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A Model of Corporate Bankruptcy in Thailand Using Multiple Discriminant Analysis

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Abstract

This study argues that it is desirable to have a system that can reliably identify firms that are likely to become financially distressed. Such a warning system will enable parties with minor interests to adjust their investments before a firm's financial distress becomes apparent. It will also enable parties with major interests to enforce corrective actions which may prevent a firm from becoming bankrupt. In either case, potential losses can be reduced.

Previous studies have used the statistical technique of multivariate discriminant analysis (MDA) for deriving models for predicting bankruptcies. This study applies the technique with the aid of financial ratios in Thailand for identifying the potential failure of listed companies.

This study provides new evidence on whether MDA can be adopted as a tool for predicting the failure of Thai listed companies. The data used in this analysis was obtained from the Stock Exchange of Thailand (SET). The failed companies were delisted from the SET during the period 1997 to 2002. The financial variables are derived from Altman's (1968) five-ratio model and a range of published articles.

The results of the univariate tests support the proposition that the financial ratios of failed firms differ significantly from non-failed firms. It is also found that the ratios of failed firms indicate lower profitability and liquidity. Leverage ratios also tend to be higher, while asset quality ratios are lower.

The study uses MDA for identifying a firm's potential status up to five years in advance of failure. The optimal models contained the variables from Altman's (1968) five-ratio model, including retained earnings to total assets, EBIT to total assets, working capital to total assets, sales to total assets and market capitalisation to total liabilities. The results found that the mean rate of success during the testing phase for MDA was 59.6%.

Overall, the results of this study expand the body of knowledge in the field of predicting bankruptcies in developing economies, by focusing on Thai firms. This study has shown that MDA can be useful for investors and regulators interested in identifying potential corporate failures. These models are likely to become more powerful and accurate over time as new additions and innovations are developed. Indeed, accounting ratios and models of bankruptcy can be of practical use for predicting the financial health of Thai corporations.

Key Words

bankruptcy prediction model, corporate distress warning system, Thai corporations, multivariate discriminant analysis (MDA)

Introduction

Considerable attention has been devoted to the analysis of accounting information for predicting corporate failures. Beaver (1966) and Altman (1968) pioneered experimental designs for examining failures in specific industries. Lev (1974) and Foster (1978) provided concise summaries and evaluations of US studies in the field. Interest has spread to the UK (Taffler & Tisshaw 1977), Australia (Castagna & Matolcsy 1981), Italy (Altman, Marco & Varetto 1993), Japan (Ko 1982), Korea (Altman, Eom & Kim 1994) and Thailand (Nittayagasetwat, Tiripat & Withisuphakorn 1997).

The identification of business failures and early warnings of impending financial distress are important for analysts and practitioners in all economies. Even non-capitalist nations are concerned with an assessment of a firm's performance. Indeed, all nations are vitally concerned with avoiding financial crises in their private and public sectors (Altman 1984).

This research analyses corporate distress in Thailand and develops a bankruptcy model for identifying problem firms. The analysis is aimed at identifying the performance measures which provide the greatest accuracy for predicting distressed firms. This is achieved by adopting classification models and t-tests for comparing the significance of variations in financial information.

Background to the Research

Thailand plunged into economic crisis in 1997 mainly due to misguided national finance policies, inefficient operational and investment decisions and the weak supervisory and regulatory standards of its financial sector. The Thai government obtained a US$17 billion loan from the International Monetary Fund (IMF) to alleviate the problem of severely tight money supplies (Boorman 1999). In accordance with IMF requirements, the Bank of Thailand suspended the operations of 58 finance companies in mid 1997. This led to the loss of thousands of jobs, low public confidence in the financial sector and substantial corporate failures.

Financial mismanagement, overspending on unproductive projects, inappropriate monetary policies and a lack of transparency in the disclosure of information also contributed to the collapse (Hathaiseree 1997). Business failures, especially those listed on the Stock Exchange of Thailand (SET), reached record levels. Although Thailand has institutions that act as agents for protecting investors, such as the Securities and Exchange Commission (SEC), these bodies are in their early stages of development. Research on Thai corporate failure is also in its early stages. Indeed, there is little knowledge on how to measure corporate distress. This is consistent with comments in a World Bank Report (1998) that claimed Thai governments are generally ill equipped to measure corporate distress.

Studies in Thailand focus on assessing traditional models that predict bankruptcies such as MDA, LOGIT and PROBIT. This study builds and applies models for identifying distress among firms listed on the SET.

Traditional Financial Distress Models

Most traditional studies suggest that financial ratios are useful for predicting bankruptcies. In general, ratios measuring profitability, liquidity and solvency have been the most popular. Their relative accuracy is not clear, however, because almost every study has cited a different ratio as the most effective indicator of financial distress.

Although the objectives of these studies may vary, they are designed in a similar fashion. Scott (1981) provided a concise overview of the process for creating a bankruptcy model. Firstly, a number of ratios are calculated from the financial statements that were published prior to failure. Secondly, a formula is developed, based on a single ratio (or combination of ratios) that best distinguishes between failed and non-failed firms. The formula is then tested on the original sample and on a holdout sample which was not employed for deriving the formula. Finally, the model is revalidated over time, based on observations after it was developed (Scott 1981).

There are two types of traditional models. The first is a univariate approach which explores the relationship between individual financial ratios and bankruptcy. The second is a multivariate approach which employs pooled ratios for predicting bankruptcies.

The univariate approach uses individual financial ratios, one at a time, for predicting distress. Beaver (1966) adopted paired sampling for assessing the accuracy of a variety of ratios. The results of the study indicated that there was variation between the ratios of failed and non-failed firms. Beaver's findings suggested that ratio analysis could be useful five years before a failure, although he cautioned that ratios should be used selectively. It was also found that not all ratios are accurate for predicting failed and non-failed firms.

Zavgren (1983) observed that the main difficulty with Beaver's approach is that classification takes place one ratio at a time. Different variables often provide a variety of predictions, and consideration of a multitude of univariate ratios can be beyond the capability of the analysis. The financial status of a firm is multidimensional and no single ratio is able to capture all dimensions (Zavgren 1983). Several studies favoured a multivariate approach because it resolves this problem.

Altman (1968) was the first to adopt a multivariate approach for predicting bankruptcies. This approach combines several financial ratios in one model. To construct an efficient multivariate model, one must determine which ratios are better for detecting potential failures, and how the weights should be established for each of these ratios.
There are three popular types of multivariate techniques in the literature, multivariate discriminant analysis (MDA), logistic regression analysis and recursive partitioning analysis (RPA).

MDA is one of the most popular techniques used for analysing financial distress (Zavgren 1983). This method assesses the predictive ability of several financial ratios. Jones (1987) described this method as a technique which assigns a Z score to each company in a sample by using a combination of independent variables. A cutoff Z score is chosen based on the sample results. Companies below the cutoff point are predicted to become bankrupt, while those above are predicted to survive (Jones 1987). The main advantage of this approach is its ability to reduce a multidimensional problem to a single score and provide a high level of accuracy.

The MDA approach has been used to develop a number of prediction models, including Altman (1968), Altman, Haldeman and Narayanan (1977), Deakin (1972, 1977), Edmister (1972), Blum (1974), Sinkey (1975) and Lincoln (1984).

Logistic regression analysis is equivalent to two-group discriminant analysis. It has the advantage of being less affected than discriminant analysis when the basic assumptions, such as the normality of the variables, are not met (Altman 1993). Logitistic regression has been used to develop prediction models such as in Ohlson (1980).

RPA is a nonparametric technique, which minimises the expected cost of misclassification by a univariate splitting procedure (Altman 1993). RPA eliminates many of the statistical problems attributed to discriminant analysis, such as the assumptions associated with the distributions of the independent or dependent variables. Frydman, Altman and Kao (1985) were the first to apply RPA to the prediction of bankruptcies.

Hamer (1983) examined the variable sets included in the Altman (1968), Deakin (1972), Blum (1974) and Ohlson (1980) models. These variables have been classified in six categories. The first four – profitability, liquidity, leverage and turnover – were commonly used when discussing financial statement analysis, while variability and size have been included as a separate category. Hamer's study indicated there was minimal consistency in the variables selected in the four models. However, he found that they all contained variables for measuring profitability, liquidity and leverage. Altman and Deakin included measures of turnover, while Blum and Ohlson included measures of the variability of income over time. In addition, Blum included several variables for measuring the variation in liquidity over time. Altman and Blum employed market price data to compute their leverage ratios, while Ohlson and Deakin relied exclusively on financial accounting information (Hamer 1983).

Table 1: Summary of Ratios Used in the Representative Multivariate Models

Financial Ratios	Altman 1968	Deakin 1972	Edmister 1972	Sinkey 1974	Altman et al. 1977	Ohlson 1980	Altman 1993
Profitability:							
Cash flow/total assets							X
Cash flow/total liabilities						X	X
Cash flow/total liabilities plus preferred stock		X					

Financial Ratios	Altman 1968	Deakin 1972	Edmister 1972	Sinkey 1974	Altman et al. 1977	Ohlson 1980	Altman 1993
EBIT/total assets	X				X		X
Net income/total assets		X				X	X
Funds from operations/total liabilities						X	
Negativeincome for two years						X	
Liquidity:							
Working capital/total assets	X	X				X	X
Cash/current liabilities		X	X				
Cash/total assets		X					
Current assets/current liabilities		X			X		X
Current assets/total assets		X					X
Current liabilities/current assets						X	
Current liabilities/equity			X				
Quick assets/current liabilities		X	X				X
Quick assets/total assets		X					X
Leverage:							
Total liabilities/total assets						X	X
Total liabilities plus preferred stock/total assets		X					
Equity mkt.value/total capitalization					X		X
Equity mkt.value/total liabilities	X						
Retained earnings/total assets	X				X		X
Turnover:							
Sales/total assets	X						X
Working capital/sales		X					X
Cash/sales		X					X
Current assets/ sales		X					X
Quick assets/ sales		X					X
Inventory/sales			X				
Equity/sales			X				
Size:							
Ln (total assets)					X		X
Log (total assets/GNP index						X	
Variability:							
Ln (interest+15)							X
Ln (EBIT/total interest payments)					X		

Financial Ratios	Altman 1968	Deakin 1972	Edmister 1972	Sinkey 1974	Altman et al. 1977	Ohlson 1980	Altman 1993
Standard deviation of EBIT/total assets					X		
(Cash + US Treasury Sec.)/total assets				X			
Interest paid on deposits/total revenue				X			
Loan revenue/total revenue				X			
Loans/(capital + reserves)				X			
Loans/total assets				X			
Operating expense/operating income				X			
Other expense/total revenue				X			
Provision for loan losses/operating expense				X			
State & local obligation/total revenue				X			
US Treasury Sec./total revenue				X			

Source: Altman (1968, 1993), Altman, Haldeman & Narayanan (1977), Deakin (1972), Edmister 1972, Ohlson (1980) and Sinkey (1975).

Table 1 presents the ratios which were found to be the most accurate predictors of financial distress under multivariate analysis. The models of Edmister (1972), Deakin (1972), Sinkey (1975) and Ohlson (1980) adopted accounting data, while both accounting and stock market data appeared in Altman's (1968) Z-score model and Altman, Haldeman and Narayanan's (1977) ZETA model. All of the models contain ratios based on stocks and flows and variables that are closely related to corporate earnings.

Scott (1981) reviewed and integrated several of the leading models including the work of Beaver (1966), Altman (1968), Deakin (1972), Wilcox (1971, 1973) and Altman, Haldeman and Narayanan (1977). He compared their accuracy and coherence with his own framework and concluded their success suggested the existence of a strong underlying regularity, although this is not based on 'explicit theory' (Scott 1981, p. 324). Scott also found it difficult to determine which model discriminated most accurately given the variation in data and procedures adopted. He concluded that:

> ... of the multidimensional models, the ZETA model is perhaps most convincing. It has high discriminatory power, is reasonably parsimonious, and includes accounting and stock market data as well as earnings and debt variables. Further it is being used in practice by over thirty financial institutions. As a result, although it is unlikely to represent the perfect prediction model, it will be used as a benchmark for judging the plausibility of the theories ... (Scott 1981, pp. 324-325).

Hamer (1983) compared the accuracy of models using four alternative variable sets with firms which had failed between 1966 and 1975. These sets were employed by Altman (1968), Deakin (1972), Blum (1974) and Ohlson (1980). A linear discriminant model, a quadratic discriminant model and a logit model were developed for each of the sets. Hamer found that the linear and logit models recorded comparable rates of misclassification and performed as accurately as the quadratic models. Using linear discriminant analysis or logit analysis, all variable sets recorded misclassification rates lower than would be expected by chance, for each of the three years prior to failure. In the fourth and fifth years, these models yielded high rates of misclassification and only Altman's variable set recorded accuracy greater than chance.

Overall, there are numerous multivariate techniques and each is confronted with a variety of issues. The successful completion of a multivariate analysis involves more than the selection of the correct methodology. Emphasis on the approach to model building, rather than just the specifics of each technique, should provide a broader base for model development, estimation and interpretation. This will improve the multivariate analyses of practitioners and academics.

Sample Selection and Data Source

The population consisted of all firms listed on the SET during the period 1997 to 2002, excluding banks and finance and insurance companies. There were approximately 300 firms in the data set. A firm was identified as 'failed' if it was delisted from the SET during this period; otherwise it was considered to be 'non-failed'.

Data were obtained from the SET's I-SIMs[1] database. Data for failed firms were also collected from the last financial statements filed before they were delisted.

This research used a matched-sample technique that compares a failed firm with more than one surviving firm. The term paired-sample technique, which refers to pairing a failed and non-failed firm on a one-to-one basis, is not used in this study, as discussed below (Deakin 1977; Lincoln 1984; Ohlson 1980).

A firm's financial status is the dependent variable in this research. However, status is an abstract concept, and a non-metric variable which cannot be measured directly. To overcome this problem, status is categorised into two groups, failed (*F*) and non-failed (*NF*). *F* takes a value of '1' while *NF* has a value of '0'.

Most previous studies have adopted bankruptcy as the dependent variable. This narrow definition of failure has restricted the size of the sample in those studies (Altman 1968; Altman, Haldeman & Narayanan 1977; Deakin 1972; Ohlson 1980). This research considers firms in financial distress because more firms will meet the criteria. For the purposes of this study, a firm in financial distress is defined as one that has been delisted[2] from the SET. The SET outlines the reasons for delisting,

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[1] I-SIMs = Integrated SET Information Management System: the online database system of the Stock Exchange of Thailand.

[2] Criteria for considering a possible delisting from the Stock Exchange of Thailand (SET 2000, p. 2):

- Shareholders' equity in a listed company is less than zero.
- Shereholders' equity in a listed company is more than zero, but the auditors report a qualified opinion, a disclaimer of opinion, or an adverse opinion.

which include 'companies that have neither the liquidity necessary nor the information required to track their operations adequately' (SET 2002, p. 1). The source used for identifying the public companies which failed between 1997 and 2002 was the 'Delisting Securities File' published by the SET.

Of the firms identified as failed, only those that were operating five years prior to the date of delisting are retained in the sample space. This will test the capability of the model for forecasting failures up to five years in advance. This approach resulted in the identification of 53 failed firms.

In 1997, Thailand's economic environment deteriorated enough to warrant using data from 1997 as a cutoff point for the start of the analysis. The period 1997 to 2002 saw a significant increase in the number of business failures. During the period September 1975 to December 1996 only 24 firms were delisted from SET, while 90 failed between January 1997 and June 2002.

Financial statements were obtained for each firm up to five years before they were delisted. The first year prior to a failure is represented by the last set of financial statements before a delisting.

Once a sample of failed firms was obtained, a control sample of non-failed firms was drawn. The number of non-failed companies is much larger than the 53 failed firms, suggesting that it may be advantageous to depart from 'pairing', by matching more than one non-failed company with each failed firm. The advantage of a larger number of non-failed firms is that sample errors are lowered. The main advantage of a large control group will be a decrease in sampling errors of the estimates of the solvent firm's economic characteristics and hence an improvement in the accuracy of measurements (Lev 1974). For example, Ohlson (1980) used 2,058 non-failed and 105 failed firms.

The sample of non-failed companies was randomly selected from the database. The non-failed firms were matched with a failed firm from the same financial statement period and industry. The total asset size was also similar.

Failed firms are often disproportionately small and concentrated in the same industries (Jones 1987). To detect maximum variation between failed and non-failed firms, many studies employ matched samples based on common characteristics. These characteristics include asset, or capital size and sales (Zhang et al. 1999), industry category or economic sector (Raghupathi, Schkade & Raju 1991), geographic location (Salchengerger, Cinar & Lash 1992), number of branches, age and charter status (Tam & Kiang 1992). Most studies employed size and industry characteristics in the matching procedure, for example; Altman (1968), Beaver (1966), Deakin (1972), Leshno and Spector (1996) and Zavgren (1983). Matching is aimed at reducing the random sampling error and ensuring the statistical tests are more sensitive. However, there is a conflict because the matching process counteracts any discriminatory power that the matching characteristic may have (Lincoln 1984).

- A liquidator, failure to be rehabilitated, financial problems and no longer qualified under clause 30 of the rules and regulations of the SET.

To limit the sample error, unequal sample sizes were employed in this analysis. Of the firms on the I-SIMs database system, 53 were identified as failed between 1997 and 2002, according to the above definition. These firms were matched with 106 non-failed firms representing the same financial statement period and industry and they were approximately matched for asset size. The data sample therefore consisted of 159 firms.
While, the Delisting Securities File (SET 2002) indicates that 53 firms[3] failed between 1997 and 2002, only 46 firms were employed in the analysis, because seven were significant outliers. A control sample of non-failed firms was selected by a matching procedure with a ratio of two non-failed firms for each failure. This ratio was chosen because there were more non-failed than failed companies. The matching process was undertaken by firm size, industry and year. During the period 1997 to 2002, however, the number of non-failed firms decreased in some industries, due to the economic crisis. Matching could not be undertaken on a two-to-one basis in some industries during this period.

During the period 1997 to 2002, the number of listed public companies in Thailand fell due to many delistings and some mergers. The number of non-failed firms fell markedly in some industries and many of these firms are included in the control group for this study. For this reason, the matching of firms could not be undertaken on a basis of two non-failed to one failed in some industries. The final sample selected included 89 non-failed and 46 failed firms.

Independent Variables: Financial Ratios

Most researchers have selected financial ratios for predicting failures because their accuracy has been demonstrated by success in previous research. Past studies provide a basis for selecting variables that are significant for predicting bankruptcies.

The procedure for selecting variables in this study has been adopted from the work of previous researchers. There are two sources of financial information where data can be obtained, namely, annual financial statements and share market prices (Altman 1968; Altman, Haldeman & Narayanan 1977). An initial list of independent variables was selected from a number of ratios that were found to be significant in earlier studies. These ratios are summarised in Table 2, although cash flow data are excluded[4].

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[3] This excluded banks and finance and insurance companies.

[4] Since a cash flow statement was not been contained in the computerised database of the SET during the periods of data collection (1992-2001).

Table 2: List of the Independent Variables

No.	Variable Set	Name	Definition	[illegible]
1	leverage	equity mkt.value to total debt	mkt.cap./total liabilities	mktcaptl
2	leverage	equity mkt.value to total assets	mkt.cap/total assets	mktcapta
3	leverage	equity mkt.value to total equity	mkt.cap/equity	mktcapeq
4	leverage	debt to equity ratio	total liability/equity	deratio
5	leverage	debt to total assets	total liability/total assets	daratio
6	leverage	financial leverage multiplier	total assets/equity	taeq
7	leverage	fixed asset to equity and long term liabilities	ppe/(equity+long term liability)	faeqltl
8	leverage	retained earnings to total assets	retained earnings/total assets	retainta
9	profitability	return on assets	net income/total assets	roa
10	profitability	return on equity	net income/equity	roe
11	profitability	gross profit margin	(sales-cos)/sales	gpmargin
12	profitability	net profit margin	net income/sales	npmargin
13	profitability	operating profit margin	EBIT/sales	ebitsale
14	profitability	EBIT to total assets	EBIT/total assets	ebitta
15	turnover	working capital to sales	(ca-cl)/sales	wcsales
16	turnover	inventory turnover	cost of sales/inventory	inveturn
17	turnover	fixed asset turnover	sales/ppe	faturn
18	turnover	total assets turnover	sales/total assets	taturn
19	turnover	equity turnover	sales/equity	eqturn
20	turnover	inventory to sales	inventory/sales	invsales
21	turnover	receivables turnover	sales/account receivables	receturn
22	turnover	quick assets to sales	(cash+account receivables)/sales	quisales
23	turnover	current assets to sales	current assets/sales	casales
24	liquidity	working capital to total assets	(ca-cl)/total assets	wcta
25	liquidity	cash ratio	cash/current liabilities	cashcl
26	liquidity	cash to total assets	cash/total assets	cashta
27	liquidity	cash to sales	cash/sales	cashsale
28	liquidity	current ratio	current assets/current liabilities	crratio
29	liquidity	current assets to total assets	current assets/total assets	cata
30	liquidity	current liability ratio	current liabilities/equity	clequity
31	liquidity	quick ratio	(cash+account receivables)/current liabilities	quiratio
32	liquidity	quick assets to total assets	(cash+account receivables)/total assets	quita
33	liquidity	inventory to current assets	inventory/current assets	inveca
34	others	Ln (total assets)	Ln (total assets)	lnta
35	others	interest expense rate	interest expense/total assets	interate
36	others	interest coverage ratio	EBIT/interest expense	intercov
37	others	EBIT per shares	EBIT/no.of shares	ebitshar

Source: Developed from this research.

Reducing the Variable Set

There are many methods for reducing the number of variables. Most statistical studies have selected effective independent variables with the aid of the stepwise approach[5], or factor analysis[6]. The number of independent variables is reduced to minimise multicollinearity between the variables. Zavgren (1983) points out that there is an implicit assumption that ratios with a specified relation to the dependent variable in the sample set will have the same relation in the prediction set. However, while a model that employs many ratios may be highly successful in classifying the sample data set, it can be less effective in application. A model with many variables is also likely to process substantial multicollinearity.

[5] The stepwise approach can be applied to discriminant analysis models by allowing a program to select variables based on the contribution of a variable towards some criterion, for example, the variable that contributes most in separating failing firms from non-failing ones will be selected first by the stepwise procedure (Jones 1987, p. 141).

[6] Factor analysis is a popular procedure for selecting the ratio with the highest absolute factor loading that makes the selection sensitive to the sample.

This research selected a number of independent variables from the list of 37financial ratios according to the method employed by Leshno and Spector (1996). This method is as follows:

1. Include all variables used in Altman's (1968) Z-score model.
2. Retain only one variable from each pair of variables with a correlation coefficient of 0.9 or more.[7]
3. Exclude the variable with a greater number of missing values from each highly correlated pair of variables.
4. If both variables have an equal number of missing values, exclude the one that is intuitively identified as less relevant to the bankruptcy.

An additional criterion adopted was to reduce the number of variables to a more manageable size by using stepwise selection techniques (Jo, Han & Lee 1997).

Multivariate Discriminant Analysis Model (MDA)[8]

The multivariate technique assigns a Z score to each company in a sample, using a combination of independent variables. A numerical score is obtained from the discriminant function which expresses the risk profile of the business. Bankruptcy is predicted for companies below the cutoff, while those above the cutoff are predicted to remain healthy (Jones 1987). MDA consists of three steps: (1) estimating the coefficients of variables; (2) calculating the discriminant score of each case; and (3) classifying the cases. The linear discriminant function is shown in figure 1.

[7] This is different from Leshno and Spector's (1996) original method, which used the correlation coefficient of 0.7 or over.

[8] For a description of the methodological aspects of discriminant analysis and the main models available in different countries, see Altman (1993, pp. 182-206).

$$D = B_0 + B_1X_1 + B_2X_2 + \ldots + B_nX_n$$

where

D = discriminant score
B_0 = estimated constant
B_n = estimated coefficients
X_n = independent variables.

The probability that a case with a discriminant score of D belongs to group 'i' is estimated by:

$$P(G_i \mid D) = \frac{P(D \mid G_i)P(G_i)}{\sum_{i=1}^{s} P(D \mid G_i)P(G_i)}$$

The prior probability, represented by $P(G_i)$, is an estimate of the likelihood that a case belongs to a particular group. Prior probability can be estimated in observed proportions of cases in each group.

Figure 1: Linear Discriminant Function

Source: Jo & Han 1996, p. 416.

Sample Characteristics

The sample selected included 89 non-failed and 46 failed firms. Table 3 indicates that these failed firms vary by size and year of delisting. The highest number of failures occurred in 1999, when 16 companies were delisted. This was two years after the 1997 economic crisis. The average value of assets for the failed companies was smaller than the non-failed companies, as indicated in Table 3.

Table 3: Sample Characteristics

	Failed 1/	Non-failed	Total
Number of firms	46	89	135
Average size ('000 Baht)	3,505,467	4,291,906	4,023,934
Number of firms by year of delisting			
1997	1	2	3
1998	13	25	38
1999	16	31	47
2000	10	18	28
2001	5	10	15

2002	1	3	4
Total	46	89	135

Source: Data analysis for this research and the SET (www.set.or.th).
Note: [1/]Statistics are based on the fiscal year of financial statements, which are available one year prior to failure.

Division of the Sample

Discriminant analysis adopts a number of procedures for dividing the sample. The most common procedure involves developing a discriminant function for one group and testing it on a second group (Hair et al. 1998). The sample of respondents was divided randomly into two sub-samples, an analysis sample for estimation of the discriminant function and a holdout sample for validation purposes. It is essential that each sub-sample is of adequate size to support conclusions from the results. No definite guidelines have been developed for dividing the sample into analysis and holdout groups. The most popular procedure is to divide the total group on a 50-50 basis. However, some researchers prefer 60-40 or 75-25 splits (Hair et al. 1998). A 73:27 split was chosen for this analysis.

Descriptive Profile of the Independent Variables

A list of 37 potentially useful ratios was compiled for evaluation. These ratios are classified into five categories, namely, leverage, profitability, turnover, liquidity and others. The descriptive statistics for the ratios consist of means and correlation coefficients.

Analysis of Ratio Means

Ratio means were analysed to establish whether they were uniformly higher or lower for failed and non-failed firms up to five years in advance of a failure. This analysis provides an understanding of the financial characteristics of both types of firms. A profile of the sample's ratio means is provided in Table 4, together with Wilks' Lambda and *F*-test statistics which show differences between the means.

An *F*-test was performed to assess the individual discriminating ability of the independent variables in the non-failed and failed samples. It tested the difference between the average values of the ratios in each group and the variability of these ratios. Many variables were found to have significantly different means at the 0.01 level, indicating strong variation between groups. It follows that these ratios are effective for discriminating between failed and non-failed firms.

Table 4: Group Means for the Independent Variables[1/]

No.	Ratios	Mean		Tests of Equality of Group			Notes
		non-failed (N=88)	failed (N=43)	Wilks' Lambda	F	Sig.	
1	LNTA	14.8183	14.6391	0.9919	1.0483	0.3078	Stability ratio
2	MKTCAP	0.7106	0.4776	0.9907	1.2134	0.2727	Stability ratio
3	MKTCAP	0.2981	0.2784	0.9993	0.0951	0.7582	Stability ratio
4	MKTCAP	0.8503	0.6808	0.9968	0.4195	0.5183	Stability ratio
5	INTERCO	6.5636	6.3209	1.0000	0.0012	0.9721	Stability ratio
6	DERATIO	1.9907	0.0379	0.9836	2.1492	0.1451	Stability ratio
7	FAEQLT	0.8164	0.7615	0.9999	0.0081	0.9286	Stability ratio
8	ROE	-0.1037	-0.1235	1.0000	0.0015	0.9691	Profitability ratio
9	GPMARG	0.2331	0.0314	0.9042	13.6713**	0.0003	Profitability ratio
10	EBITSAL	0.0851	-1.2777	0.8580	21.3576**	0.0000	Profitability ratio
11	EBITTA	0.0565	-0.2071	0.8714	19.0396**	0.0000	Profitability ratio
12	EBITSHA	0.0079	0.0023	0.9864	1.7778	0.1848	Profitability ratio
13	RETAINT	-0.0476	-0.8260	0.9101	12.7409**	0.0005	Profitability ratio
14	WCSALE	0.0035	-2.9448	0.8914	15.7210**	0.0001	Activity ratio
15	INVECA	0.4200	0.4255	0.9999	0.0162	0.8990	Activity ratio
16	FATURN	3.2862	2.8244	0.9970	0.3848	0.5361	Activity ratio
17	TATURN	0.7837	0.8321	0.9991	0.1180	0.7317	Activity ratio
18	EQTURN	2.8971	1.4654	0.9890	1.4282	0.2342	Activity ratio
19	WCTA	-0.0332	-0.6902	0.9063	13.3333**	0.0004	Activity ratio
20	INVSALE	0.7509	1.4439	0.9861	1.8185	0.1799	Activity ratio
21	CASHCL	0.0861	0.0613	0.9931	0.8995	0.3447	Liquidity ratio
22	CASHSA	0.0398	0.0864	0.9738	3.4722	0.0647	Liquidity ratio
23	CRRATIO	1.3355	0.8601	0.9744	3.3900	0.0679	Liquidity ratio
24	CATA	0.4552	0.4482	0.9998	0.0306	0.8615	Liquidity ratio
25	QUIRATI	0.4611	0.2888	0.9664	4.4905*	0.0360	Liquidity ratio
26	QUITA	0.1699	0.1668	0.9999	0.0173	0.8955	Liquidity ratio
27	RECETU	9.4197	7.2998	0.9910	1.1678	0.2819	Liquidity ratio
28	QUISALE	0.3422	0.6591	0.9807	2.5326	0.1140	Liquidity ratio
29[3/]	DARATI	0.6927	1.2461	0.9297	9.7520**	0.0022	Stability, *high-correlation*
30[3/]	TAEQ	3.0376	1.0785	0.9837	2.1340	0.1465	Stability, *high-correlation*
31[3/]	INTERAT	0.0539	0.1350	0.9164	11.7613**	0.0008	Stability, *high-correlation*
32[3/]	ROA	-0.0504	-0.3838	0.8859	16.6215**	0.0001	Profitability, *high-correlation*
33[3/]	NPMARG	-0.1597	-2.1501	0.8414	24.3221**	0.0000	Profitability, *high-correlation*
34[3/]	INVETUR	6.6029	6.3573	0.9998	0.0197	0.8886	Activity, *missing value*
35[3/]	CASHTA	0.0277	0.0281	1.0000	0.0022	0.9626	Liquidity, *missing value*
36[3/]	CASALE	1.3100	2.6740	0.9732	3.5548	0.0616	Liquidity, *high-correlation*
37[3/]	CLEQUIT	1.7878	0.1016	0.9819	2.3777	0.1255	Liquidity, *high-correlation*

Source: Data analysis for this research, and Stock Exchange of Thailand (www.set.or.th).
Note: [1/]Data based on financial statement one year prior failure.
[2/]Wilks' Lambda (U statistic) and univariate F ratio with 1 and 129 degrees of freedom.
[3/]Ratios 29 to 37 were dropped from the analysis because of high correlation and missing value problems.
[**/]Denotes 1% significance level (2-tailed).
[*/]Denotes 5% significance level (2-tailed).

The year 1 model indicates that 10 variables out of 37 have significant differences, according to the Wilks' Lambda and the *F*-tests for equality of means, with significance at the 0.01 level. These variables are marked with a double asterisk (**) in Table 4. Overall, the results provided evidence that financial ratios do have significantly different predictive abilities for detecting the bankruptcy potential of Thai listed companies. The variation in these 10 ratios ranked from highest to lowest is as follows:

1. NPMARGIN (net profit/sales)
2. EBITSALE (EBIT/sales)

3. EBITTA (EBIT/total assets)
4. ROA (net income/total assets)
5. WCSALES (working capital/sales)
6. GPMARGIN (gross profit margin)
7. WCTA (working capital/total assets)
8. RETAINTA (retained earnings/total assets)
9. INTERATE (interest expense/total assets)
10. DARATIO (total liabilities/total assets)

An additional variable, QUIRATIO (cash + account receivables/current liabilities), was significant at the 0.05 level and is marked with an asterisk (*) in Table 4.

The results shown in Table 4 are consistent with the expectations that firms in financial distress, or failed firms, are expected to have the following:

- **Low profitability**, as indicated by their significantly smaller GPMARGIN (sales-cost of sales/sales), EBITSALE (earnings before interest and tax/sales), EBITTA (earnings before interest and tax/total assets), EBITSHAR (earnings before interest and tax/number of shares), RETAINTA (retained earnings/total assets), ROA (net income/total assets), and NPMARGIN (net income/sales).

- **Higher leverage ratios**, as indicated by their significantly larger DARATIO (total liabilities/total assets), and INTERATE (interest expense/total assets).

- **Less liquidity**, as indicated by smaller a QUIRATIO (cash + account receivables/current liabilities).

- **Lower assets quality**, as indicated by lower a WCTA (current assets-current liabilities/total assets).

Analysis of Correlation Coefficients

The Pearson correlation coefficients are considered to identify possible relationships between all pairs of variables in the sample. If the correlation between any two independent variables is greater than or equal to 0.90, a high degree of interrelationship is be inferred and multicollinearity exists (Tabachnick & Fidell 1996). The results indicate that most variables are not highly correlated with each other. Table 5 indicates, however, that there are 13 pairs, out of 37, which have correlation coefficients exceeding 0.90 and are significant at the $\alpha < 0.01$ level.

After examining the 13 pairs of variables, it was clear that only nine possessed a greater number of missing values from each highly correlated pair of variables. To optimise the discriminant analysis, it was decided to delete the variables DARATIO, TAEQ, INTERATE, ROA, NPMARGIN, INVETURN, CAHSTA, CASALES and CLEQUITY. The model now consisted of 28 variables.

Table 5: High Correlation Coefficients of Independent Variables[1/]

Ratios	Pearson Correlation	Sig. (2-tailed)
CASALES & INVSALES	0.9407	0.000
CLEQUITY & DERATIO	0.9673	0.000
CLEQUITY & TAEQ	0.9680	0.000
WCTA & RETAINTA	0.9071	0.000
WCTA & DARATIO	-0.9382	0.000
WCTA & INTERATE	-0.9194	0.000
ROA & EBITTA	0.9513	0.000
ROA & RETAINTA	0.9053	0.000
NPMARGIN & EBITSALE	0.9172	0.000
RETAINTA & DARATIO	-0.9451	0.000
RETAINTA & INTERATE	-0.9270	0.000
DERATIO & TAEQ	0.9997	0.000
DARATIO & INTERATE	0.9501	0.000

Note: [1/]Data based on financial statement one year prior failure.
Source: Data analysis for the study.

Analysis of Normality Assumption

Additional analysis was undertaken for univariate normality tests and transformations to prevent problems with the data. Normality tests were constructed for the 28 ratios. Three ratios, LNTA, CATA and INVECA, were distributed approximately symmetrically and normal at the 1% level of significance. The figures for skewness and kurtosis were calculated for the 25 ratios which are highly asymmetric at the 1% level.

Studies on distributions of financial ratios have found that the requirement of normality is frequently violated (Jones 1987). Foster (1978) and Beaver (1966) found that normality could not be assumed. They suggested that it may be possible to transform the data to approximate normality. Altman, Haldeman and Narayanan (1977) successfully enhanced the normality of a distribution of asset size and an interest coverage variable by adopting log transformations.

Further analysis was undertaken to investigate how significantly a logarithmic transformation of the ratios can reduce skewness and kurtosis. The ratios were multiplied by 100, expressed logarithmically and their skewness and kurtosis were calculated. The transformation raised the number of ratios which approximate symmetry from 11% (3 ratios) to 25% (7 ratios).

After the transformation, the normality of several ratios was not improved and this affected the size of the sample. It was decided to use these variables in their original form. Seven of the ratios, however, were expressed as logarithmic transformations to mitigate the effect of normality and ensure that sample sizes were not affected.

Ratios with extreme values can be deleted to improve symmetry (Hair et al. 1998). Histograms of ratios were examined to identify whether significant departures from symmetry results from extreme values. This analysis showed that several ratios were significantly skewed and were separated from the other variables. These extreme values were traced back to specific companies and were deleted from their financial data. Skewness and kurtosis were then recalculated.

This operation raised the percentage of ratios which approximate symmetry from 25% (or 7 ratios after the logarithmic transformations) to 43% (12 ratios). These 12 ratios approximate symmetry at the 0.01 level of significance and were approximately normal. In addition, their measures of kurtosis were insignificant. The transformations did not improve normality in all cases and it was necessary to employ three ratios in their original form.

The adjusted data sets were observed to determine whether the accuracy of MDA could be enhanced. Two additional sets of linear discriminant functions were derived from the adjusted data. One set, ratio set (A), was derived from the logarithmic transformations, while the other, ratio set (B), was derived from the ratios formed after deleting the extreme values.

Evaluating Empirical Results of the MDA Model

The advantage of a discriminant function is that it does not need to be standardised to ensure zero means and unit variance prior to the commencement of the analysis. This is because the results of an analysis of discriminant functions are not affected by scaling of the individual variables (Jones 1987).

The four tasks involved in deriving the MDA model were:

- **Estimating the discriminant function**. This was a stepwise procedure for determining the variables which are the most effective for discriminating between failed and non-failed firms. The Wilks' Lambda[9] and Mahalanobis D^2 measures were employed in this case (Hair et al. 1998).

- **Testing the impact of violating the assumption that the ratios are distributed normally.** This was done by comparing the classification accuracy of the function derived from the stepwise selected sample. This sample originated from the normality-adjusted ratio of data Set (A) and data Set (B).

- **Selecting the best function.** The best function is judged in terms of classification accuracy and overall fit. A classification matrix was calculated for enhancing the accuracy of the analysis and holdout samples.

[9] Wilks' Lambda is used to test the hypothesis that the mean of the ratio vectors for each group is equal. This can be converted to an *F*-value. The *F* ratio is then used to indicate the probability of a significant separation between the scores of failed and non-failed firms.

- **Establishing if the best functions perform better than chance.** The efficiency of the best functions was compared with alternative strategies. This was undertaken to determine whether these functions adequately explain the characteristics of failed and non-failed firms.

Estimation of the MDA Model

In this study, a stepwise selection technique was employed to develop the discriminant analysis. The statistical significance of the MDA model was evaluated by examining the Wilks' Lambda statistic, which has a chi-square distribution. This analysis was also necessary for identifying the variables which are important for separating non-failed and failed firms.

A linear discriminant function was developed for the financial data representing the period five years in advance of a failure. This analysis is similar to the study of Altman, Haldeman and Narayanan (1977), which also used stepwise algorithms for selecting variables. Specifically, variables are added, or deleted from the model, according to their contribution to the model's overall fit. Only a subset of the original 28 independent variables (ratio sets A and B) would be significant for separating failed and non-failed firms. The same variables were used in the functions for each of the five years. The parameters were changed, however, to reflect variations in the data as the potential for failure became more remote. The validity of the model was tested by applying it for predicting failures in a holdout sample.

In scenarios (1), (2) and (3), MDA functions were developed for determining the most effective model for predicting company failures. The purpose of scenario (4) was to determine the predictive accuracy of the all MDA functions together.

The estimation and the statistical results produced under the four scenarios are as follows:

Scenario (1): Stepwise Regression

Tables 6 and 7 show the tests of the explanatory power of the MDA model with the selected ratios sample resulting from stepwise regression, scenario (1). The samples employed in this scenario were divided into two sets, ratio sets (A) and (B).

Ratio Set (A)

Table 6 shows the results of the MDA function derived from ratio set (A).

Panel A of Table 6 identifies the four variables, FAEQLT00, EBITSA00, EBITSH00 and RETATA00, which were significant discriminators according to their Wilks' Lambda and minimum Mahalanobis D^2 values (Hair et al. 1998).

Table 6: Results of Scenario (1) – Ratios Set (A)

Panel A: Summary table of stepwise selected ratios sample – set (A) _Year 1 model

Step	Scenario (1): ratios set (A) variables	Wilks' Lambda Value	Sig.	Min. D Squared Value	Sig.	Between Groups
1	RETATA00	0.814	0.000	1.004	0.000	0 and 1
2	EBITSA00	0.769	0.000	1.322	0.000	0 and 1
3	FAEQLT00	0.745	0.000	1.511	0.000	0 and 1
4	EBITSH00	0.720	0.000	1.715	0.000	0 and 1

Panel B: Summary of canonical discriminant functions

Function	Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-square	df	Sig.
1	0.389	0.529	0.720	30.240	4	0.000

Panel C: Canonical discriminant function coefficients

Variables	Standardised	Unstandardised
FAEQLT00	0.367	0.002
EBITSA00	0.515	0.003
EBITSH00	-0.384	-0.154
RETATA00	0.784	0.012
(Constant)		0.406

Panel D: Structure matrix[*/]

Variables	Discriminant Function Loadings	Variables	Discriminant Function Loadings
RETATA00	**0.765**	LNTA	0.200
EBITTA00	0.610	LG10RCT0	0.199
EBITSA00	**0.608**	EQUITURN	0.194
WCTA00	0.562	LG10FAT0	0.186
WCSALE00	0.405	LG10CS00	-0.157
LG10CRR0	0.380	ROE00	0.148
LG10MTL0	0.375	QUITA00	0.102
LG10QRA0	0.354	INTERC	0.100
FAEQLT00	**0.339**	**EBITSH00**	**0.098**
LG10TAT0	0.272	MKTCEQ00	0.078
GPMARG00	0.270	CATA00	0.057
LG10CC00	0.244	INVECA00	-0.048
LG10MTA0	0.239	DERATI	0.008
LG10QSA0	-0.229		

Note: [*/]Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions. (Variables ordered by absolute size of correlation within function).

Panel E: Classification results – Holdout sample

Selected ratios: Combination (a) Actual Group	Number of cases	Predicted Group Membership Non-failed (0)	Failed (1)
Non-failed (0)	24	22	2
		91.7%	8.3%
Failed (1)	12	9	3
		75.0%	25.0%
Number of Cases		31	5

Percentage Correctly classified = 69.4%
Fit equation = 0.406 + 0.002 FAEQLT00 + 0.003 EBITSA00 – 0.154 EBITSH00
+ 0.012 RETATA00 (5.1)

Panel B of Table 6 indicates that the canonical discriminant functions are highly significant with a value of 0.000, while the canonical correlation is 0.529. This correlation can be interpreted by squaring it to obtain a figure of 0.28. This indicates that 28% of the variance in the dependent variable is accounted for by this model.

In Panel C of Table 6, the unstandardised discriminant coefficients are used to calculate the discriminant Z scores that were used in the classification. The discriminant loadings are ordered from highest to lowest in terms of size. In addition, the independent variables were screened by the stepwise procedure, and four of these variables, namely, RETATA00, EBITSA00, FAEQLT00 and EBITSH00 were found to be significant. These were included in the discriminant function (Fit equation).

Panel D of Table 6 presents the weights (standardised coefficients) and loadings[10] (structure matrix) of the independent variables. The loadings RETAINTA, EBITSALE and FAEQLT00 exceeded ± 0.30 and exhibit a high degree of correspondence. RETAINTA was the most significant, while EBITSH00 was the least significant.

A classification matrix was calculated to assess the accuracy of the discriminant function (see Table 6, Panel E). From the holdout sample, the number of firms correctly assigned to group 1 (failed) is 3, whereas 9 members of group 1 were incorrectly assigned to group 0 (non-failed). Similarly, the number of correct classifications into group 0 is 22, while 2 were incorrectly assigned to group 1. The accuracy of the discriminant function was 25% for group 1 and 92% for group 0. In short, the hit ratio was 69%, an accurate result for Scenario (1) with ratio set (A).

Ratio Set (B)

Table 7 shows the results of testing the function derived from ratio set (B).

Table 7: Results of Scenario (1) – Ratio Set (B)

Panel A: Summary table of stepwise selected ratios sample – set (B) _Year 1

Step	Scenario (1): ratios set (B) variables	Wilks' Lambda Value	Sig.	Min. D Squared Value	Sig.	Between Groups
1	ROE00	0.872	0.003	0.913	0.003	0 and 1
2	MKTCEQ00	0.824	0.002	1.324	0.002	0 and 1
3	EBITTA00	0.780	0.001	1.746	0.001	0 and 1

Panel B: Summary of canonical discriminant functions

Function	Eigenvalue	Canonical	Wilks' Lambda	Chi-	df	Sig.

[10] Indicators of their discriminating power, signs do not affect the rankings; they simply indicate a positive or negative relationship with the dependent variable.

		Correlation		square		
1	0.281	0.469	0.780	15.747	3	0.001

Panel C: Canonical discriminant function coefficients

Variables	Standardised	Unstandardised
MKTCEQ00	0.779	0.011
EBITTA00	-0.532	-0.037
ROE00	1.038	0.015
(Constant)		-0.677

Panel D: Structure matrix[*/]

Variables	Discriminant Function Loadings	Variables	Discriminant Function Loadings
ROE00	**0.723**	LG10CC00	-0.132
DERATI	-0.508	LG10QRA0	-0.124
EBITTA00	**-0.395**	LG10CRR0	-0.099
EBITSA00	-0.363	LG10MTL0	0.084
EQUITURN	-0.36	LG10CS00	-0.082
FAEQLT00	-0.356	LNTA	0.078
RETATA00	-0.275	GPMARG00	-0.058
WCTA00	-0.25	**MKTCEQ00**	**0.051**
LG10MTA0	0.236	LG10FAT0	0.049
INVECA00	0.232	CATA00	0.045
EBITSH00	-0.23	LG10TAT0	0.03
INTERC	-0.168	LG10QSA0	-0.025
WCSALE00	-0.146	LG10RCT0	0.012
LG10INS0	0.14	QUITA00	-0.01

Note: [*/]Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions. (Variables ordered by absolute size of correlation within function).

Panel E: Classification results – Holdout sample

Selected ratios: Combination (b) Actual Group	Number of cases	Predicted Group Membership Non-failed (0)	Failed (1)
Non-failed (0)	23	6	17
		26.1%	73.9%
Failed (1)	11	5	6
		45.5%	54.5%
Number of Cases		11	23

Source: Data analysis from this research.
Note: Percentage correctly classified = 35.3%
Fit equation = - 0.677 + 0.011 MKTCEQ00 – 0.037 EBITTA00 + 0.015 ROE00 (5.2)

Panel A (Table 7) indicates that the variables ROE00, MKTCEQ00 and EBITTA00 were significant. In Panel B, the canonical discriminant functions display a canonical correlation of 0.469. After squaring this value, 0.22 is obtained, indicating that 22% of the variance in the dependent variable is accounted for by this model.

Table 7 presents the weights (standardised coefficients in Panel C) and loadings (structure matrix in Panel D) of the independent variables. The loadings of variables ROE00 and MKTCEQ00 exceed ± 0.30 and exhibit a high degree of correspondence. ROE00 was found to be the most significant variable, while EBITTA00 was the least significant.

Panel E (Table 7) presents the predictive accuracy of the holdout sample. The number of firms correctly assigned to group 1 (failed) was 6, while 5 members of group 1 were incorrectly assigned to group 0 (non-failed). Similarly, the number of correct classifications to group 0 is 6, and the number incorrectly assigned to group 1 was 17. The discriminant function returned classification accuracy percentages of 26% for group 1 and 54% for group 0. Overall classification accuracy was 35%, implying that scenario (1) with set (B) is not good discriminator.

Analysis of the Ratios Selected through Stepwise Regression (Scenario 1)

Table 8 presents the highest classification accuracy of functions derived from ratio set (A) and compares them with those derived from ratio set (B).

Table 8: Profiling Correctly Classified in Scenario (1)

Scenario (1)	% Correct (Holdout sample)	Cpro [1/]	Acceptable
Ratio set (A): normality adj. logarithm	69.4%	55.6%	yes
Ratio set (B): normality adj. logarithm and outliers	35.3%	56.2%	no

Note: [1/]Proportional chance criterion (Cpro) = $p^2 + (1-p)^2$
p = proportion of individuals in group 1
1-p = proportion of individuals in group 2
Source: Data analysis for this research.

The accuracy of ratio set (A) was 69.4%, which is higher than the proportion chance criterion (Cpro) of 55.6%. Predictive accuracy, therefore, is acceptable, as it is larger than can be expected by chance. An attempt can be made to interpret the discriminant functions in the hope of developing group profiles. The classification accuracy of ratio set (B), however, was 35.3%, much lower than the proportion chance criterion of 56.2%. The discriminant function of ratio set (B) was disregarded because its accuracy is less than chance and has not improved the accuracy of prediction. Differences in score profiles would provide no meaningful information for identifying group membership.

It was decided to adopt ratio set (A) for comparing the other scenarios because of its superior accuracy. It needs to be stated that many ratios were significantly skewed and the number of symmetrically distributed ratios was limited, even with adjusted data. It is well known, however, that the variables typically used in bankruptcy studies are not normally distributed (Eisenbeis 1977; Lennox 1999; McLeay 1986). In addition, the evidence indicates that the assumption of normality need not be strictly adhered to in these studies (Hamer 1983; Jones 1987).

Results of Scenario (2): Altman's Five-Ratio Model

Table 9 shows the results of the tests of the explanatory power of the MDA model using Altman's (1968) five-ratio model.

Table 9: Results of Scenario (2) – Altman's (1968) Five-Ratio Model

Panel A: Summary Table of Altman's (1968) five-ratio model_Year 1

	Scenario 2 Variables	Wilks' Lambda Value	Sig.
1	LG10MTL0	0.965	0.066
2	EBITTA00	0.837	0.000
3	RETATA00	0.811	0.000
4	LG10TAT0	0.957	0.041
5	WCTA00	0.877	0.000

Panel B: Summary of canonical discriminant functions

Function	Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-square	df	Sig.
1	0.282	0.469	0.780	23.240	5	0.000

Panel C: Canonical discriminant function coefficients

Variables	Standardised	Unstandardised
LG10MTL0	-0.316	-0.461
EBITTA00	0.320	0.013
RETATA00	0.500	0.008
LG10TAT0	0.333	0.756
WCTA00	0.370	0.007
(Constant)		-0.347

Panel D: Structure matrix*/

Variables	Discriminant Function Loadings
RETATA00	0.908
EBITTA00	0.831
WCTA00	0.705
LG10TAT0	0.397
LG10MTL0	0.357

Note: */Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions.

(Variables ordered by absolute size of correlation within function).

Panel E: Classification results – Holdout sample

Actual Group	Number of cases	Predicted Group Membership Non-failed (0)	Failed (1)
Non-failed (0)	24	20	4
		83.3%	16.7%
Failed (1)	12	6	6
		50.0%	50.0%
Number of Cases		26	10

Note: Percentage correctly classified = 72.2%

Fit equation = - 0.347 – 0.461 LG10MTL0 + 0.013 EBITTA00 + 0.008 RETATA00 + 0.756 LG10TAT0 + 0.007 WCTA00 (5.3)

Source: Data analysis for this thesis.

Panel A (Table 9) describes the five variables[11] which were used in Altman's (1968) Z-score model. The significance of the Wilks' Lambda statistic indicates that the five variables, LG10MTL0, EBITTA00, RETATA00, LG10TAT0 and WCTA00, were significant discriminators. The mean of the discriminant scores is not identical for the failed and non-failed groups. In Panel B, the canonical discriminant functions are highly significant, as the figure 0.001 indicates. A canonical correlation of 0.469 is also evident and, after squaring, the figure 0.22 is produced. This infers that 22% of the variance in the dependent variable is accounted for by this model.

Panel C (Table 9) assesses each variable's contribution to the discriminant function. Selecting variables on this basis produces models with high explanatory power. Moreover, the loading of variables RETATA00, EBITTA00, WCTA00, LG10TAT0 and LG10MTL0 exceeds ± 0.30. The level of correlation with the discriminant function is of high correspondence (Hair et al. 1998). Of the function's five variables, RETATA00 discriminates the most while LG10MTL0 discriminates the least.

The accuracy of the discriminant function was assessed by calculating a classification matrix as shown in Panel E (Table 9). From the holdout sample, the number of firms correctly assigned to group 1 is 6, while 6 members of group 1 were incorrectly assigned to group 0. Similarly, the number of correct classifications to group 0 is 20, while the number incorrectly assigned to group 1 is 4. The function's classification accuracy was 50% and 83% for groups 1 and 0 respectively. Overall classification accuracy was 72%, implying that Scenario (2) is a good discriminator.

Results of Scenario (3): Combined Ratios

Table 10 shows the tests of the explanatory power of the MDA model with the combined ratios of Scenarios (1) and (2).

[11] These five variables are: the working capital/total assets; retained earnings assets; earning before interest and taxes/total assets; market value of equity/total debt; and sales/total assets.

Table 10: Results of Scenario (3) – Combined Ratios of Scenarios (1) and (2)

Panel A: Summary Table of Altman's five ratios + ratio set (A) _Year 1

	Scenario 3 Variables	Wilks' Lambda Value	Sig.
1	LG10MTL0	0.965	0.066
2	EBITTA00	0.837	0.000
3	RETATA00	0.811	0.000
4	LG10TAT0	0.957	0.041
5	WCTA00	0.877	0.000
6	EBITSA00	0.887	0.001
7	FAEQLT00	0.960	0.047
8	EBITSH00	0.996	0.546

Panel B: Summary of canonical discriminant functions

Function	Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-square	df	Sig.
1	0.403	0.536	0.713	31.126	8	0.000

Panel C: Canonical discriminant function coefficients

Variables	Standardised	Unstandardised
LG10MTL0	-0.181	-0.264
EBITTA00	0.299	0.012
RETATA00	0.504	0.008
LG10TAT0	0.193	0.439
WCTA00	0.238	0.004
EBITSA00	0.346	0.002
FAEQLT00	0.329	0.001
EBITSH00	-0.433	-0.176
(Constant)		0.009

Panel D: Structure matrix*/

Variables	Discriminant Function Loadings
RETATA00	0.760
EBITTA00	0.696
WCTA00	0.591
EBITSA00	0.562
LG10TAT0	0.333
FAEQLT00	0.324
LG10MTL0	0.299
EBITSH00	0.097

Note: */Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions.

(Variables ordered by absolute size of correlation within function).

Panel E: Classification results – Holdout sample

Actual Group	Number of cases	Predicted Group Membership: Non-failed (0)	Predicted Group Membership: Failed (1)
Non-failed (0)	24	22	2
		91.7%	8.3%

Failed (1)	12	9	3
		75.0%	25.0%
Number of Cases		31	5

Note: Percentage correctly classified = 69.4%
Fit equation = 0.009 – 0.264 LG10MTL0 + 0.012 EBITTA00 + 0.008 RETATA00
+ 0.439 LG10TAT0 + 0.004 WCTA00 + 0.002 EBITSA00
+ 0.001 FAEQLT00 – 0.176 EBITSH00 (5.4)
Source: Data analysis for this thesis.

Panel A (Table 10) presents the eight variables which were derived from the combined samples of ratio set (A) and Altman's five ratios. It provides the overall results for the discriminant analysis. Panel B indicates that the canonical discriminant functions were highly significant, as shown by the figure 0.000. The canonical correlation was 0.536, and 28.7% of the variance in the dependent variable is accounted for by this model.

Panel C (Table 10) presents the loadings in order, from highest to lowest. The loadings of six variables, RETATA00, EBITTA00, WCTA00, EBITSA00, LG10TAT0 and FAEQLT00 exceed ± 0.30. RETATA00, discriminates the most while EBITSH00 discriminates the least.

The predictive accuracy of the discriminant function was assessed by calculating a classification matrix as indicated by Panel E (Table 10). From the holdout sample, the number of individuals correctly assigned to group 1 is 3, while 9 members of group 1 are incorrectly assigned to group 0. Similarly, 22 firms were correctly classified in group 0, while 2 were incorrectly assigned to group 1. The function's classification accuracy percentages were 25% and 92% for groups 1 and 0 respectively. Overall accuracy was 69.4%, implying that Scenario (3) is also a good discriminator.

Results of Scenario (4): All Functions

Table 11 compares the predictive accuracy of all MDA functions (Scenarios 1, 2 and 3). The main purpose is to select the best discriminant function.

Table 11: Results of Scenario (4)

Panel A: Comparing overall classification results by year prior to failure

Year prior to failure	Accuracy rate		
	Scenario (1)	Scenario (2)	Scenario (3)
1st (N=36)	69.4%	72.2%	69.4%
2nd (N=36)	66.7%	58.3%	58.3%
3rd (N=36)	58.3%	55.6%	61.1%
4th (N=36)	63.9%	66.7%	63.9%
5th (N=33)	39.4%	45.5%	45.5%
Average	**59.5%**	**59.6%**	**59.6%**

Panel B: Pairwise comparison on classification results for holdout sample

Sample	Statistic	Overall	Failed	Non-failed
Scenario (1)				
Selected ratios: 4 ratios	Mean 1/	59.5%	16.8%	80.9%
	N	36	12	24
Scenario (2)				
Altman's (1968) re-estimated ratios: 5 ratios	Mean 1/	59.6%	43.9%	67.5%
	t-statistic 2/	-0.042	-3.556*	3.792*
	p-value 2/	0.969	0.024	0.019
Scenario (3)				
Selected ratios + Altman's re-estimated ratios: 8 ratios	Mean 1/	59.6%	27.1%	75.9%
	t-statistic 2/	-0.042	-1.422	1.500
	p-value 2/	0.969	0.228	0.208
	t-statistic 3/	0.004	3.227*	-1.932
	p-value 3/	0.997	0.032	0.126

Note: 1/Mean of accuracy rates over the five years before failure.
2/Pairwise t-test comparing the accuracy rates to those in Scenario (1).
3/Pairwise t-test comparing the accuracy rates to those in Scenario (2).
*/Significant at the 0.05 level.

Panel C: Comparing on overall classification results by the holdout sample

Scenarios	% Correct (holdout sample)	Cpro	Acceptable
(1) The ratios selected through stepwise regression: ratio set (A)	69.4%	55.6%	yes
(2) Altman's (1968) 5 ratios sample	72.2%	55.6%	yes
(3) The combined of ratios selected through stepwise regression: ratio set (A) + Altman's 5 ratios sample	69.4%	55.6%	yes

Note: Data based on financial statement one year prior failure.
Source: Data analysis from this research.

Panel A (Table 11) presents the overall classification results of the MDA model by year prior to failure. The table contains three scenarios as follows:

- **Scenario (1).** The classification results from ratios selected through stepwise regression: ratio set (A)
- **Scenario (2).** The classification results of Altman's five-ratio model.
- **Scenario (3).** The classification results of the combined ratios of Scenarios (1) and (2).

The results indicate that the accuracy rates of all scenarios were highest in the year 1 model. The accuracy of the year 1 function was 72.2% in Scenario (2) and 69.4% in Scenarios (1) and (3). The average accuracy over the five-year period was 59.6% in Scenarios (2) and (3), slightly higher than the 59.5% achieved in Scenario (1). The accuracy of prediction declines for the more distant bankruptcy horizons.

Panel B (Table 11) presents the pairwise comparison for the three scenarios. For the overall category, the paired *t*-tests indicate that the variation between all scenarios is not significant and Hypothesis II cannot be rejected. There is no variation from that predicted by Altman's five ratios and ratios selected through stepwise regression sample. In addition, after analysing the categories of firms, no clear patterns emerge. For failed firms, Scenario (2) is more accurate than Scenarios (1) and (3). For non-failed firms, however, Scenario (1) is more accurate. One possible reason for there being no clear patterns for analysing the categories of firms is that the study was conducted with a small and unequal number of test cases. The random generation of cases may have led to this finding.

The results of the paired *t*-tests for the failed category indicate that Scenario (2) is more accurate than Scenarios (1) and (3). Indeed, the differences of 27.1% and 16.8% respectively, were statistically significant at the 5% level (the *p*-values were 0.024 and 0.032 respectively). The average accuracy of Scenario (2) was 43.9% over the five-year period, much higher than the 16.8% and 27.1% achieved by Scenarios (1) and (3). For non-failed firms, the average level of accuracy was 67.5% for Scenario (2), lower than the 80.9% achieved by Scenario (1). This difference is statistically significant at the 5% level and the *p*-value was 0.019.

Panel C (Table 11) compares the predictive accuracy of all MDA functions, according to the information presented in the financial statements, one year prior to a failure. In the year 1 model, the highest classification accuracy was derived from the Scenario (2) sample (see Panel A). The accuracy of this scenario was 72.2% compared with the 69.4% for Scenarios (1) and (3). However, the accuracy of all scenarios is acceptable, and is greater than can be expected by chance.

Discussion of the Successive Function

This analysis favours the selection of benchmark data for achieving accuracy when classifying failed firms. Accuracy in predicting failed firms is more beneficial than with non-failed firms (Altman, Haldeman & Narayanan 1977).

The Chosen Function

The function derived from the data for the year 1 model of Altman's five ratios was chosen as optimal, after examining successive functions. This function is as follows:

$$Z = -0.347 - 0.461\ \text{LG10MTL0} + 0.013\ \text{EBITTA00} + 0.008\ \text{RETATA00} + 0.756\ \text{LG10TAT0} + 0.007\ \text{WCTA00}$$

Table 12: Function at Group Centroids

Altman's (1968) 5 ratios function	Group centroids
Non-failed group	0.375
Failed group	-0.738
Cutting score[1/]	**-0.434**

Note: [1/] Z_{CU} = (NA*ZB+NB*ZA)/NA+NB, where:
Z_{CU}= critical cutting score value for unequal group sizes

ZA = centroid of failed group
ZB = centroid of non-failed group
NA = number in failed group
NB = number in non-failed group
Source: Data analysis for this thesis

Table 12 shows the group centroids were -0.738 for the failed group and +0.375 for the non-failed group. The cutting score indicates that firms with a Z score less than -0.434 are predicted to fail, while a Z score greater than -0.434 indicates a non-failed firm.

Non-failed firms would be expected to have:

- a higher level of retained profits (RETATA00)
- high assets productivity (EBITTA00)
- more liquid assets to meet commitments (WCTA00)
- higher turnover of assets (LG10TAT0)
- a higher market value of equity compared to debt (LG10MTL0)

The weightings attached to the variables were as expected, with the exception of LG10MTL0 (market value of equity/total liabilities). An examination of the signs indicates that LG10MTL0 has a negative weighting, although it would be expected to have a positive weighting. This negative sign creates difficulties for interpretation. This difficulty can be reduced, however, by taking the net contribution to the Z score (Lincoln 1982). Similar studies have chosen discriminant functions with conflicting signs. Deakin's (1972) 14-ratio model adopted different signed weightings for 12 ratios. Likewise, the analysis of Castagna and Matolcsy (1981) contained four out of 10 ratios with different signs.

The ratios

The contribution a ratio brings to the discriminatory power of a function can be assessed by comparing the value of discriminant loadings[12]. The function comprised ratios which were ordered by absolute size of correlation.

1. **RETATA00** (retained earnings to total assets). This ratio measures the stability of a firm. It reflects a firm's age, dividend policy and its cumulative profitability over time. Companies with a higher level of risk have a lower ratio because their retained profits and paid up capital of shareholders will quickly deteriorate after a trading loss.

2. **EBITTA00** (earnings before interest and taxes to total assets). This ratio is a measure of the productivity of the firm's assets, abstracting from any tax or leverage factors. The EBITTA ratio appears appropriate since a firm's success is based on the earning power of its assets. In addition, insolvency in a bankruptcy sense occurs when the total liabilities exceed a fair valuation of the firm's assets. This will depend on the earning power of the assets.

[12] Ratios with relatively larger weights contribute more to the discriminatory power of the function than do ratios with smaller weights.

3. **WCTA00** (working capital to total assets). This ratio is a traditional measure of a firm's net liquid assets relative to its total capitalisation. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. A firm with consistent operating losses will have shrinking current assets in relation to total assets.

4. **LG10TAT0** (sales to total assets). The total assets turnover ratio measures the sales generating ability of the firm's assets. It is a measure of management's capability in dealing with competitive conditions. The higher the value of this variable, the higher a firm's share of the market and the probability of failure is reduced. This variable may also serve as a measure of how well a firm has been replacing assets in order to enhance future sales and profitability. An improvement in asset turnover signifies greater productivity from a firm's asset base. Such an improvement arises from more efficient operations (fewer assets generating the same level of sales), or an increase in sales. An increase in sales could also signify improved market conditions for the firm's products.

5. **LG10MTL0** (market capitalisation to total liabilities). Market capitalisation or market value of equity is measured by the combined market value of preferred and common stock. Total liabilities include both current and long-term liabilities. The measure indicates the value of the firm's assets as judged by the market, compared to the value of the firm's liabilities. It is also a measure of the level a firm's assets can decline in value before its liabilities will exceed its assets and the firm becomes insolvent.

It appears that the main characteristics of a failed firm are:

(a) The firm is close to the limit of its borrowing capacity and would be pressed to meet its short-term liabilities in times of relatively low profitability or a strong build up of inventories.

(b) The firm lacks accumulated profits, because it is a young firm or has a poor record of profitability.

Discussion of the Results

After examining variability in the ratio means, many variables were found to be significant at the 0.01 level, indicating substantial differences in variables between groups. In addition, the difference in mean values was in the predicted direction for each ratio. Failed firms are less profitable than non-failed firms and they also have less liquid assets. Failed firms also have a lower capacity for meeting their obligations and tend to incur more debt than non-failed firms.

This study is concerned with identifying the ratios which are the most important for detecting potential bankruptcies of Thai companies. This problem was addressed by the analysis of Scenarios (1) to (4). In this case, the equality of group means was tested and the optimal MDA models were developed to compare with Altman's (1968) five-ratio model. Altman's five ratios were found to be the most important variables for detecting potential bankruptcies. These ratios include the following: working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/total liabilities and sales/total assets.

It can be concluded that there is strong evidence to support the view that financial ratios have different predictive abilities for detecting financial failures among Thai listed companies. The results indicate that there is strong variation between the equality of group means of failed and non-failed firms. The results also identify 10 ratios which may be the most significant for detecting potential bankruptcies in Thailand. These ratios are consistent with those proposed by Beaver (1966), Altman (1968), Scott (1981), Zavgren (1983), Jones (1987) and Altman (1993). These studies found that failed firms tend to have the following:

- *Low profitability*, as indicated by their significantly smaller GPMARGIN, EBITSALE, EBITTA, EBITSHAR, RETAINTA, ROA and NPMARGIN.
- *Higher leverage ratios*, as indicated by their significantly larger DARATIO and INTERATE.
- *Less liquidity*, as indicated by a smaller QUIRATIO.
- *Lower asset quality*, as indicated by lower a WCTA in this study.

It also appears that the profitability ratios have a larger number of significantly different pairs of group means than other ratios. To develop an optimal MDA model, this study employed a stepwise regression method for selecting variables as proposed by Altman, Haldeman and Narayanan (1977). The original 28 independent variables were screened and four, namely, retained earnings/total assets, EBIT/sales, PPE/(equity + long-term liability) and EBIT/number of shares were included in the optimal model. This study supports Altman, Haldeman and Narayanan's (1977)[13] conclusion that retained earnings to total assets is the most important variable for detecting bankruptcies with univariate and multivariate methodologies. This ratio is a proxy for factors such as the age of the firm, its dividend policy as its record of profitability over time. This ratio was useful in past studies (Altman 1968; Altman, Haldeman & Narayanan 1977; Frydman, Altman & Kao 1985). This may indicate that earnings power discriminates more effectively between the failed and non-failed firms in Thailand.

Implications of the Research

This study contributes in three ways: (1) it demonstrates that Altman's (1968) five-ratio model can be employed effectively in Thailand; (2) it illustrates the importance of using MDA models for predicting potential bankruptcies of Thai companies; and (3) it demonstrates that care needs to be taken in developing predictive models, if they are to be used in practice.

The results of this study confirm that financial ratios can be effective for predicting bankruptcies. Profitability, leverage, asset quality and liquidity are all statistically significant estimates. The empirical results imply that Altman's five-ratio model, with

[13] Seven variables included EBIT/total assets, standard error of estimate around a 10-year trend in return on assets, EBIT/total interest payments, retained earnings/total assets, current assets/current liabilities, common equity/total capital and total tangible assets.

some variation, can be significant for identifying the financial failure of Thai listed companies.
The results of this analysis could be useful to a variety of stakeholders such as managers, investors, listed companies and Thai policymakers.

From a public policy perspective, regulatory agencies face problems when evaluating the risk of insolvency. Policymakers in Thailand's capital market are concerned with maximising returns to investors, transparency of regulation, ensuring fair trade practices and boosting confidence among both domestic and international investors. Confidence is essential for attracting foreign investment and enhancing the health of the capital markets. The SEC and other agencies, including the Bank of Thailand, Board of Investment and Ministry of Finance, face similar concerns. A number of bankruptcies may affect a country's economic confidence. An early warning system such as MDA may help reduce this problem.

The SEC needs to focus more on the solvency and performance of listed companies. This study demonstrates that significant explanatory variables are effective for predicting financial failures. The results also suggest the need for additional disclosures in financial statements. When considering the criteria for listing companies, the SEC could include performance measures such as the five-ratio model to help assist potential investors to screen out undesirable investments.

References

Altman, E. 1968, 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', *The Journal of Finance*, vol. 23, no. 4, pp. 589-609.

Altman, E. 1984, 'The success of business failure prediction models: an international survey', *Journal of Banking and Finance*, vol. 8, no. 2, pp. 171-198.

Altman, E. 1993, *Corporate Financial Distress and Bankruptcy*, 2nd edn, John Wiley & Sons, New York, NY.

Altman, E., Eom, Y. & Kim, D. 1994, 'Distress classification of Korean firms', New York University Solomon Center, *Working Paper*, No. S-94-6, March.

Altman, E., Haldeman, R. & Narayanan, P. 1977, 'Zeta analysis: a new model to identify bankruptcy risk of corporations', *Journal of Banking and Finance*, vol. 1, no. 1, pp. 29-54.

Altman, E. I., Marco, G. & Varetto, F. 1993, 'Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (The Italian Experience)', New York University Solomon Center, *Working Paper*, No. S-93-59, December.

Beaver, W. 1966, 'Financial ratios as predictors of failure,' *Journal of Accounting* Research, vol. 4, no. 1, pp. 71-111.

Blum, M. P. 1974 'Failing company discriminant analysis', *Journal of Accounting Research*, vol. 12, no.1, pp. 1-25.

Boorman, J. 1999, 'Lessons from the Asian crisis: the view from 1999', *Capital Markets Research Center*, McDonough School of Business Georgetown University, Washington D.C.

Castagna, A. D. & Matolcsy, Z. P. 1981, 'The prediction of corporate failure: testing the Australian experience', *Australian Journal of Management*, vol. 6, no. 1, pp. 23-50.

Deakin, E. B. 1972, 'A discriminant analysis of predictors of business failure', *Journal of Accounting Research*, vol. 1, no. 10, pp. 167-179.

Deakin, E. B. 1977, 'Business failure prediction: an empirical analysis', in Altman, E. and Sametz, A. (eds) *Financial Crises: Institutions and Markets in a Fragile Environment*, John Wiley, New York, NY.

Edmister, R. 1972, 'An empirical test of financial ratio analysis for small business failure prediction', *Journal of Financial and Quantitative Analysis*, vol. 61, no. 2, pp. 1477-1493.

Eisenbeis, R. A. 1977, 'Pitfalls in the application of discriminant analysis in business, finance and economics', *Journal of Finance*, vol. 22, no. 3, pp. 875-890.

Foster, G. 1978, *Financial Statement Analysis*, Prentice-Hall Inc., New Jersey, NY.

Frydman, H. E., Altman, I. & Kao, D. 1985, 'Introducing recursive partitioning for financial classification: the case of financial distress', *Journal of Finance*, vol. 40, no. 1, pp. 269-291.

Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. C. 1998, *Multivariate Data Analysis*, 5th edn, Prentice-Hall Inc., New Jersey, NY.

Hamer, M. M. 1983, 'Failure prediction: sensitivity of classification accuracy to alternative statistical methods and variable sets', *Journal of Accounting and Public Policy*, vol. 2, no. 4, pp. 289-307.

Hathaiseree, R. 1997, 'The spread of the Asian Crisis to the world: the reverse contagion effect on Thailand', *Chulalongkorn Review*, vol. 41, no. 1, pp. 12-45.

Jo, H., Han, I. & Lee, H. 1997, 'Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis', *Expert Systems with Applications*, vol. 13, no. 2, pp. 97-108.

Jones, F. L. 1987, 'Current techniques in bankruptcy prediction', *Journal of Accounting Literature*, Fisher School of Accounting, University of Florida, vol. 6, pp. 131-164.

Ko, C. J. 1982, 'A delineation of corporate appraisal models and classification of bankruptcy firms in Japan', thesis, New York University, New York.

Lennox, C. 1999, 'Identifying failing companies: a re-evaluation of the Logit, Probit and DA approaches', *Journal of Economics and Business*, vol. 51, no. 4, pp. 347-346.

Leshno, M. & Spector, Y. 1996, 'Neural network prediction analysis: the bankruptcy case', *Neurocomputing*, vol. 10, no. 2, pp. 125-147.

Lev, B. 1974, *Financial Statement Analysis: A New Approach*, Prentice-Hall Inc., New Jersey, NY.

Lincoln, M. 1984, 'An empirical study of the usefulness of accounting ratios to describe levels of insolvency risk', *Journal of Banking and Finance*, North-Holland, vol. 8, no. 2, pp. 321-340.

McLeay, S. S. 1986, 'Student's and the distribution of financial ratios', *Journal of Business Finance and Accounting*, vol. 13, no. 2, pp. 209-222.

Nittayagasetwat, A., Tirapat, S. & Withisuphakorn, P. 1997, 'An investigation of Thai listed firms' financial distress using macro and micro variables', *Working Paper*, Listed Company Association, Thailand.

Ohlson, J. 1980, 'Financial ratios and probabilistic prediction of bankruptcy', *Journal of Accounting Research*, vol. 18, no. 1, pp. 109-131.

Raghupathi, W., Schkade, L. S. & Raju, B. S. 1991, 'A neural network approach to bankruptcy prediction,' in Trippi, R. and Turban, E. 1996 (eds), *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance*, IRWIN Professional Publishing, London, pp. 227-242.

Salchengerger, L. M., Cinar, E. M. & Lash, N. A. 1992, 'Neural networks: a new tool for predicting thrift failures,' in Trippi, R. & Turban, E. (eds) 1996, *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance*, IRWIN Professional Publishing, London, pp. 303-328.

SET (Stock Exchange of Thailand) 2002, viewed 22 October 2003, <http://www.set.or.th/download/highlight_October 2003>.

Scott, J. 1981, 'The probability of bankruptcy: a comparison of empirical predictions and theoretical models,' *Journal of Banking and Finance*, vol. 5, no. 3, pp. 317-344.

Sinkey, J 1975, 'A multivariate statistical analysis of the characteristics of problem banks', *The Journal of Finance*, vol. 30, no. 1, pp. 21-36.

Tabachnick, B. G. & Fidell, L. S. 1996, *Using Multivariate Statistic*, 3rd edn, Harper Collins Publishers, USA.

Taffler, R. J. & Tisshaw, H. J. 1977, 'Going, going, gone – four factors which predict', *Accountancy*, vol. 88, no. 1003, pp. 50-54.

Tam, K. Y. & Kiang, M. Y. 1992, 'Predicting bank failures: a neural network approach', *Management Science*, vol. 38, no. 7, pp.926-947.

Wilcox, J. 1971, 'A simple theory of financial ratio on predictors of failure', *Journal of Accounting Research,* vol. 8, no. 4, pp. 389-395.

Wilcox, J. 1973, 'A prediction of business failure using accounting data', *Journal of Accounting Research*, vol. 8, no. 11, Supplement, pp. 163-179.

World Bank Report 1998, 'World Bank grant proposal for the development of a corporate monitoring and reporting system', Report to Royal Thai Government, Thailand.

Zavgren, C. 1983, 'The prediction of corporate failure: the state of the art', *Journal of Accounting Literature*, vol. 2, no. 1, pp. 1-37.

Zhang, G., Hu M. Y., Patuwo, B. E. & Indro, D. C. 1999, 'Artificial neural networks in bankruptcy prediction: general framework and cross-validation analysis', *European Journal of Operational Research*, vol. 116, no. 1, pp. 16-32.