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Abstract
Credit scoring is one of the tools used to analyze the creditworthiness of a firm. The implementation of enormous financial data in credit scoring could lead to the emergence of unnecessary data in determining the credit score of a firm. In past studies, modifications to the credit scoring methodology were repeatedly done to obtain accuracy. In this paper, a novel approach where the credit score of a firm is determined based on the estimation of the probability of default from the KMV-Merton model, the selected financial ratios, and credit ratings. The study is distinctive in providing credit scores and ranking of firms based on qualitative and quantitative firms' historical financial information and current market value. The merger of the KMV-Merton model, financial ratios, and credit rating is incorporated in this study by acquiring information of 10% each to find the credit scores of firms. In conclusion, this merger can provide credit scores and credit ranking for the selected firms that have a good/average/below average credit quality. It also can differentiate the ranking position between investment-grade and speculative-grade firms. Furthermore, the KMV-Merton model and credit ratings provide an estimate of credit scores that is more consistent compared to financial ratios. Practically, credit scoring helps risk analysts, investors, and lenders to make informed decisions.
Keywords: Credit Score, Credit Rating, Default, Financial Ratio, KMV-Merton Model

Introduction

Credit scoring is one of the credit risk measurement tools used to analyze the financial position of firms and it has been used for a long period. It uses numerical expression to represent the creditworthiness of a firm based on a level analysis of a firm's credit information. Tripathi et al (2018) mentioned that a credit score is an effective decision-maker. Commonly, lenders use the credit score to decide firms' qualifications for a loan, the amount of interest rate, and the limits of the credit. The importance of credit score is not only for the credit risk measurement but to the extent of determining the firm's expected returns. Redundancy in information is a common weakness in credit scoring (Chen & Xiang, 2017; Tripathi et al., 2018). Moreover, not all information that has been utilized is significant and easy to obtain as some information is confidential or not exposed by the creditors. Therefore, various methods have been established such as using machine learning (Handhika et. Al., 2019; Pławiak et. Al., 2020;), the Weighted Vote approach (Tripathi et. al., 2018), and regression analysis (Chen & Xiang, 2017). Some studies used regression analysis and machine learning (Wang et. Al., 2012; Guegan & Hassani, 2018) in determining the credit scores of firms, banks, and households.

Most of the current methods used information from the firm financial ratios as parameters for credit score modeling. Myšková and Hájek (2017) stated that financial ratios are preferable to linguistic assessment as it is much better than depending on the willingness of managers to provide the information. Sohn and Kim (2012) used financial ratios as a credit scoring model to resolve the financial problems of SMEs in Korea. Samreen et al (2013) used financial ratios and credit ratings in collecting data for the credit scoring of a firm. Previous studies have shown that statistical approaches such as logistic regression and multiple discriminant analysis utilize financial ratios for forecasting credit risk. It was also mentioned that with a small list of financial ratios, credit ratings can be forecasted using the statistical approach (Chen et al., 2010). For these reasons, a list of financial ratios and credit ratings has been used in this study.

In this study, we also utilized the information from the KMV-Merton model to find the credit scores of firms. This is due to the information on financial ratios lies solely on historical financial statements, unlike the KMV-Merton model that can predict firms' default in advance based on current market value. Moreover, Demerjian (2007) examined that there exists a relationship between financial ratios and distance to default of the KMV-Merton model in credit risk assessment. Although credit rating is a well-known tool for measuring the creditworthiness of firms, it is expressed in a letter-based system. This contradicts the KMV-Merton model that focuses on the likelihood to default of firms and its offers numeric value. Thus, this combination of information from financial ratios, credit ratings and the KMV-Merton model resembles the historical and future information of the firm. Overall, the study focuses solely on whether these three common credit indicators; the KMV-Merton model, financial ratios, and credit ratings can be merged to provide information on the credit score of Malaysian publicly traded companies.

The KMV Merton Model

KMV Merton model is a modified version of the Merton model, whereby the focus is on firms' default prediction. If the firm's asset values hit a critical level somewhere between the value of the overall liability and the value of the short-term debt, then firms are most likely to default. Accordingly, the default point, *P*, is defined as the summation of the short-term borrowings with half of the long-term borrowings. The distance to default, *d*, of a firm can be calculated using the following equation (Zieliński, 2013)

$$d = \frac{\ln\left(\frac{V}{P}\right) + \left(\mu - 0.5\sigma^2\right)t}{\sigma\sqrt{t}} \tag{1}$$

The variable *V* is the market value of a firm that is calculated by adding the total borrowings of the firm with its total market value of equity. The market value of equity is obtained by multiplying the firm's historical price with its outstanding share. Next is the annual expected returns on firm value, μ, that is determined by finding the average of the daily returns of *V* generated for one year. In the meantime, the annualized volatility, σ, is also estimated by multiplying the standard deviation of the generated daily returns of *V* with the square root of the one-year trading days, which is assumed to be 252 days in this case. Since default is estimated annually and thus *t* is assumed one year (Norliza & Maheran, 2014).

Based on equation (1), the probability of default, *D*, can be estimated using the following expression

$$D = NORMSDIST\left(-d\right) \tag{2}$$

where *NORMSDIST* stands for the standard normal distribution function since asset returns are assumed to be normally distributed in the Merton model.

Selection of Financial ratios

There are tons of ratios that exist and yet this study only uses eight different financial ratios. Altman (1968) said that the selection of ratios is based on the popularity of the ratios used in previous studies and their relevance of it in determining creditworthiness.

Yap et al (2010) utilized 7 out of 16 ratios in the multiple discriminant analysis to predict companies' failure. Yap et al. showed that liquidity and profitability are strong ratios in determining the success of firms. Ghecham & Salih (2019) evaluated the financial performance of banks during the financial crisis in 2008 by measuring the profitability, liquidity, and efficiency of the banks. Delen et al (2013) concluded that net profit margin is one of the most powerful ratios to determine the profitability of a firm. The leverage and debt ratios were important ratios as well in predicting the performance of a firm. Horrigan (1968) stated that the current ratio is the mandatory ratio analysis used by many parties such as banks, lenders, and firms to focus on their assets and liabilities. According to (Delen et al., 2013), the ratios that are usually implemented in a firm are liquidity, profitability, and leverage. Hence, these are the financial ratios selected in this study as given in Table 1.

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Table 1
Financial Ratios (Delen et al., 2013)

Liquidity	
Current Ratio	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$
Profitability	
Gross Profit Margin, GPM (%)	$\frac{\text{Gross Profit}}{\text{Revenue}}$
Net Profit Margin, NPM (%)	$\frac{\text{Net Profit}}{\text{Revenue}}$
Return on Assets, ROA (%)	$\frac{\text{Net Profit}}{\text{Total Assets}}$
Return on Capital Employed, ROCE (%)	$\frac{\text{Net Profit}}{\text{Total Assets - Current Liabilities}}$
Leverage	
Debt to Asset	$\frac{\text{Total Liabilities}}{\text{Total Assets}}$
Debt to Equity	$\frac{\text{Total Liabilities}}{\text{Total Equity}}$
Interest Coverage	$\frac{\text{EBIT}}{\text{Interest Expenses}}$

Table 1 cont.

Liquidity is used to measure and analyze the ability of a firm to pay its short-term obligations. Meanwhile, profitability is to measure and evaluate a firm's performance. The purpose of leverage is to measure the overall debt obligation and compare it with the assets or equity.

Credit Rating

Credit ratings are used by credit agencies to evaluate a company's creditworthiness. The credit rating agencies include Malaysian Rating Corporation Berhad (MARC)'s and Rating Services Berhad (RAM) and it is expressed as in Figure 1.

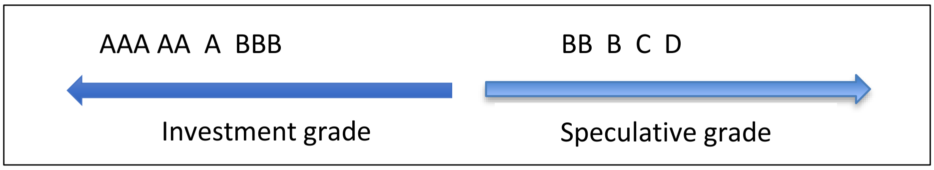

Figure 1. Credit Ratings

Methodology

Figure 2 shows the research process of the study. There are five steps conducted to determine the credit score ranking of the selected firm using a merging of the KMV-Merton model, financial ratios, and credit ratings.

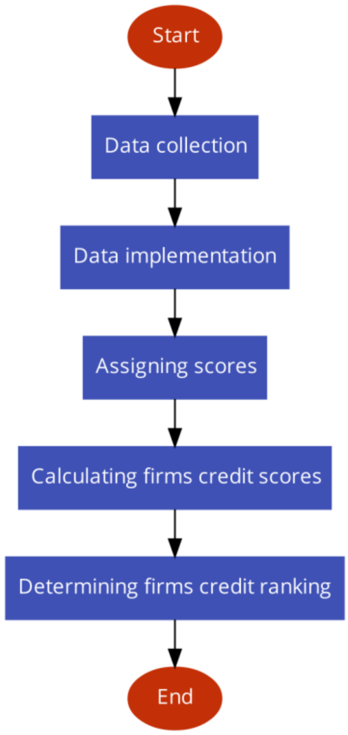

Figure 2. Research Process

Data Collection and Implementation

The financial data of nine firms rated by the rating agencies (MARC or RAM) is used in this study as a data sample. In estimating the probability of default, data such as the number of outstanding shares, short-term and long-term liabilities are obtained from the firm's quarterly reports. Meanwhile, the daily historical prices of the firms are obtained from the website of Yahoo Finance. In addition, financial information such as current assets, current liabilities, gross profit, revenue, net profit, total assets, total liabilities, total equity, earnings before interest and tax (EBIT), and interest expenses obtained from the firms' quarterly reports are used to calculate the selected financial ratios is. All data is collected for one year according to the year the firms were rated, that is around 2017 to 2019.

Table 2 is the summarization of the data used in this study. The data is implemented into equations (1) and (2) to obtain the probability of default of the firms. Meanwhile, eight financial ratios are calculated by implementing the data into the formula given in Table 1. The outputs obtained from the data implementation, including data on ratings are combined to determine the credit score and credit ranking of the selected firms.

Table 2
Data Summarization

Credit indicator	Type of data	Input	Input frequency	Input size	Output
KMV-Merton model	Malaysian public-listed firm	Stock prices	daily	2268	Probability of Default
		Outstanding shares	quarterly	36	
		Short term borrowings	quarterly	36	
		Long term borrowings	quarterly	36	
Financial ratios		Current assets	yearly	9	
		Current liabilities	yearly	9	
		Gross profit	yearly	9	
		Revenue	yearly	9	
		Net profit	yearly	9	
		Total assets	yearly	9	
		Total liabilities	yearly	9	
		Total Equity	yearly	9	
		Earnings before interest and taxes (EBIT)	yearly	9	
		Interest expenses	yearly	9	
Credit ratings		Ratings	yearly	9	9 Ratings

Assigning Scores to the Credit Risk Indicators

There are ten credit risk indicators used in this study involving the KMV-Merton probability of default, *D,* eight financial ratios, and credit ratings. Scores were assigned to the values estimated by the credit risk indicators according to Table 3.

Table 3
Assigning Score to the credit risk indicators

Credit Risk Indicator	**Score, *S***		
	1	**2**	**3**
Probability of Default, D (%)	> 0.87	0.27 - 087	<0.27
Current Ratio, X_1	<1	1-1.5	>1.5
GPM, X_2 (%)	<1.5	1.5-5	>5
NPM, X_3 (%)	<1.5	1.5-5	>5
ROA, X_4 (%)	<5	5-15	>15
ROCE, X_5 (%)	<10	10-20	>20
Debt to Equity, X_6	>1.2	0.8-1.2	<0.8
Debt to Asset, X_7	>1.2	0.8-1.2	<0.8
Interest Coverage, X_8	<1	1-1.5	>1.5
Credit Rating, R	C	BBB-B	AAA-A

Table 3 shows the scores 3, 2, and 1 assigned to the credit risk indicators based on the studies of (Samreen et al., 2013; CreditRiskMonitor, 2020). Score-3 is the 'best' score, followed by score-2 as the 'good' score, and lastly, score-1 is the 'bad' score.

Calculating the Credit Score of Firms

The credit score of a firm is calculated by obtaining the scores assigned to the firm's credit risk indicators given in Table 3. The assigned scores are applied to the following equation to get the credit score, Z of a firm (Samreen et al., 2013)

$$Z = 0.1\left(\frac{S_D + \sum_{i=1}^{8} S_{X_i} + S_R}{3}\right) \quad (3)$$

Total credit score, Z, is defined as the summation of scores of the credit risk indicators based on certain weightage. 80 percent of the total credit score is contributed by the financial ratio scores, where 10 percent is distributed equally among the 8 ratios. Meanwhile, the remaining 20 percent is divided equally between the probability of default score, $S_{D,}$ and credit ratings, S_R. Denominator 3 shows the maximum score that can be assigned to the credit risk indicators.

Determining the Credit Ranking of Firms

Table 4 shows how the credit ranking can be done based on the calculated credit score, *Z*.

Table 4

Credit Score Ranking (Samreen et.al., 2013)

Credit Score, *Z* (%)	**Credit Ranking**	**Credit Quality**
91 - 100	1	Very Good
76 - 90	2	Good
55 - 75	3	Average
< 55	4	Below Average

There are four rankings given in Table 4. Ranking '1' shows the highest credit score which indicates that the firm has very *good* credit quality. Next, ranking '2' shows the second-highest credit score after ranking '1' which indicates that the firm has good credit quality. Followed by Ranking '3' that shows the *average* credit quality. Lastly, the lowest ranking '4' shows a credit quality *below average*.

Results and Discussions

Based on the credit risk indicators utilized in this study, the credit score of a firm is determined. The first indicator comes from the KMV-Merton probability of default which is estimated by using equations (1) and (2). The results of implementing the KMV-Merton model are presented in Table 5.

Table 5

The annualized volatility, Distance to Default, and Probability of Default of Firms by using KMV Merton Model

Firm	**Volatility, σ**	**Distance to Default, *d***	**Probability of Default, *D***
MISC Berhad	0.27498	8.16023	0
Sunway Berhad	0.09353	7.61135	1.38E-14
MBSB	0.26071	5.27473	6.65E-08
DRB-Hicom BHD	0.13465	4.59412	2.17E-06
WCT Holdings Berhad	0.1809	4.08821	2.17E-05
MASTEEL	0.2076	1.65545	0.05
Malakoff Power Berhad	0.4485	0.84227	0.20
Talam Transform Berhad	1.67166	-0.1815	0.57
MMC Corporation	1.19715	-0.28736	0.61

Risk is usually measured by volatility. Higher volatility tends to take a higher risk as shown in Table 5. These firms, Talam Transform Berhad and MMC Corporation are the top two firms that are estimated to have the highest volatility and hence, the potential of the firms to default is high as estimated by parameter *D*. Both firms also have a negative value of *d* that makes the possibility of the firm to default is certain. Malakoff Power Berhad also has a high *D* of around 20% and followed by Masteel which has a slight *D* of around 5%. The rest of the companies were estimated to have zero *D*. Clearly, lower values of *D* come from lower *d* and lower *σ*. Our next result is based on the second credit risk indicator which is financial ratios, and it is represented in Table 6.

Table 6
The liquidity, profitability, and leverage of the selected firms

Firm / Ratio	Liquidity	Profitability (%)				Leverage		
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
MMC Corporation	0.76	49	-7	0	0	1.67	0.63	-2.17
Sunway Berhad	1.01	1	16	1	2	1.32	0.57	-7.55
MASTEEL	1.21	7	0	0	0	1.08	0.52	9.54
MBSB	1.23	47	15	0	1	5.29	0.84	-2.63
Malakoff Power Berhad	2.21	16.06	6.92	0.45	0.52	2.99	0.75	-2.31
Talam Transform Berhad	0.51	10.72	-162.1	-0.81	-1.12	1.15	0.53	0.85
DRB-Hicom BHD	0.58	50.21	-4.03	-0.29	-0.77	3.2	0.76	1.39
WCT Holdings Berhad	1.39	16.92	10.21	0.73	1.01	1.58	0.61	-6.15
MISC Berhad	1.28	29.59	53.77	2.47	2.90	1.51	0.69	3.41

There are eight financial ratios presented in Table 6 to indicate the liquidity, profitability, and leverage of the selected firms. Table 6 shows the liquidity of the firms measured by the current ratio (X_1). A higher current ratio means higher liquidity and hence, the ability to pay off short-term debt is also higher. It was found that Malakoff Power Berhad has the highest liquidity while Talam Transform Berhad has the lowest liquidity.

The profitability of the firms has also been represented in Table 6 by the values of GPM (X_2), NPM (X_3), ROA (X_4), and ROCE (X_5). MISC Berhad has the highest profitability as it owns the highest ratios of NPM (X_3), ROA (X_4), and ROCE (X_5). In contrast to Talam Transform Berhad where the values of the three ratios are at the lowest level.

Lastly is the leverage of the firms which is calculated based on their Debt to Equity (X_6), Debt to Asset (X_7), and Interest Coverage (X_8). Good leverage is indicated if the firms have lower values of Debt to Equity (X_6) and Debt to Asset (X_7), and higher value of Interest Coverage (X_8). Among all the selected firms, MASTEEL is found to have good leverage as it holds the lowest values in two of the ratios which are Debt to Equity (X_6), Debt to Asset (X_7), and has the highest value for Interest Coverage (X_8).

Based on Tables 5 and 6, the scores for each credit risk indicator are assigned as shown in Tables 7 and 8.

Table 7
The financial ratio scores

Firm	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
MISC Berhad	2	2	3	3	3	1	3	2
WCT Holdings Berhad	2	2	3	2	3	1	3	1
Sunway Berhad	2	1	3	2	3	1	3	1
MBSB	2	3	3	2	2	1	2	1
DRB-Hicom BHD	1	3	1	1	3	1	3	2
Malakoff Power Berhad	3	2	3	2	2	1	3	1
MASTEEL	2	1	1	2	2	2	3	3
MMC Corporation	1	3	1	2	2	1	3	1
Talam Transform Berhad	1	1	1	1	1	2	3	1

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Table 8
The credit risk indicator scores

Firm	Credit Score			Total score
	D	***X_i***	***R***	
MISC Berhad	3	2	3	25
WCT Holdings Berhad	3	2	3	23
Sunway Berhad	3	2	3	22
MBSB	3	2	3	22
DRB-Hicom BHD	3	2	3	21
Malakoff Power Berhad	1	2	3	21
MASTEEL	1	2	3	20
MMC Corporation	1	2	3	18
Talam Transform Berhad	1	1	1	13

Table 7 shows the scores assigned to the estimated probability of default*,* financial ratios, and credit ratings for each firm. The score is represented by the numbers 3, 2, and 1 (best to bad score). Overall, MISC Berhad has the highest total score, which is 22, compared to the other firms. The score is reasonably high as MISC was estimated to have the lowest probability of default (Table 5), highest profitability (Table 6), and it is an AAA-rated firm. This makes MISC the most stable firm compared to the other firms. In the meantime, we found that Talam Transform Berhad is financially unstable with the lowest total score of 12. This occurs as Talam was estimated as the second company with a high probability of default (Table 5) with the lowest liquidity and profitability (Table 6). Moreover, the company had been rated C in 2019 by the rating agency.

Comparatively from Table 8, we discovered that Talam's score matched every score predicted by KMV-Probability Merton's of Default, *D*, Financial Ratios, X_i, and Credit Ratings, *R*. The scores of KMV- Merton's Probability of Default, *D* matched the Credit Ratings, *R* in about 67% of cases. This matching percentage is significantly higher than the 11% we got between the financial ratios with KMV-Probability Merton's of Default, *D*, and Credit Ratings, *R*. For the financial ratios, most companies' score is 2.

The scores in Tables 7 and 8 are also used to determine the credit scores in total and credit rankings of the firms as shown in Tables 9.

Table 9
Credit scores and credit ranking of firms

Firm	Credit Score, *Z* (%)	Credit Ranking
MISC Berhad	83	2
WCT Holdings Berhad	77	2
Sunway Berhad	73	3
MBSB	73	3
DRB-Hicom BHD	70	3
Malakoff Power Berhad	70	3
MASTEEL	67	3
MMC Corp	60	3
Talam Transform Berhad	43	4

Table 9 shows the credit scores and credit rankings of the selected firms. The ranking is determined based on the credit score, *Z*, calculated using equation (3). According to Table 4, the ranking is expressed numerically from 1(*very good*) to 4(*below average*). Apparently, MISC has the highest percentage of credit score (83%) followed by the other firms and ended with Talam with a credit score of 43%. It is shown that the best ranking is 2 given to MISC and WCT, indicating they have good credit quality. Meanwhile, Talam ranking shows that its credit quality is *below average*. The rest of the firms have a rank-3 indicating average credit quality. Therefore, among nine firms, only one firm is found to have financial difficulty. This is supported by their credit ratings where only Talam was rated as C while the other firms were rated between A to AAA.

Conclusion

Credit risk is generally described as the most significant risk that affects the performance of the firms. To measure the credit risk of firms, this study uses credit scores of firms calculated based on the combination of information of KMV-Merton's probability of default, financial ratios, and credit rating. The calculated credit scores are used to determine the credit ranking of the firms. This credit scoring technique introduced here is said to be able to rank firms that have a *good*/*average*/below average credit quality. Overall, it describes the creditworthiness of firms under three factors which are the possibility to default, historical financial statements, and ratings. We believe that more data acquired, especially on the default data firms, to validate the study.

In addition, the probability of default is found to be affected by the volatility of firms. It is observed that firms with high volatility tend to have a high probability of default. Meanwhile, from the perspective of financial ratios, firms with high liquidity, high profitability, and low leverage lead to the ideal state of financial health. In comparison to financial ratios, the KMV-Merton model and credit ratings do have a higher degree of coherence in determining a company's credit score.

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