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BUSINESS FAILURE PREDICTION FOR KOREAN LODGING FIRMS USING MULTIPLE DISCRIMINANT ANALYSIS AND LOGIT ANALYSIS

by

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ABSTRACT

Business Failure Prediction for Korean Lodging Firms Using Multiple Discriminant Analysis and Logit Analysis

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The recent changes in the world economy and as more firms, regardless of their sizes, seem to fail now more than ever, business failure prediction is of increasing importance. To this date, there has been no previous study conducted on the business failure for Korean lodging firms. Even in other countries, there has been only a small amount of research done into the field of lodging firms and lodging firm failures.

This study makes an attempt to develop business failure prediction models for lodging firms located in South Korea using multi-variate analyses. These multi-variate analyses include Multiple Discriminant Analysis (MDA) and logit analysis. This study looked at the financial statements from a total of 154 firms to develop the prediction models, and used 11 different financial ratios from liquidity, solvency, leverage, and efficiency categories as classifying variables. The descriptive statistics of the 11 ratios for the failed and non-failed groups indicated that non-failed hospitality firms were significantly better than failed hospitality firms in terms of liquidity, leverage, and

solvency, demonstrating the potential classifying ability of the financial ratios between failed and non-failed groups.

A MDA model and a logit model were then developed based on sample firms' financial ratios one year prior to failure. For MDA, stepwise procedure was used and a model with three ratios was established. These three ratios were debt ratio, interest coverage ratio, and total assets turnover ratio. The classification results indicated that the MDA model could achieve an overall in-sample classification accuracy of 86.36 percent and an out-of-sample accuracy rate of 83.33 percent one year prior to failure.

For the logit analysis, maximization of the log-likelihood function was used to derive a logit model also with three variables. These variables were debt ratio, interest coverage ratio, and EBITDA to CL ratio. The classification results of logit model showed that it had an overall prediction accuracy rate of 87.66 percent for in-sample firms and 79.17 percent accuracy rate for out-of-sample firms. Overall, there were no significant differences in performance between these two models.

Researchers have noted that MDA requires the assumptions of multi-variate normality and equal covariances, and that these assumptions are typically violated. Since logit analysis does not suffer from this weakness, it is theoretically preferable. Empirically, this study shows that the logit model is not inferior to the MDA in terms of prediction accuracy. Therefore, due to the theoretical soundness of the logit model, it is recommended that the logit model be considered as the preferred method for predicting lodging firm failures in Korea.

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CHAPTER 1

INTRODUCTION

Background of the Study

Due to recent changes in the world economy and as more firms, regardless of their sizes, seem to fail now more than ever, business failure prediction is of increasing importance (Neophytou & Molinero, 2004). Business failure prediction is not only an interesting but also a challenging task that has led to numerous studies over the past four decades. Efforts to predict business failure continues to be of interest from finance, economics, and accounting perspectives (Johnsen & Melicher, 1994).

Korean small business firms in the hospitality sector have not been exceptions from business failures, as corporate bankruptcies have put numerous firms on the brink of insolvency (Shin & Lee, 2002). During 2003, the Korean economy witnessed drastic growth slow down and inflation rise compared to the previous year. By sector, the restaurant and hotel industry failed to break free of its downward trend and continued on a downward path throughout the year (The Bank of Korea, 2005).

This study investigates the business failure for Korean lodging companies, as these firms have been striving to survive in such a hyper competitive market with limited demands. The study of business failure and the ability to identify it early enough has never been more important since corporate financial distress is expected to increase with the onset of market principles in the Korean economy (Shin & Lee, 2002).

Purpose of the Study

In recent years, a large number of researchers and practitioners have studied the prediction of business failure. Evaluation of the business failure has been a major preoccupation of researchers and practitioners for a long time (Ahn, Cho, & Kim, 2000). Altman (1968), Argenti (1976), and Lincoln (1977) argued that business failure is not an immediate event but is a process that evolves over a considerable period of time, thus providing a foundation for predicting business failure.

To this date, there has been no previous study conducted on the business failure for Korean lodging firms. Even in other countries, there has been only a small amount of research done into the field of lodging firms and lodging firm failures. This is not only because of the difficulty of obtaining accurate information from these sources, but also because of the lack of financial or personal incentives (Boer, 1992).

This study attempts to analyze financial conditions of Korean lodging firms in order to identify those heading for business failure. Utilizing financial data of these firms, the study has developed a business failure classifying model based on multiple discriminant analysis (MDA) and logit analysis. Financial ratios were used as the classifying variables. The primary purpose of this paper is to predict business failure in the lodging industry in South Korea.

Contribution of the Study

Identifying business failure and early warning signs of approaching financial crisis are important to both analysts and practitioners. Because business failure leads to potentially severe consequences for both private individuals and society, there has been considerable interest in developing models to predict business failure.

Countries throughout the world are concerned with individual firm performance assessment. Developing countries and smaller economies are significantly concerned with avoiding financial crisis in the private and public sectors, as smaller nations are particularly vulnerable to financial crisis resulting from failures of individual entities (Altman, 1984). Research on business failure has shown that not all firms fail in an unforeseen manner. The crisis causing the failure of a business seldom erupts overnight. Warning signals of a company heading for business failure arise much earlier than the actual failure, therefore these signals could be used to predict business failure in advance.

According to Altman (1984), the first sign of trouble are usually found in financial statements. Yet one of the main problems in this area has been incompetent management that lacks sufficient familiarity with financial statements (Moncarz & Kron, 1993). Moncarz and Kron (1993) claimed that hospitality managers have an imperative need to be familiar with financial statements as a means of identifying problem areas and early warning signs since these managers are faced with rising costs, slowly rising room rates, and stagnant economy.

The number of failing firms is an important indicator for the health of the economy. Undoubtedly, failure affects a firm's entire existence and it has high costs not only to the firm but also to the society and the country's economy (Warner, 1977). Therefore, the prediction of failure is important for all those involved – owners or shareholders, managers, workers, lenders, suppliers, clients, the community, and the government (Casey, McGee, & Stinkey, 1986).

The development and use of models for predicting business failure in advance can be very significant for the firms in two different ways. First, as "early warning systems", such models can be very useful to those (i.e. managers, authorities, etc.) who have to prevent failure and ensure the successful operation of the firm (Casey, McGee, & Stinkey, 1986). Second, such models can be useful to decision-makers of financial institutions when evaluating and making a selection of the firms to invest in (Ahn, Cho, & Kim, 2000).

Definitions of Terms

Business failure - The inability of a firm to meet its obligations when they are due. For the purposes of this study, business failure was defined as an economic failure of a firm. Economic failure occurs when a firm's costs exceed its revenues or when the internal rates or return on its investments are less than its cost of capital (Tavlin, Moncarz, & Dumont, 1989).

Liquidity ratios - Financial ratios used to measure the ability of the establishment to meet its current short-term obligations.

Leverage ratios - Financial ratios used to assess the extent to which a firm is relying upon borrowed funds.

Solvency ratios - Financial ratios used to evaluate the ability of the enterprise to meet its long-term debt obligations. They measure the degree of indebtedness and the ability of paying off debt interest and principal.

Profitability ratios - Financial ratios used to reflect the overall effectiveness of management in producing the returns on sales and investment.

Efficiency ratios - Financial ratios used to determine the productivity for a given level of inputs.

Current ratio (CR) - A liquidity ratio that evaluates the ability of a company to meet its current obligations. It can be computed by dividing current assets by current liabilities.

Quick ratio (QR) - A liquidity ratio that is a more refined version of the current ratio. It is calculated by dividing quick assets by current liabilities.

Debt ratio - A leverage ratio that indicates what proportion of debt a company has relative to its assets. It can be computed by dividing total debts by total assets.

Interest coverage ratio - A solvency ratio that determines how easily a company can pay interest on its outstanding debt. The ratio is obtained by dividing a company's earnings before interest and taxes (EBIT) of one period by the company's interest expenses of the same period.

Earnings before interest, taxes, depreciation and amortization to current liabilities (EBITDA to CL) - A liquidity ratio calculated by dividing EBITDA by CL.

Earnings before interest, taxes, depreciation and amortization to total liabilities (EBITDA to TL) - A solvency ratio which can be obtained by dividing EBITDA by TL.

Long-term debt to total capitalization ratio - A solvency ratio that shows what portion of capitalization is long-term debt as opposed to equity. It can be computed by dividing the long term debt by the total capital. The total capital is made up of long term debt and shareholder's equity.

Inventory turnover ratio - An efficiency ratio that represents the number of times that the inventory is turned over during the period under consideration. It is calculated by dividing cost of sales by average inventory.

Total assets turnover ratio - An efficiency ratio that measures how efficiently a company uses its assets to generate sales. It is calculated by dividing total sales for a period by total assets to determine the number of times each dollar of assets becomes a dollar of sales during the period.

Accounts receivable turnover ratio - An efficiency ratio that assesses how quickly a firm collects its accounts receivable. It is computed by dividing net credit sales by average accounts receivable.

Fixed Assets turnover ratio - An efficiency ratio that evaluates how well the business is using its fixed assets to generate sales. It is obtained by dividing total sales by fixed assets.

Organization of the Study

This study empirically investigates business failure in the Korean lodging industry using MDA and logit analysis. Chapter 1 provides a background of the study with the purpose, contributions and definitions of terms. Chapter 2 reviews the literature on business failure studies and business failure prediction models. Chapter 3 discusses the data, variables, and research methodologies used in this study. Chapter 4 reports findings of the empirical investigation and analyzes the results. Finally, Chapter 5 concludes the study, discusses the implications of the results and the limitations of the study, and provides suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

Introduction

This chapter will provide a thorough background of previous failure prediction studies. Both MDA and logit analysis models used in this study will be discussed individually. The literature review also includes a summary of financial ratios that have been found useful in previous business failure studies.

Business Failure Definitions

One of the most difficult tasks in analyzing business failures is to define the term "failure." The definition of business failure varies across different studies depending on purpose and scope of studies or on specific interest or condition of the firms under examination. The term "business failure" is both an emotive subject and a thorny definitional problem (Storey, Keasey, Watson, & Wynarczyk, 1990).

Table 1 illustrates some of the failure definitions that have been used in previous business failure studies.

Table 1

Definitions of Business Failure

Study	Definition
Ulmer & Neilsen (1947)	Failed firms are those that are disposed of with losses, in order to avoid further losses. This includes bankruptcies.
Beaver (1966)	A business defaulting on interest payments on its debt, overdrawing its bank account or declaring bankruptcy.
Altman (1968)	Firms that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act.
Altman (1969)	A firm has failed if its return on capital is significantly and consistently lower than that obtainable on similar investments.
Blum (1969)	Entrance into a bankruptcy proceeding or an explicit agreement with creditors which reduced the debts of the company.
Deakin (1972)	Firms which experienced bankruptcy insolvency or were liquidated for the benefit of creditors.
Taffler & Tisshaw (1977)	Failure was defined as entry into receivership, creditors' voluntary liquidation, compulsory winding up by order of the court, or government action undertaken as an alternative.
Cahill (1980)	Business failure occurs when the firm is deemed to be legally bankrupt.
Taffler (1982)	Failure was defined as receivership, voluntary liquidation, winding up by court order or equivalent.
Hamer (1983)	Filing a petition under the national bankruptcy act.
Olsen, Bellas, & Kish (1983)	Firms with a cumulative negative cash flow for six consecutive months.
Storey et al. (1990)	Business failure occurs when a business ceased trading and when it has no likelihood of restarting.
Kwansa & Parsa (1991)	Companies which had filed for bankruptcy under Chapter 11 of the Bankruptcy Code.
Laitinen (1991)	The inability of the firm to pay its financial obligations when they come due.

Table 1 *(Continued).*

Study	Definition
Cho (1994)	Firms with 3 or more years of consecutive negative net income.
Dun and Bradstreet (1994)	Filing for bankruptcy protection, liquidation, or other closing of a firm's operations that involves loss to creditors.
Dimitras,Zanakis, & Zopounidis (1996)	The situation that a firm cannot pay lenders, preferred stock shareholders, suppliers, etc., or a bill is overdrawn, or the firm is bankrupt according to the law.
Gu & Gao (1999)	Bankruptcy of a firm.
Gu (2002)	Firms that filed Chapter 11 of the Bankruptcy Code.

In this study, business failure is defined as firms with one or more years of negative net income. According to Dun and Bradstreet (1994), failures include distresses involved in court proceedings or voluntary actions that result in loss to creditors. An entrepreneur may discontinue operations for a variety of reasons, but if the creditors are paid in full, the business is not marked as a failure. A diverse set of definitions have emerged to explain "failure" from a financial perspective as well. These are negative net worth, non-payment of creditors, bond defaults, inability to pay debts, over-drawn bank accounts, omission of preferred dividends, receivership, etc. (Karels & Prakash, 1987).

Tavlin, Moncarz, and Dumont (1989) also provided three terminologies to characterize business failure – economic failure, technical insolvency, and bankruptcy (Table 2).

Table 2

Types of Business Failures

Term	Definition
Economic Failure	Occurs when a firm's costs exceed its revenues or that the internal rates or return on its investments are less than its cost of capital.
Technical Insolvency	Occurs when a company cannot pay its obligations. The book value of its assets may exceed its liabilities, indicating positive net worth, but the company does not have sufficient liquidity to pay its debts.
Bankruptcy	Occurs when the company's liabilities are actually greater than the fair market valuation of its assets, indicating negative net worth. The firm is totally unable to meet its maturing obligations and is in the legal process of reorganization or dissolving.

As shown in Table 2, economic failure, a firm's costs exceeding its revenues, is the least severe type of business failure. In this study of business failure, economic failure of hospitality firms was adopted as the definition of failure. According to Johnsen and Melicher (1994), bankruptcy represents only an extreme result of business failure. They described financial distress as a continuum ranging from being "financially weak" to "bankrupt", with the possibility of various degree of financial weakness.

Previous Studies in Business Failure Prediction

A considerable amount of effort has been devoted to the prediction of business failure over the last four decades. The methodologies employed have been based on various editions of statistical classification models. Such models have become more and more sophisticated, requiring advanced technical expertise in their development, understanding and implementation (Neophytou & Molinero, 2004).

Studies relating the behavior of financial ratios to business failures have now been with us for more than half a century. All these research showed either a systematic difference between the ratios of successful and unsuccessful firms or a steady deterioration over time in the ratios of firms that eventually failed. Since the late 1960s there has been considerable interest among researchers in the development and testing of models for classifying and predicting business failures. Probably the two most influential studies were conducted by Beaver (1966) and Altman (1968). Both presented failure prediction models that have been duplicated and improved for many different types of firms and in a number of foreign environments.

Beaver (1966) was the first one to point out that the financial ratio structures of failing companies differ from the financial ratio structures of companies that are healthy, and that this information can be used to classify firms as being healthy or at risk. In an extensive research study, Beaver (1966) used financial ratios to predict business failure. The study included a sample of 79 relatively large firms that failed during the 1954-1964 period. For each of these companies, another firm was selected that did not fail but was in the same industry and was of approximately the same size as the firm that failed. These samples were used to test the predictive ability of 30 financial ratios. Beaver's work (1966) was a type of univariate analysis whereby it dealt with one ratio at a time. Observed evidence for five years prior to failure indicated that ratio analysis can be useful in the prediction of failure. He also found that the cash flow to total debt ratio was the best classifier.

Beaver's work has been extended by Altman (1968). While Beaver used an univariate analysis to determine the predictive ability of individual financial ratios, Altman used a multi-variate analysis to build the failure prediction model. The discriminant scores were used to distinguish between failed and non-failed firms. Although individual financial performance indicators measure certain important aspects of the firm's performance, the discriminant analysis is a means of capturing the information provided by individual indicators into one composite score. Altman utilized a paired sample design, which incorporated 33 pairs of manufacturing companies. The pairing criteria were based upon size and industrial classification. Using MDA, Altman established his bankruptcy prediction model which incorporated five financial ratios from an initial list of 22 variables. These five financial ratios were:

1. Working capital to total assets
2. Retained earnings to total assets
3. EBIT to total assets
4. Market value of equity to par value of debt
5. Sales to total assets

The predictive ability of the model on the original sample was 95 percent one year before failure, and 79 percent on the hold-out sample one year prior to business failure.

Dimitras, Zanakis, and Zopounidis (1996) studied a total of 158 articles that were published between 1932 and 1994 in various journals. Their study presents a comprehensive survey of literature on business failures that have been summarized according to a new framework. The main findings of their study were:

1. There is a world-wide interest for business failure studies. Such studies were made in industrial countries (i.e. USA, UK, France) as well as in countries under development (i.e. Greece).
2. The discriminant analysis method was the most frequently used in business failure studies and logit analysis ranked second among the methods used.
3. A number of newer methods appeared mainly after the 1980's for the prediction of business failure in order to overcome the limitations of discriminant analysis.
4. The most important financial ratios came from the solvency category. The profitability ratios were also important, indicating that the viability of a firm largely depends on profit making.

Previous Business Failure Studies in the Hospitality Industry

Previous failure prediction studies have developed models using combined samples of companies from manufacturing, wholesale, retail, and other non-financial industries. Recent literature regarding failure prediction models, however, questions the use of such mixed industry samples. Brigham and Gapenski (1994) questioned whether it was logical to assume that the financial characteristics of a failed or non-failed firm in one industry were the same as those of a failed or non-failed firm in another industry. They suggested that failure prediction studies should use an industry-specific sample. Single industry failure prediction studies have been conducted in the railroad, banking, brokerage, and retailing industries. However, there are only a few industry-specific studies that have been conducted on the hospitality industry despite the recognition that this industry is highly vulnerable to failure. According to Boer (1992), undercapitalization is likely to be an influential factor in business failure in the hospitality industry. Although he provides little analysis to validate this particular finding, it is reasonable to believe that an industry with comparatively high investment in fixed assets will be likely to have a high breakeven point and consequently a smaller margin of safety.

According to Dun and Bradstreet (1994), two-thirds of retail and service businesses in the United States do not remain in existence past their first five years. McQueen (1989) suggested that one of the most important reasons for business failure in these sectors is because barriers to entry are low, therefore permitting inefficient operators who are lacking skill, experience and capital, to enter the business. The persistently high lodging bankruptcy rate deserves a thorough investigation, and models capable of predicting lodging bankruptcy with reasonably high accuracy is needed (Gu, 2002).

For the hospitality industry, there are several published business failure prediction studies. Olsen, Bellas, and Kish (1983) first attempted to predict business failures in the food service industry. They used a graph analysis of financial ratios instead of sophisticated models. While a major benefit of their analysis is its easy application in a real-life situation, the major drawback of the study is the limited sample size and the lack of sophisticated statistical analysis. The implication is that a statistical model, such as MDA, could be a good complement to an unsophisticated ratio analysis for restaurant bankruptcy prediction.

Kwansa and Parsa (1991) conducted a study of business failure in restaurant companies. Instead of using a discriminant analysis, they utilized an event approach to identify events in the bankruptcy process that characterized restaurant companies that had filed for bankruptcy under Chapter 11. Their research found a number of events that were unique to the bankrupt restaurant companies:

1. Net losses
2. Management turnover
3. Loan default
4. Credit accommodation
5. Royalty default
6. Decline in unit sales
7. Renegotiation of franchise contracts

While their study contributed to the literature of business failure in the restaurant industry, the event approach to bankruptcy is indeed an ex post facto research design whose purpose was not to predict bankruptcy but to determine the characteristics of the failure process. Although it does not discriminate between failing and non-failing firms, it compares the two groups based on the characteristics common to failing firms, which are absent in the non-failing group.

Cho's study (1994) extensively investigated business failure in the hospitality industry and developed logit models for predicting restaurant and hotel failures. While the two-variable restaurant model achieved in-sample classification accuracy rate of 91 percent one year prior to bankruptcy, the one-variable hotel model classified 92 percent of the sample firms correctly. In that study, business failure was defined as three or more years of consecutive negative net income. Most of the sample firms used in the analysis were restaurants with negative net income rather than bankrupt firms.

Gao (1999) found from her study that it is possible to predict business failure of hospitality firms fairly accurately by using financial ratios and discriminant analysis. She used 17 financial ratios in her study, which represented liquidity, leverage, solvency, profitability, and efficiency. For the discriminant model, she incorporated four main ratios that were total equity to TL, retained earnings to total assets, EBIT to TL, and sales to fixed assets ratio. Gao (1999) found that these ratios showed significant differences between the failing and non-failing groups. Hence, it is possible for managements to predict the failure of a hospitality firm in advance and get a chance to take necessary actions to turn the company around.

Gu (2002) analyzed bankruptcy in the restaurant industry using MDA model. He selected 12 financial ratios representing liquidity, solvency, profitability, and efficiency as variables for estimating a MDA model. Out of these 12 ratios, he chose EBITDA to TL and TL to total assets as the best classifiers and incorporated into the model. Although this is not a common practice, it is clear that a MDA model does not need to include all the ratios that are different between two groups. The model used in his study achieved a 92 percent accuracy rate in classifying the in-sample firms into bankrupt and non-bankrupt groups. The results of his study suggest that restaurant firms with low EBIT and high TL are more likely to head for business failure, and in order to prevent the risk, restaurateurs should adopt a careful growth strategy along with less debt financing and tighter cost control.

Previous Business Failure Studies in South Korea

Although most business failure studies have been performed in the U.S., there have been at least a few dozens of studies devoted to other countries. The one pre-requisite for any meaningful work on failure prediction is the availability of a data base with information on failed firms in the region. With the increasing amount of corporate financial distress in many parts of the world, along with a global trend toward privatization of government owned and subsidized firms, the study of business failure and the ability to identify it early enough has never been more important (Altman & Kim, 1995).

The South Korean economy has been growing at a significant rate during the last 30 years and business failure was not considered a major problem until recently. One main characteristic of Korean firms has been that they are heavily leveraged, perhaps the most heavily leveraged in the world (Choi, Hino, Min, & Oh, 1983). Therefore, there has always been possibility of increase in business failure, as it is always present with such a relatively large recent growth rate and a high leveraged ratio for firms (Altman & Kim, 1995).

There are only a few studies conducted on business failures of Korean companies.

Lee and Oh (1990) utilized two computerized procedures, recursive partitioning analysis and an artificial intelligence technique, in order to classify failed and non-failed business firms. Although the main purpose of their study was to analyze the effectiveness of the above two techniques, they incorporated a data set made up of Korean firms into their study. Their sample involved 51 firms which failed between 1984 and 1988, and a control sample of 115 non-failed firms. They emphasized that the specification of prior probabilities of bankruptcy and estimates of misclassification costs are critical in determining which technique is superior. Their study primarily discussed about these two techniques. The financial ratios and the explanatory power of the model were hardly discussed.

Altman and Kim (1995) carried out a study to test a distress classification model for Korean companies. Their samples consisted of 34 failed firms from 1990 to 1993, and a matched sample of non-failed firms. Two different models were used, one for non-publicly traded firms and the other for the public firms. They attempted to use industry, year of failure, and size of the firms for matching samples. During this process they noticed that size variable, measured by total assets, was extremely hard to control as it differed greatly among each categories. Out of 20 initially-selected financial ratios, they chose four variables – total assets, sales to total assets, retained earnings to total assets, and book value of equity to TL ratio – for the final model. Both models demonstrated excellent classification in the first two years prior to distress with 89.36 percent and 93.10 percent accuracy. They concluded that early warning financial indicators of firm distress in Korea are not as effective as in the U.S. as Korean distressed firms have continued to grow in size, and in some cases, raise equity capital as late as a year or two prior to distress.

Lee (1998) attempted to address the failure of the overall business sector in South Korea. Based on the review of literature and secondary data, he identified two key elements that have contributed to the failure of the business sector. The first one is the lack of effective corporate governance mechanisms that failed to prevent business firms from engaging in excessive or wrong investment activities. The second one is the government-led credit allocation policy that has induced business firms to engage in activities based on severe moral hazards. While his study was valuable contribution to the business failure literature in Korea, he solely concentrated on the causes of business failure with macro-perspectives.

Nam and Jinn (2000) empirically studied the predictive model of business failure using the sample of 46 companies that went bankrupt during the period from 1997 to 1998 when deep recession driven by the IMF crisis started in Korea. The companies they studied were from a variety of industries with assets ranging from ₩39 billion ($32.5 million) to ₩6,945 billion ($4.18 billion). They used logit analysis to construct and test a business failure prediction model. 33 variables were chosen and three of them turned out to be significant predictors of corporate bankruptcy. These three variables were:

1. Financial expenses to sales
2. (Net income + depreciation + financial expenses) to (total borrowings + bonds payable + financial expenses)
3. Receivables turnover

The results of their study demonstrated that these three variables had a high degree of explanatory power in identifying financially solvent or insolvent firms. The model demonstrated decent prediction accuracy and robustness. The type I accuracy was 80.4

percent and the type II accuracy was 73.9 percent One interesting thing was that, according to the results, most of firms that went bankrupt during the Korean economic crisis from 1997 to 1998 had shown signs of financial distress long before the crisis. The application of the model based on data from 1991 to 1996 showed that the prediction accuracy remained consistent as the time prior to bankruptcy increases. The results can be interpreted as implying that the IMF crisis was not just a temporary foreign exchange crisis, rather a result from poor performance of Korean firms over a long period.

Business Failure Prediction Models

Since business failure prediction became a field of study, researchers introduced a number of methods for the classification and the selection of firms. Different views, requirements, and reliability needs have led researchers in using more sophisticated methods that are already applied to other scientific fields. The diversity and large interest on this subject have been addressed partially in a few review articles. Scott (1981) reviewed the empirical models developed as well as the bankruptcy theories presented to identify the overlap between them, focusing mainly on US studies. Zavgren (1983) investigated different methods and empirical models developed for the prediction of corporate failure in the U.S. Altman (1984) also presented a review of models developed in several countries for the prediction of business failure. Jones (1987) examined the techniques used for bankruptcy prediction in U.S., while Keasey and Watson (1991) explored the limitations and usefulness of methods used for the prediction of firm financial crisis.

In general, business failure prediction models have progressed from univariate financial ratio analysis to multi-variate models and from discriminant models to logit models that offer an opportunity to estimate the probability of failure under less restrictive statistical assumptions. Several statistical classifiers have also been developed for the prediction of business failure. The main techniques used include discriminant analysis, logistic regression, probit analysis, artificial neural networks, and rough sets (Lin & McClean, 2001).

A variety of methodologies have appeared in the literature for modeling business failures. Each method has its own assumptions and different contributions to the field of business failure. The basic assumption is that firms can generally be split into two groups, usually the group of failing and the group of non-failing firms. Accordingly firms are characterized by a variable such that (Zopounidis, 1987):

$$Y_i = \begin{cases} 0 \text{ if the i-th firm is non-failed,} \\ 1 \text{ if the i-th firm is failed.} \end{cases}$$

Because of the general acceptance of the two group classification, the interest has been mainly focused on dichotomous classification methods, being referred to as discriminating approaches. Methods in this category include a discriminant analysis and its alternatives, a logit or probit analysis, and linear probability models (Dimitras, Zanakis, & Zopounidis, 1996).

Earlier studies mainly utilized statistical methods such as univariate statistical methods, MDA, linear probability models, and logit and probit analysis for business classification problems (Ahn, Cho, & Kim, 2000). Recently, however, numerous studies have showed that artificial intelligence such as neural networks (NNs) can be an alternative model for classification problems to which traditional statistical method have long been applied (Shin & Lee, 2002).

Conventional Statistical Methods

Prediction of business failure using past financial data and statistical tools is a well-documented topic. These conventional statistical methods, however, have some restrictive assumptions such as linearity, normality, and independence among input variables (Deakin, 1972). Traditional statistical methods also assume certain data distributions and focus on optimizing the likelihood of correct classifications (Liang, Chandler, & Han, 1990). Considering that the violation of these assumptions for independent variables commonly occurs with financial data, the methods can have limitations to obtain the effectiveness and validity (Shin & Lee, 2002).

MDA

MDA is a statistical technique used to classify an observation into one of several a priori groupings based on the observation's individual characteristics (Neophytou & Molinero, 2004). MDA has an established history of accurate performance in studies of failure classification and prediction. Except for Beaver's (1966) univariate study, most of the studies on business failure prediction used multi-variate models. A number of these studies used MDA in which the financial ratios of failed and non-failed companies were analyzed to determine which ratios best discriminate between failed and non-failed companies.

Financial data are collected for each firm during several years prior to the failure date and for a same period for the matching non-failed firms. From these data, the most commonly used ratios are computed for each company in each of the observed years. The ratios are usually selected so that they represent measures of liquidity, profitability, activity and turnover, indebtedness, and cash flow among others (Dambolena, 1983). Models are then developed whereby the most efficient ratios in the discrimination process are given weights used as coefficients in the models. When the models are applied to a company's financial information, an overall score is obtained. The calculated score is then compared to a cut-off score in order to divide the results into groups of expected failed companies and expected surviving companies (Zavgren, 1983).

The primary advantage of using MDA is the potential of analyzing the entire variable profiles of the object simultaneously rather than sequentially examining its individual characteristics (Altman, 1968).

On the other hand, the use of MDA is valid only under following assumptions (Karels & Prakash, 1987). The first assumption is that financial ratios are normally distributed. Discriminant analysis, which has been the most common tool in predicting financial distress, requires that independent variables be multi-variate normal (Storey, Keasey, Watson, & Wynarczyk, 1990). According to Ezzamel and Molinero (1987), this is not always the case. Frecka and Hopwood (1983) examined 11 financial ratios over the 1950-1979 periods for a large population of manufacturing firms. Statistical tests indicated that ten of the 11 ratios tended to depart from normality in a highly significant fashion. However, by making a square root transformation of the variables and eliminating a relatively few outliers, they were able to obtain distributions of the ratios that were not statistically different from normality for a majority of the ratios.

The second assumption is that the financial ratios of failed companies have the same variance-covariance structures as the financial ratios of non-failed companies. This is also known not to be the case (Richardson & Davidson, 1983). In addition, the major drawback of using MDA has been that it does not provide any estimate of the associated risk of failure (Dimitras, Zanakis, & Zopounidis, 1996). Therefore, researchers proposed logit analysis and linear probability model as replacements, as these methods are able to provide a probability of failure.

Logit Analysis

The relaxation of the multi-variate normality assumptions led to the use of the logit analysis. A number of studies developed conditional probability models using logistic regression techniques in which the financial ratios of a sample of failed and non-failed firms are placed in a regression formula that uses a dichotomous dependent variable coded either 0 or 1 representing non-failing or failing (Dimitras, Zanakis, & Zopounidis, 1996). Logit analysis does not classify firms into failed and non-failed. Instead, it assigns every firm a probability of failure on the basis of a linear combination of explanatory variables. It has the advantage that it takes the form of a non-linear regression equation, and regression-type diagnostics can be used to assess the quality of the fit, the relevance of the various explanatory variables, and how influential individual observations are on the results (Lo, 1986).

Logit analysis was first introduced for predicting bank failure (Martin, 1977) and for predicting business failure (Ohlson, 1980). This method provides the probability of a firm belonging to one of the prescribed classes, given the financial characteristics of the firm. When the model is applied to a company's financial statements, the resulting dependent variable, stated between 0 and 1, represents the probability of the company failing. Often cut-off score of 0.5, halfway between the two choices for the dependent variable, is used to determine if the company should be classified as failing or non-failing (Zavgren, 1983). The coefficient of each variable can be interpreted as the effect of a unit change in an independent variable on the probability of the dichotomous variable (Neophytou & Molinero, 2004).

Unlike MDA, logit analysis requires no assumptions about the distribution of the variables. While logit analysis seems preferable to MDA due to less restrictive assumptions, comparative studies between the two methods have not proved higher classification accuracy for all cases and types of samples (Dimitras, Zanakis, & Zopounidis, 1996). According to Lo (1986), there are close relationships between discriminant analysis and logit analysis. It is, therefore, not surprising to find that the two approaches produce very similar classification results.

The choice of discriminant analysis or a conditional probability model depends mostly on the use for which the results are intended (Neophytou & Molinero, 2004). If the decision requires only the dichotomous classification of failing or non-failing, then discriminant analysis may be adequate, even if the violation of statistical assumptions makes the evaluation of any result other than sample-specific predictive accuracy unfeasible. If the research is intended to isolate the variables that should be given further theoretical consideration, a logit model would be more appropriate. The coefficient on each variable can be interpreted separately as to its importance, which is a key advantage.

Summary of Financial Ratios Found Useful in Previous Studies

Most published failure prediction studies use financial ratios as predictors. The usual technique in these studies is to estimate a cross-sectional model, in which the variables are financial ratios, to discriminate between failing and non-failing firms. Altman (1983) stated that financial ratios are being more and more used as simple summary measurements of complicated financial relationships and for the prediction of corporate bankruptcy and financial distress. Van Horne (1998) also pointed out that the probability of a firm's failure can be estimated through financial ratio analysis, and ratios are popular tools for predicting bankruptcy. In most cases, the probability of bankruptcy is implied in a firm's financial statements and can be estimated through financial ratio analysis. Financial ratios were introduced early as characteristics able to predict the failure of a firm. The early studies were using only the ratios from specific year(s) to make predictions. However, failure is a continuous process. This means that although the appraisal of failure happens at a certain time, it is the result of a specific policy of the firm for a number of years. Therefore, the values of the ratios should be inspected over time to provide full information about the progress of a firm. To get this information over time, researchers used the time trend, the coefficient of variation, and shift away from the trend in the period(s) prior to failure (Dimitras, Zanakis, & Zopounidis, 1996).

According to Whittington (1980), ratio analysis had been used widely in financial statement analysis for both normative and positive purposes. He explained that the normative approach compares a firm's ratio to a benchmark in order to judge its performance while the positive approach uses ratios to predict future performance and also to predict business failure. The use of financial ratios in failure prediction is based on the assumption that the failure process is characterized by a systematic deterioration in the values of the ratios (Laitinen, 1991).

One of relevant points dealing with failure prediction models is the way in which the financial ratios are selected for consideration. Barnes (1987) stated that the financial ratios were usually selected on the basis of their popularity in the literature together with a few new ones initiated by the researcher. The theoretical importance of the results is also restricted because the ratios for the final model are chosen purely according to their ability to improve its prediction accuracy. Thus the selection of financial ratios is left as an empirical question.

Table 3 presents a list of the financial ratios that have been found useful in previous studies. The financial ratios used in this study were selected based on these ratios.

Table 3

Financial Ratios Found Useful in Previous Studies

Study	Financial Ratios Used in the Model
Beaver (1966)	Cash flow/ total debt, Net income/ total assets, total debt/ total assets, working capital/ total assets, current assets/ current liabilities
Altman (1968)	Working capital/ total assets, retained earnings/ total assets, EBIT/ total assets, market value of equity/ par value of debt, sales/ total assets
Blum (1969)	Net working capital/ total assets, cash flow/ total debts, trend breaks of net quick assets/ inventory, net quick assets/ inventory, rate of return/common shareholders
Deakin (1972)	Cash flow/ total debt, Net income/ total assets, total debt/ total assets, current assets/ total assets, quick assets/ total assets, working capital/ total assets, cash/ total assets, current assets/ current liabilities, quick assets/ current liabilities, cash/ current liabilities, current assets/ sales, quick assets/ sales, working capital/ sales, cash/ sales
Edmister (1972)	Cash flow/ current liabilities, equity/ sales, working capital/ sales, current liabilities/ equity, inventory/ sales, quick ratio/ industry average trend, quick ratio/ industry level
Altman, Haldeman, & Narayanan (1977)	EBIT/ total assets, EBIT/ interest expenses, current assets/ current liabilities, retained earnings/ total assets, market value of equity/ total capital
Taffler (1982)	Operating income/ total assets, quick assets/ total assets, return on stock, TL/ net capital employed, working capital/ net worth
El hennaway & Morris (1983)	Cash flow/ total assets, current assets/ total assets, long term debt/ net capital, quick assets/ current liabilities, quick assets/ total assets
Olsen, Bellas, & Kish (1983)	Current assets/ current liabilities, working capital/ total assets, EBIT/ total assets, EBIT/ total revenue, total assets/ revenue, working capital/ revenue
Cho (1994)	Cash flow/ share, total debt/ total investment capital

Table 3 *(Continued).*

Study	Financial Ratios Used in the Model
Dimitras, Zanakis, & Zopounidis (1996)	Working capital/ total assets, total debt/ total assets, current assets/current liabilities, EBIT/ total assets, net income/ total assets
Gao (1999)	Current assets/ current liabilities, quick assets/ current liabilities, working capital/ total assets, TL/ total assets, long term liabilities/ total assets, total equity/ total long-term liabilities, EBIT/ TL, net income/ total assets, total equity/ TL, retained earnings/ total assets, sales/ fixed assets, EBIT/ current liabilities, EBIT/ total assets, gross profit/ net sales, net profit/ net sales, EBIT/ equity plus long term liabilities, sales/ total assets, sales/ fixed assets
Gu (2002)	Current assets/ current liabilities, quick assets/ current liabilities, EBIT/ current liabilities, TL/ total assets, equity/ long term debt, EBIT/ TL, EBIT/ total assets, gross profit/ net sales, net profit/ net sales, net income/ total assets, sales/ total assets, sales/ fixed assets

CHAPTER 3

METHODOLOGY AND DATA DESCRIPTION

Introduction

The purpose of this study is to develop a model, which would differentiate between firms that are likely to fail and those that are likely to succeed, by using the financial ratios of the firms. These ratios are used to generate a prediction of failure for both MDA and logit analysis models. The results will be evaluated to test the accuracy of each model.

Data Collection and the Sample

For the business failure prediction in this study, the data source of Korean lodging firms is Korean financial supervisory service database, which is available in http://dart.fss.or.kr/.The financial statements of lodging firms under lodging and restaurant category were searched. From the database, initial samples of 59 lodging firms that had negative net income in 2001 and 45 lodging firms that had negative net income in 2002 were identified. Due to unavailable or incomplete financial information, 19 firms in 2001 and eight firms in 2002 were excluded from the sample, and 40 firms in 2001 and 37 firms in 2002 were finally selected for the analysis. All the sample firms selected for analysis were from the lodging industry. The sample in 2001 had average assets of \$36.40 million, ranging from \$6.07 million to \$317.31 million. The sample in 2002 had average assets of \$38.09 million, ranging from \$5.93 million to \$296.33 million. All the sample firms were publicly traded companies. Financial ratios of these lodging firms one year prior to the failure were calculated. For the control sample, all available non-failed lodging companies were searched from the same data source. These non-failed firms were then stratified by the year and similar size in terms of assets to match the original sample.

The use of a one-to-one match of failed and non-failed companies is consistent with predictive bankruptcy studies throughout the last 40 years (e.g. Altman, 1968; Beaver, 1966; Blum, 1974; Platt & Platt, 1990; Zavgren, 1985). This methodology has been challenged because of potential bias due to "over sampling" of distressed firms. Use of a one-to-one sampling rate of failed to non-failed firms might lead to a choice-based sample bias. However, Zmijewski's review of 17 financial distress studies showed that although choice-based sample biases may be present, "The results do not indicate significant changes in overall classification and prediction rates" (Zmijewski, 1984). In addition, matching of sample in terms of size is very important in this study of business failures in Korea because of the "too big to fail" problem prevalent in Korea (Nam & Jinn, 2000). Therefore, the typical procedure of one-to-one matching of failed and non-failed firms was used in this study.

Financial ratios calculated for the non-failed lodging firms were from the same year as compiled for failed firms. Table 4 and Table 5 present a list of failed lodging firms included in this study, and Table 6 and Table 7 provide the control-sample of non-failed lodging firms.

Table 4

The Sample of Failed Firms in 2001

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	Kawon Leisure	2001	8,547.35	7.12
2	Kawon Housing	2001	35,482.21	29.57
3	Green and Blue	2001	18,355.99	15.30
4	International Tourist hotel	2001	17,465.14	14.55
5	South Jirisan Tourism	2001	11,665.94	9.72
6	Naksan Development	2001	30,898.04	25.75
7	Daegu Park Hotel	2001	74,788.81	62.32
8	Dong-a Tourism	2001	10,714.89	8.93
9	Mibong	2001	18,224.11	15.19
10	Bokwang	2001	380,774.65	317.31
11	City Touist Hotel	2001	7,806.85	6.51
12	Shinhan Development	2001	19,012.83	15.84
13	Don Beach Tourist Hotel	2001	14,504.21	12.09
14	Central Tourism Development	2001	114,979.37	95.82
15	Lakehills	2001	28,220.69	23.52
16	Ansan Touism Development	2001	11,956.53	9.96
17	Ilsung Leisure Industry	2001	87,194.33	72.66
18	Woojoo	2001	17,420.45	14.52
19	Jinwon Touism	2001	11,139.98	9.28
20	Chunjoo Coa Hotel	2001	15,255.34	12.71
21	Hyunsung	2001	10,350.37	8.63
22	Crown Tourist Hotel	2001	7,285.64	6.07
23	Taean	2001	11,516.91	9.60
24	PhilKorea	2001	160,701.50	133.92
25	Paradise Hotel Dogo	2001	11,008.74	9.17
26	Hotel Daegoo	2001	9,343.47	7.79
27	Hando Tourism	2001	15,743.16	13.12
28	Kookdo	2001	11,637.20	9.70
29	Grand	2001	12,589.47	10.49
30	EastSouth	2001	17,189.43	14.32
31	MarcoPolo	2001	63,342.11	52.79
32	Bomoon	2001	70,873.44	59.06
33	Sunong	2001	36,945.45	30.79
34	Namyoung	2001	20,674.95	17.23
35	Woochang	2001	15,672.87	13.06
36	Dae Wong	2001	25,324.98	21.10

Table 4 (*Continued*).

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
37	Sema	2001	7,337.14	6.11
38	Sinan Tourism	2001	72,656.09	60.55
39	Ambastel	2001	28,275.06	23.56
40	Hanmoo	2001	204,438.78	170.37

Note. Assets in Millions.

Table 5

The Sample of Failed Firms in 2002

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	Kawon Leisure	2002	15,878.76	13.23
2	Kawon Housing	2002	48,259.85	40.22
3	Green and Blue	2002	17,853.69	14.88
4	Naksan Development	2002	29,909.43	24.92
5	Namyoung	2002	20,156.96	16.80
6	Newstar Tourism Development	2002	30,125.85	25.10
7	Daegu Park Hotel	2002	74,757.33	62.30
8	Lakehills Golftel	2002	46,164.45	38.47
9	Mibong	2002	18,834.33	15.70
10	Bokwang	2002	355,592.93	296.33
11	Seoul Lakeside	2002	265,185.98	220.99
12	City Touist Hotel	2002	7,472.91	6.23
13	Shinhan Development	2002	18,345.88	15.29
14	Donbeach	2002	32,283.91	26.90
15	Samkwang Development	2002	21,856.48	18.21
16	Samdoo Industry	2002	21,175.01	17.65
17	Songok Development	2002	13,899.48	11.58
18	Ansan Touism Development	2002	11,512.88	9.59
19	Yeonjun Development	2002	21,263.12	17.72
20	Woojoo	2002	17,200.28	14.33
21	Chunjoo Coa Hotel	2002	14,954.42	12.46
22	Jungwon Hotel	2002	7,115.44	5.93
23	Bugok hawaii	2002	35,750.11	29.79
24	Junglim Development	2002	69,041.85	57.53
25	Taean	2002	10,677.84	8.90

Table 5 *(continued).*

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
26	Phil Korea Limited	2002	157,904.35	131.59
27	Paradise Incheon	2002	34,535.75	28.78
28	Paradise Hotel Dogo	2002	9,328.04	7.77
29	Dong-A	2002	10,182.78	8.49
30	Hando	2002	16,063.00	13.39
31	Hyunsung	2002	12,398.29	10.33
32	Ilsung	2002	87,528.63	72.94
33	Kookdo	2002	13,724.52	11.44
34	Grand	2002	11,272.82	9.39
35	East South	2002	23,771.28	19.81
36	Marcopolo	2002	63,032.04	52.53
37	Ambastel	2002	26,027.99	21.69

Note. Assets in Millions.

Table 6

The Sample of Non-Failed Firms in 2001

No.	Non-Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	Kwangjoo Tourist Hotel	2001	7,223.90	6.02
2	Gumdolsan Development	2001	13,841.46	11.53
3	Newstar Tourism Development	2001	11,334.92	9.45
4	Namwoo Tourism	2001	91,618.47	76.35
5	Donggeon Development	2001	18,313.26	15.26
6	Donbang Tourist Hotel	2001	18,808.15	15.67
7	Daemyung Leisure Industry Corporation	2001	345,480.40	287.90
8	Royal Kingdom Hotel	2001	9,971.49	8.31
9	Royal Tourist Hotel	2001	14,297.48	11.91
10	Sihung Tourist Hotel	2001	18,654.13	15.55
11	Suan	2001	8,535.88	7.11
12	Itaewon	2001	7,358.02	6.13
13	Sunshine Hotel	2001	17,107.35	14.26
14	ICMD	2001	27,200.05	22.67
15	DuckGoo	2001	17,612.37	14.68
16	Centro	2001	8,021.00	6.68
17	Songok Development	2001	10,560.81	8.80

Table 6 *(continued).*

No.	Non-Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
18	Ambatel	2001	64,200.79	53.50
19	Ora Tourism	2001	134,074.53	111.73
20	Yeonjeon Development	2001	17,969.95	14.97
21	Yongchang Industrial Corporation	2001	10,237.08	8.53
22	Jirisan	2001	14,191.68	11.83
23	Jeil	2001	38,728.03	32.27
24	Wooyoung Development	2001	9,347.09	7.79
25	Yousung Oncheon Development	2001	12,237.15	10.20
26	Jungwon Hotel	2001	7,223.45	6.02
27	Komodo Hotel	2001	34,732.57	28.94
28	Newgumosan	2001	9,927.44	8.27
29	Seoul Lake	2001	215,332.81	179.44
30	Daehan	2001	74,898.31	62.42
31	Samdoo	2001	30,590.45	25.49
32	SamKwang	2001	20,948.65	17.46
33	Sun and Moon	2001	28,774.32	23.98
34	Daehyup	2001	25,583.75	21.32
35	Sunsan	2001	13,013.95	10.84
36	Sejong	2001	77,021.48	64.18
37	Remian	2001	6,670.93	5.56
38	Ambasordorz	2001	99,673.52	83.06
39	Boryung	2001	17,318.15	14.43
40	Tower hotel	2001	118,516.02	98.76

Note. Assets in Millions.

Table 7

The Sample of Non-Failed Firms in 2002

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	International Tourist Hotel	2002	15,693.17	13.08
2	Gumdolsan Development	2002	11,861.07	9.88
3	Daehyup Tourism	2002	31,974.22	26.65
4	Dukgoo Oncheon	2002	21,509.37	17.92
5	Donggeon Development	2002	22,605.18	18.84
6	Donbang Tourist Hotel	2002	18,062.58	15.05

Table 7 *(continued)*.

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
7	Daemyung Leisure Industry	2002	404,286.51	336.91
8	Royal Kingdom Hotel	2002	9,955.10	8.30
9	Royal Tourist Hotel	2002	13,643.21	11.37
10	Baknam Tourism	2002	19,784.48	16.49
11	Bomoon Tourism	2002	65,103.23	54.25
12	Sihung Tourist Hotel	2002	23,218.36	19.35
13	CDL Hotel Korea	2002	258,490.22	215.41
14	Sunshine Hotel	2002	17,373.36	14.48
15	Samjung Tourist Hotel	2002	30,316.24	25.26
16	ICMD	2002	28,675.06	23.90
17	Royal D	2002	37,719.93	31.43
18	Jirisan	2002	13,819.75	11.52
19	Sunsan Terminal	2002	11,672.74	9.73
20	Ambatel	2002	61,382.43	51.15
21	Ora Tourism	2002	137,521.96	114.60
22	Yongchang Industrial Corporation	2002	10,755.77	8.96
23	Younsung Hotel	2002	42,821.10	35.68
24	Itaewon Hotel	2002	7,175.93	5.98
25	Wooyoung Development	2002	18,885.32	15.74
26	Yousung Oncheon Development	2002	12,282.86	10.24
27	Komodo Hotel	2002	34,326.52	28.61
28	Hamilton Hotel	2002	33,144.82	27.62
29	Samwha	2002	12,228.01	10.19
30	South Jirisan	2002	15,249.59	12.71
31	Daehan	2002	75,486.45	62.91
32	Sunong	2002	86,319.46	71.93
33	WooChang	2002	16,364.49	13.64
34	Daewong	2002	24,765.25	20.64
35	Remian	2002	9,345.01	7.79
36	Boryung	2002	18,966.43	15.81
37	Crown	2002	7,861.80	6.55

Note. Assets in Millions.

Variables

Previous studies of business failure have used financial ratios representing liquidity, leverage, solvency, profitability, and efficiency as variables in developing failure prediction models. Based on the ratios used by previous studies and the availability of the ratios of the sample firms, 11 financial ratios, measuring liquidity, leverage, solvency, and efficiency, were selected as applicant variables for estimating the failure prediction of this study. The ratios representing profitability were excluded from the variables, as these ratios could directly affect the predictability of the models.

Liquidity ratios indicate a firm's ability to meet its current financial obligations, while leverage ratios measure the extent to which the company is relying upon borrowed fund. Solvency ratios evaluate a firm's capability to cover all of its financial charges. Solvency of a company is critical to its survival and, although long-term insolvency is equivalent to company failure, it is short-term insolvency which precipitates the event. Efficiency ratios measure the productivity for a given level of inputs. The four groups of ratios reflect the overall financial condition and performance of a firm. The 11 ratios used in this study are listed below:

Liquidity

1. CR
2. QR
3. EBITDA to CL

Leverage

4. Debt ratio

Solvency

5. EBITDA to TL
6. Interest coverage ratio
7. Long-term debt to total capitalization ratio

Efficiency

8. Inventory turnover
9. Total assets turnover
10. Accounts receivable turnover
11. Fixed assets turnover

Failure Prediction Methods

The techniques for failure prediction consist mainly of three parts (Dimitras, Zanakis, & Zopounidis, 1996):

1. Sample selection and collection of data,
2. Selection of method and specific variables (ratios) to develop a predictive model,
3. Model validation, i.e. statistical significance and accuracy of results.

The selection of the method can be the most important part. This selection depends on the data to be analyzed and the objectives of the study. The data selection is influenced by the availability or reliability, the definition of failure or underlying failure theory, and the study objectives (Dimitras, Zanakis, & Zopounidis, 1996).

Both MDA and logit analysis will be used in this study to develop failure prediction models. The two models will be compared afterwards to identify which method appears to be more accurate for predicting business failure for Korean lodging firms.

MDA

MDA classifies a company into one of two groups – failed or non-failed – on the basis of a Z-score which is a combination of ratios that best separates failed from non-failed firms. The discriminant analysis is a linear function and can be specified as (Storey, Keasey, Watson, & Wynarczyk, 1990):

$$Z = a_0 + a_1x_1 + a_2x_2 \dots\dots\dots\dots\dots\dots\dots a_nx_n$$

where,

Z	= Discriminant score
a_0	= Constant term
a_1-a_n	= Weights or coefficients
x_1-x_n	= Explanatory variables

The coefficients are determined based on the objective to maximize the distance between groups while simultaneously minimizing the distance between each firm's value and its own group's average (Neophytou & Molinero, 2004).

When a company has to be classified as failed or non-failed, the relevant ratios are determined and multiplied by the coefficients in the Z function. This will produce a score which is compared to the critical discriminating Z-score. The output of the application of an MDA model, however, is a score which has little intuitive interpretation, since it is basically an ordinal ranking device (Ohlson, 1980).

The final step is the classification of the individual firms into the failed or non-failed groups based on the Z-score. A cut-off score is calculated according to the a-priori probabilities of group membership and the costs of misclassification. Based on its Z-score and the cut-off score, a firm is classified to the failure or the non-failure group. The value of the dividing point of the two groups is calculated as (Storey, Keasey, Watson, & Wynarczyk, 1990):

$$C = \frac{(Z_b + Z_{nb})}{2}$$

where,

Z_b = The mean value of the Z-scores in the failed group

Z_{nb} = The mean of the Z-scores in the non-failed group.

The quality of the model's predictability is measured by the accuracy of classification in reclassifying the two groups of firms correctly. In summary, MDA provides the decision maker with a dichotomous classification of the firms. This classification, although important, does not provide any estimate of the associated risk of failure.

Logit Analysis

An alternative to using MDA is the use of conditional probability models to estimate the probability of occurrence of a choice or outcome. The major problem with using MDA for predicting company failure is that it does not explicitly identify the predictive power of individual variables. MDA is primarily designed to provide a failure or non-failure prediction, rather than estimating the probability of failure or non-failure. The econometric methodology of the conditional logit analysis was chosen to avoid some fairly well known problems associated with MDA (Ohlson, 1980). Conditional probability models are used to estimate a relationship between a set of variables describing an entity and the probability that the entity will be in a given final state. The simplest form of probability model is the linear probability model with a single explanatory variable (Storey, Keasey, Watson, & Wynarczyk, 1990):

$$Y_i = \alpha + BX_i + E$$

where,

X_i = value of attribute-ratio for company $_i$

Y_i = 1 – if company fails

0 – if company does not fail

$E_i =$ Independently distributed random variable with 0 mean – assume X_i is fixed or, if random, is independent of E_i

The interpretation of above equation as a linear probability model comes about when the expected value of each dependent variable observation Y_i is taken:

$$E\,(Y_i) = \alpha + BX_i$$

Since Y_i can take on only two values, 1 and 0, the probability distribution of Y_i can be described by letting:

$P_i = \text{Prob}\,(Y_i = 1)$ and $1\text{-}P_i = \text{Prob}\,(Y_i = 0)$,

Then $E\,(Y_i) = 1\,(P_i) + 0\,(1\text{-}\,P_i) = P_i$.

Thus the regression equation can be interpreted as describing the probability that an entity will end up in a given state, given information about the entity's attributes.

CHAPTER 4

RESULTS AND FINDINGS

Introduction

The results and findings of the study will be presented in this chapter. In the first part of this chapter, summary of ratio statistics for failed and non-failed firms are presented and comparisons are made between these two groups. In the second part of this chapter, the results of the MDA are discussed. A prediction model is established, and its predictive ability is tested. In the third part of this chapter, the results of the logit analysis are presented. A prediction model is developed based on the results, and its accuracy in failure prediction is assessed. The fourth part of this chapter compares the results from these two prediction models and draws the conclusion.

Overview of the Financial Health of Failed and Non-failed Groups

Prior to applying the discriminant analysis and the logit analysis to develop the failure prediction models, the overall financial conditions of failed and non-failed groups are observed. Table 8 lists the group average for 11 financial ratios calculated based on the data from one statement prior to failure and the corresponding year for the non-failed group. The significance level of their T test is also presented. The list of variables represents liquidity, solvency, leverage, and efficiency.

Table 8

Summary of Ratio Statistics of Failed and Non-failed Groups One Year prior to failure

Ratios	T	Average of Failed Group	Average of Non-Failed Group	Sig.
Liquidity				
CR	-0.8695	0.5442	0.7503	0.3873
QR	-1.2338	0.4191	0.6748	0.2211
EBITDA to CL	-0.5968	0.8224	1.0155	0.5524
Leverage				
DEBT	7.4341	1.2553	0.6895	0.0000**
Solvency				
EBITDA to TL	-2.0252	0.2749	0.4529	0.0464*
Capitalization	-0.9993	-7.1602	0.2989	0.3208
Interest Coverage	-6.6670	-3.5634	2.7788	0.0000**
Efficiency				
Inventory turnover	-2.8698	21.4856	36.8383	0.0053**
TA turnover	-5.5819	0.1757	0.5003	0.0000**
AR turnover	-2.0092	26.4805	44.6063	0.0481*
FA turnover	-4.4688	0.2243	0.6166	0.0000**

Note. *$p < .05$ **$p < .01$

The results of paired-samples T tests show that at the 0.01 significant level, the two groups are significantly different in regard to five ratios – debt, interest coverage, inventory turnover, total assets turnover, and fixed assets turnover ratio. If the significant level is set at 0.05, two more ratios become significantly different and these are EBITDA to TL and AR turnover. Hence, the null hypothesis that the two group means are equal is rejected at 0.05 significant level for the following seven ratios – interest coverage, debt, EBITDA to TL, inventory turnover, TA turnover, AR turnover, and FA turnover.

The results of previous studies indicate that the ratios for failed firms should have lower values in the measures of liquidity and solvency, but higher values in the measures of leverage compared to those of non-failed firms (Altman, 1968). Table 8 illustrates that the mean values of the liquidity ratios and the solvency ratios are noticeably lower for the failed group compared to the non-failed group. On the other hand, the mean value of the leverage ratio is higher for the failed group than those for the non-failed groups. These findings are consistent with previous studies and the expectations.

Results of the MDA

Development of the Failure Prediction Model

The SPSS program was utilized to perform the discriminant analysis on firms' financial ratios one year prior to failure in order to develop the failure prediction model. A stepwise procedure was used to select an optimal set of discriminating variables from the original 11 candidate variables for the model. With the significance level set at the 0.05 level, the final model included three financial ratios:

$$Z = 0.913 - 0.734X_1 + 0.569X_2 + 0.395X_3,$$

where,

X_1 = Debt ratio

X_2 = Interest coverage ratio

X_3 = Total Assets turnover ratio

The Wilk's Lambda statistic, 0.523, and the chi-square value, 97.621, of the model suggest that the null hypothesis of the two groups being from the same population can be rejected at the 0.000 significance level with 3 degrees of freedom.

The Z score of each company in the sample and their reclassified membership based on the ratios one year before failure are shown in Table 9. The SPSS program has adjusted the dividing point between failed and non-failed groups to a cut-off value of zero. Companies which have negative Z scores are classified into the failed group, whereas companies which have positive Z scores are classified into the non-failed group. Table 9 shows that the higher the Z score a firm has, the higher the probability of being classified as non-failed firm. In contrast, the lower the Z score a company has, the higher the probability of being classified as going failure. Table 9 also shows that among the 77 failed firms, 13 firms were misclassified into non-failed group. Among the 77 non-failed firms, 8 firms were misclassified as failed firms.

Table 9

Reclassified Membership, Z scores, and Probabilities One Year Prior to Failure using MDA

Firms	Reclassified Membership[a]	Z score[b]	Probability 1[c]	Probability 2[d]
1	1	-0.5473	0.7387	0.2613
2	1	-0.7623	0.8096	0.1904
3	1	-1.6689	0.9596	0.0404
4	1	-1.1311	0.8954	0.1046
5	1	-2.3079	0.9876	0.0124
6	1	-2.6813	0.9939	0.0061
7	1	-1.2859	0.9199	0.0801
8	1	-1.8964	0.9734	0.0266
9	1	-1.3421	0.9274	0.0726
10	1	-0.0614	0.5291	0.4709
11	1	-1.0237	0.8747	0.1253
12	1	-0.4800	0.7133	0.2867
13	1	-2.5280	0.9918	0.0082
14	1	-0.4574	0.7044	0.2956
15	1	-1.5154	0.9467	0.0533
16	1	-0.2068	0.5969	0.4031
17	1	-0.9009	0.8469	0.1531
18	1	-1.2692	0.9176	0.0824
19	1	-0.8248	0.8272	0.1728
20	1	-0.9667	0.8624	0.1376
21	1	-0.9367	0.8555	0.1445
22[e]	0	0.0286	0.5135	0.4865
23	1	-0.9667	0.8624	0.1376
24[e]	0	1.1377	0.8966	0.1034
25	1	-0.9009	0.8469	0.1531
26	1	-0.4326	0.6945	0.3055
27[e]	0	0.9474	0.8580	0.1420
28	1	-0.5178	0.7277	0.2723
29	1	-0.4499	0.7014	0.2986
30	1	-0.5969	0.7564	0.2436
31	1	-0.5178	0.7277	0.2723
32	1	-0.4499	0.7014	0.2986
33	1	-0.4326	0.6945	0.3055
34[e]	0	0.4881	0.7164	0.2836
35	1	-1.0217	0.8743	0.1257
36	1	-0.4326	0.6945	0.3055
37	1	-1.0663	0.8833	0.1167
38	1	-1.2967	0.9214	0.0786

Table 9 *(Continued).*

Firms	Reclassified Membership[a]	Z score[b]	Probability 1[c]	Probability 2[d]
39[e]	0	0.3762	0.6713	0.3287
40	1	-1.5499	0.9499	0.0501
41[e]	0	0.0091	0.5043	0.4957
42	1	-0.8478	0.8333	0.1667
43	1	-1.5155	0.9467	0.0533
44	1	-1.5835	0.9529	0.0471
45	1	-1.6114	0.9552	0.0448
46[e]	0	0.5395	0.7358	0.2642
47	1	-0.0843	0.5399	0.4601
48	1	-2.8659	0.9957	0.0043
49	1	-1.3884	0.9331	0.0669
50	1	-1.9654	0.9766	0.0234
51[e]	0	0.7861	0.8164	0.1836
52	1	-1.3041	0.9224	0.0776
53	1	-0.9154	0.8504	0.1496
54	1	-3.2088	0.9977	0.0023
55	1	-1.6718	0.9598	0.0402
56	1	-0.5178	0.7277	0.2723
57	1	-0.4499	0.7014	0.2986
58	1	-0.5969	0.7564	0.2436
59[e]	0	0.5297	0.7322	0.2678
60	1	-1.4898	0.9442	0.0558
61	1	-0.7747	0.8132	0.1868
62	1	-1.1780	0.9035	0.0965
63	1	-2.8781	0.9958	0.0042
64[e]	0	0.1659	0.5781	0.4219
65	1	-1.6388	0.9574	0.0426
66	1	-2.3530	0.9887	0.0113
67[e]	0	1.0415	0.8784	0.1216
68	1	-1.7814	0.9671	0.0329
69	1	-2.4999	0.9914	0.0086
70[e]	0	0.9465	0.8578	0.1422
71	1	-0.4691	0.7090	0.2910
72	1	-4.0127	0.9995	0.0005
73	1	-0.3327	0.6529	0.3471
74	1	-0.6113	0.7614	0.2386
75	1	-1.1445	0.8978	0.1022
76	1	-3.3598	0.9983	0.0017
77[e]	0	0.3883	0.6764	0.3236
78	0	0.8485	0.8335	0.1665
79	0	0.4683	0.7087	0.2913
80	0	0.4093	0.6850	0.3150

Table 9 *(Continued).*

Firms	Reclassified Membership[a]	Z score[b]	Probability 1[c]	Probability 2[d]
81	0	1.5350	0.9485	0.0515
82	0	2.9267	0.9962	0.0038
83	0	1.3554	0.9291	0.0709
84[e]	1	-0.9282	0.8535	0.1465
85	0	0.5241	0.7301	0.2699
86	0	1.4112	0.9358	0.0642
87	0	0.8572	0.8358	0.1642
88	0	0.1957	0.5918	0.4082
89	0	0.0146	0.5069	0.4931
90	0	0.2385	0.6113	0.3887
91	0	2.1246	0.9826	0.0174
92	0	0.5337	0.7337	0.2663
93	0	0.3548	0.6623	0.3377
94	0	0.6685	0.7806	0.2194
95	0	1.1627	0.9009	0.0991
96	0	1.2410	0.9134	0.0866
97	0	0.4976	0.7201	0.2799
98	0	2.6963	0.9941	0.0059
99	0	0.9466	0.8578	0.1422
100	0	0.1278	0.5604	0.4396
101	0	1.6981	0.9617	0.0383
102	0	1.2542	0.9154	0.0846
103[e]	1	-0.9495	0.8585	0.1415
104	0	1.2129	0.9091	0.0909
105[e]	1	-0.8999	0.8466	0.1534
106	0	0.6600	0.7778	0.2222
107	0	1.7387	0.9645	0.0355
108	0	0.5639	0.7447	0.2553
109	0	0.8582	0.8361	0.1639
110	0	0.4594	0.7052	0.2948
111	0	1.4115	0.9358	0.0642
112	0	0.0330	0.5156	0.4844
113	0	1.5316	0.9482	0.0518
114[e]	1	-0.0322	0.5153	0.4847
115	0	1.3552	0.9291	0.0709
116	0	1.2949	0.9212	0.0788
117	0	0.9807	0.8655	0.1345
118	0	0.4759	0.7117	0.2883
119	0	0.3810	0.6734	0.3266
120	0	1.2280	0.9114	0.0886
121	0	1.3763	0.9317	0.0683
122	0	2.3938	0.9895	0.0105

Table 9 *(Continued).*

Firms	Reclassified Membership[a]	Z score[b]	Probability 1[c]	Probability 2[d]
123	0	1.3818	0.9323	0.0677
124[e]	1	-0.8218	0.8264	0.1736
125	0	0.5032	0.7222	0.2778
126	0	0.9548	0.8597	0.1403
127	0	1.5379	0.9488	0.0512
128	0	0.1315	0.5621	0.4379
129	0	0.4421	0.6983	0.3017
130	0	0.5180	0.7278	0.2722
131	0	0.6396	0.7711	0.2289
132	0	2.1909	0.9846	0.0154
133	0	3.0275	0.9968	0.0032
134	0	3.6652	0.9991	0.0009
135	0	1.4470	0.9398	0.0602
136	0	0.1283	0.5606	0.4394
137	0	1.1472	0.8983	0.1017
138	0	1.4586	0.9410	0.0590
139	0	2.9383	0.9962	0.0038
140	0	0.8231	0.8267	0.1733
141	0	1.9132	0.9742	0.0258
142[e]	1	-0.6341	0.7692	0.2308
143	0	0.4147	0.6873	0.3127
144	0	1.3368	0.9268	0.0732
145	0	0.4147	0.6873	0.3127
146	0	1.3368	0.9268	0.0732
147	0	0.2027	0.5950	0.4050
148	0	0.4147	0.6873	0.3127
149	0	1.3368	0.9268	0.0732
150[e]	1	-0.2158	0.6010	0.3990
151	0	2.0025	0.9782	0.0218
152[e]	1	-0.0322	0.5153	0.4847
153	0	2.9310	0.9962	0.0038
154	0	0.3220	0.6483	0.3517

Note. The first 77 firms are failed hospitality firms in the sample. The second 77 firms are non-failed firms in the sample.

a. Membership 1 is failed group and Membership 0 is non-failed group.
b. Z scores were based on the financial ratios one year prior to failure.
c. Probability 1 refers to the probability of membership in the failed group.
d. Probability 2 refers to the probability of membership in the non-failed group.
e. Misclassified firms.

Discussions of the Individual Ratios in the Model

Debt ratio is a leverage ratio that indicates what proportion of debt a company has relative to its assets. The negative sign of its coefficient in the model implies that the higher the value of this ratio, the greater the chance of failure for a company. A debt ratio greater than 1 indicates that a company has more debt than assets, or a negative net worth, and a debt ratio less than 1 indicates a company has more assets than debt. In general, the lower the company's reliance on debt for asset formation, the less risky the company is since excessive debt can lead to a very heavy interest and principal repayment burden.

Interest coverage ratio is a solvency ratio that determines how easily a company can pay interest on its outstanding debt. The positive sign of its coefficient in the model suggests that the higher coverage that EBIT has on interest expenses makes the Z score larger and increases the probability of non-failure. On the other hand, the lower the coverage that EBIT has on interest expenses, the lower the Z sore which means higher probability of a company's failure.

Total asset turnover ratio is an efficiency ratio that measures how efficiently a company uses its assets to generate sales. The higher the total asset turnover ratio, the more efficiently a firm's asset has been used. The positive sign of its coefficient suggests that a higher ratio of total asset turnover leads to a greater Z score and hence reduces the probability of failure. Zavgren (1983) found the efficiency ratios such as the asset turnover, receivables turnover and inventory turnover to be important for long-term predictions.

Significance and Contribution of the Individual Ratios

As shown in Table 8, all three variables included in the prediction model were significantly different between the failed and non-failed groups at the level of 0.01. In addition to the unstandardized coefficients of the ratios in the prediction model, the discriminant analysis also provided a standardized coefficient for every ratio in the model which indicates the relative contribution of each variable to the model. Table 10 summarizes the results.

Table 10

Relative Contribution and Ranks of Variables in the Prediction Model

Variables	Standardized Coefficient	Ranking
Debt ratio	- 0.6637	1
Interest Coverage ratio	0.5487	2
Total Assets turnover	0.5072	3
Fixed Assets turnover	0.4575	4
Inventory turnover	0.1789	5
Accounts Receivable turnover	0.1067	6
EBITDA to Current Liabilities	- 0.0918	7
Current ratio	0.0421	8
Capitalization	0.0260	9
EBITDA to Total Liabilities	0.0145	10
Quick ratio	- 0.0034	11

The standardized coefficients in Table 10 indicate that the biggest contributor to group separation of the discriminant function was the debt ratio. This is not surprising as the debt ratio gives an indication of the gearing level of the business. The debt ratio also shows the proportion of a company's assets which are financed through debt. Companies with high debt ratios are said to be "highly leveraged", and could be in danger if they could not pay interests and matured principal. As mentioned earlier, Korean firms, in general, are heavily leveraged, perhaps the most heavily leveraged in the world. Therefore, it is logical to find that debt ratio is the biggest contributor in classifying the firms into either failed or non-failed group.

Predictive Ability of the Discriminant Model

The purpose of developing a failure prediction model is to accurately predict failure before it occurs. Therefore, the predictive ability of the model was examined and the results are presented in the following part. Before presenting the model's classification accuracy, types of misclassification errors are discussed. There are two types of misclassification errors – Type I error and Type II error (Altman & Levallee, 1981). Type I error is the probability of misclassifying a failed firm into the non-failed group while the type II error is the probability of misclassifying a non-failed firm into the failed group.

As already shown in Table 9, the Z score and reclassified membership of the sample of 154 firms were examined using data from financial statements one year prior to failure for the failed group and the identical years for the non-failed group. The classification matrix for the sample one year prior to failure is given in Table 11.

Table 11

Prediction Accuracy One Year prior to Failure using MDA

		Predicted	
Actual	N	Failed	Non-failed
Failed	77	64	13
		83.12%	**16.88%**
Non-failed	77	8	69
		10.39%	**89.61%**

Note. Accuracy percentages in bold. Overall accuracy = 133/154 = 86.36%

Table 11 lists the classification results of the Z-score model on the original 154-firm sample. The overall accuracy is 86.36 percent with 13.64 percent errors recorded – 16.88 percent type I and 10.39 percent type II.

Validation of Results

An effective discriminant model is one that has much between-group variability of Z-scores when compared to within-groups variability of Z-scores. Coefficients of the discriminant model are chosen so that the ratio of the between-groups to within-groups sum of squares of Z-scores is as large as possible. The eigenvalue statistic is the ratio of the between-groups to within-groups sum of squares of Z-scores. Large eigenvalue in this study, 0.913, shows that the estimated discriminant model has high discriminating ability. The canonical correlation will measure the percentage of the variation in discriminant scores "explained" by the variance between groups (Jones, 1987). In this study, the canonical correlation is 0.691, which means that 69.1 percent of the variations in discriminant scores are explained by the variance between groups. In other words, the correlation value between the discriminant scores and the groups is 69.1 percent.

It is well known that a model will generally fit the sample from which it was derived better than any other sample (Jones, 1987). In the case of failure prediction, this means that mere success in classifying firms as failing or healthy based on the derivation sample is not sufficient.

The problem can be handled in two basic ways (Jones, 1987): the sample can be split into a derivation sub sample and prediction sub sample; or the entire sample can be used to derive the parameters, and the model can be tested using a statistical technique such as the Lachenbruch method. In the Lachenbruch procedure, a model is constructed using "n-1" observations (Lachenbruch, 1975). The model is then used to predict the missing observation. The process is repeated n times and the percentage misclassified is used to estimate the misclassification rate. The method will give an almost unbiased estimate of the misclassification rate, so that the statistical over-fitting problem will be taken into consideration. Nevertheless, the Lachenbruch method does not provide the test of external validity that a hold-out procedure offers (Lachenbruch, 1975). A hold-out sample that is obtained from a different time setting can be used to test for over fitting and can improve the validity of the model. Original sample accuracy results are potentially biased due to both sample and search (for the best ratios) bias (Altman & Levallee, 1981). Most reliable discriminant analysis studies utilize various types of hold-out or secondary sample tests to remove these biases.

This study first used the Lachenbruch method (Table 12) to test the validation of the model.

Table 12

Prediction Accuracy One Year prior to Failure using MDA (Lachenbruch test)

		Predicted	
Actual	N	Failed	Non-failed
Failed	77	64	13
		83.12%	**16.88%**
Non-failed	77	9	68
		11.69%	**88.31%**

Note. Accuracy percentages in bold. Overall accuracy = 132/154 = 85.71%

Table 12 reports on results for the Lachenbruch tests. For the sample used in this study, the type I accuracy remained at 83.12 percent, establishing a greater confidence in the model. The type II accuracy was at 88.31 percent – a remarkable result.

The results and discussions above have indicated that the failure prediction model developed in this study can classify the in-sample firms into failed and non-failed groups with an 86.36 percent accuracy rate one year prior to failure. With the Lachenbruch test, the model was still able to achieve an accuracy rate of 85.71 percent which was almost as high. The model's fairly high predictive accuracy is similar to those of other failure prediction models developed in previous studies.

Test of Predictive Ability on Hold-out Firms

In order to further examine the model's predictive ability, a set of hold-out firms from the year 2003 were used to test if the model could accurately predict out-of-sample failure events. A hold-out sample of 36 failed firms in 2003 was selected from the same data source. The sample in 2003 had average assets of $37.43 million, ranging from $5.74 million to $219.73 million. Using the same sampling methods, 36 non-failed firms were selected in order to match the failed sample firms by assets size. Financial ratios were derived for the failed and non-failed lodging firms from their financial statements in 2002, one year prior to the 2003 failure. Table 13 lists the failed lodging firms in 2003 and Table 14 provides the non-failed matching lodging firms in the same year.

Table 13

The Sample of Failed Firms in 2003

No.	Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	Kawon Leisure	2003	19,829.81	16.52
2	KwangJoo Tourist hotel	2003	7,201.50	6.00
3	Green and Blue	2003	16,822.03	14.02
4	Don Beach Tourist Hotel	2003	34,152.85	28.46
5	Naksan	2003	28,661.02	23.88
6	Dongbang	2003	18,275.96	15.23
7	Mibong	2003	19,604.85	16.34
8	Dong-A	2003	9,585.80	7.99
9	Sihung Tourist Hotel	2003	24,498.25	20.42
10	Samjung Tourist Hotel	2003	30,752.85	25.63
11	Samkwang Development	2003	21,877.86	18.23
12	Songok Development	2003	14,078.71	11.73
13	Sinan Tourism	2003	34,804.33	29.00
14	Hyunsung	2003	12,408.64	10.34
15	Grand	2003	9,320.99	7.77
16	Seoul Lake	2003	263,672.12	219.73
17	Daehan	2003	78,203.66	65.17
18	Itaewon Hotel	2003	7,525.65	6.27
19	Junglim Development	2003	74,089.56	61.74
20	Koreana Hotel	2003	105,061.32	87.55
21	Komodo Hotel	2003	41,869.70	34.89
22	Taean	2003	10,014.68	8.35
23	Tower Hotel	2003	98,343.86	81.95
24	Phil Korea Limited	2003	157,997.66	131.66
25	Paradise Incheon	2003	31,593.22	26.33
26	Paradise Hotel Dogo	2003	10,725.30	8.94
27	Hanmoo Convention	2003	172,764.02	143.97
28	Sun and Moon	2003	82,015.81	68.35
29	Namyoung	2003	19,757.61	16.46
30	Ansan	2003	11,169.65	9.31
31	Yeonjun	2003	25,783.22	21.49
32	Jinwon	2003	9,585.60	7.99
33	Ambatel	2003	61,535.86	51.28
34	Jungwon	2003	6,885.96	5.74
35	Ambastel	2003	37,672.46	31.39
36	Hotel Daegu	2003	8,939.53	7.45

Note. Assets in Millions.

Table 14

The Sample of Non-Failed Firms in 2003

No.	Non-Failed Firms	Reference Year	Asset (₩ M)	Asset ($ M)
1	Kawon Housing	2003	60,254.71	50.21
2	Daehyup Tourism	2003	31,738.32	26.45
3	Dukgoo Oncheon	2003	23,710.17	19.76
4	Donggeon Development	2003	22,883.04	19.07
5	Daegu Park	2003	74,455.24	62.05
6	Remian	2003	9,611.15	8.01
7	Royal Kingdom	2003	10,740.25	8.95
8	Gumdolsan	2003	11,986.19	9.99
9	Royal Development	2003	37,928.35	31.61
10	Baknam Tourism	2003	19,857.66	16.55
11	ICMD	2003	33,280.90	27.73
12	Dae gyo	2003	24,656.24	20.55
13	Namwoo	2003	96,542.25	80.45
14	Suam	2003	8,002.10	6.67
15	Sunshine	2003	17,114.98	14.26
16	Suhansa	2003	130,652.40	108.88
17	Centro	2003	8,947.55	7.46
18	Sejong	2003	82,091.69	68.41
19	Samdoo	2003	19,519.76	16.27
20	Central	2003	103,312.46	86.09
21	Sunsan Terminal	2003	11,270.60	9.39
22	Ora Tourism	2003	139,828.54	116.52
23	Ambasodorz	2003	99,532.55	82.94
24	Yongchang Industry	2003	12,273.18	10.23
25	Yousung Hotel	2003	43,391.54	36.16
26	Oil Tourism	2003	33,456.21	27.88
27	Bugok Hawaii	2003	39,464.39	32.89
28	Hamilton Hotel	2003	33,422.52	27.85
29	Jirisan	2003	13,470.48	11.23
30	City	2003	7,300.02	6.08
31	Junwon	2003	244,640.16	203.87
32	New Gumosan	2003	9,862.02	8.22
33	Dae wong	2003	26,767.61	22.31
34	Sema	2003	8,665.43	7.22
35	Boryung	2003	23,001.69	19.17
36	Crown	2003	6,814.15	5.68

Note. Assets in Millions.

The Z-score for each firm in the 2003 hold-out sample was calculated based on the MDA model ($Z = 0.913 - 0.734X_1 + 0.569X_2 + 0.395X_3$) previously estimated from the 2001-2002 data. Table 15 lists the classification results based on the calculated Z scores as compared to the cut-off zero Z score.

Table 15

Classification Results for 2003 Sample using the MDA Model

Firms	Debt	Interest	TA turnover	Z scores[a]	Reclassified Membership[b]
1	1.1163	-128.3286	0.3430	-72.79	1
2	1.7076	0.3759	0.1910	-0.05	1
3	1.8017	-0.3518	0.2178	-0.52	1
4	1.4249	0.0511	0.0722	-0.08	1
5	1.6245	-3.0658	0.1720	-1.96	1
6[c]	0.7978	1.7863	0.3702	1.49	0
7	1.7830	-31.1699	0.1717	-18.06	1
8	1.1451	-0.4000	0.3795	-0.01	1
9	1.7273	0.4557	0.1644	-0.03	1
10[c]	2.1349	11.9192	0.3098	6.25	0
11	1.7691	0.3155	0.4886	-0.01	1
12	1.7809	-0.4443	0.4020	-0.49	1
13	1.8366	0.3568	0.5686	-0.01	1
14	1.4126	-0.1108	0.0000	-0.19	1
15	1.3968	-1.7637	0.1298	-1.06	1
16[c]	0.7412	6.8602	0.1445	4.33	0
17	2.0625	0.5548	0.3365	-0.15	1
18[c]	1.1059	3.5082	0.5997	2.33	0
19	0.9793	-13.6040	0.1275	-7.5	1
20[c]	2.2337	3.0166	0.2194	1.08	0
21[c]	0.2369	3.1392	0.3990	2.68	0
22	1.4997	0.0406	0.2476	-0.07	1
23	2.4386	0.7627	0.2050	-0.36	1
24	0.6263	-1.0100	0.1393	-0.07	1
25	1.2641	-0.8040	0.9624	-0.09	1
26	2.4297	-0.2646	0.4690	-0.84	1
27	0.9877	-0.4733	0.0932	-0.04	1
28[c]	0.9235	3.3047	0.2226	2.2	0
29	0.7989	-0.8308	0.3256	-0.02	1
30	1.7942	0.3618	0.2648	-0.09	1
31	0.8061	-3.9554	0.6122	-1.69	1
32	1.4749	-0.8664	0.1469	-0.6	1
33[c]	0.3548	3.1599	0.2759	2.56	0
34	1.6514	0.0428	0.2404	-0.18	1
35	0.5597	-1.8855	0.0492	-0.55	1
36[c]	0.9554	0.9556	0.4544	0.93	0
37[c]	1.1675	-9.5012	0.0945	-5.31	1
38	0.6004	4.0341	0.4988	2.96	0
39	0.8061	7.9208	1.1380	5.28	0
40	0.6930	0.8994	1.6325	1.56	0

Table 15 *(Continued)*

Firms	Debt	Interest	TA turnover	Z scores[a]	Reclassified Membership[b]
41[c]	0.7657	-1.6513	0.3034	-0.47	1
42	1.0128	1.3508	0.1694	1.01	0
43	0.7089	1.0230	0.2828	1.09	0
44	0.8764	1.8222	0.4746	1.49	0
45	0.8713	55.6521	0.4415	32.11	0
46	0.7349	8.1362	1.1248	5.45	0
47	0.6506	2.4812	2.3612	2.78	0
48	0.5626	1.3993	1.4230	1.86	0
49	0.2223	25.7314	0.5636	15.61	0
50	0.8427	3.2437	0.2680	2.25	0
51	0.7125	3.9998	0.3073	2.79	0
52	0.3502	2.5130	0.2378	2.18	0
53	0.9219	2.7557	0.4937	2	0
54	0.3219	3.3533	0.4580	2.77	0
55	0.4403	0.9215	0.1851	1.19	0
56	1.0002	1.2232	0.5645	1.1	0
57	0.9406	1.3670	0.5284	1.21	0
58	0.2728	8.0560	0.3382	5.43	0
59	0.3606	3.6732	0.3257	2.87	0
60	0.5353	22.7680	1.0124	13.88	0
61	0.5247	2.0960	0.3391	1.85	0
62	0.4101	17.3795	0.3020	10.62	0
63	0.7110	-0.4062	0.3848	0.31	0
64	0.4471	6.5807	0.2527	4.43	0
65	0.8084	2.4888	0.2461	1.83	0
66[c]	1.8008	-0.4134	0.1325	-0.59	1
67	0.5694	1.4982	0.3341	1.48	0
68	1.1285	1.1320	0.0347	0.74	0
69	0.1428	10.0043	0.0805	6.53	0
70	1.2282	1.2877	0.0806	0.78	0
71	0.5681	9.3385	3.2742	7.1	0
72	0.9575	1.0254	0.5994	1.03	0

Note. The first 36 firms are failed hospitality firms in the sample and the second 36 firms are non-failed firms in the sample.

a. Z scores were based on the financial ratios one year prior to failure.
b. Membership 1 is failed group and Membership 2 is non-failed group.
c. Misclassified firms.

Table 15 shows that among the 36 failed firms, 9 firms were misclassified into non-failed group. Among the 36 non-failed firms, 3 firms were misclassified as failed firms.

Table 16

Prediction Accuracy One Year prior to Failure for 2003 Hold-out Sample using MDA Model

		Predicted	
Actual	N	Failed	Non-failed
Failed	36	27	9
		75.00%	**25.00%**
Non-failed	36	3	33
		8.33%	**91.67%**

Note. Accuracy percentages in bold. Overall accuracy = 60/72= 83.33%

Table 16 demonstrates the prediction accuracy for the hold-out sample of 72 firms. The overall accuracy is 83.33 percent with 16.67 percent errors recorded – 25.00 percent type I and 8.33 percent type II.

A comparison was made between the results from this hold-out sample and the previous results from the original sample. The model's accuracy decreased slightly when it was used against the hold-out sample (83.33 percent overall accuracy) compared to that of the original sample (86.36 percent overall accuracy). However, this is considered as a respectable result due to the following two reasons. First, the model was developed from the financial data of the original sample, therefore it is very likely that the model classifies the original sample the best. Second, one of the main drawbacks of MDA has been that the model developed is likely to be sample-specific, thus the accuracy of the model is expected to decrease when the model is used against out-of-sample data.

Based on the results from previous studies of business failure, the MDA model developed in this study appears to be significant in classifying firms into failed or non-failed groups.

Results of the Logit Analysis

Development of the Failure Prediction Model

The STATA program was employed for the logit analysis in this study based on firms' financial ratios one year prior to failure. The STATA, developed by UCLA Academic Technology Services, is an advanced statistic program that is utilized mainly for econometric analyses.

First, the program relates "failure (1 for failure and 0 for non-failure)" to the entire set of regresssors – 11 financial ratios. Chi-square test was then performed to test for redundancy and re-estimated the model with only significant variables at 0.05 significance level. The re-estimated model contained three financial ratios: debt ratio, interest coverage ratio, and EBITDA to CL ratio. Table 17 presents the calculated test statistics for the estimated coefficients of the logit model.

Table 17

Summary of Ratio Statistics for Re-estimated Model with 3 Regressors

	Coef.	Std. Err.	z	P>z
DEBT	2.6937	0.7102	3.79	0.000
INTEREST	-0.7026	0.1823	-3.85	0.000
EBITDA_CL	-0.3005	0.1267	-2.37	0.018
_Constant	-2.1392	0.7510	-2.85	0.004

The z Values and associated P values indicate that all parameters, including the constant and variable coefficients, are significant at least at the 0.01 level (Table 17).

The negative coefficients for interest coverage and EBITDA to CL ratios indicate that the larger the values of these ratios, the smaller the probability of a firm's failure. On the other hand, the positive coefficient for debt ratio can be interpreted as the larger the value of this ratio, the larger the probability of a firm's failure. This is because, in logit analysis, all the values lie between 0 and 1 – 0 being 0.00% probability of failure and 1 being 100.00% probability of failure. Above results along with maximization of the log-likelihood function provided the following equation:

$$Y_i = -2.1392 + 2.6937F_{1a} - 0.7026F_{2a} - 0.3005F_{3a},$$

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

where,

F_{1a} = Debt ratio

F_{2a} = Interest coverage ratio

F_{3a} = EBITDA to CL ratio

The obtained Y value, through the above equation, is placed on the extreme value distribution to get the odds of failure. Afterwards, the probability of failure (P) is computed.

A firm is classified to the failed or healthy group according to the estimated logit model, based on a cut-off probability of 0.50 (P_c=0.50) and calculated failure probabilities. The classifications were made by the following procedure:

- If failure probability < P_c, the firm is classified to the healthy group,
- If failure probability $\geq P_c$, the firm is classified to the failed group.

The assigned probability of failure for each company in the sample and their reclassified membership based on the ratios one year before failure are shown in Table 18. Table 18 also shows that among the 77 failed firms, 11 firms were misclassified into non-failed group. Among the 77 non-failed firms, 8 firms were misclassified as failed firms.

Table 18

Reclassified Membership and Probabilities of Failure using Logit Model

Firms	Y	Equation	Probability of Failure[a]	Reclassified Membership[b]
1	0.9765	2.6552	0.7264	1
2	4.4653	86.9495	0.9886	1
3	4.9871	146.5057	0.9932	1
4	2.1359	8.4650	0.8943	1
5	18.3059	89155975.1872	1.0000	1
6	11.0618	63692.1369	1.0000	1
7	2.3253	10.2297	0.9110	1
8	11.5555	104349.2005	1.0000	1
9	2.6358	13.9546	0.9331	1
10	0.5944	1.8119	0.6444	1
11	3.0616	21.3620	0.9553	1
12	1.0034	2.7275	0.7317	1
13	17.8874	58665773.0432	1.0000	1
14	3.1775	23.9857	0.9600	1
15	7.9187	2748.1381	0.9996	1
16	0.0951	1.0998	0.5238	1
17	1.7756	5.9039	0.8552	1
18	2.3878	10.8894	0.9159	1
19	1.8036	6.0714	0.8586	1
20	1.3779	3.9666	0.7987	1
21	1.5148	4.5484	0.8198	1
22[c]	-0.8241	0.4386	0.3049	0
23	1.3779	3.9666	0.7987	1
24[c]	-1.9304	0.1451	0.1267	0
25	1.7756	5.9039	0.8552	1
26	9.4244	12387.3210	0.9999	1
27[c]	-1.1670	0.3113	0.2374	0
28	1.2682	3.5546	0.7804	1
29	2.3207	10.1829	0.9106	1
30	0.8957	2.4491	0.7101	1
31	1.2682	3.5546	0.7804	1
32	2.3207	10.1829	0.9106	1
33	9.4244	12387.3210	0.9999	1
34[c]	-0.7766	0.4600	0.3151	0
35	5.7898	326.9402	0.9970	1
36	9.4244	12387.3210	0.9999	1
37	3.1388	23.0770	0.9585	1
38	5.4832	240.6258	0.9959	1
39[c]	-0.7086	0.4923	0.3299	0
40	3.9320	51.0101	0.9808	1

Table 18 *(Continued)*.

Firms	Y	Equation	Probability of Failure[a]	Reclassified Membership[b]
41	1.0213	2.7767	0.7352	1
42	3.2821	26.6327	0.9638	1
43	3.1889	24.2622	0.9604	1
44	0.3521	1.4220	0.5871	1
45	5.3219	204.7695	0.9951	1
46[c]	-1.3811	0.2513	0.2008	0
47	2.4094	11.1271	0.9175	1
48	17.9715	63815817.9605	1.0000	1
49	2.1396	8.4959	0.8947	1
50	4.5894	98.4361	0.9899	1
51[c]	-3.4504	0.0317	0.0308	0
52	1.2978	3.6612	0.7855	1
53	1.6674	5.2985	0.8412	1
54	6.0258	413.9868	0.9976	1
55	1.9810	7.2502	0.8788	1
56	1.2682	3.5546	0.7804	1
57	2.3207	10.1829	0.9106	1
58	0.8957	2.4491	0.7101	1
59	0.0628	1.0648	0.5157	1
60	2.5309	12.5647	0.9263	1
61	1.5782	4.8461	0.8289	1
62	2.3820	10.8269	0.9154	1
63	5.9200	372.4037	0.9973	1
64[c]	-0.8307	0.4357	0.3035	0
65	2.8903	17.9983	0.9474	1
66	5.2497	190.5103	0.9948	1
67[c]	-1.2205	0.2951	0.2279	0
68	3.6154	37.1655	0.9738	1
69	3.8140	45.3315	0.9784	1
70[c]	-1.2114	0.2978	0.2295	0
71	1.7490	5.7490	0.8518	1
72	24.7611	56705420967.3644	1.0000	1
73	0.0836	1.0872	0.5209	1
74	2.2386	9.3805	0.9037	1
75	5.9924	400.3690	0.9975	1
76	5.4511	233.0058	0.9957	1
77[c]	-0.0914	0.9127	0.4772	0
78	-1.6971	0.1832	0.1548	0
79	-1.1032	0.3318	0.2491	0
80	-1.2523	0.2858	0.2223	0
81	-2.6110	0.0735	0.0684	0
82	-3.5274	0.0294	0.0285	0

Table 18 *(Continued)*.

Firms	Y	Equation	Probability of Failure[a]	Reclassified Membership[b]
83	-2.3051	0.0997	0.0907	0
84[c]	1.7750	5.9002	0.8551	1
85	-0.9580	0.3837	0.2773	0
86	-5.6813	0.0034	0.0034	0
87	-1.7335	0.1767	0.1501	0
88	-1.1523	0.3159	0.2401	0
89	-0.6275	0.5339	0.3481	0
90	-0.8620	0.4223	0.2969	0
91	-3.6640	0.0256	0.0250	0
92	-1.6769	0.1869	0.1575	0
93	-1.5047	0.2221	0.1817	0
94	-0.4539	0.6351	0.3884	0
95	-2.8625	0.0571	0.0540	0
96	-3.1793	0.0416	0.0400	0
97	-0.0451	0.9559	0.4887	0
98	-11.2394	0.0000	0.0000	0
99	-2.2598	0.1044	0.0945	0
100[c]	0.2261	1.2537	0.5563	1
101	-12.9097	0.0000	0.0000	0
102	-2.4806	0.0837	0.0772	0
103[c]	2.0228	7.5595	0.8832	1
104	-2.3590	0.0945	0.0864	0
105[c]	1.3529	3.8685	0.7946	1
106	-3.0770	0.0461	0.0441	0
107	-4.0857	0.0168	0.0165	0
108	-2.3843	0.0922	0.0844	0
109	-1.4698	0.2300	0.1870	0
110	-1.2507	0.2863	0.2226	0
111	-2.4477	0.0865	0.0796	0
112	-0.3978	0.6718	0.4018	0
113	-3.6677	0.0255	0.0249	0
114	-1.3509	0.2590	0.2057	0
115	-3.9927	0.0185	0.0181	0
116	-1.0955	0.3344	0.2506	0
117	-1.8792	0.1527	0.1325	0
118	-0.7647	0.4655	0.3176	0
119	-1.0808	0.3393	0.2534	0
120	-3.0625	0.0468	0.0447	0
121	-2.5853	0.0754	0.0701	0
122	-3.1531	0.0427	0.0410	0
123	-2.5443	0.0785	0.0728	0
124[c]	1.2846	3.6132	0.7832	1

Table 18 *(Continued).*

Firms	Y	Equation	Probability of Failure[a]	Reclassified Membership[b]
125	-1.0466	0.3511	0.2599	0
126	-2.5884	0.0751	0.0699	0
127	-4.5475	0.0106	0.0105	0
128[c]	0.2565	1.2924	0.5638	1
129	-1.2759	0.2792	0.2182	0
130	-1.1976	0.3019	0.2319	0
131	-2.5920	0.0749	0.0697	0
132	-8.6040	0.0002	0.0002	0
133	-2.5153	0.0808	0.0748	0
134	-23.2411	0.0000	0.0000	0
135	-3.1279	0.0438	0.0420	0
136	-0.7539	0.4705	0.3200	0
137	-3.3288	0.0358	0.0346	0
138	-4.8988	0.0075	0.0074	0
139	-12.9908	0.0000	0.0000	0
140	-1.6903	0.1845	0.1557	0
141	-4.1373	0.0160	0.0157	0
142[c]	4.4010	81.5283	0.9879	1
143	-1.3190	0.2674	0.2110	0
144	-2.7573	0.0635	0.0597	0
145	-1.3190	0.2674	0.2110	0
146	-2.7573	0.0635	0.0597	0
147	-0.2071	0.8129	0.4484	0
148	-1.3190	0.2674	0.2110	0
149	-2.7573	0.0635	0.0597	0
150	-0.2668	0.7658	0.4337	0
151	-3.3848	0.0339	0.0328	0
152	-1.3509	0.2590	0.2057	0
153	-2.9990	0.0498	0.0475	0
154[c]	0.5255	1.6913	0.6284	1

Note. The first 77 firms are failed hospitality firms in the sample. The second 77 firms are non-failed firms in the sample.

a. Probability of failure is based on the financial ratios one year prior to failure.
b. Membership 1 is failed group and Membership 2 is non-failed group.
c. Misclassified firms.

Discussions of the Individual Ratios in the Model

Both MDA model and logit model incorporated three variables into their prediction models. While MDA model included debt ratio, interest coverage ratio, and total assets turnover ratio, the logit model contained debt ratio, interest coverage ratio, and EBITDA to CL ratio. The logit analysis revealed that EBITDA to CL ratio was more significant in predicting the failure compared to the total assets turnover ratio. Since both debt ratio and interest coverage ratio were discussed in depth earlier, this section will concentrate mainly on a discussion of EBITDA to CL ratio.

EBITDA to CL ratio is a liquidity ratio which measures the ability of using operating earnings to cover current liabilities. The higher coverage that EBITDA has over the CL indicates the higher possibility of not going bankrupt. While previous studies have put more emphasis on EBITDA to TL ratio, the results of this study point out that EBITDA to CL is more significant when it comes to assign probabilities of failure for Korean firms.

Predictive Ability of the Logit Model

The probability of failure and reclassified membership of the sample of 154 firms were observed using data from one statement prior to failure for the failed group and the identical years for the non-failed group (Table 18). Since the logistic equation was derived from this sample, a high degree of classification accuracy is estimated. The classification matrix for the sample one year prior to failure is given in Table 19.

Table 19

Prediction Accuracy One Year prior to Failure using Logit Model

		Predicted	
Actual	N	Failed	Non-failed
Failed	77	66	11
		85.71%	**14.29%**
Non-failed	77	8	69
		10.39%	**89.61%**

Note. Accuracy percentages in bold. Overall accuracy = 135/154 = 87.66%

The overall accuracy is 87.66 percent with 12.34 percent errors recorded – 14.29 percent type I and 10.39 percent type II.

Test of Predictive Ability on Hold-out Firms

An identical set of hold-out firms that were used for MDA were utilized to examine whether the model could accurately predict out-of-sample failure events. Their relevant financial ratios in 2002 were used for calculating the failure probability based on the logit model. Table 20 presents the classification results.

Table 20

Classification Results for 2003 Sample using the Logit Model

Firms	DEBT	INTEREST	EBITDA/ CL	Probability of failure[a]	Reclassified Membership[b]
1	1.1163	-128.3286	-0.0290	1.0000	1
2	1.7076	0.3759	0.7770	0.8768	1
3	1.8017	-0.3518	0.5904	0.9418	1
4	1.4249	0.0511	0.0844	0.8372	1
5	1.6245	-3.0658	13.9285	0.5510	1
6[c]	0.7978	1.7863	0.3756	0.2046	0
7	1.7830	-31.1699	1.2213	1.0000	1
8[c]	1.1451	-0.4000	8.1981	0.2249	0
9	1.7273	0.4557	0.3982	0.8883	1
10[c]	2.1349	11.9192	2.5010	0.0040	0
11	1.7691	0.3155	1.1117	0.8880	1
12	1.7809	-0.4443	0.3634	0.9459	1
13	1.8366	0.3568	1.1470	0.9014	1
14	1.4126	-0.1108	0.0002	0.8511	1
15	1.3968	-1.7637	0.5768	0.9364	1
16[c]	0.7412	6.8602	0.3968	0.0062	0
17	2.0625	0.5548	3.4977	0.8782	1
18[c]	1.1059	3.5082	1.6697	0.1065	0
19	0.9793	-13.6040	-0.1981	1.0000	1
20	2.2337	3.0166	0.4984	0.8332	1
21[c]	0.2369	3.1392	1.6179	0.0149	0
22	1.4997	0.0406	0.6659	0.8418	1
23	2.4386	0.7627	0.4510	0.9772	1
24[c]	0.6263	-1.0100	0.9315	0.4944	0
25	1.2641	-0.8040	0.0867	0.8587	1
26	2.4297	-0.2646	0.3966	0.9887	1
27	0.9877	-0.4733	0.3838	0.6766	1
28[c]	0.9235	3.3047	0.3624	0.1108	0
29	0.7989	-0.8308	0.4425	0.6138	1
30	1.7942	0.3618	0.3203	0.9124	1
31	0.8061	-3.9554	0.2212	0.9396	1
32	1.4749	-0.8664	0.0079	0.9198	1
33[c]	0.3548	3.1599	1.6623	0.0198	0
34	1.6514	0.0428	0.1703	0.9027	1
35	0.5597	-1.8855	-0.2321	0.6820	1
36[c]	0.9554	0.9556	0.5185	0.4030	0
37[c]	1.1675	-9.5012	-0.0549	0.9995	1
38	0.6004	4.0341	0.8328	0.0264	0
39	0.8061	7.9208	0.5922	0.0033	0
40	0.6930	0.8994	0.3325	0.2681	0

Table 20 *(Continued)*.

Firms	DEBT	INTEREST	EBITDA/ CL	Probability of failure[a]	Reclassified Membership[b]
41[c]	0.7657	-1.6513	1.4071	0.6594	1
42	1.0128	1.3508	0.3450	0.3860	0
43	0.7089	1.0230	0.3364	0.2593	0
44	0.8764	1.8222	0.4009	0.2352	0
45	0.8713	55.6521	2.0856	0.0000	0
46	0.7349	8.1362	8.9778	0.0002	0
47	0.6506	2.4812	0.3308	0.0971	0
48	0.5626	1.3993	0.9444	0.1312	0
49	0.2223	25.7314	5.9221	0.0000	0
50	0.8427	3.2437	1.0108	0.0793	0
51	0.7125	3.9998	3.0249	0.0191	0
52	0.3502	2.5130	0.7779	0.0393	0
53	0.9219	2.7557	0.6452	0.1436	0
54	0.3219	3.3533	0.8346	0.0203	0
55	0.4403	0.9215	3.2743	0.0701	0
56	1.0002	1.2232	4.4171	0.1635	0
57	0.9406	1.3670	0.3694	0.3369	0
58	0.2728	8.0560	8.0925	0.0001	0
59	0.3606	3.6732	2.3115	0.0116	0
60	0.5353	22.7680	1.9089	0.0000	0
61	0.5247	2.0960	0.7345	0.0817	0
62	0.4101	17.3795	2.6072	0.0000	0
63	0.7110	-0.4062	2.6118	0.3266	0
64	0.4471	6.5807	3.0603	0.0015	0
65	0.8084	2.4888	0.2711	0.1428	0
66[c]	1.8008	-0.4134	7.7002	0.6655	1
67	0.5694	1.4982	0.8425	0.1288	0
68[c]	1.1285	1.1320	0.0609	0.5217	1
69	0.1428	10.0043	0.7794	0.0001	0
70[c]	1.2282	1.2877	0.0692	0.5606	1
71	0.5681	9.3385	0.6056	0.0006	0
72	0.9575	1.0254	1.0856	0.3528	0

Note. The first 36 firms are failed hospitality firms in the sample and the second 36 firms are non-failed firms in the sample.

a. Probability of failure is based on the financial ratios one year prior to failure.
b. Membership 1 is failed group and Membership 2 is non-failed group.
c. Misclassified firms.

Table 21 is a summary of the prediction accuracy for the hold-out sample. Among the 36 failed firms, 10 firms were misclassified into non-failed group. Among the 36 non-failed firms, 5 firms were misclassified as failed firms. The overall accuracy was 79.17 percent, with 20.83 percent errors recorded – 27.78 percent type I and 13.89 percent type II. The overall accuracy was slightly lower than that of the MDA model (83.3 percent) for the same hold-out sample.

Table 21

Prediction Accuracy One Year prior to Failure for 2003 Hold-out Sample using the Logit Model

		Predicted	
Actual	N	Failed	Non-failed
Failed	36	26	10
		72.22%	**27.78%**
Non-failed	36	5	31
		13.89%	**86.11%**

Note. Accuracy percentages in bold. Overall accuracy = 57/72= 79.17%

A comparison between the results from this hold-out sample and the previous results from the original sample was made (Table 22).

Table 22

Comparison between Original and Hold-out Sample

		Original Sample			Hold-out Sample	
Actual	N	Failed	Non-failed	N	Failed	Non-failed
Failed	77	66	11	36	26	10
		85.71%	**14.29%**		**72.22%**	**27.78%**
Non-failed	77	8	69	36	5	31
		10.39%	**89.61%**		**13.89%**	**86.11%**
Overall accuracy			**87.66%**			**79.17%**

The model's accuracy decreased obviously when it was used against the hold-out sample compared to that of the original sample. While the accuracy rate for both type I and type II error declined, it was more significant for type I error – the model's ability in predicting failed firms as failed decreased by 13.49 percent when it was used against the hold-out sample. While the question of validity remains, the overall prediction accuracy of 79.17 percent seems to be still acceptable as the model was used against out-of-sample firms. Based on the results from previous studies of business failure, the logit model developed in this study appears to be noteworthy in assigning probability of failure to firms.

Comparison between the Results from MDA and Logit Analysis

Two different comparisons are made between MDA and logit analysis based on the results from the original sample (Table 23) and the hold-out sample (Table 24).

Table 23

Comparison between MDA and Logit Model (Original Sample)

		MDA		Logit Analysis	
Actual	N	Failed	Non-failed	Failed	Non-failed
Failed	77	64	13	66	11
		83.12%	**16.88%**	**85.71%**	**14.29%**
Non-failed	77	8	69	8	69
		10.39%	**89.61%**	**10.39%**	**89.61%**
Overall accuracy			**86.36%**		**87.66%**

In comparison with the results from MDA, the logit analysis appeared to be slightly more accurate. This is especially true for the case of failed firms as the logit analysis was able to predict the failures with 85.71 percent whereas MDA had 83.12 percent accuracy. When it came to non-failure, both the models had identical accuracy levels.

Table 24

Comparison between MDA and Logit Model (Hold-out Sample)

		MDA		Logit Analysis	
Actual	N	Failed	Non-failed	Failed	Non-failed
Failed	36	27	9	26	10
		75.00%	**25.00%**	**72.22%**	**27.78%**
Non-failed	36	3	33	5	31
		8.33%	**91.67%**	**13.89%**	**86.11%**
Overall accuracy			**83.33%**		**79.17%**

When the models were tested against the hold-out sample, however, the MDA model outperformed the logit model but the difference in accuracy was not so significant. Overall, the two models are not significantly different in terms of classification or prediction accuracy. Previous studies have also reported that these two models produce very similar classification results (Lo, 1986).

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Summary of the Study

This study first looked at a sample of 77 failed firms and a control sample of 77 non-failed hospitality firms for the business failure prediction. Eleven financial ratios representing liquidity, leverage, solvency, and efficiency of a firm were calculated for the sample firms one year prior to failure. The descriptive statistics of the 11 ratios for the failed and non-failed groups indicated that non-failed hospitality firms were significantly better than failed hospitality firms in terms of liquidity, leverage, and solvency, demonstrating the potential classifying ability of the financial ratios between failed and non-failed groups.

A MDA model and a logit model were then estimated based on sample firms' financial ratios one year prior to failure. For MDA, a stepwise procedure was used and a model with three ratios was established. These three ratios were debt ratio, interest coverage ratio, and total assets turnover ratio. The classification results indicated that the MDA model could achieve an overall in-sample classification accuracy of 86.36 percent one year prior to failure. The model was also tested on a hold-out firm for its accuracy. The results indicated that the model could correctly classify 83.33 percent of the out-of-sample firms.

For the logit analysis, the maximization of the log-likelihood function was used to derive a logit model also with three variables. These variables were debt ratio, interest coverage ratio, and EBITDA to CL ratio. The classification results of logit model showed that it had an overall prediction accuracy rate of 87.66 percent for in-sample firms and 79.17 percent accuracy rate for out-of-sample firms. Overall, there were no significant differences in performance between these two models.

Researchers have noted that MDA requires the assumptions of multi-variate normality and equal covariances, and that these assumptions are typically violated. Since logit analysis does not suffer from this weakness, it is theoretically preferable. Empirically, this study shows that the logit model is not inferior to the MDA in terms of prediction accuracy. Therefore, due to the theoretical soundness of the logit model, it is recommended that the logit model be considered as the preferred method for predicting lodging firm failures in Korea.

Implications for Management

The models developed in this study and their retained variables carry several important managerial implications for the Korean lodging industry.

First, the crisis causing the failure of a business seldom erupts overnight. Warning signals of a company heading toward business failure arise much earlier than the actual failure. These signals, along with the aid of prediction models, could be used to predict business failure in advance. Therefore, Korean hotel managers have an urgent need to be familiar with financial statements as a means of identifying problem areas and early warning signs.

Second, the debt ratio was contained in both MDA and logit models. Overly relying on debt financing has been a major cause of the business failure in the Korean lodging industry. The findings suggest that to avoid business failure, lodging firm owners and/or operators must change their debt-inclined financing policy or habit. It is a high time for the Korean lodging industry to switch from its pro-debt financing to pro-equity financing. Lowering the overall debt ratio of the industry will lead to higher Z scores in the MDA model and lower failure probabilities in the logit model for Korean lodging firms, thus helping reduce business failure occurrences.

Third, the interest coverage ratio was also included in both MDA and logit models. There are two basic ways to increase the interest coverage ratio. The first one is to increase EBIT and the second one is to lower the interest expenses. Since there is such an intensive competition among Korean lodging firms, it seems more feasible to lower the interest expenses in order to increase the interest coverage ratio. The more a firm relies on debt-financing, the higher the interest expenses and the lower the interest coverage ratio. Both MDA and logit models in this study indicate that the firm can lower its chance of failure by improving its interest coverage ratio. Korean lodging firms need to move away from heavily leveraged financial structure that has been prevalent in the industry for a long time. Increasing the overall interest coverage ratio of the industry will also lead to higher Z scores in the MDA model and lower failure probabilities in the logit model for Korean lodging firms, thus help avoiding business failure.

Fourth, the total assets turnover ratio was incorporated in the MDA model. It has been prevalent among the Korean firms to grow in size and/or raise equity capital as late as a year or two prior to failure. Korean lodging firms should pay more attention to using existing hotel assets to generate sales rather than investing in new properties or assets. A lodging firm that can efficiently use its existing room assets to generate revenue will have a higher assets turnover ratio and hence a higher Z score in the MDA model. The lodging industry is typically fixed assets intensive and new investment in fixed assets involves large amount of capital and leads to lower assets turnover. In a saturated lodging market, while assets maintenance and upgrading are necessary for maintaining competitive ability, excessive investment in new fixed assets or expansion should be avoided.

Finally, the EBITDA to CL retained in the logit model reveals the importance of EBITDA or operating cash flow to the financial health of a Korean lodging firm. With the current liability held constant, a lodging firm that is able to generate sufficient operating cash flows will have a higher EBITDA to CL ratio, thus lowering probability of failure. Therefore, a tight control of the operating costs of a lodging operation, ranging from costs of goods sold to payroll and marketing expenses, will help Korean lodging firms avoid business failure.

Limitations

There are four major limitations in this study.

The first limitation is the exclusion of private firms. The sample used to develop the failure prediction model is limited to the publicly traded lodging firms. Privately held lodging firms were excluded due to the unavailability of financial information. Therefore the model may not be applicable for predicting private firm failures.

The second limitation is that the failure prediction in this study only looked at microeconomic variables. Many unobservable factors exist that may influence the vulnerability of an individual firm (Demister, 1972). These factors include the ability of management to perform well under new and unfavorable circumstances, random events in either the internal or the external environments, and activities of regulators and courts of law. A failure prediction model containing only financial statement information would not provide a highly accurate classification of failed and non-failed firms.

The third limitation of this study is that the two models developed can predict business failure just one year in advance, whereas signs of failure may occur much early. Due to the limited data availability, the models could not be tested for longer period prior to the failure. Many failure prediction studies emphasize that business failure is not an immediate event but is a process that evolves over a considerable period of time. Predicting the failure just one year in advance may be too late for a firm to take necessary actions to turn the company around in order to prevent further loss.

The fourth limitation of this study is that while it identified both type I and type II errors, no attempts was made to quantify the relative costs of these errors. This is due to the fact that the relative costs of these errors are specific to the individual users of the models.

Suggestions for Future Research

The 11 financial ratios used to estimate the failure prediction model were all based on the firm's historical information. Market-value ratios of the sample firms were not used in the study due to data unavailability. However, when a firm is experiencing financial distress and heading toward failure, market-value ratios of the firm, such as ratios related to its stock price, would be significant indicators (Gao, 1999). Therefore, it is suggested that future studies should collect and utilize firms' market-value ratios as classifying variables in the models.

Macroeconomic variables could also be important in making a distinction between failing and non-failing firms (Dambolena, 1983). Variables such as rising interest rates, a recessionary environment, the availability of credit, and other macroeconomic factors could all affect the firm's vulnerability to failure. Future studies on Korean hospitality firm failure prediction may incorporate these variables into the analysis and identify the effects of those variables. Involving macroeconomic variables in prediction models may hopefully lead to higher prediction accuracy.

The two models developed in this study can predict business failure just one year in advance as financial information of the firms prior to year 2000 was unavailable. Korean lodging firms have long been reluctant in providing their financial information to the public and the information, if provided, is often obscure. With the help of Korean financial supervisory service database, however, many lodging firms have started posting their financial statements on-line and the number of firms doing so is increasing over time. Therefore, it is presumed that after a few years, it may be possible to get more years of financial information. As such, future studies on Korean lodging firm failures may consider extending the prediction period to several years ahead, rather than just one year in advance.

While the business failure prediction studies have been conducted for more than four decades in various areas, there are only small amounts of research done in the field of hospitality industry. Yet, it is well known that the hospitality firms are highly vulnerable to failure, especially in Korea. Therefore, future research should be expanded into other sectors of the Korean hospitality industry, such as restaurants and tourism and convention firms. Developing failure prediction models with reasonably high accuracy for various sectors of the Korean hospitality industry is a challenging task for researchers interested in Korea's hospitality businesses.

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