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Default Prediction for Small-Medium Enterprises in Emerging Market: Evidence from Thailand

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Abstract

Small-medium enterprises (SMEs) play an important role in the economy worldwide and they normally need to borrow funds from financial institutions. Thus, an accurate credit risk model to predict the probability that these firms might be bankrupt and cannot pay back the loans on time is very crucial. However, the studies based on SME data are very rare especially for those in emerging markets. This study develops the SME models by employing both the Multivariate Discriminant Analysis (MDA) and Logistic Regression Analysis (Logit) model in predicting bankruptcy of SMEs in Thailand. The samples cover the period 2000 – 2010. The result shows that the Logit model gives higher predictive accuracy level at 85.5 percent for out-of-sample test. Moreover, the combined forecasts of bankruptcy firms from both MDA and Logit models could help achieve even higher predictive accuracy level.

Keywords: credit risk model, SMEs, Thailand, MDA, Logit model

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INTRODUCTION

Credit risk always arises from lending activities, which means that it dates back at least as far as 1800 B.C. (Caouette, Altman and Narayanan 1998). There is always an uncertainty that the lenders especially financial institutions will not receive the full payments (either the principle or interest or both) from the borrowers on the agreed dates. Credit risk models have been developed to predict the probability that the borrowers cannot meet their payback obligations. There are numerous studies on credit risk based on financial data of listed companies, which are mostly large corporations, but very few studies utilized the data of small and medium enterprises (SMEs). This could be mainly due to the concern of the reliability of the data since large firms listed at the stock exchanges are closely monitored by the authority to ensure that the financial data provide accurate and useful information for investors and shareholders. Moreover, some data like market value and stock price is only available for listed firms only.

However, studies on SMEs are important because SMEs are viewed as the backbone of the economy of many countries all over the world since they are the incubators of employment, innovation and growth (Craig, Jackson and Thomson 2004). Financial institutions lending to these SMEs must also develop credit risk models for their customers. Among the few SME credit risk studies that exist, most of them are based on data from developed economies (e.g. Italy, U.K. and U.S.A.). Those studies from emerging markets are particularly rare perhaps due to both availability and reliability of financial data. In this study, we utilize a SME dataset from Thailand to shed further light on credit risk of SMEs in emerging markets.

For Thailand, 99.8 percent of total enterprises were small and medium size enterprises generating 37.8 percent of total GDP in 2009 (Source: Office of Small and Medium Enterprises Promotion, OSMEP, Thailand). Since these SMEs use borrowings from financial institutions as the major source of their external funding, it is crucial for the financial institutions to have a sound credit risk model for these SMEs to avoid future loan losses. The interesting question remains whether the credit risk models for large corporations and for SMEs should be the same.

According to the Basel II, the retail credits or SME loans receive a different treatment than those of large corporate loans by requiring less regulatory capital for given default probabilities. The Internal Ratings-Based Approach (IRB) specifies two different asset correlation formulas for SME loans and large corporate loans. The main reason for this differential treatment is the supposedly low degrees of SME obligor's exposure to the state of the global economy. Bank of Thailand, as the regulator, has also followed and announced this general criterion since 2008. With different risk exposure, a credit risk model for SMEs could be different from that for large corporations.

Therefore, our main objective for this study is to develop default prediction models (or credit risk models) based on the well-known Multivariate Discriminant Analysis (MDA) and Logistic Regression Analysis (Logit) approaches for SMEs in Thailand.

The contributions of this study are at least three folds. First, we extend Altman and Sabato (2007) model and process by using both the MDA and Logit process. We will also include all standard financial ratios and those that have been found to be important for Thai firms which are different from those studies employing the U.S. and U.K. data. Second, this is the first paper to develop default prediction model (or credit risk model) for Thai SMEs, which could be different from the previous models used for Thai large corporations. This would also shed some light on credit risk of SMEs in emerging markets. Third, the financial institutions with their own unique data set of their SMEs customers can further enhance and develop their own internal credit risk models by following the steps explained in this paper. With the more accurate credit risk models, the risk management of the financial system as a whole could be improved.

The remainder of this paper is organized as follows. We first provide the literature reviews in section 2. Research methodology is explained in section 3 and empirical results are shown in section 4. Finally, section 5 summarizes and presents concluding remarks.

LITERATURE REVIEW

For many years, researchers have explored several alternatives to predict the default probability of customers or business failure by applying financial ratios as the predictors. The seminal works in this field were Beaver (1966) and Altman (1968). Beaver (1966) analyzed 14 financial ratios using a univariate discriminant analysis and found that working capital cash flow to total assets ratio and net income to total assets ratio correctly identified 90 percent and 88 percent of the samples respectively (cited by Bernhardsen 2001). Altman (1968) was the first paper that succeeded in applying Multiple Discriminant Analysis (MDA) to develop a failure prediction model. He found 5 financial ratios achieving high predictive accuracy rate. These five ratios are (1) Working capital to total assets ratio, (2) Retained earnings to total assets ratio, (3) Earnings before interest and taxes (EBIT) to total assets ratio, (4) Market value of equity to book value of total debt ratio, and (5) Sales to total assets ratio. Due to the success of Altman's model, MDA became the widespread statistical technique that has been applied to many prediction models (Edmister 1972; Deakin 1977; Altman 1983; Fulmer et al. 1984; Altman 1993; McGurr 1996).

Buggakupta (2004) and Kiatkhajornvoung (2008) also used MDA to develop their models for the Thai corporations. Buggakupta (2004) model consisted of four variables which are (1) Sales to Total Assets, (2) Total Equity to Total Liabilities, (3) Current Liability to Total Assets, and (4) Long-term Liabilities to Total Assets. The study concluded that the predictive accuracy level of his model and the Altman (1993) model was very similar. Kiatkhajornvoung (2008) model consisted of three variables which are (1) Operating Income to Total Assets, (2) Shareholders' Equity to Total Assets, and (3) Net income for the last two years. They found that the leverage ratio and frequency of losses were the important predictors to signal the financial failure.

Nevertheless, most of the studies pointed out three limitations when using MDA which were (1) a violation of the assumption of multivariate normal distribution, (2) unsuitable for the interpretation of independent variables (Eisenbeis 1977), and (3) the lack of associated risk (Zopounidis and Doumpos 1999).

Ohlson (1980) was the first to apply the Multiple Logistic Regression Analysis (Logit) to the failure prediction study and he claimed that the model is superior to MDA due to lesser limitations. He successfully developed the model with nine predictors (7 financial ratios and 2 categorical variables). The two categorical variables are (1) whether total liabilities are equal or larger than Total Assets and (2) whether net income is negative for the last two years. Many works followed his study by using Logit analysis instead of MDA (Zavgren 1985; Altman and Sabato 2007; Altman, Sabato, and Wilson 2008).

Most of the previous studies were based on data set of large corporations as such data set is readily available and believed to be reliably audited by major accounting firms. On the other hand, Altman and Sabato (2007) seem to be the first to develop the default prediction model for U.S, SMEs using financial ratios. They covered 120 failed and 1,890 non-failed firms that had annual sales less than $65 million during the period 1994-2002. They selected five variables—(1) EBITDA to total assets, (2) Short-term debt to Total Equity, (3) Retained earnings to total assets, (4) Cash to total assets, and (5) EBITDA to interest expenses. These variables are different from those used by Altman models based on large corporations. They concluded that banks would likely enjoy significant benefits in terms of SME business profitability by modeling credit risk for SMEs separately from large corporations and the famous MDA failure prediction model from Altman (1993) would have lower ability to separate failed and non-failed clients than Logit model even when the same variables are used as predictors. Ciampi and Gordini (2009) used MDA and Logit models for small manufacturing firms in Italy and found that both methods are effective to predict the default probability for the sample firms. They also concluded that the default prediction model for small firms should be modeled separately from that of large and medium-sized firms.

Altman, Sabato and Wilson (2008) extended Altman and Sabato (2007) model using SMEs data set in the United Kingdom and qualitative information such as legal action by creditors to recover unpaid debts, company filing histories, comprehensive audit report/opinion data and firm specific characteristics. By using a very large data set of 66,833 failed firms and 5,749,188 non-failed firms that generated annual sales less than €50 million during the period 2000-2007, the study confirmed that Altman and Sabato (2007) model, developed from U.S. SME data, could give high predictive accuracy level in a different market and time period. Moreover, the additional qualitative information helped improve the predictive accuracy level.

More recent developments in default prediction models include the works of Duffle, Saita and Wang (2007) and Duan, Sun and Wang (2011). Duffle, Saita and Wang (2007) developed an econometric method for estimating term structures of corporate default probabilities over multiple future periods. The method combines traditional duration analysis of the dependence of event intensities on time varying covariates with conventional time-series analysis of covariates, in order to obtain maximum likelihood estimation of multi-period survival probabilities. Duan, Sun and Wang (2011) developed a reduced-form model for predicting corporate defaults over different prediction horizons. Their approach relies on constructing forward intensities.

Unfortunately, similar qualitative information used by Altman, Sabato and Wilson (2008) is unavailable for Thai SMEs. Moreover, the new approaches like Duan, Sun and Wang (2011) require stock market information, which is also unavailable for Thai SMEs. Therefore, it would still be interesting to follow the Altman and Sabato (2007) process to estimate a model based on a Thai SME data set.

RESEARCH METHODOLOGY

List of Candidate Variables

In the process of selecting candidate variables to be used in a model, we first explore all the financial ratios from the previous literatures review section. We also add some financial ratios that are normally required in the SMEs loan application forms in Thailand. Subject to the data availability, the final list of 22 candidate financial ratios that are included in our test together with the expected sign of the correlations with the probability of failure are shown in panel A of table 1. Panel B shows four categorical variables that are also included as candidate variables. These categorical variables are similar to those used by Kiatkhajornvong (2008) model.

To construct the default prediction model from MDA and Logit Method, we explore two sets of candidate variables-- set 1 where only financial variables are candidate variables and set 2 where financial variables and categorical variables are candidate variables.

The Data Set

Our samples are from BOL database provided by the Business

Table 1. Candidate Financial Ratios and Categorical Variables

Panel A of the table shows the detail of candidate financial ratios used for developing failure prediction model. These ratios are divided into five groups--liquidity, leverage, coverage, profitability and activity ratios. Panel B shows the list of categorical variables used for developing failure prediction model. The detail and the expectation sign of the correlations of each variable with the probability of failure (y=1) are also included.

Panel A: Candidate Financial Ratios

Categories	Candidate Financial Ratios	Name of Variables	Expected Sign of the Correlations with the Probability of Failure
Liquidity	Cash/Total Assets	CashToTA	-
	Cash/Current Liabilities	CashToCL	-
	Current Assets/Current Liabilities	CAToCL	-
	Current Liability/Total Assets	CLToTA	+
	Working Capital/Total Assets	WCToTA	-
	Working Capital/Total Liabilities	WCToTL	-
Leverage	Current Liability/Total Equity	CLToTE	+
	Total Equity/Total Liability	TEToTL	-
	Total Liability/Total Equity	TLToTE	+
	Long-Term Liability/Total Assets	LTDebtToTA	+
	Total Liabilities /Total Assets	TLToTA	+
	Total Equity/Total Asset	TEToTA	-
Activity	Sales/Current Assets	SalesToCA	-
	Sales/Total Assets	SalesToTA	-
	Operating Income/Total Assets	OptIncToTA	-
	EBT/Total Equity	EBTToTE	-
Profitability	EBT/Total Assets	EarnBfTaxToTA	-
	Net Income/Sales	NetIncTosales	-
	Net Income/Total Assets	ROA	-
	Net Income/Total Equity	ROE	-
	EBITDA/Total Assets	EBITDAToTA	-
	EBIT/Total Assets	EBITToTA	-

Online Public Company Limited. BOL database is commonly used by universities and financial institutions in Thailand. They claim that the financial information of Thai companies in their database is based on document officially submitted to the Ministry of Commerce of Thailand. Following the guideline of Bank of Thailand (BOT), the SMEs in this study are those with their annual sales less than 1,000 million baht and the failed companies are the bankruptcy

Table 1. (continued)

Panel B: Categorical Variables		
Name of Variables	Value	Expected Sign of the Correlations with the Probability of Failure
TwoYearsProfit	1 if Net income is positive for the last two years; 0 otherwise	-
ThreeYearsProfit	1 if Net income is positive for the last three years; 0 otherwise	-
TwoYearsLoss	1 if Net income is negative for the last two years; 0 otherwise	+
ThreeYearsLoss	1 if Net income is negative for the last three years; 0 otherwise	+

companies reported in the BOL database. We first collect data of failed companies over the period 2000–2010 and then we match each of a failed company with two non-failed companies. Following Altman (1993), Buggakupta (2004), Kiatkhajornvong (2008) and Treewichayapong (2010), we use the following matching criteria--similar asset size and same industry ISIC code. The selected samples also need to pass the following three criteria—have a fiscal year-end as of December 31st, have all required financial information and a failed company must have at least 2-year complete data of all required financial information prior to bankruptcy.

The outliers can have a major impact to the estimated coefficients. From our data set, the two variables—TEToTA and TEToTL ratios have some major outliers. Thus, we arbitrary exclude the samples with TEToTA and TEToTL having the values at the top 5 percent of all samples. The total sample is divided into two sub-samples. The sample over the period 2000-2007 is used to develop the model (in-sample estimation) and the sample over the period 2008-2010 is used to validate the model (out-of-sample test). There are 353 failed firms and 706 non-failed firms (1:2) which are 199 failed firms and 398 non-failed firms for in-sample estimation and 154 failed firms and 308 non-failed firms for out-of-sample test. We are aware that the sample size is not large but the 353 failed firms are almost triple the sample size of Altman and Sabato (2007) covering 120 failed firms in the U.S.A.

Statistical Models

Although, there are many different techniques used to develop the bankruptcy prediction model, the two widely-used techniques are Multiple Discriminant Analysis (MDA) and Logistic Regression Analysis (Logit). Moreover, the required financial information of the two techniques are ready available from the BOL database.

Multiple Discriminant Analysis (MDA)

MDA is a multivariate analytical method that can characterize the differences of features among the categorical variables in a sample with respect to several variables simultaneously. Altman (1968) was the first to apply the MDA technique to predict firm failure by using financial ratios. The final model became the well known "Z-Score" model. This analysis was later used by many researchers (Edmister 1972; Blum 1974; Deakin 1977; Eisenbeis 1977; Taffler and Tisshaw 1977, Bilderbeek 1979; Altman 1983; Micha 1984; Fulmer et al. 1984; Gombola et al. 1987; Altman 1993; McGurr 1996; Lussier 1995; Altman, Hartzell and Peck 1995).

Using data of Thai listed firms, Buggakupta (2004) and Kiatkhajornvoung (2008) also applied this technique. Buggakupta (2004) developed the model from a match-paired sample of 88 failed and 88 non-failed firms during the period 1998–2002. The final model had the following explanatory variables—Sales to Total Assets, Total Equity to Total Liabilities, Current Liability to Total Assets, Long-term Liabilities to Total Assets, and Overall Failure Index. Kiatkhajornvoung (2008) model was developed from 31 failed and 62 non-failed firms which were matched with the bankruptcy firms (with the same industry and a similar asset size) in the proportion of 1:2. They defined the failed firms as the rehabilitation companies classified by the Stock Exchange of Thailand (SET). The final model had the following explanatory variables—Operating Income to Total Assets, Shareholders' Equity to Total Assets, Dummy variable for negative Net income for the last two years, and Overall Failure Index.

For our study, a dependent variable or a discriminator variable is the failed event and the independent variables are the set of predictive financial ratios.

The dependent variable is related to the independent variables in the following way:

$$D = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i \tag{1}$$

We called the equation (1) as the (Fisher) discriminant function where D is called the Discriminant Score. The β_i are the discriminant coefficients, the X_i are independent variables or discriminator variables and α is a constant. We estimate the linear regression with the coefficients that maximize the fraction of between-groups sum square and within groups sum square by following the simple linear regression principle and the analysis of variance (ANOVA).

Forecasting Error Index

Counted R-Squared transforms the continuous predicted probabilities into a binary variable on the same scale as the outcome variable and then assesses the predictions as correct or incorrect. For MDA, counted R-Squared treats any record that has the discriminant score near the centroid of failed firms (y=2) as having a predicted outcome of 2 and any record that has the discriminant score near the centroid of non-failed firms (y=1) as having a predicted outcome of 1.

Then, the predicted 1s that match actual 1s and predicted 2s that match actual 2s are tallied. The R-square is the correct count divided by the total count.

$$\text{Counted } R^2 = \frac{\text{No. of Correct Prediction}}{\text{Total No. of observation}} \tag{2}$$

Logistic Regression Analysis (Logit)

This technique is very similar to MDA as it also can explain a categorical variable. However, it is a useful technique for analyzing data that includes dichotomous or binary response variable. The Logistic Regression Analysis assumes that the probability function is the logistic distribution that resembles the normal distribution in shape but it has heavier tails; higher kurtosis. The result will yield a score between zero and one which conveniently gives the probability of the chosen situations. Logistic Regression Analysis has been used in many researches as well (Casey and Bartczak 1985; Gentry, Newbold and Whitford 1985; Zavgren1985; Keasy and Watson 1987; Aziz, Emanuel and Lawson 1988; Platt and Platt 1990; Platt, Platt and Pederson 1994; Mossman et al. 1998; Charitou and Trigeorgis 2002; Becchetti and Sierra 2002; Altman and Sabato 2007; Altman, Sabato, and Wilson 2008).

Altman and Sabato (2007) used a logistic regression technique on a panel over 2,000 SME firms including 120 failed firms in the USA during the period 1994–2002. The process started from constructing the US SMEs dataset, selecting the variables, and finally estimating the model using forward stepwise selection. During the step of variables selection, they included the financial ratios successful in predicting firms' bankruptcy from the prior studies and also graphically analyzed (side-by-side box plots) the relationship between the selected financial ratios and the default event in order to understand how they were related. Their final model had the following explanatory variables—EBITDA to Total Assets, Short-term Debt to Total Equity, Retained Earnings to Total Assets, Cash to Total Assets, EBITDA to Interest Expenses, and the probability of non-defaulting.

For logistic regression where the dependent variable (y) is the categorical variables (e.g. 0 and 1), the relationship between the independent variables (x_i) and dependent variable (y) are not linear. Therefore, many textbooks show that we can arrange the linear relationship by modifying the related equation into linear equation in terms of Log-odds ratio.

$$\text{Odds} = \frac{\Pr(y = 1|}{\Pr(y = 0|} \tag{3}$$

$$\begin{aligned} \log(\text{Odds}) &= \log\left[\frac{\Pr(y = 1|\ x}{\Pr(y = 0|\ x}\right. \\ &= \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p \end{aligned} \tag{4}$$

The equation (3) is called *Odd Ratio* and indicates how much more likely, with respect to odds, a certain event occurs in one group relative to its occurrence in another group. The equation (4) was in linear equation form which is called *Logit Response Function*. The slope can be interpreted as the change in the average value of y, from one unit of change in x_i.

Forecasting Error Index

Similar to the case of MDA, we can also use *Counted R-Squared*.

For example, assuming that 0.5 is a threshold value, counted R-Squared treats any record with a predicted probability greater than 0.5 as having a predicted outcome of 1 and any record with a predicted probability of 0.5 or less than as having a predicted outcome of 0.

$$\text{If } \Pr(y = 1|x) \text{ or } \hat{p} > 0.5, \text{ then, } \hat{y} = 1$$
$$\text{If } \Pr(y = 1|x) \text{ or } \hat{p} \leq 0.5, \text{ then, } \hat{y} = 0 \qquad (5)$$

Then, the predicted 1s that match actual 1s and predicted 0s that match actual 0s are tallied. The counted R-squared is the same as shown in equation (3).

Stepwise Selection Method

Stepwise selection method is an attempt to find the best set of predictors using stepwise regression. It is often used in a situation, where a researcher needs to choose a few major variables from among a larger number of variables. Stepwise regression allows some or all of the variables in a standard linear multivariate regression to be chosen automatically, using various statistical criteria, from a set of variables. The main approaches are;

(1) Forward Selection: the process automatically starts by entering the variables one by one based on the discriminate power of each variable. Then it selects the best two variables among those that contain the first selected variable. The process continues and stops when it reaches the point where no additional variables have p-value level < 0.5.

(2) Backward Elimination: the process automatically starts with the full model. Next, the variable that is least significant, given the other variables, is removed from the model. The process continues until all of the remaining variables have p-value < 0.10.

(3) Stepwise Selection: this method is the combination of the two approaches. It statistically tests at each stage for variables to be included or excluded.

We chose the stepwise selection method as they combined both forward selection and backward section.

Hypothesis Testing

In order to compare the predictive power of each model in predicting failed firms of Thai SME, we use the Z-test statistic for two sample proportion test, by stating the null and the alternative hypotheses that:

H_0: There is no difference between the levels of predictive accuracy of the two models.
H_1: There is a difference between the levels of predictive accuracy of the two models.

The formula for the significance of the difference between proportions is:

$$Z = \frac{P_1 - P_2}{\sqrt{\frac{P_1(1 - P_1)}{n_1} + \frac{P_2(1 - P_2)}{n_2}}} \qquad (6)$$

Where P_1 is the proportion of firms correctly classified by the first model, P_2 is the proportion of firms correctly classified by the second model, n_1 is the sample size of the first model and n_2 is the sample size of the second model.

EMPIRICAL RESULTS

Selection of the Variables

The test of equality of group means for each independent variable

In order to proceed with Multivariate Discriminant Analysis (MDA) or Logistic Regression Analysis (Logit), it is important to first test whether the mean of candidate variables are significantly difference between the failed and non-failed companies. We use the test of equality of group means for each independent variable. The result is shown in table 2. We can reject the null hypothesis for thirteen variables—CashToTA, CLToTA, WCToTA, CLToTE, TLToTE, LTDebtToTA, TLToTA, TEToTA, SalesToTA, OptIncToTA, EarnBfTaxToTA, NetIncTosales and ROA. Therefore, we only keep these thirteen variables and proceed to the next step.

Table 2. The Test of Equality of Group Means for each Independent Variable

The table shows the result of F-test of equality of group means for each independent variable. The null hypothesis is that the mean of each independent variable between the failed and non-failed group equals. At 95% confidence level, we will reject the null hypothesis when the probability is lower than 0.05.

Categories	Candidate Variables	Wilks' Lambda	F	df1	df2	Sig.	Decision
Liquidity	CashToTA	0.979	12.7647	1	595	0.0004	Reject H_0
	CashToCL	0.9989	0.673	1	595	0.4123	
	CAToCL	0.9982	1.0505	1	595	0.3058	
	CLToTA	0.931	44.1041	1	595	0.0000	Reject H_0
	WCToTA	0.9258	47.6597	1	595	0.0000	Reject H_0
	WCToTL	0.9982	1.061	1	595	0.3034	
Leverage	CLToTE	0.9887	6.7947	1	595	0.0094	Reject H_0
	TEToTL	0.9989	0.6364	1	595	0.4253	
	TLToTE	0.9923	4.6384	1	595	0.0317	Reject H_0
	LTDebtToTA	0.9632	22.7449	1	595	0.0000	Reject H_0
	TLToTA	0.9122	57.304	1	595	0.0000	Reject H_0
	TEToTA	0.9124	57.158	1	595	0.0000	Reject H_0
Activity	SalesToCA	0.9983	1.0371	1	595	0.3089	
	SalesToTA	0.9901	5.9236	1	595	0.0152	Reject H_0
	OptIncToTA	0.9884	6.9939	1	595	0.0084	Reject H_0
	EBTToTE	0.9995	0.2935	1	595	0.5882	
Profitability	EarnBfTaxToTA	0.9907	5.584	1	595	0.0184	Reject H_0
	NetIncTosales	0.9653	21.4192	1	595	0.0000	Reject H_0
	ROA	0.9896	6.2489	1	595	0.0127	Reject H_0
	ROE	0.9995	0.3116	1	595	0.5769	
	EBITDAToTA	0.9938	3.7059	1	595	0.0547	
	EBITToTA	0.9939	3.6773	1	595	0.0556	

Multicollinearity tests

The objective of this testing is to detect whether the chosen variables might have the multicollinearity problem. We perform the correlation testing with the thirteen variables from the previous section. We use two correlation tests--Pearson Correlation and Spearman Correlation. Pearson Correlation is the first statistical tool that we use. If the result shows that there is high correlation (the value is greater than 0.5) between some independent variables, then we calculate Spearman Correlation of those highly correlated

Table 3. The Descriptive Statistics of the Selected Candidate Ratios

The table shows the mean and standard deviation of eight candidate ratios of 2 groups—non-failed firm and failed firm. These ratios have passed the test of equality of group means as shown in Table 2 and the multicollinearlity test.

Company Status/Candidate Ratios		Mean	Std. Deviation	Number of Observations
Non-failed Firm	CashToTA	0.1568	0.2314	398
	WCtoTA	0.3702	0.3914	398
	CLToTE	2.4368	13.4012	398
	LTDebtToTA	0.2243	1.7734	398
	TLToTA	0.5344	1.806	398
	OptIncToTA	0.0739	0.6867	398
	EarnBfTaxToTA	0.067	0.644	398
	NetIncToSales	-0.0116	0.4932	398
Failed Firm	CashToTA	0.0879	0.2024	199
	WCtoTA	-3.5287	11.2631	199
	CLToTE	-0.1236	4.9548	199
	LTDebtToTA	2.8853	10.8539	199
	TLToTA	6.95	16.7278	199
	OptIncToTA	-0.9568	7.7204	199
	EarnBfTaxToTA	-0.9771	8.7743	199
	NetIncToSales	-9.1736	39.5213	199
Total	CashToTA	0.1338	0.2244	597
	WCtoTA	-0.9294	6.755	597
	CLToTE	1.5833	11.3685	597
	LTDebtToTA	1.1113	6.5428	597
	TLToTA	2.6729	10.2125	597
	OptIncToTA	-0.2697	4.5113	597
	EarnBfTaxToTA	-0.2811	5.1084	597
	NetIncToSales	-3.0656	23.1893	597

variables with the dependent variable or company status. We will then keep the variable having the highest value of Spearman Correlation with the dependent variable. Following Altman and Sabato (2007), we categorize the financial ratios into four groups and we only test the multicollonearity problem within each group. This is to maintain important information of financial ratios of all the groups.

We manage to eliminate five variables, which are CLToTA, TLToTE, TEToTA, SalesToTA and EarnBfTaxToTA, and keep only eight variables for the next process. The list of the eight candidate financial ratios and their descriptive statistics are shown in table 3.

Developing MDA Model

The model is developed from the sample of 199 failed and 398 non-failed firms. We assign the dependent variable as the value of 1 when firm is a non-failed case and the value of 2 when firm is a failed case. The SPSS program is used to estimate the model with stepwise procedure.

We develop two models; (1) Model with only financial ratios and (2) Model with financial ratios and categorical variables.

MDA Model 1: Developing the model from financial ratios as the independent variables

After the stepwise procedure, the final model contains six variables, which are CashToTA, WCToTA, CLToTE, LTDebtToTA, TLToTA, and NetIncTosales. The estimated constant and coefficients are shown in equation (7).

$$D = -0.704 + 1.271X_1 + 1.175X_2 + 0.022X_3 - 1.127X_4 + 1.080X_5 + 0.014X_6 \tag{7}$$

where, D = Discriminant Score

X_1 = CashToTA

X_2 = WCToTA

X_3 = CLToTE

X_4 = LTDebtToTA

X_5 = TLToTA

X_6 = NetIncTosales

We perform the significance test and find the Chi-square statistic value to be 102.748. At 95 percent confidence level, we reject the null hypothesis that all and each of the coefficients in equation (7) equal zero.

To validate the model, we test the out sample of 154 failed and 308 non-failed firms by using equation (7) and classify the sample by the group centroid. The classification result of Model 1 is shown in Table 4.

The model can correctly predict 27.6 percent and 41.6 percent of the failed firms in in-sample test and out-of sample test while it can correctly predict 99.0 percent and 100.0 percent of non-failed firms.

Table 4. Classification Result: MDA Model 1

This table shows the accuracy of MDA Model 1 in predicting the failed and non-failed by using only financial variable in the analysis. For MDA, we treat any case that has the discriminant score near the centroid of failed firms (y = 2) as having a predicted outcome of 2 and any record that has the discriminant score near the centroid of non-failed firms (y = 1) as having a predicted outcome of 1.

			Company Status	Predicted Group Membership		Total
				1	2	
In-sample test	Original	Count	1	394	4	398
			2	144	55	199
		%	1	99.0	0.01	100.0
			2	72.4	27.6	100.0
Out-of-sample test	Original	Count	1	308	0	308
			2	90	64	154
		%	1	100.0	0.0	100.0
			2	58.4	41.6	100.0
a. In-sample test	Counted R-Squared		75.2%			
b. Out-of-sample test	Counted R-Squared		80.5%			

So if the model predicts that the sample belongs to a failed group, it stands a very high chance that the sample is correctly predicted. As a result, model 1 achieves a moderate level of classification accuracy by showing the counted R-squared of 75.2 percent and 80.5 percent for the in-sample test and out-of-sample test, respectively.

MDA Model 2: Developing the model from financial ratios and categorical variables as the independent variables

We use eight candidate financial ratios and four candidate categorical variables. After the stepwise procedure, the final model contains three financial ratios; CashToTA, CLToTE and TLToTA, and two categorical variables; TwoYearsLoss and ThreeYearsProfit. The constant and the estimated coefficients are shown in equation (8).

$$D = -0.255 + 1.075X_1 + 0.014X_2 - 0.048X_3 - 1.039X_4 + 1.219X_5 \qquad (8)$$

Table 5. Classification Result: MDA Model 2

This table shows the accuracy of MDA Model 2 in predicting the failed and non-failed by using both financial variable and categorical variable in the analysis. For MDA, we treat any case that has the discriminant score near the centroid of failed firms (y=2) as having a predicted outcome of 2 and any record that has the discriminant score near the centroid of non-failed firms (y=1) as having a predicted outcome of 1.

			Company Status	Predicted Group Membership		Total
				1	2	
In-sample test	Original	Count	1 2	348 96	50 103	398 199
		%	1 2	84.4 48.2	12.6 51.8	100.0 100.0
Out-of-sample test	Original	Count	1 2	278 58	30 96	308 154
		%	1 2	90.3 37.7	9.7 62.3	100.0 100.0
a. In-sample test	Counted R-Squared		75.5%			
b. Out-of-sample test	Counted R-Squared		81.0%			

where, D = Discriminant Score
X_1 = CashToTA
X_2 = CLToTE
X_3 = TLToTA
X_4 = TwoYearsLoss
X_5 = ThreeYearsProfit

From the significance test, the Chi-square statistic value is 192.004 of, so we reject the null hypothesis at 95 percent confidence level that all and each of the coefficients in equation (8) equal zero. The classification result is shown in Table 5.

The classification table shows that Model 2 can correctly predict 51.8 percent and 62.3 percent of the failed firms in in-sample test and out-of sample test while it can correctly predict 84.4 percent and 90.3 percent of non-failed firms. This means that model 2 can better predict bankruptcy group as compared to model 1. Thus, the counted R-Squared is slightly higher at 75.5 percent and 81.0 percent in in-sample test and out-of-sample test, respectively.

Comparisons of MDA Models

Model 2 contains only five variables but it manages to achieve slightly higher counted R-Squared. Model 2 can also correctly predict the non-failed firm at highly rate of 62.3 percent in the out-of sample test compared to only 41.6 percent for Model 1. Therefore, MDA Model 2 is preferred.

Developing Logit Model

This section describes the development of a model using Logistic Regression Analysis (Logit). We assign the dependent variable as the value of 0 when firm is a non-failed case and the value of 1 when firm is a failed case. The SPSS program is used to estimate the model with stepwise procedure.

Similar to the MDA method, we develop two models; Model 1 with only eight financial variables and Model 2 with added four categorical variables.

Logit Model 1: Developing the model from financial ratios as the independent variables

From the stepwise process, our final model contains three variables which are WCToTA, TLToTA, and NetIncTosales. The constant and the estimated coefficients are shown in equation (9).

$$W = -1.277 - 0.950X_1 + 0.405X_2 - 0.725X_3 \tag{9}$$

where, W = The probability of failed firms

X_1 = WCToTA

X_2 = TLToTA

X_3 = NetIncTosales

From the significant test, we are able to reject the null hypothesis at 95 percent confidence level that all coefficients in equation (9) do not equal zero.

To validate the model, we use the out sample of 154 failed and 308 non-failed firms. The classification result is shown in Table 6.

The result shows that the model can correctly predict 54.8 percent

Table 6. Classification Result: Logit Model 1

This table shows the accuracy of Logit Model 1 in predicting the failed and non-failed where the cutoff value is 0.5.

			Company Status	Predicted Group Membership		Total
				1	2	
In-sample test	Original	Count	1	395	3	398
			2	90	109	199
		%	1	99.2	0.8	100.0
			2	45.2	54.8	100.0
Out-of-sample test	Original	Count	1	306	2	308
			2	65	89	154
		%	1	99.4	0.6	100.0
			2	42.2	57.8	100.0
a. In-sample test	Counted R-Squared		84.4%			
b. Out-of-sample test	Counted R-Squared		85.5%			

and 57.8 percent of the failed firms in in-sample test and out-of-sample test while it can correctly predict 99.2 percent and 99.4 percent of non-failed firms. So if the model predicts that a firm is a failed firm, it is likely that the firm is an actual failed firm. The result also shows that the model achieves a rather high level of classification accuracy by showing the counted R-squared of 84.4 percent and 85.5 percent for the in-sample test and out-of-sample test, respectively.

The three independent variables—TLToTA, WCToTA and NetIncTosales, are also presented in the MDA Model 1 with six variables. It is interesting to note that with fewer variables, the Logit model can give a higher predictive accuracy than that of MDA model.

Logit Model 2: Developing the model from financial ratios and categorical variables as the independent variables

After the stepwise process, the final model contains WCToTA, CLToTE, and TLToTA and two categorical variables, which are TwoYearsLoss and ThreeYearsProfit. The constant and the estimated

Table 7. Classification Result: Logit Model 2

This table shows the successive accuracy of Logit Model 2 in predicting the failed and non-failed firms where the cutoff value is 0.5.

			Company Status	Predicted Group Membership		Total
				1	2	
In-sample test	Original	Count	1 2	379 84	19 115	398 199
		%	1 2	95.2 42.2	4.8 57.8	100.0 100.0
Out-of-sample test	Original	Count	1 2	296 64	12 86	308 154
		%	1 2	96.1 41.6	3.9 58.4	100.0 100.0
a. In-sample test	Counted R-Squared		82.7%			
b. Out-of-sample test	Counted R-Squared		83.5%			

coefficients are computed and shown in equation (10).

$$W = -0.484 - 1.058X_1 - 0.101X_2 + 0.249X_3 + 0.603X_4 - 1.498X_5 \tag{10}$$

where, W = The probability of failed firms

X_1 = WCToTA

X_2 = CLToTE

X_3 = TLToTA

X_4 = TwoYearsLoss

X_5 = ThreeYearsProfit

For the significant test, we are able to reject the null hypothesis at 95 percent confidence level that all coefficients in equation (10) do not equal zero.

The classification results for in-sample test and out-of-sample test are shown in Table 7.

The result shows that the model can correctly predict 57.8 percent and 58.4 percent of the failed firms in in-sample test and out-of-sample test, respectively. The predictive accuracy of failed firms is higher than that of the Logit Model 1. However, it can correctly predict 95.2 percent and 96.1 percent of non-failed firms in in-sample test and out-of sample test. The predictive accuracy of non-failed firms is lower than that of the Logit Model 1. The result also shows that the model achieves a rather high level of classification accuracy by showing the counted R-squared of 82.7 percent and 83.5 percent for the in-sample test and out-of-sample test, respectively.

Comparisons of Logit Models

There are two variables, which are WCToTA and TLToTA, that appear in both Logit Model 1 and Model 2. However, the counted R-Squared in Model 1 are higher than those in Model 2. Moreover, Model 1 contains only three variables, while Model 2 contains five variables. So, Logit Model 1 is preferred.

The comparison between MDA Model 2 and Logit Model 1

We compare the predictive accuracy of the MDA Model 2 and the Logit Model 1 by focusing on the out-of-sample test. The counted R-squared of MDA Model 1 is 81.0 percent, which is lower than 85.5% of the Logit Model 2. Thus, the latter has higher predictive accuracy. The Z-test statistic is selected to determine the significance of difference between both models. The null and alternative hypotheses are shown below.

H_0: There is no difference between the levels of predictive accuracy of MDA Model 2 and Logit Model 1 in predicting failed SME firms in Thailand.

H_1: There is a difference between the levels of predictive accuracy of MDA Model 2 and Logit Model 1 in predicting failed SME firm in Thailand.

The Z-test statistic is -1.85 and we can reject the above null hypothesis at the confidence level of 90 percent. Thus, the Logit Model 1 has higher predictive accuracy and the difference is significant using the Z test.

We explore further by combining the predicted results in terms of bankruptcy from MDA and Logit models to investigate whether these combined results can improve the predictive accuracy of the failed firms. If either the MDA Model 2 or the Logit Model 1 predicts that a firm is classified as bankruptcy, that sample will be recorded as bankruptcy. The previous result shows that the MDA Model 2 and the Logit Model 1 can correctly predict 62.3 percent and 57.8 percent of the bankruptcy firms in out-of- sample test, respectively. Using the combined results as described above, we can correctly predict 70.1 percent which is a lot higher than using one model alone. Thus, while previous studies either use MDA or Logit alone, our results show that we can increase the accuracy of default prediction by combining the forecast of both methods.

Robustness Checks: The comparison of large corporate model and SME model

This section compares Logit Model 1 with other two default prediction models from Buggakupta (2004) and Kiatkhajornvong (2008), which are developed from listed companies a the Stock Exchange of Thailand (SET). The counted R-squared is used to compare the predictive accuracy of the three models. The Z-test statistic is selected to determine the significance of difference in accuracy rate between models.

Because of different period of time and sample companies, we reestimate the coefficients of independent variables of the above two large corporate models with our SME data using the same methods as described in those papers.

Revised Buggakupta Model

The newly estimated constant and coefficient from discriminant procedure when using the independent variables in Buggakupta model is shown in equation (11).

$$B = -0.060 - 0.079X_1 + 0.000X_2 + 0.119X_3 + 0.073X_4 \tag{11}$$

where, X_1 = SalesToTA
X_2 = TEToTL
X_3 = CLToTA
X_4 = LTDebtToTA
B = Overall Failure Index

The classification result of this model is shown in Table 8.

The result shows that the model achieves 69.5 percent and 74.2 percent of counted R-squared for the in-sample test and out-of-sample test, respectively. It is interesting to note that the model is

Table 8. Classification Result: Revised Buggakupta Model

This table shows the accuracy of MDA in predicting the failed and non-failed by using the variables from the Buggakupta model. For MDA, any case that has the discriminant score near the centroid of failed firms (y=2) as having a predicted outcome of 2 and any record that has the discriminant score near the centroid of non-failed firms (y=1) as having a predicted outcome of 1.

<table>
<tr><th colspan="3" rowspan="2"></th><th rowspan="2">Company Status</th><th colspan="2">Predicted Group Membership</th><th rowspan="2">Total</th></tr>
<tr><th>1</th><th>2</th></tr>
<tr><td rowspan="2">In-sample test</td><td rowspan="2">Original</td><td>Count</td><td>1
2</td><td>382
166</td><td>16
33</td><td>398
199</td></tr>
<tr><td>%</td><td>1
2</td><td>96.0
83.4</td><td>4.0
16.6</td><td>100.0
100.0</td></tr>
<tr><td rowspan="2">Out-of-sample test</td><td rowspan="2">Original</td><td>Count</td><td>1
2</td><td>298
109</td><td>10
45</td><td>308
154</td></tr>
<tr><td>%</td><td>1
2</td><td>96.8
70.8</td><td>3.2
29.2</td><td>100.0
100.0</td></tr>
<tr><td>a. In-sample test</td><td colspan="2">Counted R-Squared</td><td>69.5%</td></tr>
<tr><td>b. Out-of-sample test</td><td colspan="2">Counted R-Squared</td><td>74.2%</td></tr>
</table>

able to predict the failed firm in the out-of-sample correctly at only 29.2 percent.

Revised Kiatkhajornvong Model

For Kiatkhajornvong models, the newly estimated constant and coefficients are shown in equation (12).

$$Z = -0.605 + 0.008X_1 - 0.061X_2 + 1.1958X_3 \quad (12)$$

where, X_1 = OptIncToTA
X_2 = TEToTA
X_3 = TwoYearsLoss
Z = Overall Failure Index

The classification result of this model is shown in Table 9.

The result shows that the model achieves 74.7 percentand 80.3 percent of counted R-squared for the in-sample test and out-of-

Table 9. Classification Result: Revised Kiatkhajornvong Model

This table shows the accuracy of MDA in predicting the failed and non-failed by using the variables from the Kiatkhajornvong model. For MDA, any case that has the discriminant score near the centroid of failed firms (y=2) as having a predicted outcome of 2 and any record that has the discriminant score near the centroid of non-failed firms (y=1) as having a predicted outcome of 1.

			Company Status	Predicted Group Membership		Total
				1	2	
In-sample test	Original	Count	1	341	57	398
			2	94	105	199
		%	1	85.7	14.3	100.0
			2	47.2	52.8	100.0
Out-of-sample test	Original	Count	1	276	32	308
			2	59	95	154
		%	1	89.6	10.4	100.0
			2	38.3	61.7	100.0
a. In-sample test	Counted R-Squared		74.7%			
b. Out-of-sample test	Counted R-Squared		80.3%			

sample test, respectively.

Results Comparison

We have tested in earlier section that the Logit Model 1 gives higher predictive accuracy, so we now compare the result of both large corporate models with the Logit Model 1. When comparing chosen variables across all three models, we find that chosen variables in the Logit Model 1 are totally different from those from the Buggakupta model and Kiatkhajornvong model. This is consistent with our expectation that the SME model should be developed separately as the explanatory variables are totally different from those chosen in the large corporate models.

The results of predictive accuracy level and Z-score of out-of-sample test for revised Buggakupta model, revised Kiatkhajornvong model, and Logit Model 1 are presented in Table 10.

The table shows that both large corporate models can still give high predictive accuracy level for the SME data (74.2 percent from

Table 10. Comparison of Level of Predictive Accuracy: SME Model and Large Corporate Models

This table shows level of predictive accuracy and the result of Z-test statistic of out-of-sample test.

Out-of-sample test	Level of Predictive Accuracy (Counted R-Squared)	When compared with Logit Model 1	
		Z Score	At 95% Confidence level
Revised Buggakupta Model	74.2%	-4.31	Reject H0
Revised Kiatkhajornvong Model	80.3%	-2.10	Reject H0
Logit Model 2	85.5%		

Buggakupta model and 80.3 percent from Kiatkhajornvong model). However, our Logit Model 1 gives the highest predictive accuracy level of 85.5 percent. We are also able to reject the null hypothesis that there is no difference between the levels of predictive accuracy of the large corporate models and the Logit Model 1.

CONCLUSION

Due to bankruptcy risk, numerous studies have attempted to develop credit risk or default prediction models by using several statistical methods. Multivariate Discriminant Analysis (MDA) and Logistic Regression Analysis (Logit) are two of the most commonly used statistical techniques in this field of studies. Similar to international studies, previous studies on Thai companies was concentrated on developing the credit risk model from the large companies listed in the Stock Exchange. The studies based on SME data are rare and this study might help to shed some light for credit risk of SME in a developing market like Thailand. This is because the SMEs play important role in Thai economy and also to almost all economies in the world. We develop default prediction models for Thai SMEs by using both the MDA and Logit models. The study covers Thai SME firms during year 2000 to 2010 from the BOL database. The SPSS program and stepwise analysis are used to select variables for the MDA and Logit models. The extensive set financial ratios and categorical variables were included as candidate variables.

For the MDA Model 2, the predictive accuracy level or counted R-Squared is 81.0 percent for out-of-sample test, while the Logit Model 1 has the predictive accuracy level of 85.5 percent for out-of-sample test. It is interesting to note that Logit Model 1 with higher accuracy level contains only 3 variables which are WCtoTA (Working Capital/Total Assets), TLToTA (Total Liability/Total Assets) and NetIncTosales (Net Income/Sales). We also combine the forecasts from the MDA and Logit models for bankruptcy cases only, and the predictive accuracy level has improved to 70.1 percent for out-of- sample test, compared to 62.3 percent and 57.8 percent from MDA and Logit model respectively. Hence, financial institutions might benefit by combing the forecasts from both models to achieve higher predicting accuracy level of bankruptcy firms. For robustness check, we compare the models based on large corporations with our newly developed model based on SME data. Due to different data set and time periods, we reestimate the coefficients of both large corporate models with our available SME data. We find that our newly developed model is superior and such evidence would support the idea that the credit risk models for SMEs should be developed separately from models based on large corporations. Last, financial institutions with their own unique data of their customers can also benefit from developing their own models by following the process as shown in this study.

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