# Identifying an SME's debt crisis potential by using logistic regression analysis

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## Abstract

The overall financial stability of the business sector has been a major concern of people involved with the economy, such as policy makers, financial institutions, and investors. The growth of a business, or a lack thereof, will directly affect the stability of that business, and thus the economy in which it operates. The aims of this article are to determine whether a statistical model can identify a firm's debt crisis. The groups focused on in this article are Small and Medium-sized Enterprises (SMEs) for both those financially distressed and non-financially distressed in the Thai economic market. A total sample of one hundred and fifty-nine firms, comprising both financially distressed and non-financially distressed firms has been chosen for this study. Parametric *t*-test and Mann-Whitney U test were undertaken to distinguish the differences between the financial characteristics of the two SME groups. This study employs a logistic regression analysis to predict the likelihood of survival or failure of SMEs by developing a predictive model called $\hat{Y}_{Thai\text{-}SME}$. This model achieves a result of 95.6 per cent regarding the classification accuracy of a business, and shows that liquidity and leverage ratios are the most predictive characteristics of Thai SMEs in financial distress. The results suggest that Thai SME failure is largely related to a business developing a debt crisis. The implication of the model could be employed by several stakeholders to identify financially distressed firms and provide an early warning in order to establish the foundations needed to make an informed decision regarding the allocation of resources.

***Keywords***: *financial distress, financial characteristics, Small and Medium-sized Enterprises (SMEs), bankruptcy, logistic regression analysis*

## 1. Introduction

The financial stability of small and medium enterprises (SMEs) has been a major concern for policy makers and the business community owing to the substantial contribution these businesses and enterprises play in most economies. In the United States of America (U.S.) for instance, in 2007, SMEs comprised 99.7 per cent of all enterprises; provided approximately 75 per cent of all employment positions added to the economy in that year, and employed 50 per cent of the total workforce in the private sector (Altman & Sabato, 2007). Similarly, in the OECD (Organisation for Economic Co-operation and Development) countries, SMEs constitute over 97 per cent of the total number of firms. These statistics illustrate that the importance of the SME sector has been increasing within the economies of several nations. This is also reflected in the increased interest from academic research in developing models predicting potential business failure, which has been a major concern for several decades (Ahn, Cho & Kim, 2000). In the U.S., and elsewhere, the number of small businesses has generally increased, with the number of large enterprises is decreasing (Hutchinson & Michaelas, 2000). The success, or the failure, of SMEs will inevitably, therefore affect other associated businesses. Nevertheless, relatively little academic attention has been given to modeling a formula to calculate the credit risk for SMEs (Altman & Sabato, 2007; Altman, Sabato & Wilson, 2008) thus such a study of SME failure and the identification of factors that predict the future possibility of failure is warranted. In view of the significance of SMEs, the need to understand the underlying causes for their failure has attracted research attention in recent times (Altman & Sabato, 2007; Altman et al., 2008). As SMEs tend to exhibit risk characteristics that are different from those of large corporations an understanding arguably assists in the development of measures to prevent failure. It is apparent that there is limited literature on modeling financial risk for SMEs in general and even more so in regard to emerging economies such as in Thailand. This being so, this paper seeks to provide further empirical evidence required for modeling SME credit risk in Thailand.

In general, the significance of SMEs in the employment sector by creating jobs and stimulating economic growth has been recognised (Bàkiewicz, 2005; Veskaisri, 2007). SMEs comprise a fundamental unit in the Thai economy, constituting over 99 per cent of total number of enterprises in the country (Office of SMEs

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Promotion, 2007). As a result of this recognition and its importance to the nation's economy, the issue of the sustainability of SMEs has become increasingly important in the development of policies in Thailand. Although the Thai government has recognised the significant role of SMEs, and has implemented policies to enhance their viability, the problems associated with the failure of SMEs continue. The Committee for the Promotion of SMEs has summarised the obstacles facing SMEs in Thailand in the following four main categories: 1) limited financial access; 2) loss of competitive advantage; 3) lack of good corporate governance; and 4) ineffective support from the Thai government (Office of SMEs Promotion, 2006, 2007).

The financial aspect of SME failure has attracted particular policy attention in Thailand since the financial crisis of 1997. At that time the percentage of non-performing loans (NPLs) to the total credit in the country's financial system rose to 47.7 per cent, which was the highest percentage in the country's history (Bank of Thailand, 2008). This economic crisis also promoted a greater concern on the part of the government for economic recovery and growth (Bàkiewicz, 2005; Swierczek & Ha, 2003). The Thailand Ninth National Economic and Social Development Plan (2001-2006) (Thai 9th NESDP; Office of The National Economic and Social Development Board, 2001) emphasized a concern for economic growth, including greater focus on SME development. The Thai government, through the Office of SME Promotion (OSMEP), formulated the 1st SMEs Promotion Plan (2002 - 2006), a plan that aimed to resolve and limit the negative effects of the economic crisis as well as encourage and support the revival of SMEs.

However, despite the recent generalized emphasis on SMEs, this sector in the economy of Thailand has received insufficient research attention (Bàkiewicz, 2005). Against this background, this study aims to develop a model for predicting the likelihood of SME success or failure in Thailand using logistic regression. SME failure prediction models can help facilitate business managers to distinguish financial problems as an early warning mechanism; they can also facilitate other decision makers to understand the financial profile of businesses (Ahn et al., 2000), and inform policy-makers by highlighting key priority areas.

In Section Two this paper reviews literature and then develops research hypotheses in Section Three. Section Four outlines the research methods with Section Five presenting and discussing the empirical results of the study. Then finally, Section Six concludes the paper.

## 2. Literature

### 2.1 Identifying SMEs

The literature shows that SMEs are identified in various ways in different countries. They can be identified through several characteristics such as the amount of fixed assets, total assets, total sale volume, the number of employees, or by a combination of these factors. For instance, in the United States of America the classification of businesses is based on the number of employees. They are classified as very small enterprises if they employ less than twenty people, as small enterprises if they employ between twenty and one hundred people, and as medium enterprises if they employ between one hundred and five hundred people (Office of Advocacy, 1984). Altman and Sabato (2007), by adapting the definition of SMEs from the new Basel Accord, considered businesses with a sales volume of less than US $65 million as SMEs. The European Commission, whose definition is used by many countries, states that small and medium-sized enterprises are companies that employ less than two hundred and fifty staff and have an annual turnover not exceeding EUR 50 million, or an annual balance sheet total not exceeding EUR 43 million (European Commission, 2003). The nations of China, Indonesia, Japan, Korea, Malaysia, and Singapore also use the number of employees as the basis for classifying firms, with different levels used as cut off points (Khader & Gupta, 2002)

In Thailand, SME sectors are divided into production, service and trading firms. They are classified as medium or small enterprises based on both the number of employees and the amount of fixed assets, excluding land (Institute for Small and Medium Enterprises Development, 2006). For example businesses in the production and service sectors are classified as small enterprises if their assets are not more than THB 50 million and employ no more than fifty people; while medium enterprises are those with assets between THB 50 to 200 million and employ between fifty and two hundred people. On the other hand, businesses in the wholesale trading sector are classified as small enterprises if their assets are less than THB 50 million and employ no more than twenty-five people and as medium enterprises if their assets are between THB 50 to 100 million and employ between twenty-six and fifty people. However, in situations where the number of employees and the value of fixed assets place the firm in both categories, that is either small or medium, the lower of the two determines how the enterprise will be classified.

2.2 Forms and consequences of business failure

Business failure can take several forms, including excessive liability, financial deficit, bankruptcy, insolvency, default, distress, non-performing loans, business termination, and/or liquidation (Kraus & Litzenberger, 1973). Interestingly, not every firm with financial difficulties goes bankrupt and ceases operation. Bernanke and Campbell (1988) argue that bankruptcy costs are actually quite small and can often be avoided by the renegotiation of debt terms or by the acquisition of the firm by a third party. However, Bernanke and Campbell (1988) indicate that the most important costs occur when firms are close to bankruptcy. Firms that are close to bankruptcy may be unable to borrow from financial institutions, or suppliers, or to take advantage of productive opportunities as they have difficulties convincing lenders to enter into long-term relationships with them. Thus, these difficulties reduce their ability to operate profitably and to obtain new funds on reasonable terms, which is a major cost to firms with excessive debts. Such firms will have additional incentive to move even closer to declaring bankruptcy.

Thus, to determine the actual cost of business failure it is often difficult because the line between business success and failure is not always clear and therefore determining the cost of failure may not be explicit. Dealing with financial distress, total bankruptcy-related costs to firms and claimants are approximate 13 to 20 per cent of the distressed firms' pre-distress value. Further, indirect bankruptcy costs include the loss of sales, profits and goodwill. These losses are incurred on account of reduced consumer confidence that result from individual customers'/client's decisions towards distressed firms and their inability to obtain goods, credit or to issue securities. Beyond these losses, the distressed companies may be occupied in taking steps to avoid bankruptcy to the extent that normal business operations are disregarded (Ross, Westerfield & Jordan, 2008; Warner, 1977). Therefore, as going bankrupt is expensive, firms will spend much of their resources and put in a lot of effort to avoid it.

In addition to the substantial direct and indirect costs of business failure, there are other dimensions to SME failure that should be considered. First, the probability of both personal and business bankruptcy, including the subsequent liquidation, is much higher with small enterprises. Second, the direct costs of bankruptcy and liquidation fall more heavily in relative terms on small enterprises. Third, there may be some other indirect costs associated with bankruptcy and liquidation that are not readily apparent (Holmes, Hutchinson, Forsaith, Gibson., & McMahon, 2003).

2.3 Financial ratios and business failure prediction

Financial ratios have been used in numerous studies to predict business failure. Jen (1963) stated that financial ratios could be fairly efficient as predictors of a variety of financial difficulties. It was found that financial ratios consistently and clearly distinguished between profitable and unprofitable firms during the period 1949-1955 (Jackendoff, 1962). Examples of, financial ratios include current ratios (current assets divided by current liabilities); working capital (current asset less current liabilities) to total assets ratios; and net worth (liabilities less equity) to total debt ratios of profitable firms were consistently high. Total asset turnover (earnings after interest and tax expenses divided by total assets) was found to be inversely related to the size of firm. The best predictors identified by Fitzpatrick (1931) were the net profit to net worth ratio and the net worth to total debt ratio. Whereas, the net working capital to total assets ratio has been stated as the most accurate and steady indicator of failure (Horrigan, 1968). Most bankruptcy prediction studies have been used to construct bankruptcy prediction models by classifying failing and non-failing firms several years prior to the actual failure event.

2.4 Approaches to failure prediction

In the wake of the collapse of several corporations, the question arises as to whether pertinent financial information should have been used to alert stakeholders to potential problems before they actually occurred. Such an approach would have protected stakeholders from possible losses by enabling the possibility of introducing measures and taking the actions required to avoid corporate bankruptcy. Therefore, one major benefit of being able to distinguish between distressed and non-distressed firms would be to provide early indicators of financial stress and to warn all parties so they may introduce and implement remedial actions. Financial concerns should be addressed as quickly as possible after their identification so that firms remain solvent.

Davidson and Dutia (1991) found that small firms have less liquidity and are more leveraged than large firms, yet tend to have lower profit margins. In the case of financially distressed firms, the financial characteristics are even more extreme with low liquidity, high leverage and low or negative profits (losses). As financially distressed firms tend to exhibit low liquidity and high levels of long term debt, financial ratios can be examined to predict the chances of business failure.

Furthermore, numerous business failure prediction models have been suggested since the 1960's, with the development of such models starting with the univariate analysis by Beaver (1966, 1968). Subsequently, the best-known technique for predicting business failure, developed by Altman (1968), is multivariate discriminant analysis (MDA). As Fulmer, Moon, Gavin & Erwin (1984) argued, discriminant analysis is particularly useful when the objective is to categorize a variable as falling into one of several groups, such as good or bad, male or female, bankrupt or non-bankrupt. The discriminant function is also derived in a way that minimizes the possibility of misclassification. Practically, using discriminant analysis may raise several questions regarding the percentage of accuracy that is required for classification, as well as the question of unequal sample sizes, of missing data, and of absences in multivariate normality, outliers, multicollinearity and singularity. Several studies, for instance those by Deakin (1972, 1977), Edmister (1972), Blum (1974), McGurr and Devaney (1998), have employed this technique as a tool for the prediction of bankruptcy.

The artificial neural network (ANN) technique has also been used by several researchers such as Tam and Kiang (1992) and Lee, Han and Kwon (1996) to predict bankruptcy. More recent studies, for example those by Ohlson (1980), Gentry, Newbold and Whitford (1985), and Platt and Platt (1990, 1991) employed logistic regression (logit) and probit techniques. Logistic regression is relatively free of restrictions and assumptions regarding the distribution of predictors which are not required. The lack of restrictive assumptions and the uncomplicated use of its prediction have increased the popularity of this form of analysis. However, when the assumption of distribution of predictors is met, discriminant function analysis is more effective and seems to be a more efficient approach for analysis (Tabachnick & Fidell, 2001).

## 3. Setting objectives and hypotheses

The objectives of the study are 1) to observe the similarities or differences of the characteristics of distressed and non-distressed SMEs, 2) to develop a model that can be used in predicting the financial status of Thai SMEs and whether they are more likely to become failures by considering their financial ratios from past years. Financial rations used in this study are separated into three categories: liquidity, leverage and profitability, further detailed as follows.

i) Liquidity refers to how quickly and cheaply an asset can be converted into cash, or in other words, the ability of current assets to meet current liabilities when due.
ii) Leverage, also known as gearing or levering, refers to the use of debt to supplement investment, or the degree to which a business is utilizing borrowed money.
iii) Profitability refers to an ability of a firm to generate net income on a consistent basis.

The following hypotheses were tested.

H1: There are significant differences in the financial ratios between Thai financially distressed and non-financially distressed SMEs as listed on the Market for Alternative Investment (MAI) in terms of liquidity, financial leverage and profitability.

H2: A logistic regression model predicts Thai financially distressed SMEs and non-financially distressed SMEs more accurately than a possible classification by chance.

## 4. Research methodology

Due to the available resources on-line, this study utilized secondary data. Financial ratios from the designed sampling groups represented by the MAI and those of the non-financially distressed firms, were used to determine the differences in Thai financially stressed SMEs' characteristics.

This study employed both parametric and nonparametric approaches in the Statistical Package for the Social Sciences (SPSS) program, Logistic regression analysis is considered to be more flexible than discriminant analysis, therefore, to avoid the impact of the lack of multivariate normality, outliers, multicollinearity and singularity, the logistic regression model is used to develop the bankruptcy prediction models in this study. The percentage of accuracy from the model is then later compared with the percentage of accuracy by chance.

The study employed an analysis of the financial ratios of two groups, one hundred and fifty-nine cases from between 2002 to 2005 to develop a logistic predictive financial distress model for Thai SMEs. The validation of the constructed is made through examining the classification accuracy for both initial and holdout samples. Later, to investigate the prediction model and further test the suspected non-stationarity over time, sixty-five new cases drawn from between 2006 to 2008 were entered into the analysis.

The details of sampling and variable selection, with definitions are discussed as follows.

4.1 Thai SMEs definition

As outlined in the preceding section, the commonly used bases for categorizing the size of firms include the number of employees, the amount of fixed assets, the volume of sales, the balance sheet outstanding, and the structure of shareholders. Even though the number of employees is the most frequently used criterion in most countries around the world, with some difficulties in obtaining such data in the case of Thailand, asset size of an enterprise was therefore chosen as the criterion to classify the size of Thai firms. This method is in accord with the recommendation of the European Commission, to the effect that the annual balance sheet (or total assets) of a firm should not exceed EUR 43 million (European Commission, 2003), or THB 2,000 million, to be classified as a small and medium-size enterprise. In accordance with this criterion; firms for which the total assets do not exceed THB 2,000 million at year's end are classified as SMEs.

4.2 Non-financially distressed SME: Market for Alternative Investment (MAI) perspective

As the companies that are listed on the MAI are also listed on the Stock Exchange of Thailand (SET), none of them were identified in the non-performing group on the SET, and none of them possessed total assets at the end of the research years exceeding THB 2,000 million, therefore, the MAI-listed companies can be regarded as a representative sample of non-financially distressed SMEs. Of the financial statements collected from 2002 to 2005, ninety-one financial statements are used for comparison with financially distressed SMEs.

4.3 Financially distressed SMEs definition

The companies that applied to the Thai Bankruptcy Court, the Central Bankruptcy Court and the Civil Court for debt restructuring during the years 2002 to 2005 were used as a sampling frame[1]. Then, according to the definition of SMEs in this study, companies with assets below BHT 2,000 million were selected as financially distressed SMEs. The financial data of the sixty-eight financially distressed SMEs were then collected[2].

4.4 The variables

With these two different groups of SMEs sixty-eight financially distressed and ninety-one non-financially distressed - a total of nine independent variables were selected for use in this study. As defined in Table 1, these variables were divided into three categories: 1) liquidity, 2) leverage and 3) profitability. Nine independent variables, the most commonly used by previous studies, were identified and also included into the analyses.

**Table 1** Variables

| Measure | Unit | Name |
|---|---|---|
| Liquidity | | |
| 1. CA/TA | % | Current assets to total assets ratio |
| 2. CL/TA | % | Current liability to total assets ratio |
| 3. WC/TA | % | Working capital to total assets ratio |
| Financial leverage | | |
| 4. LL/TA | % | Long-term liability to total assets ratio |
| 5. TL/TA | % | Total liability to total assets ratio |
| 6. DE | Time | Debt to equity ratio |
| Profitability | | |
| 7. TI/TA | % | Total income to total assets ratio |
| 8. EBIT/TA | % | Total earnings before income and tax expenses to total assets ratio |
| 9. EAIT/TA | % | Total earnings after income and tax expenses to total assets ratio |

## 5. Empirical results and discussion

5.1 Test of hypothesis One

The study examined the differences between Thai financially distressed SMEs and non-financially distressed SMEs on the MAI by using both a parametric test (independent sample *T*-Test) and a nonparametric test (Mann-Whitney U Test) to analyse the first hypothesis.

The variables of interest in this study are the ratios relating to current liabilities, financial leverage, and profitability. The distressed firms had liabilities, which were much greater than their assets. Table 2 shows total liability ratios were over 100% of total assets (LL/TA and TL/TA ratios) for financially distressed SMEs, which resulted in the financially distressed firms having a negative equity (DE ratio). Under ideal

[1]The name list of the companies that applied to a court in Thailand can be found on the website of the Legal Execution Department, Ministry of Justice, Thailand (http://www.led.go.th)

[2]The financial data of the 68 financially distressed SMEs were obtained from the website of the Department of Business Development (DBD), the former Ministry of Commerce, Thailand (http://www.dbd.go.th)

circumstances, liabilities would be kept below the level of total assets so that the debt-to-equity ratio shows a positive value. The Parametric *t*-test was conducted to analyse the nine variables in order to find the significant differences between the samples, as every tested ratio shows the results matched the expectation. The results (Table 2) show that the financial characteristics of financially distressed SMEs are different from those of the non-financially distressed enterprises. All variables show statistically significant differences in both the parametric and non-parametric tests at a 0.1% level of significance. The financially distressed SMEs exhibit low liquidity and profitability with high leverage. On the other hand, the non-financially distressed SMEs exhibit higher liquidity and profitability accompanied with lower leverage. Therefore, the evidence supports the first hypothesis.

5.2 Test of hypothesis Two

After the variables used in this analysis were tested, to assess the Goodness-of-Fit of the estimated model, logistic regression maximized the "likelihood" that the event would occur. The four variables were entered using Forward Stepwise Wald, in which one variable was entered into the model at a time, making four steps in total. The overall measure of the fitness of the model is assessed by the likelihood value (-2 times the log of the likelihood value referred to as -2LL or -2 likelihood). As Hair, Anderson, Tatham and Black (1998) indicated, a well-fitting model will have a small value for -2LL, and the minimum value for -2LL is zero. The result shows that the -2LL value was reduced from the base model value (Step 1) 131.228 to 39.291, a decrease of 91.937. The Cox and Snell $R^2$ indicates a greater model fit with higher values where the maximum value is 1, which in this study, was .417 at the first step, and increasing to .673 at the last step. Nagelkerke $R^2$ proposed a modification that had the range of 0 to 1, which in this study the Nagelkerke $R^2$ was .904. It can be seen that this model had a high degree of fit. Lastly, the HoSMBr and Lemeshow measurements showed no significance, indicating that there were no significant differences in the distribution of the actual and predicted dependent values. The model coefficient was found to be statistically significant at every single step. The first variable that was selected to enter into the equation (or Step 1) was LL/TA ratio with 83.0 per cent correct classification, to be followed by the WC/TA ratio (Step 2) with 93.7 per cent, then the TI/TA ratio (Step 3) with 95 per cent and finally the EBIT/TA ratio (Step 4) with 95.6 per cent respectively.

**Table 2** *T*-Test and Mann Whitney U-Test summary results

| Hypo-theses | Variables | Mean | | Parametric t-test | | Mann-Whitney U Test | |
|---|---|---|---|---|---|---|---|
| | | FD**-SMEs | NFD*-MAIs | *t* | Confidence Interval Result | Z | Confidence Interval Result |
| ***1) Liquidity*** | | | | | | | |
| 1.1 | CA/TA of FD < of NFD | 42.77 | 61.33 | -4.59 | *** | -4.24 | *** |
| 1.2 | CL/TA of FD > of NFD | 181.21 | 35.56 | 4.20 | *** | -5.82 | *** |
| 1.3 | WC/TA of FD < of NFD | -138.44 | 25.76 | -4.73 | *** | -7.54 | *** |
| ***2) Financial leverage*** | | | | | | | |
| 2.1 | LL/TA of FD > of NFD | 127.65 | 7.61 | 6.96 | *** | -7.28 | *** |
| 2.2 | TL/TA of FD > of NFD | 308.87 | 43.17 | 6.95 | *** | -10.63 | *** |
| 2.3 | DE of FD < of NFD | -2.77 | 0.78 | -5.13 | *** | -8.93 | *** |
| ***3) Profitability*** | | | | | | | |
| 3.1 | TI/TA of FD < of NFD | 68.32 | 118.93 | -4.23 | *** | -7.07 | *** |
| 3.2 | EBIT/TA of FD < of NFD | -12.14 | 12.52 | -4.41 | *** | -8.25 | *** |
| 3.3 | EAIT/TA of FD < of NFD | -28.37 | 8.87 | -4.76 | *** | -5.90 | *** |

***Significance at .1% level

** FD: Financially Distressed (68 firms)

* NFD: Non-Financially Distressed (91 firms)

As the technique enables selection of the most powerful discriminatory variables to be included into the equation followed by the next most powerful, accuracy percentages were increased as every step was completed. Consequently, the model to discriminate between financially distressed and non-financially distressed SMEs was developed as follows.

$$\hat{Y}_{\text{Thai-SME}} = \frac{e^{1.031+0.065X1-0.049X2+0.018X3+0.082X4}}{1+e^{1.031+0.065X1-0.049X2+0.018X3+0.082X4}}$$

Where,

$\hat{Y}_{\text{Thai-SME}}$ = Overall score of Thai-SMEs

$e$ = Mathematical constant (2.71828), the base of natural logarithm

$X_1$ = Working capital to total assets ratio (WC/TA)

$X_2$ = Long-term liabilities to total assets ratio (LL/TA)

$X_3$ = Total income to total assets ratio (TI/TA)

$X_4$ = Earnings before interest and tax expenses to total assets ratio (EBIT/TA)

The model's classification result (Table 3) achieved an accuracy of at least 90 per cent. Using $\hat{Y} \geq 0.50$ to determine non-financially distressed SMEs, with $\hat{Y} < 0.50$ to determine financially distressed SMEs, four cases of misclassification were revealed from the distressed group to the non-distressed group (Type I error), or 5.9 per cent being misclassified. There were three cases (or 3.3 per cent) of misclassification from the non-distressed group to the distressed group (Type II error). With a total of accuracy of 94.1 per cent regarding the non-financially stressed SMEs and 96.7 per cent regarding the financially stressed SMEs being classified correctly, this gave an overall accuracy rate of 95.6 per cent, which is much higher than the classification by chance, which is 51.046 per cent[3]. The overall accuracy of 95.6 per cent of the model leads to the conclusion that the logistic regression model is useful for distinguishing between financially distressed and non-financial distressed firms. The high overall accuracy rate also shows that the method adopted here leads to a more reliable outcome than the proportional chance criterion. Thus, Hypothesis Two is supported.

The model was further tested by entering a new set of variables from a sample of sixty-five firms from the years 2006, 2007 and 2008. Three groups of old and new cases of samples were used and the classification accuracy of the logistic regression model was tested. The first twenty cases are non-financially distressed firms, which were ranked according to their profitability as recorded on data from 2009. Cases 21 to 40 are selected randomly from SMEs that went to the bankruptcy court during 2002-2005 (these are the old cases that were used as samples in developing the model). The use of this selection of companies enables identification of the model's ability to identify companies that have recovered from financial distress once they had lodged bankruptcy applications. A third group of twenty-five cases (cases 41-65) was then derived from companies that filed for bankruptcy after 2006 (new cases that have never been used in the developed model) to test the model with collected data from new cases of financially stressed SMEs. The result of the new test is promising. It is found that the developed model can be used in predicting the failure likelihood with about 70 per cent of accuracy in the new cases.

## 6. Conclusion

The results of this study were not surprising as they were in line with the conclusions of many previous researches in this area. The differences of the financial characteristics between financially distressed and the non-financially distressed companies were tested and confirmed. The non-financially distressed companies, understandably, exhibited a better financial performance when compared to the financially distressed companies. The characteristics of the non-distressed companies included, as expected, high liquidity and profitability, with low debt; while distressed companies were characterized with low liquidity and profitability, but with the burden of carrying high debt. It is important to note that a negative debt-to-equity (DE) ratio in financially distressed companies readily illustrates the ramifications of the tremendous strain caused by the great amount of liability, specifically long-term debt mostly over their assets, as a result the DE ratio of the distressed firms become negative. Thus the evidence from the test supports the first hypothesis.

[3]Classification by chance or proportional chance criterion ($C_{PRO}$) when group sizes are unequal is calculated by using the following formula.

$$C_{PRO}=P^2 + (1-p)^2$$

Where p=Proportion of individuals in group 1;

1-p=Proportion of individuals in group 2

$$C_{PRO} =(.42767)^2 + (.57232)^2=0.18290+ 0.32755$$

$$=0.51046 \quad \text{or} \quad 51.046 \text{ per cent}$$

**Table 3** Classification

| Step | | Observed | Predicted status | | |
|---|---|---|---|---|---|
| | | | FD-SMEs | NFD-MAIs | Accuracy (%) |
| Step 1 | Status | FD-SMEs | 46 | 22 | 67.6 |
| | | NFD-MAI | 5 | 86 | 94.5 |
| | | Overall Percentage | | | 83.0 |
| Step 2 | Status | FD-SMEs | 62 | 6 | 91.2 |
| | | NFD-MAI | 4 | 87 | 95.6 |
| | | Overall Percentage | | | 93.7 |
| Step 3 | Status | FD-SMEs | 64 | 4 | 94.1 |
| | | NFD-MAI | 4 | 87 | 95.6 |
| | | Overall Percentage | | | 95.0 |
| Step 4 | Status | FD-SMEs | 64 | 4 | 94.1 |
| | | NFD-MAI | 3 | 88 | 96.7 |
| | | Overall Percentage | | | 95.6 |

a. The cut value is .500 point

With respect to the nine variables used to construct the logistic predictive model, which was utilized for predicting the likelihood of survival, or failure, of Thai SMEs was established and is shown as follows.

$$\hat{Y}_{\text{Thai-SME}} = \frac{e^{1.031+0.065X1 - 0.049X2+ 0.018X3 +0.082X4}}{1+ e^{1.031+0.065X1 - 0.049X2+ 0.018X3 +0.082X4}}$$

Four main variables, namely the working capital to total assets ratio (WC/TA), long-term liabilities to total assets (LL/TA), total income to total assets ratio (TI/TA) and earnings before interest and tax expenses to total assets ratio (EBIT/TA) were found to be the most powerful discriminatory variables. The holdout sample indicated that there was an overall accuracy of 95.6 per cent, which is much higher and reliable than the classification by chance (51.046 per cent). Thus, concluding that Hypothesis Two is supported, yet, the result revealed some errors, with four cases of Type I error (misclassification from the distressed to the non-distressed group) and three cases of Type II error (misclassification from the non-distressed to the distressed group).

The new sixty-five cases were entered into the formulae to test the validity of the developed logistic model. A favorable result was found even though some errors were seen, even so the results led to the conclusion that the model is promising and that it is at an acceptable level of accuracy, thereby providing a useful means to distinguish financially distressed firms from non financially-distressed firms.

The results of this study have implications in both the fields of financial/economic theory and in practice. As the consequence of business failures affects the sustainability of business over a wide range, there is a need to develop a systematic study of failures, rather than accepting failures as they come. A study of this kind will enhance the body of knowledge and hopefully reduce the number of failures. The model developed here could be employed by several stakeholders to identify financially distressed firms and assist with making decisions regarding resource allocation. Many areas need to be focused on, such as the identification of the causes of failure, the identification of the indicators of potential future failure and the development of sophisticated mathematical models for predicting failures. Additional variables used in the model and non-financial data are suggested to be included in future research.

At a glance, working capital to total assets ratio (WC/TA) and long-term liabilities to total assets ratio (LL/TA) are the most predictive ratios to separate companies of financial concern and whether they potentially exhibit the characteristics of potential future financial distress. The companies that exhibit low WC/TA and high LL/TA ratios would be more likely to become financially distressed, while on the other hand high WC/TA and low LL/TA ratios could safely be assumed as predictors of non-financially distressed firms. Yet, to distinguish the financially distressed firms from the non-financially distressed firms or in other words to identify the debt crisis of a firm, use of the model $\hat{Y}_{Thai\text{-}SME}$ gives us good results, confirming the potential status of a firm.

## 7. References


Ahn, B.S., Cho, S.S., & Kim, C.Y. (2000). The integrated methodology of rough set theory and artificial neural network for business failure prediction. *Expert Systems with Applications,* 18, 65-74.

Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance,* 23 (4), 589-609.

Altman, E.I., & Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the U.S. market. *Abacus Journal,* 43 (3), 332-357.

Altman, E.I., Sabato, G. & Wilson, N. (2008). The value of qualitative information in SME risk management. Retrieved December 1, 2010, from http://pages.stern.nyu.edu/~ealtman/SME_EA_GS_NW.pdf

Bàkiewicz, A. (2005). Small and medium enterprises in Thailand. Following the leader. *Asia and Pacific Studies, 2,* 131-151.

Bank of Thailand. (2008). NPLs and Loans. Retrieved July 2, 2008, from http://www2.bot.or.th/statistics/ReportPage.aspx?reportID=431&language=th

Beaver, W.H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research [Empirical research in Accounting: Selected Studies],* 4, 71-111.

Beaver, W.H. (1968). Alternative accounting measures as predictors of failure. *The Accounting Review Journal,* 43 (January), 113-122.

Bernanke, B.S., & Campbell, J.Y. (1988). *Is there a corporate debt crisis?*, Washington, D.C., U.S.: Brookings Institution Press, 1988 (1), 83-139.

Blum, M. (1974). Failing company discriminant analysis. *Journal of Accounting Research,* 12 (1), 1-25.

Davidson, W.N., & Dutia, D. (1991). Debt, liquidity and profitability problems in small firms. *Entrepreneurship: Theory and Practice,* 16 (1), 53-64.

Deakin, E.B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research,* 10 (2), 167-179.

Deakin, E.B. (Ed.). (1977). *Business failure prediction: An empirical analysis,* New York: Wiley.

Edmister, R.O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis,* 7 (March), 1477-1493.

European Commission. (2003). Commission recommendation: Definition of small & medium sized enterprises. *Official Journal of the European Union,* C(2003) 1422, L 124/39. Retrieved July 5, 2010, from http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:124:0036:0041:en:PDF

Fitzpatrick, P.J. (1931). *Symptoms of industrial failures*. Washington, D.C.: Catholic University of America Press.

Fulmer, J.G., Moon, J.E., Gavin, T.A., & Erwin, J.M. (1984). A bankruptcy classification model for small firms. *Journal of Commercial Bank Lending,* 11 (July), 25-37.

Gentry, J., Newbold, P., & Whitford, D.T. (1985). Classifying bankrupt with fund flow components. *Journal of Accounting Research,* 23 (1), 146-160.

Hair, J F., Anderson, R.E., Tatham, R.L., & Black, W. (1998). *Multivariate data analysis,* 5th ed., New Jersey: Prentice Hall.

Holmes, S., Hutchinson, P., Forsaith, D., Gibson, B., & McMahon, R. (2003). *Small enterprise finance*, Australia: John Wiley & Sons Australia, Ltd.

Holmes, S., & Kent, P. (1991). An empirical analysis of the finanical structure of small and large Australian manufacturing enterprises. *Journal of Small Business Management, 1* (2), 141-154.

Horrigan, J.O. (1968). A short history of financial ratio analysis. *The Accounting Review Journal,* 43 (April), 284-289.

Hutchinson, P., & Michaelas, N. (Eds.). (2000). *The current state of business disciplines* (Vol. 3). Rohtak, India: Spellbound Publications Ltd.

Institute for Small and Medium Enterprises Development. (2006). *Definition of SMEs (in Thai).*

Jackendoff, N. (1962). A study of published industry financial and operating ratios. *Economics and Business Bulletin (Temple University),* 14 (3), 34.

Jen, F.C. (1963). The determinants of the degree of insufficiency of bank credit to small business. *Journal of Finance,* 18 (December), 694-695.

Khader, S.A., & Gupta, C.P. (Eds.). (2002). *Enhancing SME competitiveness in the age of globalization*. Tokyo: National

Statistical Coordination Board, Asian Productivity Organization.

Kraus, A., & Litzenberger, R.H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance, 28* (4), 911-922.

Lee, K.C., Han, I., & Kwon, Y. (1996). Hybrid neural network models for bankruptcy predictions. *Decision Support Systems,* 18 (1), 63-72.

McGurr, P.T., & Devaney, S.A. (1998). Predicting business failure of retail firms: An analysis using mixed industry models. *Journal of Business Research,* 43 (3), 169-176.

Office of Advocacy. (1984). *The state of small business: A Report of the President*. Washington D.C.: Small Business Administration.

Office of SMEs Promotion. (2006). *White Paper, in Export and Import by SMEs*.

Office of SMEs Promotion. (2007). *White Paper, in Export and Import by SMEs*.

Office of The National Economic and Social Development Board. (2001). The Ninth National Economic and Social Development Plan (2001 - 2006). Retrieved November 2, 2010, from http://www.nesdb.go.th/ Default.aspx?tabid=139

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research,* 18 (1), 109-131.

Platt, H.D., & Platt, M.B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance and Accounting,* 17 (1), 31-51.

Platt, H.D., & Platt, M.B. (1991). A note on the use of industry-relative ratios in bankruptcy prediction. *Journal of Banking and Finance,* 15 (6), 1183-1194.

Ross, S.A., Westerfield, R.W., & Jordan, B.D. (2008). *Corporate finance fundamentals*, New York: McGraw-Hill Irwin.

Swierczek, F.W., & Ha, T.T. (2003). Entrepreneurial orientation, uncertainty avoidance and firm performance: An analysis of Thai and Vietnamese SMEs. *The International Journal of Entrepreneurship and Innovation,* 4 (1), 46-58.

Tabachnick, G.B., & Fidell, S.L. (2001). *Using multivariate statistics*, 4th ed., Needham Heights, MA: Allyn & Bacon.

Tam, K.Y., & Kiang, M.Y. (1992). Managerial applications of neural networks: The case of bank failure predictions. *Management Science,* 38 (7), 926-947.

Veskaisri, K. (2007). The relationship between strategic planning and growth in small and medium enterprises (SMEs) in Thailand. *RU International Journal,* 1 (1), 55-67.

Warner, J.B. (1977). Bankruptcy costs: Some evidence. *The Journal of Finance, 2* (May), 337-347.