritta

Northcentral University

Informed Consent Form

Non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry

Purpose. You are invited to participate as a Subject Matter Expert (SME) in a research study being conducted for a dissertation at Northcentral University in Prescott, Arizona. The purpose of this study is to examine the non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry. I am interested in your opinions and research on financial distress issues in the all-cargo cargo airline industry.

Participation requirements. Phone, email, and/or personal interviews will be conducted using open-ended questions to learn of your opinions on financial distress issues in the all-cargo airline industry. These interviews may be recorded for later transcription.

Research Personnel. The following people are involved in this research project and may be contacted at any time: Robert Walton waltonr@erau.edu

Potential Risk/ Discomfort. Although there are no known risks in this study, you may withdraw at any time and you may choose not to answer any question that you feel uncomfortable in answering.

Potential Benefit. There are no direct benefits to you of participating in this research. No incentives are offered. The results will have scientific interest that may eventually have benefits in the field of prediction of financial distress in companies.

Anonymity/ Confidentiality. The data collected in this study is not confidential. As a SME your input may be used as a source of data in the research. Your comments will be properly cited in the report.

Right to Withdraw. You have the right to withdraw from the study at any time without penalty. You may omit questions if you do not want to answer them.

I would be happy to answer any question that may arise about the study. Please direct your questions or comments to me at: waltonr@erau.edu.

Signatures

I have read the above description of the Non-statistical factors influencing predictions of financial distress and managerial implications in the all-cargo industry study and understand the conditions of my participation. My signature indicates that I agree to participate as a subject matter expert for this research.

Participant's Name: Dr. Richard Gritta

Researcher's Name: Robert O. Walton

Participant's Signature: Richard Gritta

Researcher's Signature: Robert O. Walton

Date: 28 Oct 11