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Determinants of Malaysian Bond Ratings

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ABSTRACT

This paper seeks to investigate the determinants of Malaysian bond ratings. Bond has become Malaysia's leading source of fund. The failures of credit rating agencies are no stranger to world's financial market. They are blamed for the slow responses during Asian financial crisis and bankruptcy cases of large corporations. Moreover, the presence of information asymmetry problem in the market has complicate credit rating agencies and external stakeholders to correctly assess the true value of the firm and its probability of default. Hence, this paper provides a new and adequate model that takes into account various risk factors to further understands the factors that affect firms' creditworthiness. This model could reduce investors' over-reliance on credit ratings, information asymmetry problems and become a substitute of the current credit ratings model. This paper specific objective is to investigate which risk factors are the best determinants of bond ratings. The final sample includes a total of 175 fixed-rated bond issuances from 37 corporate listed firms between the years 2005 to 2013. Multinomial logistic regression is used in investigating the relationships. The study finds that there is a significant relationship between risk factors and bond ratings, where firm's risk factor alone is enough to explain higher rated bonds, while the other two risk factors are only significant in determining bonds with lower ratings. Moreover, robustness check finds that the model has 91.67% classification accuracy, with a total of only 10 wrongly classified observations out of 120 total observations.

Keywords: Bond ratings; Corporate bond; Accounting-based ratio; Systematic risk factors; Malaysia

INTRODUCTION

The debate on the failure of credit rating agencies is no stranger to world's financial market [29,32,37]. Established to reduce information problems and for betterment of investment decisions; credit rating agencies' inadequacy are to be blamed for numbers of large corporations' mishaps and the financial crisis in the Asian region as of late. Among the highlights of their failures are the slow responses during the 1990's Asian financial crisis and bankruptcy cases of large corporations, such as Enron in 2001, WorldCom's in 2002 and Parmalat's in 2003. In their defense, these rating agencies claimed that their ratings did not reflect the firm's current default probability. Instead, they were said to reflect more on the long run, which is more appealing to fellow investors. Hence, in cases of great and sudden changes of the market conditions, credit rating agencies tend to lag behind and become inadequate. Thus, their constant failures in identifying corporations' insolvency warrant for a revision in their assessment method and mathematical models, taking into account all possible risk factors [32].

Changes in credit ratings, either upgrade or

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downgrade can caused prices of bonds to fluctuate [20]. Investors rely on bond's price fluctuations to capitalize their investments. Credit rating changes imply changes in investment risks which would lead to potential loss or gain. In an event of a rating downgrade, the price of bond could go down thus devaluing the investors' claim on debt. Hence, ratings provide an informational role to investors, as downgrade could indicate an unfavorable change in firms' prospect, cash flow, capital allocation, and financial costs [23].

In the real world market scenario where information asymmetry problem is high, the informational role provided by credit ratings could be distorted. Rating agencies claimed that both quantitative aspect of a firm are looked into in deducing ratings [30,36,40]. The drawback of using financial ratios in deducing credit ratings is that the information are at least 6 months old, thus creating an information gap between firm's last available annual report and the coming up of the rating [24]. Moreover, evidence of information asymmetry problem arises from firms' financial data being manipulated by management [15], information withholding [3] and lack of information disclosure quality [9]. These unethical acts of firm's management are often to obscure their self-interest objectives and appear more appealing to investors [39]. This predicament complicates credit rating agencies and external stakeholders to correctly assess the true value of the firm and its probability of default [6].

The major problem for investors relating to credit rating is the degree of promptness of rating agencies in reacting to informational changes [10,29,32,37]. The question is whether rating agencies are fast enough to react to rating changes in firm's informational content and subsequently conveying those informational changes through their rating; either downgrades or upgrades. These changes are highly crucial to investors in securing their investment returns as it relates to price adjustment of the securities in trade [10].

2. Objectives:

Given the significant informational role that credit ratings provide [8,19,23], investors are motivated in understanding and finding out the relevant determinants of credit ratings and credit risks. Problems of information asymmetry and rating agencies' promptness create ambiguity to investors in making a correct investment decision. Moreover, self-interest managerial behavior is no stranger to the nature of today's modern corporation, which often leads to misfortune as such in the case of Enron, Refco, WorldCom and Malaysian's infamous case of Transmile Group Berhad in 2008.

Rafailov [32] highlights that the lag of rating agencies are caused by inadequate method and model used in assessing risks, resulting blame on numbers of large corporations' bankruptcy cases and global financial crisis. Hence, the need for a new and adequate model that takes into account various risk factors, should be critically look into and of the utmost importance. In doing so, it could further expand various market participants' understanding on firms' creditworthiness. Moreover, the new model could become a substitute of the current credit ratings model.

Thus, a study on determinants of bond ratings could help investor in evaluating a firm's inability to fulfill its debt obligation and avoiding excessive reliance on credit rating agencies. Consequently, it will mitigate bond investors' problem of information asymmetry. The reduce reliance on credit rating agencies is hope to cope with future financial crisis in Malaysia and avoiding occurrence of cases such as the Transmile Group Berhad. During the 2006 to 2012 period, there were 134 Malaysian corporate bond issuers experienced credit rating changes. RAM [33] stated that rating downgrades have outpaced upgrades for two consecutive years of 2011 and 2012 which result negative rating drift. Moreover, despite Malaysia's resilient economic growth, company-specific factors are often the main reasons of these negative rating shifts [35].

Bond has become a main instrument of raising funds in Malaysia's economy (Bank Negara Malaysia, 2013) following the 1997 Asian financial crisis. Malaysian corporate bond market represents 43.4% of the country's GDP, which is the second highest behind South Korea's 78.8% in the emerging market of East Asia [1]. This signifies the importance of bond market in the Malaysian economy and the attractiveness of the country's bond market to bond investors both international and locally.

This study does not claim that the assigned credit ratings to be wrong, but the possibility of it to be inaccurate is undeniable based on thorough literature review. Factors or determinants that could affect the potential return of corporate bonds are of high importance to investors. Thus, the objective of this study is to fill this gap by investigating the determinants of bond ratings in Malaysian developing economic setting. Understanding and identifying which risk factors that affect bond ratings could help mitigate the information asymmetry problem faced by bondholders.

Materials and Methods

3.1 Sample and Data Source:

The final sample for this study includes a total of 175 issuances from 37 corporate firms, from 2005 to 2013. This time period is selected for convenience, since Bond Pricing Agency of Malaysia (BPAM) was first to track YTM of bonds in 2005. The sample includes all fixed-rated corporate bonds, from both conventional and Islamic issuances, with ratings from both RAM and MARC. This study omits issuances from financial companies and government related firms since their debt structures vary greatly and are strongly influenced by laws and regulations. Specific data for bond issuances are collected through RAM and Bondstream, which both subscribed to BPAM.

3.2 Theories, Hypothesis and Research Model:

Corporate liabilities pricing theory [28], risk premiums determinants theory [12] and contingent claims theory [28] are used in developing this study's models and hypotheses. Firstly, the theory of corporate liabilities pricing by Merton [28] empirically proven to price risky bonds. Merton's model is confined only to default risk of the corporate liabilities, hence it comprises of three items which are, return of riskless debt, bond's covenants, and firm's default probability. Secondly, in determining firm's default probability, theory of risk premiums determinants [12] is used. According to the theory, risk premiums depend on the investors' estimation of the securities' default risk and the ease to turn the securities into cash. Fisher [12] estimation of firm's creditworthiness and quality of bonds can be measured through firm's default risk and marketability risk. Lastly, contingent claims theory by Merton [28] states that due to the ability to hedge risk, securities prices should be independent of asset's return and systematic risk factors. However, firm's systematic risk is only constant when there are no changes in the firm's risk class. Hence, unexpected changes of leverage in firm's capital structure could cause firm's systematic risk to be non-stationary and affecting debt returns [13,14].

Based on these theories, there are three risks factors identified and believed to have influences on bond ratings. Moreover, they embodied the economic rationale of rating agencies' judgement in deducing credit ratings [2]. The risk factors are firm's risk (default risk), issuance's risk (bond's covenants) and market's risk (systematic risk). Hence, the hypothesis developed as follows:

H_{01}: There is no significant relationship between risk factors and bond ratings.

The model is developed to test and identify the relationship between various risk factors with bond ratings. In order to fulfil the objective of this study, the model examines the impact of the three risk factors in the determination of bond ratings. This model is developed in accordance to the three selected theories. The estimation is as follows:

$$BR_j = f(F_j, I_j, M_j, e_j) \quad (1)$$

Where BR_j is the Bond rating assigned by RAM to a specific bond issue. F_j is a set of issuer's firm-specific financial information measured in accounting-based ratios, which are considered relevant in assessing firm's default risk. I_j represents bond's issuance characteristic that signify issuance's risk, which are expected to have influence on bond ratings. M_j is a measure of firm's systematic market risk that is expected to have an influence on bond ratings. Lastly, e_j is the function's random error term.

3.3 Dependent Variable:

Bond rating (BR_j) is the proxy for information asymmetry. The bond ratings by RAM are divided into seven categories numerically and ordinally [4,7,26]. It ranges from highest to lowest according to the measure of default risk of the issuing firms. For example, a firm with AAA, the highest rating signifying the lowest probability of default is assigned with numerical value of 7, followed with AA with 6, A with 5 and so on, until the lowest rating of D with 1. All bond ratings data are collected from RAM and Bondstream, where both subscribe to BPAM.

3.4 Independent Variables:

3.4.1 Firm's Risk, F_j:

The first issuer's firm-specific financial ratio is firm's total asset (TOA). It is a measure of firm's size, calculated by log of firm's total assets. Size of firm is also used as a measure of firm's marketability [4,7], since bonds outstanding is highly correlated to firm's size. Thus, firm's size is positively related to bond ratings.

Secondly, return on asset (ROA) ratio is a measure of firm's profitability, calculated by dividing firm's net income with its total assets. Firm with higher profitability ratio indicates that the firm is efficient in generating profit through its assets and investments. Thus, profitability ratios are positively related to bond ratings.

Thirdly, debt ratio is a measure of firm's leverage (LTD), calculated by dividing firm's long-term debt with its total assets. Higher leverage ratio indicates that the firm is financed more by debt and often considered riskier and prone to default. Thus, leverage ratios are negatively related to bond ratings.

Lastly, firm's interest coverage (INT_COV) ratio is a measure of firm's coverage capability, calculated by the sum of earnings before interest and tax and interest expense, divided by interest expense. Higher coverage ratio indicates that the firm is stable and reliable in meeting its debt obligations. Thus, coverage ratios are positively related to bond ratings.

3.4.2 Issuance's Risk, I_j:

The first bond's issuance characteristics that signify issuance's risk is bond's coupon rate (COUP) in percentage. Coupon affects bond ratings negatively since higher coupon indicates higher tax to be incurred by the bondholders [11,22,5].

Secondly, the size of the bond issuance (SIZE_ISS) is calculated by log of the amount issued in millions of RM. This particular variable is a proxy for external liquidity factor [41], since large issuance often thought to be more liquid in trading [41,22]. SIZE_ISS is positively related to bond ratings [38].

Lastly, maturity of the bond (MATUR) is calculated by the years until the bond matures. It represents the remaining life left of the bond. Maturity relates closely to the shape of term structure of a bond yield spread. Since it is upward sloping, longer maturities will results greater exposure to interest risk [38,16]. MATUR is negatively related to bond ratings.

3.4.3 Market's Risk, M_j:

Market beta (M_BETA) measures the responsiveness of firm's securities return relative to market's return. It is use to represent the measure of systematic risk in the market. The calculation for M_BETA is calculated by dividing firm's $Cov\ (R_i, R_M)$ with market's $Var\ (R_M)$. Where $Cov\ (R_i, R_M)$ is the covariance between the specific firm's return asset *i* and the return on the market portfolio of Bursa Malaysia Emas return index. $Var\ (R_M)$ is the variance of the return on the market of Bursa Malaysia Emas return index. This calculation is similar to Bhojraj and Sengupta [4], where they use firm's daily stock returns over a period of their calculated financial ratios. Moreover, market beta integrates both operating and financial risk of a firm, which relates positively with a firm's probability of default [4,21]. Hence, market beta is negatively related to bond ratings.

These financial ratios are taken annually and calculated on average of five years ending on the bond's issuance year [4,7,10,17,21,22,25,26,31]. For example, if the bond is issued in the year 2013, the calculation period of the average ratios would be from 2008 to 2012.

4. Findings:

4.1 Descriptive Statistics:

Panel A of Table 1 provides the descriptive statistics for the study's sample of 175 corporate bond issues. The size (TOA) of the listed firms in this study's sample has an average of RM 6.87 million in assets, with a range of RM 45.85 million. Moreover, their average ROA and LTD are 0.06 and 0.19 respectively. The firm's INT_COV have a large variation in range and standard deviation of 345.2 and 37.12 respectively.

Descriptive statistics for issuance's risk indicates that the full bond sample has an average coupon rate (COUP) of 4.94% and an average maturity (MATUR) of 5.94 years. While the size of bond issuance (SIZE_ISS) has a mean of RM 163.52 million, with minimum and maximum issuance size of RM 1 million and RM 2,200 million respectively. Lastly, the market's risk variable (M_BETA) shows a mean of 0.11, with a minimum value of -0.003 and maximum value of 2.4.

Panel B reports the descriptive statistics for the dependent variable; bond ratings (BR). The full sample includes a total of 175 bond issuances from the year 2005 to 2013, where 50 issuances have AAA rating, 84 issuances have AA rating and 41 issuances have A rating. There are no issuances with rating lower than A. The sample's bond rating has a mean of 1.95, which indicates that the sample's average rating is AA and ranges between AA1 to AA3 rating.

Table 1: Descriptive Statistics.

Panel A					
Risk Factors	Variables	Mean	Std Dev.	Minimum	Maximum
Firm's Risk	TOA	6.87	10.05	0.12	45.98
	ROA	0.06	0.06	0.001	0.46
	LTD	0.19	0.14	0.004	0.54
	INT_COV	18.48	37.12	1.82	347.02
Issuance's Risk	COUP	4.94	1.44	2.00	9.8
	SIZE_ISS	163.52	296.78	1.00	2,200.00
	MATUR	5.94	3.98	3.00	15.00
Market's Risk	M_BETA	0.11	0.23	-0.003	2.40
Panel B					
Bond Ratings (BR)		Ordinal Value	Frequency	Valid Percentage	Cumulative Percentage
AAA		1	50	28.57	28.57
AA		2	84	48.00	76.57
A		3	41	23.43	100.00
Total			175	100.00	

4.2 Correlation Analysis:

Since bond rating (BR) is an ordinal variable, Spearman rank-order correlation is used. Table 3 provides the bivariate correlations that exist between the total data items. Prior to conducting correlation analysis, the data sample is checked for outliers. 55 outliers are found and removed, which result a total of 120 observations as the study's final sample. Outliers are removed according to the method as described by Hoaglin and Iglewicz [18]. Since Spearman correlation is a non-parametric measure, it makes no assumption for the data collected to be normality distributed.

Table 2 shows that five out of eight independent variables correlate highly with bond ratings at 1% ($p \leq 0.01$). The variables are TOA, COUP, SIZE_ISS,

MATUR and M_BETA. Other variables (ROA, LTD and INT_COV) are found to be insignificant. Only two of the significant variables (MATUR and M_BETA) agreed with their predicted direction, while others (TOA, COUP and SIZE_ISS) did not.

Moreover, the matrix indicates few variables that are highly correlated with each other (r>0.5). TOA is highly correlated with SIZE_ISS (0.60), ROA with M_BETA (0.71) and LTD with INT_COV (0.65). Hence, the correlation matrices present possibility of multicollinearity. Variance inflation factors (VIF) test is conducted to test for multicollinearity and it is not a problem if the mean VIF value is not greater than 10 (Menard, 1995). The test presents a VIF value ranging from 1.28 (COUP) to 4.50 (ROA) with a mean VIF of 2.80 (VIF<10). This range indicates that muticollinearity is not a problem in this study.

Table 2: Spearman Correlation Coefficients.

	BY	TOA	ROA	LTD	INT_COV	COUP	SIZE_ISS	MATUR	M_BETA	VIF
BY	1									
TOA	-0.29**	1								3.28
ROA	-0.16	-0.28**	1							4.50
LTD	0.11	0.21*	-0.17	1						2.46
INT_COV	0.16	-0.48**	0.43**	-0.65**	1					3.89
COUP	0.66**	-0.28**	0.08	0.03	0.04	1				1.28
SIZE_ISS	-0.43**	0.60**	0.30**	0.09	-0.28**	-0.12	1			3.28
MATUR	-0.29**	0.12	0.28**	-0.05	-0.01	0.20*	0.49**	1		1.47
M_BETA	-0.27**	-0.01	0.71**	-0.21*	0.16	0.02	0.32**	0.15	1	2.26
										2.80

** Indicates significance at the 0.01 level. * Indicates significance at the 0.05 level.

4.3 Multinomial Logistic Regression:

In examining the relationship between the three risk factors in determination of bond ratings, multinomial logistic regression is used to cater for the bond rating's ordinal nature and having more than two categories. In the final data sample, there are three categories of bond rating used; AAA, AA and A, they are denoted as 1, 2 and 3 respectively for the model. No bonds with lower rating than A is recorded. Note that any types of logistic regression do not require for the data of the independent variables to be normally distributed.

Table 4 presents the results of the multinomial logistic regression, between the ordinal scale dependent variables (bond rating) and eight independent variables from three different risk factors. Panel A reports a total of 120 observations are recorded for investigation. Out of these 120 observations, 35 are AAA (29.17%) rated bonds, 63 (52.5%) are AA rated bonds and 22 are rated A (18.33%). Based on these findings, it is noted that minimum threshold value of the data is 52.5%. Furthermore, Pseudo R-Squared is used to evaluate logistic model's fit. Panel B reports values of three Pseudo R-Squared which are Cox and Snell, Nagelkerke and McFadden; each value at 0.75, 0.86, 0.68 respectively.

A-rated bond is set as the reference category by default, therefore there are two estimated model which are (1) AAA-rated bond relative to A-rated bond and (2) AA-rated bond relative to A-rated bond. By using Forward-Entry of Stepwise method, the variables that are included in the model by default are ROA, LTD, INT_COV, SIZE_ISS, and M_BETA. Panel C shows the results of multinomial logistic regression.

In the first estimated model of AAA-rated bond relative to A-rated bond; three out of five variables are found to be statistically significant predictors at 0.01 ($p \leq 0.01$) level, which are ROA, LTD and INT_COV, whereas SIZE_ISS and M_BETA are found to be non-significant predictors. The Wald statistic for ROA is 8.09 with an associated *p*-value of 0.006. Each increased in a firm's ROA, the multinomial log-odds of preferring AAA to A-rated bond would increase by 143.11 units (holding other variable constant). The Wald statistic for LTD is 7.93 with an associated *p*-value of 0.005. Each increased in a firm's LTD, the multinomial log-odds of preferring AAA to A-rated bond would decrease by 27.55 units (holding other variable constant). However, INT_COV is found to deviate from its predicted relationship, despite being highly significant. With a Wald statistic of 8.09 the findings indicate that, with each increased in a firm's INT_COV, the multinomial log-odds of preferring AAA to A-rated bond would decrease by 1.06 units (holding other variable constant).

For the second estimated model of AA-rated bond relative to A-rated bond; out of five variables included in the model, four of them are found to be statistically significant predictor (LTD, INT_COV, SIZE_ISS, and M_BETA).). Both SIZE_ISS and M_BETA are found to be a significant predictor at 0.01 level, with Wald statistic of 11.38 and 14.96 respectively. Furthermore, each increased in the bond's SIZE_ISS, the multinomial log-odds of preferring AA to A-rated bond would increase by 5.64 units (holding other variable constant). While, each increased in a firm's M_BETA, the multinomial log-odds of preferring AA to A-rated bond would decrease by 86.81 unit (holding other variable constant). INT_COV is a statistically significant predictor at 0.05 ($p \leq 0.05$) level, with a Wald statistic of 5.35 and *p*-value of 0.021. Each increased in a firm's INT_COV, the multinomial log-odds of preferring AA to A-rated bond would increase by 0.75 unit (holding other variable constant). Similar to the first estimated model, one statistically significant variable (LTD) is found to stray away from its predicted relationship. LTD is significant at 0.05. The results show that for each increased in a firm's LTD, the multinomial log-odds of would increase by 20.77 units (holding other variable constant).

4.4 Robustness Check:

Panel D of Table 4 shows the classification accuracy that the model has. Based on the table, the model has relatively high overall percentage of correctly classified rating observations of 91.67%, with a total of only 10 observations wrongly classified. 100.00% of AAA-rating observations are correctly classified. For AA-rating observations, 96.83% are correctly classified with only one observation wrongly classified one rating class above (AAA-rating) and one observation wrongly classified one rating class below (A-rating). Finally, 63.64% of the A-rating observations are correctly classified, with seven observations wrongly classified one rating class above (AA-rating) and one observation wrongly classified two rating class above (AA-rating).

5. Discussions:

The null hypothesis of this study is successfully rejected, indicating that there is a significant relationship between risk factors and bond ratings. The model demonstrates an excellent model fit with accuracy of 91.67% as shown in Panel D of Table 3. The model's classification accuracy surpasses its threshold value of 52.5%. Moreover, all three Pseudo R-Squared values are highly close to 1.00 further solidify that the logistic model fit of this study is good. With A-rating as the reference category, the two multinomial logistic estimated models show that bond ratings can be explained relatively well by only few variables.

In the first estimated model, it is noted that measurement of firm's profit, long-term debt and interest coverage ability are significant determinants of bond ratings. The results indicate, the bond issued by firm with higher ROA will have a higher relativity of moving towards AAA-rating. Moreover, the bond issued by firm with higher LTD and INT_COV have a higher relative risk of moving towards A-rating. The findings show that firm's risk factors alone are enough to explain higher rated and lower risk bonds.

Table 3: Relationship between Risk Factors and Bond Ratings.

Panel A				
	N	Marginal Percentage		
AAA	35	29.17		
AA	63	52.50		
A	22	18.33		
Total	120	100.00		
Panel B				
Pseudo R-Squared				
Cox and Snell	0.746			
Nagelkerke	0.860			
McFadden	0.679			
Panel C				
			Multinomial Logistic Estimator	
Risk Factors	Variables	Predicted Sign	AAA vs A B (Std. Err)	AA vs A B (Std. Err)
Firm's Risk	TOA	+		
	ROA	+	143.11*** (51.97)	-30.83 (46.96)
	LTD	-	-27.55*** (9.78)	20.77* (9.90)
	INT_COV	+	-1.06*** (0.37)	0.75* (0.02)
Issuance's Risk	COUP	-		
	SIZE_ISS	+	0.98 (1.76)	5.64** (1.67)
	MATUR	-		
Market's Risk	M_BETA	-	24.62 (26.43)	-86.81** (22.45)
Panel D				
		Predicted		
Observed	AAA	AA	A	Percentage Correct
AAA	35	0	0	100.00
AA	1	61	1	96.83
A	1	7	14	63.64
Overall Percentage	30.83	56.67	12.50	91.67

In the second estimated model, measurement of firm's debt, coverage ability, issuance size of bond and systematic risk are significant determinants of bond ratings. The results indicate the bond with larger SIZE_ISS, higher INT_COV and higher LTD will have a higher relativity of moving towards AA-rating. While, bond issued by firm's with higher M_BETA will have a higher relativity of moving towards A-rating. Bond's issuance size and measure of firm's systematic risk became significant determinants only to lower rated bonds. This indicates that the other two risk factors; issuance and market risk factors are only significant in determining bonds with higher risk and lower rated bonds.

It is noted that INT_COV deviates from its predicted sign in the first estimated model and not in the second model. In contradiction, LTD deviates from its predicted sign in the second estimated model but not in the first model. This is probably because of these two variables being highly significant of each other according to Spearman correlation (r=0.65, refer Table 2). These findings are similar to Belkaoui [2], Bhojraj and Sengupta [4], Crabtree and Maher [7] and Ho and Rao [17].

6. Conclusion:

To conclude, this study's H_0 is rejected indicating that there is a significant relationship between risk factors and bond ratings. The multinomial logistic regression model used to examine the determinants of bond ratings did significantly well with high Pseudo R-Squared values demonstrating an excellent model fit. With A-rating as the reference category, the two multinomial logistic estimated models show that bond ratings can be explained relatively well by only few variables.

It is noted that firm's risk factors are enough to explain higher rated bonds, as measurement of firm's profit, long-term debt and interest coverage ability are significant. However, issuance risk factors and market risk factors became significant determinants to lower rated bonds. Moreover, measurement of firm's debt, coverage ability and market risk are significant in determining lower rated bonds. Additionally, with a high correct classification accuracy of 91.67%, it further cemented the significance of this model's findings. These findings are similar to Belkaoui [2], Bhojraj and Sengupta [4], Crabtree and Maher [7] and Ho and Rao [17].

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