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Credit Rating: A New Quotation Approach

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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ABSTRACT

Credit rating agencies rate companies and states by assigning them scores depending on their level of solvency. These scores are inversely proportional to default risk and then proportional to quotes which are proportional to bonds value. Consequently, scores are calculated depending on companies and states bankruptcy risk. In our paper, we assess company solvency using numerical symbols and an accelerating risk model. Although the Big3 [1] rating agencies use uniformly distributed risk to rate corporate bonds, we think that the distribution should vary uniformly. Our theoretical model is based on a homogeneously risk varying path with a fluctuating speed but a constant acceleration of risk. We measure this acceleration and calculate risk intervals by using a linear regression where asset volatility represents the dependent variable, and a set of 20 company categories representing the independent variable.
Comparative statics are used to illustrate our analysis. We obtain a very significant coefficient for the exogenous variable, representing homogeneous risk intervals. We use 20 classes of risk to be consistent with the "US equivalent rating", as the Big3 rating agencies do, which allows us to determine risk classes and rate companies according to the numerical scale obtained.
We compare our numerical scale to the equivalent rating tables used by Moody's, Fitch Ratings and S&P. According to our findings, companies with a risk level under 16 are considered to be solvent, while those with a 17-to-20-risk level are considered to be in trouble. Indeed, the length of

[1]*Moody's, Standard & Poor's and Fitch Ratings.*

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risk intervals and the risk acceleration should vary depending on industry sector and population size. Our model is useful for both public and private companies.

Keywords: Accelerating risk; risk motion; equivalent rating; risk classes; scores; volatility range.

1. INTRODUCTION

According to the Big3 rating agencies, corporate bond credit ratings are based on a scale of 20 alphabetical classes. These risk classes are obtained proportionally to default risk and then to the bankruptcy level of companies and states rated according to their bonds value. Hence, as bonds value weakens, the company or state quote goes down. As a result, it is downgraded by credit rate agencies which assign it a lower score than the one it had before. The three agencies use similar symbols in their credit ratings, drawing on several models to determine a company's solvency level. Moody's and Fitch Ratings consider the weighted average rating factor (WARF) in determining scores, while S&P has a threshold that companies must observe in order to preserve their score [1]. Hence, companies with a high credit level are classified at the top of the scale, those with a relatively high level of solvency are placed in the middle of the rating table, and companies in trouble are classified at the bottom of the scale.

This method of classifying corporate bonds is somewhat ambiguous because it measures risk uniformly even though this factor varies homogeneously. Our model[2] examines a non-uniform risk motion between two consecutive classes of risk. By doing so, we classify corporate bonds according to their level of risk and give them numerical scores, allowing us to obtain bond equivalent ratings. We also use an accelerated risk motion with a constant acceleration. In fact, the quotes should go down as bonds become risky. This variation should occur homogeneously but not uniformly.

Models based on stock options and simulations, such as Monte-Carlo, could also be used to rate corporate bonds if the derivatives used to produce the quote are obtained from companies' financial statements. Structural models allow for this risk assessment method.

Our model is rather simple and easy to operationalize. The only factor that should be determined to measure risk motion is its acceleration. We determine this parameter by performing a linear regression where volatility and risk classes represent the dependent and exogenous variables respectively. We use comparative statics to determine risk class range, a parameter that also lets us determine risk acceleration value.

The rest of the paper is organized as follows. We present a literature review in section II, our methodology in section III, our credit rating assessment model in section IV, comparative statics in section V, and our conclusion in section VI.

2. LITERATURE REVIEW

Beaver [3] was among the first authors to establish a relationship between market price changes and accounting information. The author focuses on the earnings announcement as a source of information to correctly measure market changes and help the market achieve equilibrium. According to the author, investors should use earnings to look for information value by analyzing stock prices after the financial statement announcement. But this financial statement should not be overstated so not to bias earnings [4], which should bias the solvency level of companies rated. [3] concludes that price fluctuations are explained by the information contained in these financial reports, especially earnings. Financial statement fluctuations can then explain fluctuations in market price. As a result, asset volatility can be used to measure a company's bankruptcy risk exposure.

Altman [5] rates corporate bonds by using five financial ratios as exogenous variables in his discriminant analysis. To weigh up companies' solvency, the author succeeded in transforming static financial ratios into dynamic ones by using statistics and obtained numerical scores. Given positive proportionality between a bond value and its quote, as the score goes up, the company becomes more solvent and its assets less risky. Conversely, as the score goes down, the company turns out to be more exposed to financial distress. In other words, the Z-score obtained by the author determines a company's solvency level. Hence, as the company's corporate bonds become riskier, the Z-score

[2]*Inspired from the homogenous accelerated motion* [2].

becomes weaker and vice-versa. The author established a 1.81 threshold under which the evaluated company should be considered in financial distress. This model is suitable for manufacturing companies.

A host of other authors [6] relied on the same method to rate companies but used financial ratios that are convenient for both manufacturing and non-manufacturing companies. The results thus obtained are similar to [5]. [7] also uses financial statements to measure the bankruptcy threshold but he considers a logistic function rather than a linear one. The author obtains a statistically significant relationship between the companies' financial structure and their probability of failure.

Conversely, some researchers used distance to default to weigh up companies' solvency [8]. This parameter is measured by comparing company assets to corporate debt. As debt value remains lower than asset value level, the company is considered to be solvent. However, if debt becomes higher than the named threshold, the company goes bankrupt. That means that equity value becomes nil. This way of analyzing risk default is similar to the method used to calculate the intrinsic value of a call option. Hence, as the underlying asset—in our case, company total asset value—remains higher than the strike price, represented by debt, the option value is obtained by subtracting the second variable from the first one, which means a positive equity value. But if debt value becomes higher than asset value, the option vanishes and the company goes bankrupt.

The Black and Scholes [9] formula can be used to determine a financial option value. According to the authors, returns should be normally distributed when assessing this type of financial security. Although Moody's KMV uses this model to rate corporate bonds, the model becomes less useful when assessing real assets. In fact, volatility becomes difficult to determine, as these assets are not sold on the market. The real options concept is difficult to apply with this sophisticated model. In this case, structural models should be used numerically to determine debt value, considered as the strike price of the call option written on the company. This call option is represented by equity. This form of assigning credit ratings is called "Market implied rating" as it allows measuring scores by using bonds market price [1] which helps measuring each company's default threshold.

Merton [10] pioneered research into this technique to determine debt value. He indicated that the company's liabilities consist of a long-term zero-coupon bond, and equity value is calculated at maturity. If the company value is less than its liabilities, equity value becomes nil and the company goes bankrupt. Debt should be used to achieve financial leverage but could drive the company into financial distress. In fact, if debt interests are not covered by the marginal yield this debt allows to achieve, the company sees its value vanish. Other authors [11,12,13,14] used the same technique as [10] but considered bankruptcy cost and tax shield arbitrage in their respective models while measuring the default distance. In fact, structural models establish a negative relationship between bankruptcy and bonds value as both are considered as financial securities. Their dynamic equations are then derived from the partial differential equation of these models and have respectively positive and negative signs in the company value expression. This means that a high bond value contributes to enhance company value and that bankruptcy costs which are proportional to the default level of the company lead to reduce this value [15,16,17,18,19].

Both financial-statements-based and structural-based models allow measuring bankruptcy probability[3]. They help the investor to optimally determine the level of returns he/she should claim depending on the risk he/she is exposed to. The partisans of financial statements use multivariate models to explain the quote and then the value of the company's bonds by using financial ratios as exogenous variables while the Big3[4] agencies use the Black & Scholes formula to determine this value as a call option written on the asset value of the company. The bankruptcy is triggered when this value declines below a default threshold. Scores are calculated depending on this default level.

The model we propose is rather numerical and uses asset volatility[5] as a measure of risk to rate corporate bonds. This risk accelerates uniformly as companies become riskier.

[3] "The default history of financial institutions shows that credit risk is the most important threat to insolvency." [20]
[4] "Bonds with a Moody's "Aaa" rating are considered to have almost no chance of defaulting in the near future." [21]
[5] As bonds become risky, asset value becomes risky as well because of higher debt costs, which negatively affect company value.

3. METHODOLOGY

As mentioned earlier, bonds market value helps determining the companies' bankruptcy level. Structural models are used to implicitly measure these companies' solvency by assigning them scores according to their bonds prices. But the Big3 rating agencies use a uniform distribution of risk to rate corporate bonds. Our analysis is based on a uniformly accelerating risk model. We first determine risk intervals by performing a linear regression where asset volatility represents the dependent variable, and a set of 20 classes of risk, the exogenous variable. We expect a statistically significant relationship between volatility and risk classes. The exogenous variable coefficient represents risk class width. Once the homogeneous range of risk is determined, we analytically derive risk acceleration magnitude. Our theoretical model is based on a uniformly accelerated risk motion. This motion equation is used to determine the risk acceleration.

We then associate each risk class with the range to which it should belong. To do so, we attribute a risk class to each company depending on its risk level represented by its volatility range. Twenty levels of risk are used according to the Big3 rating agencies classification. The first class of risk contains companies with the lesser level of risk while the higher level of risk is attributed to companies that belong to the higher volatility range. A class length is measured by the regression of volatility on the twenty classes considered and represents the distance between two consecutive levels of risk. This risk will vary according to an arithmetic progression with a «γC_w^2» step, where «γ» represents its acceleration and «C_w» a class width.

Finally, we establish the bridge between the result obtained and the corresponding "US equivalent rating", as the Big3 rating agencies do. Comparative statics are used to illustrate our model's usefulness.

4. OUR MODEL

To rate company solvency, by using implied scores based on bonds market value, risk should be correctly assessed. According to the Big3 rating agencies, there are 20 main rating classes [1]. To quantify risk, 20 thresholds should be considered. Given that risk is inversely proportional to quotes, we use this number as a common denominator for all the scores we consider. However, risk should vary homogeneously. Quotes should go up when risk diminishes and down as bonds become risky. We use a uniformly accelerating motion with a «γC_w^2» step. This parameter represents risk variation between two consecutive quotes that follow an arithmetic progression. In our model, this step corresponds to a 1/20-interval length. In the first interval, we should find companies rated 'Aaa' as in Moody's rating table.

Conversely, companies that are in trouble should have the highest risk levels and belong to the last risk interval. To use this rating model, we consider asset volatility as the risk measure. Hence, the highest range of volatility should correspond to a 100% risk level, while the lowest range should indicate the first risk level. To measure these risk levels accurately, homogeneous intervals should be used. To do so, we perform a linear regression where volatility represents the dependent variable, and classes from 1 to 20, the independent variable. The coefficient of the independent variable corresponds to the risk intervals' length.

The general formula we use to assess corporate bond risk level is the following:

$$R_H = [R_L + (N - 1) \times \gamma \times C_W^2] \quad (1)$$

Where:

- R_H represents the highest level of risk;
- R_L represents the lowest level of risk;
- γ represents the risk acceleration;
- C_W represents a risk class width and then the coefficient of the exogenous variable in the linear regression we operate;
- N represents the number of risk classes.

The term N could be obtained by simply using the following expression:

$$N = H_V - L_V + 1 \quad (2)$$

Where:

- H_V represents the sequence number of the highest volatility level;
- L_V represents the sequence number of the lowest volatility level.

Equation (1) allows us to determine risk acceleration. This parameter formula can be presented as follows:

$$\gamma = [R_H - R_L] / [(N - 1) \times C_W^2] \quad (3)$$

The result obtained makes it possible to rate bonds depending on the risk class to which they belong.

5. COMPARATIVE STATICS

To illustrate, consider a set of 20 companies, assumed to be exhaustive, with various volatilities. We will rate these companies by using numerical equivalent ratings. Company ratings are presented in Table 1 below.

As shown in Table 1, the respective minimum and maximum volatility values are 10% and 201%, corresponding to a 192% [6] volatility interval width. Table 1 classifies risk into 20 classes. We match these numerical categories to the ratings given by the Big3 rating agencies in order to be able to measure the rated companies' solvency level. Hence, company 2 presents the lowest level of risk and should be ranked at the top of solvent companies. By contrast, company 10 presents the highest volatility. It is in trouble.

To determine the length of classes, we simply divide the main range by the number of classes. A class width is determined by performing the linear regression with volatility representing the endogenous variable, and risk classes, the independent variable. The results of this regression are given in Tables 2, 3 and 4 below. A high-adjusted R-squared level means that our ranges represent the classes chosen and confirms the strong linear relationship between volatility and risk classes.

The equation for our regression is presented as follows:

$$\text{Volatility} = ß_0 + [ß_1 \times \text{Class}] + \varepsilon \qquad (4)$$

Where:

$$C_w = \text{Total Volatility} \,/\, \text{Number of Classes} \qquad (5)$$

As shown in Table 2, the coefficient of the exogenous variable is about 9.96 and is statistically significant with a .00 *P value*. The coefficient obtained represents the length of risk intervals. We use this result to determine the risk acceleration.

Table 2 also shows a very high exogenous variable t-statistic value (66.480). This allows us to conclude that the relationship between the dependent variable and the independent one is strongly linear[7]. In fact, at a significance level of 1%, risk classes can positively, significantly and linearly explain volatility, which means that as we go up in the risk classes scale, volatility goes up too and vice-versa. Conversely, companies' solvency level diminishes as they become riskier. Therefore, their quotes go down, which is coherent with the Big3 rating method. The main difference between our model and the Big3 technique of quoting is that in our case we use a uniformly accelerated risk while the Big3 agencies use a uniform risk motion to rate bonds and states.

The exogenous variable coefficient, representing a risk class width, is used to calculate risk acceleration and then the twenty numerical risk levels that we match to the Big3 quotation tables according to the US equivalent rating [1].

Table 3 shows a very high adjusted R-squared (99.57%), meaning that the ranges of risk level and volatility are linearly and significantly related. We can then confirm that the distance separating two consecutive classes, expressed in terms of volatility, is about 9.96%.[8]

Now let R_1 be the lowest risk level, and $R_{20,}$ the highest. According to our model, the equation that links the two risk levels should be the following:

$$R_{20} = R_1 + [19 \times \gamma \times C_W^2]$$

This means that risk acceleration can be obtained as follows:

$$\gamma = [R_{20} - R_1] \,/\, [19 \times C_W^2]$$

By replacing each parameter with its numerical value, we obtain a risk level acceleration of about 10.1425[9]. We can therefore determine the risk level of each risk class, as shown in Table 4. A company position is obtained depending on its level of risk [1]. Table 4 establishes a relationship between this position and the level of

[6] *Risk range = 201% – 10% + 1% = 192%.*

[7] *We use theoretical data to illustrate how our model is constructed. Future empirical analyses will be conducted to measure more precisely classes' width using volatility.*

[8] *In fact, this coefficient should vary depending on the industry to which the company belongs.*

[9] $\gamma = [201\% - 10\%] / [19 \times 0.099556^2]$

Table 1. Risk classification matched to the Big3 corporate bond ratings

Company category	Volatility (%)	Class	Big3 equivalent rating		
			Moody's	S&P	Fitch ratings
1	130	13	Ba3	BB-	BB-
2	10	1	Aaa	AAA	AAA
3	188	18	Ca	CCC	CCC
4	21	2	Aa1	AA+	AA+
5	34	3	Aa2	AA	AA
6	191	19	C	CCC-	C
7	95	9	Baa2	BBB	BBB
8	103	10	Baa3	BBB2	BBB2
9	114	11	Ba1	BB+	BB+
10	201	20	-	D	D
11	72	7	A3	A-	A-
12	88	8	Baa1	BBB+	BBB+
13	53	5	A1	A+	A+
14	45	4	Aa3	AA-	AA-
15	160	15	B2	B	B
16	152	16	B3	B-	B-2
17	171	17	Caa	CCC+	Caa
18	144	14	B1	B+	B+
19	121	12	Ba2	BB+	BB+
20	62	6	A2	A	A

Table 2. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	BETA		
1	(Constant)	3.2158	1.79253		1.793	.090
	Class	9.9556	.14975	.99797	66.480	.000

a. Dependent variable: Volatility

Table 3. Identification coefficients

Model	R	R-squared	Adjusted R-squared	Std. Error of Estimate
1	.99797[a]	.99594	.99570	3.86179

a. Predictors: (Constant), Class

risk calculated by using our model. The table also shows the association made between the solvency level of each company and its supposed equivalent quote according to the Big3 rating agencies.

Table 4 shows that the highest risk level is about 16 times greater than the lowest one, corroborating our assumption about homogeneous variability of risk, but not linear variability. As we indicated earlier, consecutive variations in risk level differ according to an arithmetic progression with a «γC_w^2» step. In other words, the risk level rises homogeneously between two consecutive classes of risk.

As we can see, companies with a risk level lower than R_{10} should be considered solvent, while companies with a risk level belonging to the [R_{11}; R_{16}] risk range should be considered moderately solvent. Lastly, companies with a risk level over R_{17} should be ranked as being in trouble. They are at least 13 times riskier than companies in the first risk level, whereas the first set comprises firms with fewer than eight levels of risk.[10]

[10] The results obtained should be generalized to all indebted companies so as to achieve a more accurate risk level. In the process, exploding volatilities and risk-free bonds should be eliminated from the population of risk levels analyzed.

Table 4. Risk levels and corresponding equivalent ratings

Risk rank	Risk level	Company position	Corresponding equivalent quotes		
			Moody's	**S&P**	**Fitch ratings**
R_1	1.00	High credit value	Aaa	AAA	AAA
R_2	1.76		Aa1	AA+	AA+
R_3	2.53		Aa2	AA	AA
R_4	3.29		Aa3	AA-	AA-
R_5	4.05		A1	A+	A+
R_6	4.82		A2	A	A
R_7	5.58		A3	A-	A-
R_8	6.34		Baa1	BBB+	BBB+
R_9	7.11		Baa2	BBB	BBB
R_{10}	7.87		Baa3	BBB2	BBB2
R_{11}	8.63	Low credit value	Ba1	BB+	BB+
R_{12}	9.40		Ba2	BB	BB
R_{13}	10.16		Ba3	BB-	BB-
R_{14}	10.92		B1	B+	B+
R_{15}	11.69		B2	B	B
R_{16}	12.45		B3	B-	B-2
R_{17}	13.21	In default	Caa	CCC+	CCC
R_{18}	13.97		Ca	CCC	
R_{19}	14.74		C	CCC-	C
R_{20}	15.50		-	D	DDD D DD

6. CONCLUSION

This paper presents a new theoretical credit rating model. The Big3 rating agencies use uniformly distributed risk models to rate corporate bonds and give alphabetical ratings to companies based on their numerical rankings. Our model is based on a numerical scale as well, but also uses an accelerating risk motion to calculate scores. Risk is considered to vary homogeneously, and its acceleration is constant. To measure this acceleration, we first used a linear regression where asset volatility represented the dependent variable, and risk classes, the independent variable. The coefficient of the exogenous variable allowed us to determine the length of classes. We then used this result to derive the risk acceleration formula. As the Big3 rating agencies do, we considered 20 categories of companies and then linked our rating scale to the alphabetical scale produced by the three rating agencies.

The regression we performed allowed us to measure the width of risk classes. This parameter was used to determine the acceleration, given that the homogeneous risk intervals vary according to an arithmetic progression with a «γC_w^2» step. The term «γ» was calculated simply by considering two consecutive levels of risk relationship as derived by the model. We obtained 20 levels of risk, similarly to the Big3 rating agencies. We used comparative statics to determine intervals of risk length and risk acceleration. The two parameters could be measured more precisely by using an exhaustive set of companies. The model's parameters should vary depending on industry sectors.

In our analysis, we used volatility to obtain risk classes width. This means that we know its lowest and highest values. The lowest border corresponds to riskless company bonds, but the highest level of risk could be infinite. Our model gives scores only in the case of finite volatility values. Besides, the model allows having a better perception of companies and states solvency than many credit agencies' models do. Its use in the determination of scores could allow, in the future, avoiding a world economic crisis similar to the one observed since a few years and which is due in our humble opinion to a bad conception of risk measurement tools.

Further empirical analyses should measure scores according to the research context. Our model is useful for both publicly traded financial assets and private companies. For the latter, volatility should be determined only by measuring the standard deviation of cash flows realized by the company or asset variability, using information in financial statements available in public databases.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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