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Early Warning Signals on Credit Risk Mitigation among SME's in Malaysia

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Abstract
By combining financial and non-financial characteristics, the research creates a credit risk mitigation model for SME's. These variables were used to analyse the impact of owner education level, gender, and business age as an early warning signal to the credit risk mitigation. To analyse the impact of owner education level, gender, and business age as an early warning signal to the credit risk mitigation, the research developed a credit risk mitigation model for SME's by combining financial and non-financial characteristics. Utilizing all relevant information, a Multiple Discriminant Analysis (MDA) model was applied. 400 observations make up the final sample for the estimation model, of which half are distressed and non-distressed SME's, for the years 2015 to 2020. The prediction models perform relatively well in the financial and non-financial variables. This evidence shows that the models serve as efficient early warning signals and can thus be beneficial for monitoring and evaluation of credit risk.
Keywords: Credit Risk Mitigation, SME's, Multiple Discriminant Analysis

Introduction

SMEs play a significant role in the Malaysian economy, producing more than one-third of the country's GDP and creating employment possibilities for more than four million people. SMEs require both financial and non-financial support to grow their businesses. Financial institutions are increasingly providing a wide range of financial solutions to fund the businesses. Over 90% of all finance is provided to SMEs by banking institutions, making them the primary source of funding. The Development Financial Institutions, Bank Negara Malaysia's Funds for SMEs, and Government Funds are other sources of SME financing.

Since Malaysia's bad loan issues in the 1990s and 2000s, banks have made significant advancements in their analysis of the creditworthiness of SMEs. One strategy is to implement an internal credit rating system that assigns companies a financial stability score. In addition to important financial indicators like the capital adequacy ratio, qualitative factors like management's abilities and financial transparency are also considered. In order to determine loan extensions and rate spreads, scoring models for lending use statistical techniques to predict the risk that loan claims will default. Instead of handling each loan individually on a case-by-case basis, the scoring technique employs the rule of large numbers to restrict risks on loans. Due to this, the accuracy of the data tends to increase as the pool gets larger, making database design crucial.

However, there are theoretical restrictions on the internal ratings and scoring of banks (Hirata, 2005). First, there are typically concerns with SMEs' financial statements' accuracy. According to a Small and Medium Enterprise Agency survey, only about 30% of businesses are considering setting up accounts using appropriate accounting to enhance their capacity to get funding (Small and Medium Enterprise Agency, 2004).

The information's time lag is the second problem. It was regularly challenging to assess the current state of the companies because the most recent financial records for the settlement dates that were available for inspection were frequently from 3 to 15 months earlier. After financing, monitoring is also insufficient. With only financial information, banks find it difficult to comprehend the situations of their clients, which may change every day during the fiscal year.

Even if they had the best model, defaults would still happen since every bank had a different way of assessing how well its business were performing. A corporation's financial performance can be evaluated in several ways. According to prior studies, it's crucial to look at exact measurement from a range of perspectives rather than just focusing on one.

This study aims to develop a model to assess company especially the SMEs credit risk. The model is estimates to provide creditors in analyzing financial strength of SMEs before making important decisions in giving out loan to SMEs. Early sign can be traced to anticipate the event of default. Prudent measurement will improve effectiveness in the banking system in operating with low costs and low NPL.

Before considering providing a loan or making an investment in a firm, a financial institution or creditor has used the best model to evaluate and forecast the company's financial health. However with the help of the existing model, non-performing loan still occur. Therefore, it is necessary to enhance the current model in order to minimise and manage any debt default from the organisation. This model will give financial institutions, creditors, and investors detailed information and serve as an extra tool for evaluating business performance.

In addition, the paper's objective is to suggest a non-financial component for the assessment of credit risk for SME's. Through the creation of a model to forecast business loan default, this study focuses on evaluating the credit risk of SME's. The model will consider both financial and non-financial factors. Financial ratios will be used to measure the company financial performance. In addition to size, other non-financial factors that are considered include the owner's educational background, gender, and age of the organisation.

Literature Review

Credit Risk

Credit typically refers to money borrowing and lending. Essentially, it refers to a financial instrument that has pre-determined fixed payments that are made over a predetermined period, such as a loan that is issued to a borrower. Anita (2008) defines credit risk as the potential loss of valuable assets brought on by the expected deterioration of the counterparty's creditworthiness or its failure to uphold contractual obligations. Given that loan lending and deposit activities make up most of the a bank's primary activity, it has been regarded as the main risk for banking organisations (Basel Committee, 2001). Credit risk depends on the ability of borrowers to generate sufficient cash flows through operation, earnings, or asset sales to meet their future interest and principle payment of the outstanding debt.

According to Lopez and Saidenberg (2000), credit risk is the extent to which the value of debt instruments and derivatives changes as a result of changes in the underlying credit standing of counterparties and borrowers. The possibility of financial loss because of financing default is known as credit risk. It involves the borrower's failure to fulfil an obligation or make a payment. While according to Norlida et al (2015), credit risk is based on the borrower's ability to generate enough cash flows through operations, earnings, or asset sales to satisfy their future interest and principal payments of the outstanding debt.

The Basel Committee devotes particular attention to credit risk in developing regulations for financial institution guidance (Basel Committee, 2001). The committee concluded that credit risk is the main threat to banks and companies that participate in lending and deposit-taking. A credit risk assessment system is therefore necessary to determine a company's or an individual's capacity to pay back a loan. The inaccurate interpretation that results from a lack of information and experience in predicting credit evaluation can produce misleading findings.

Mechanism of Credit Risk Management

Every financial institution whose primary activity is lending needs to have an ideal and suitable credit evaluation model. When evaluating a company's performance, financial stability is a crucial factor. In addition, based on the extensive literature, the measurement should take all factors into account to estimate the company's overall performance. An important component of analysing a company's performance is financial information. It helps decision-makers make wise decisions by combining a variety of financial information quantities (Godfrey et al., 2010).

The default prediction model has grown to be one of the most significant and traditional tools available for estimating the probability of default. Back to 1960s saw the beginning of empirical investigations on default prediction where Beaver created a univariate discriminant analysis in 1966, and Altman improved on it in 1968 to create a multivariate discriminant analysis (MDA), which is still used today in the well-known Z-score model (Beaver, 1960; Altman, 1968).

Impact of Credit Risk Management

According to Franke et al (2011), the main purpose of risk management models is to assist credit analysts in determining whether or not to provide a loan, the appropriate risk premium, and the appropriate amount of modification to the loss reserve account. The firm's performance would be impacted by credit risk management. Financial reporting is essential for giving current and potential investors and creditors information they may use to make decisions about investments, loans, and trading activities (Spiceland et al., 2007). According to Shen et al (2012), the degree of information asymmetries has a major impact on how financial ratios affect credit ratings. They also recommended that the information asymmetry in the country be reduced for banks to boost the credit rating.

The increasing number of borrower defaults on loans has caused financial institutions to place a lot of emphasis on credit risk assessment, which is considered the most important topic in contemporary finance. They consider both internal and external credit scoring when deciding whether to approve a loan (Dean & Silvia, 2008). Credit risk management is essential for them to remain competitive globally. To prevent loan default, financial institutions are being more cautious and vigilant when making loans to prospective applicants (Lin, 2009).

Financial institutions have been compelled to concentrate on credit risk management in recent years due to financial market volatility and economic unpredictability. The existing methodologies for determining a company's credit worthiness are still insufficient and require improvement; as a result, creditors continue to bear the brunt of a high percentage of SME loan defaults. Since SMEs are considered to be riskier than large businesses, it is essential to identify the suitable loan recipient (James & Hwan, 2006). Barbara, Massililiano, and Antonello (2008) stated that financial institutions have their own credit risk models that they use when disbursing loans. It is crucial to have separate credit risk models for large and small businesses (Altman & Sabato, 2007). They stated that, small and medium-sized businesses face greater financial and institutional constraints than large corporations.

As a developing nation, credit risk assessment is essential to attracting and maintaining investors' trust to invest in Malaysia; hence, careful credit risk assessment should aid in strengthening the nation's financial system. The increasing pattern of Malaysia's bankruptcy rate reflects the rising rate of debt repayment failure (Norlida et al., 2015). There is a plenty of work on predicting SME credit risk. The component included evaluation from various perspectives while still adding to the sound empirical study. For assessing the performance of the company, no single measurement of financial performance is sufficient. The most current analysis used four different assessment criteria to evaluate the companies which are liquidity, leverage, profitability, and efficiency.

Financial Factor

A wide literature on credit risk has taken into account financial factors or quantitative data in its studies (Fabi et al., 2005). The three factors that have the strongest explanatory power for a company's financial performance are profitability, leverage, and liquidity ratio (James & Hwan, 2006) and (Kanitsorn & Dessalegn, 2011). A popular and effective technique for evaluating a company's success is the financial ratio. It is quite important for imagining a relationship between earning potential and default risk (Barbara et al., 2008). The ratio can provide a clear picture of the company's financial position (Dean & Silvia, 2008). In order to identify the company with prudent creditworthiness, Altman and Sabato (2007) devised a model utilising a whole set of financial ratios that takes profitability, leverage, and liquidity ratio into account. These ratio categories are used to forecast the likelihood that a SME would get into financial difficulties. When a variety of ratios are taken into account instead of only one, the financial capacity of SME is stronger (Kanitsorn & Dessalegn, 2011).

According to Jaroslav et al (2014), a borrower's financial capacity is a significant aspect that represents their ability to repay their debt to the bank, which is decided by the company's level of financial success. Additionally, it will have an impact on corporate operations and worsen the financial crisis. The financial analysis was the first step in determining financial feasibility, according to (Kalogeras, 2005).

Financial ratios are created using data from financial statements, therefore the corporation must supply accurate accounting figures (Norlida et al., 2015). Transparency among all parties is a crucial requirement for effective SMEs bank loan funding (European Association of Craft, Small and medium-sized Enterprises (2007); Bain & Company, Inc. and the Institute of International Finance, 2013). SME should offer accurate and true information since this is what commercial banks use to rate SME, and banks should employ open lending standards.

Non-financial Factor

A credit risk assessment model must take non-financial factors into account when evaluating a company's performance. Qualitative data is essential since it serves as an additional tool for predicting credit risk (Dean & Silvia, 2008). It is believed that qualitative information, such as the number of employees, location of the organisation, and industry, is necessary to complement quantitative information in describing a company's performance.

In addition, non-financial aspects like the company's age and the owner's educational background must be taken into account (Kanitsorn & Dessalegn, 2011). Carter et al (2007) looked at how gender and educational background affected bank lending to small firms. They discovered that the applicant's educational background plays a significant effect in the decision-making process and that female applicants with lesser levels of education are more likely to be rejected. The loan officer is more likely to be familiar with the company plan, financial background, and general qualities of the applicant when he is a male loan applicant. However, when a woman applies for a loan, the officers are more concerned with whether she has done enough research and focus more on her educational history.

Irwin & Scott (2010) look at the difficulties SMEs experience in obtaining bank financing in the UK. They have particularly examined at the entrepreneur's characteristics in terms of their ethnicity, gender, and level of education earned. According to the paper's empirical findings, 18% of males and 12% of women had difficulty raising money for their start-ups. It implies that because of their history of late payments and less dedication to their businesses, males are more financially limited than women.

Existing credit risk assessment models incorporate a variety of hard data types (quantitative data), despite the model's accuracy being close to 80%. In order to comprehend how this type of data affect financial and credit historical determinants, Francesco, Francesco and Fabrizio (2013) highly advise taking non-financial component into consideration in future models. Bogdan (2013) asserts that in order to make better informed lending decisions, banks must employ a variety of facts, including market share, ownership quality, management team expertise, and market skills.

Male and female respondents showed a considerable difference in their willingness to take risks, according to (Lim and Envick, 2011). When they discover an opportunity to enter a market which is competitive, men tend to be more aggressive. Women are much more satisfied when their businesses are stable rather than growing, which doesn't interest them as much. But it has been discovered that women are more innovative than men, which is one of their benefits in starting a new business. In this regard Langowitz and Minniti (2007) claim that women are more risk averse than males and increased riskiness does not prevent men from beginning the firm.

It was reaffirmed by Garwe and Fatoki (2012) that gender has no appreciable influence on SME financing. According to their study, commercial banks do not treat male- and female-owned SMEs differently when offering credit since they discovered no variation in the issue of credit availability to commercial banks for SMEs with male and female owners. Their study revealed that when applying for bank loans, both men and women received the same priority. The only difference was that women were more reluctant to use bank financing than men because they feared being rejected because of their lack of education and lack of personal assets or collateral.

Hypotheses and Research Framework

These papers develop the following hypotheses to test or define the relationship between both components for the financial provider evaluation of SME's based on the existing literature review for financial and non-financial factors for credit risk evaluation

H_1: SME's with a good financial position have lower credit risk.

H_2: SME's with a good financial position and qualified non-financial factors have lower credit risk.

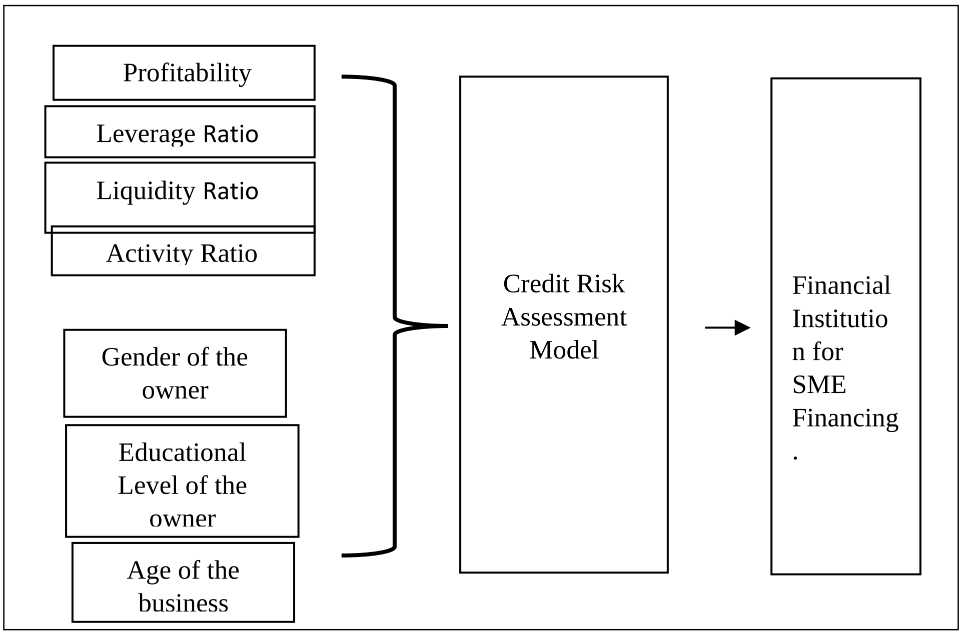

Table 1: Research Framework

Method and Measurement

All of the information used in this study was gathered from the Companies Commission of Malaysia (SSM) database, and the sample was chosen in accordance with the National SME Development Council's definition of a SME. The sample is made up of many fields and industries. The financial variables are extracted from financial statements, and the non-financial factors are obtained from the company profile.

The final sample for the estimating model consists of 400 SME enterprises from the years 2015 to 2020, of which 50% are distressed and the other 50% are not. Both the list of distressed and non-distressed company was collected from Companies Commission of Malaysia (SMM). The distressed company is the company classified under winding off by court order or creditors request in Part X Section 218 of 1 (e) and (2) of Malaysian Companies Act 1965. One of the reasons the corporation was dissolved by a court was because it was unable to pay its debts. The definition of inability to pay debts is when it is proved to the satisfaction of the Court that the company is unable to pay its debts and the Court shall take into account the company's contingent and prospective liabilities.

An MDA model function of the following kind was calculated to examine if financial and non-financial variables affect the occurrence of SME's high credit risk:

$$D = \alpha + \beta_1 TLA + \beta_2 SLA + \beta_3 LQT + \beta_4 STA + \beta_5 EDU + \beta_6 AGE + \beta_7 GENDER$$

Where D refers to discriminant score, α refers to estimated constant, TLA is ratio of total liabilities to total assets, SLA is ratio short term liabilities to total assets, LQT is ratio of current assets to current liabilities, STA is ratio of total sales to total assets, EBIT is ratio of earnings before interest and tax to total asset, EDU is a dummy for education level that is equal to 1 otherwise zero, AGE is a years of firm business operations, GENDER is a dummy for gender of managing director that equal to 1 otherwise zero.

The predictor variables were only included depending on the contribution they made during the application of a forward stepwise procedure. A stepwise procedure is usually applied when there is lack of theoretical basis in the selection of the predictor's variables. Two models have been developed, they are Model 1 (include financial variables only) and Model 2 (include financial and non-financial variables). Model 2 is designed to produce a superior result to those obtained from Model 1.

Model 1 : $D = \alpha + \beta_1 TLA + \beta_2 SLA + \beta_3 LQT + \beta_4 STA$

Model 2: $D = \alpha + \beta_1 TLA + \beta_2 SLA + \beta_3 LQT + \beta_4 STA + \beta_5 EDU + \beta_6 AGE + \beta_7 GENDER$

Results and Findings

Table 1 presented the results of mean differences on the variables used to estimated Multiple Discriminant Analysis model. Out of seven independent variables that are used, TLA, LQT, AGE and GENDER are not significantly different between distressed and non-distressed SME's. For financial variables, result indicates that average TLA for distressed SME's is 0.64 while non-distressed SME's only have 0.54. Besides that, the average of short term liabilities to total asset for distressed SME's is 0.75 while for non-distressed SME's only have an average of 0.004. In terms of LQT, the average is much higher for non-distressed SME's when compared with distressed SME's. For non-financial variables, the average for EDU under distressed SME's is 0.675 which is somewhat higher than non-distressed SME's 0.61. While for AGE the average for distressed SME's is 4.64 few than non-distressed SME's 4.75. For GENDER, the average for distressed SME's 0.66 while for non-distressed SME's is 0.59.

Table 1: Descriptive statistics

,,*** significant at 10 percent, 5 percent and 1 percent levels respectively. The variables are total liabilites to total assets (TLA), short term liabilities to total assets (SLA), liquidity (LQT), sales to total assets (STA), education levels (EDU), age of company (AGE), gender of the owner (GENDER).*

Variables	Mean	Standard deviation	Mean	Standard deviation	Sig.
	Distressed SME's		Non-Distressed SME's		
TLA	0.6402	0.2376	0.5441	0.2723	0.907
SLA	0.7597	0.065	0.004	0.0026	0.001***
LQT	0.8419	0.3872	380.59	692.64	0.833
STA	0.0535	0.0697	0.0848	0.0747	0.011**
EDU	0.675	0.4695	0.61	0.4889	0.042**
AGE	4.645	1.584	4.75	1.568	0.849
GENDER	0.66	0.4748	0.59	0.493	0.141
OBSERVATION	200		200		

Multicollinearity is not problematic in this analysis as indicated by a variance inflating factor (VIF) reported in Table 2. The R^2 are relatively low for all the variables. The VIF ranges from

1.011 to 1.522 which is less than 10, indicating that there is no issue of multicollinearity to this analysis.

Table 2
Variance inflating factor

Variables	R^2	VIF = $1/(1-R^2)$
TLA	0.343	1.522
SLA	0.258	1.347
LQT	0.132	1.15
STA	0.045	1.047
EDU	0.036	1.037
AGE	0.011	1.011
GENDER	0.052	1.054

Using a sample of distressed and non-distressed SME's a stepwise discriminant analysis is used to ascertain the discriminating power of the variables. Stepwise MDA allows the variables selected for analysis to be ranked according to their influence on the final results. The variable with the highest influence that passes the test of eligibility is then included in the examination.

Model 1: $D = \alpha + \beta_1 TLA + \beta_2 SLA + \beta_3 LQT + \beta_4 STA$

Table 3
Canonical Linear Discriminant Analysis

Fcn	Canon. Corr.	Eigenvalue	Variance Prop.	Variance Cumul.	Likelihood Ratio	F	df1	df2	Prob>F
1	0.9926	66.89	1	1	0.0147	6606	4	395	0.000

Table 4
Standardized canonical discriminant function coefficient

	Function 1
TLA	-0.0012
SLA	-1.003
LQT	0.0093
STA	0.1215

Model 2: $D = \alpha + \beta_1 TLA + \beta_2 SLA + \beta_3 LQT + \beta_4 STA + \beta_5 EDU + \beta_6 AGE + \beta_7 GENDER$

Table 5
Canonical Linear Discriminant Analysis

Fcn	Canon. Corr.	Eigenvalue	Variance Prop.	Variance Cumul.	Likelihood Ratio	F	df1	df2	Prob>F
1	0.9927	67.639	1	1	0.0146	3787.8	7	392	0

Table 6
Standardized canonical discriminant function coefficient

	Function 1
TLA	0.0065
SLA	-0.1931
LQT	0.0109
STA	0.1479
EDU	0.1823
AGE	-0.0097
GENDER	-0.1309

Based on Table 7, the stepwise procedure, it appears that model 2 outperformed models 1 based on Wilk's Lambda and classification accuracy. Wilk's Lambda indicates the significance of the discriminant function. The smaller the Wilk's Lambda for an independent variable, the more likely that the variable adds to the discriminant function. Wilk's Lambda is used in the second context of discriminant analysis to test significance of the discriminant function as a whole. It also shows that model 2 has 52.58 percent unexplained variation in the group variables, while model 1 have 96.57 percent respectively. Therefore, the discriminate function in model 2 revealed a significant association between groups and all predictors, accounting for 47.42 percent of between-group variability as compared to model 1 for just 3.43 percent. A closer analysis of the standardized canonical discriminant function coefficient in model 3, which combined financial, non-financial and governance variables and has the lowest Wilks' lambda, revealed three significant predictors that have the highest discriminating power, namely SLA (-0.1931), STA (0.1479) and EDU (0.1823).

Table 7
Stepwise MDA for estimated model

Variables	Category	Model 1		Model 2	
		Standardized canonical discriminant function coefficient	Wilks Lambda	Standardized canonical discriminant function coefficient	Wilks Lambda
TLA	Financial	-0.0012	0.9657 (0.000)***	0.0065	0.5258 (0.000)***
SLA	Financial	-1.003	0.015 (0.000)***	-0.1931	0.4767 (0.000)***
LQT	Financial	0.0093	0.8688 (0.000)***	0.0109	0.8972 (0.0021)***
STA	Financial	0.1215	0.955 (0.000)***	0.1479	0.892 (0.0032)***
EDU	Non-financial			0.1823	0.9954 (0.1759)

AGE	Non-financial		-0.0097	0.9989 (0.5058)
GENDER	Non-financial		-0.1309	0.9948 (0.1489)
Wilk Lambda		0.9657 (0.000)***	0.5258 (0.000)***	
Observation		400	400	

Conclusion

This study improves upon the existing models from the literature of SME distressed prediction in various ways. attempts to enhance the research contributions in the aspects of measuring the credit risk among SME's by considering from both financial and non-financial factor. A few aspects in four categories of financial ratio were explained and bring information in detail on financial part, while three factors represent non-financial factor.

Most of the previous research only focused on financial factor namely profitability, leverage, liquidity and activity. They believes that these aspects are very powerful in determining the company financial performance and the information are enough in developing a model on credit risk assessment. Besides an additional category of financial ratio, this study proposed to consider non-financial factors, specifically educational level of the owner, the age of the SME's and gender of the owner into the model as they will bring in depth picture of the company performance in assessing credit risk.

In addition, financial institution will have a better reference in assessing company's credit risk. Creditor, investor and fund provider will have precise model in assessing company's credit risk in order to reduce loan default. SME's and financial consultant can use the model in setting their business strategies and advising client in developing good and prudent financial standing.

Contributions

The study recommends to combined both financial and non-financial variables in measuring the credit risk among SME's in Malaysia. It extends the limited research on the credit risk mitigation where most of the research focusing on financial factors only while this research combined also with non-financial variables specifically educational level of the owner, the age of the SME's and gender of the owner into the model as they will bring in depth picture of the company performance in assessing credit risk. Besides that, our study focuses on SMEs as it among biggest contributor to Malaysia economy and most of the previous research focusing on big firm or listed companies only.

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