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ASSESSING CORPORATE RISK: A PD MODEL BASED ON CREDIT RATINGS

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Abstract. *This paper proposes a model which tries to mimic agencies' corporate ratings. Using financial data for more than 1,400 firms across several years, a model based on financial statements was estimated and yielded reasonable accuracy for companies of diverse sizes and industries. The model was able to predict ratings within 3 notches of accuracy for about 90% of the cases.*

Introduction

Rating agencies provide valuable credit information despite suffering widespread criticism since the subprime crisis. Their credit risk assessments are still broadly used by the financial industry globally. However, only about 3,000 corporates are rated, at the same time as most of them are located in the US. This severely limits the applicability of ratings to emerging markets. With this concern in mind, we developed a model that tries to approximate agencies' ratings by using solely financial data. This class of models is usually called shadow rating models.

The text is divided into four major sections. After this brief introduction, we introduce a summary of the methodology and its theoretical references, followed by details of the model development, and the conclusions of the study.

Relevant Literature

There is little literature on the subject of replicating agencies' ratings, but several papers (amongst them papers by rating agencies themselves) aimed at discussing probability of default models and can shed some light on the problem this paper tries to address. Erlenmaier (2006) reported aspects of the development of a corporate rating methodology by KfW. Moody's (2004) also discusses properties of a purely statistical model based solely on financial data.

A larger, well studied, and relevant strand of the credit risk literature, initiated with Altman (1968), relies basically on financial ratios to predict default. Therefore, as ratings reflect expected default rates, an indirect link can be established between firm's financial statements and ratings, since one can infer default rates from these ratings.

The shadow rating approach is typically used when default data is scarce and external ratings of the major rating agencies (Standard and Poor's, Moody's or Fitch Ratings) are available for a significant portion of the loan portfolio. The common purpose to all quantitative methodologies developed for credit ratings is to identify risk factors that provide good information about the probability of default (Moody's Investor Service, 2000).

The shadow rating approach does that indirectly by identifying the most important factors and by estimating the relative weights of each of them in order to mimic external ratings as faithfully as possible. To make the estimated model useful for regulatory purposes and for credit risk management, it is still necessary to calibrate it to a probability of default (Erlenmaier, 2006).

Model Development

The model development process employed five steps:

1. Data management[1]
2. Mapping external ratings to probabilities of default;
3. Analysis of risk factors and variable selection;
4. Model estimation; and
5. Model validation.

Step 1: Data management

Our data comprises a set of financial statements of global non-financial companies along with their credit ratings as issued by international rating agencies. The data is comprehensive and covers a large sample of the rated corporate universe, summing up to 2314 companies.
We considered the financial information of those companies as of December 31st of the year preceding the date of publication of rating. We considered only ratings issued by Standard & Poor's, Moody's and Fitch Ratings.
Financial firms were removed from the database, and the cleaning of missing data left 1614 companies for the model estimation. After collecting and processing the data, we proceeded to the mapping of external ratings to a probability of default.

Step 2: Mapping external ratings to probabilities of default

An important step in building a shadow rating model is mapping the ratings from international agencies to relevant default probabilities. We favored the unsecured long-term issuer ratings, since they do not take in consideration possible credit risk mitigants and are consistent with the Basel Accord II (BCBS, 2004).

Table 1. Corporate ratings and five year PD (%), 1983-2009

Moody's Rating	Equivalent S&P Rating	Default Probability (%)
Aaa	AAA	0.086
Aa1	AA+	0.141
Aa2	AA	0.195
Aa3	AA-	0.324
A1	A+	0.854
A2	A	0.746

[1] We used two different samples. One sample for the development of the model comprised 1614 companies and another sample for validating and testing the model comprised 2053 firms

Moody's Rating	Equivalent S&P Rating	Default Probability (%)
A3	A-	0.83
Baa1	BBB+	1.18
Baa2	BBB	2.024
Baa3	BBB-	3.081
Ba1	BB+	7.289
Ba2	BB	8.084
Ba3	BB-	16.948
B1	B+	20.077
B2	B	25.211
B3	B-	36.907
Caa1	CCC+	47.262
Caa2	CCC	49.868
Caa3	CCC-	66.96
Ca-C	CC - SD	70.176

Source: (Moody's Investor Service, 2010)

Table 1 depicts the default probabilities. The use of five-year mean probabilities is important because credit events in shorter time horizons are rare, especially for credits of better quality. In particular, according to Keenan, Shtogrin and Sobehart (1999), in periods of one or two years, the main reason for default is some kind of fraud, which is beyond the scope of this paper. In addition, five-year probabilities show lower volatility for both the probabilities given by agencies and for model prediction (Moody's Investor Service, 2000). Finally, Basel II rules require an estimate of a Long Run Probability of Default.

After mapping external ratings to default probabilities (interpolating the only non-monotonicity exhibited by the A1 rating), we proceeded to identify a list of candidate variables to test during the model development.

Step 3. Analysis of risk factors and variable selection

We analyzed several risk factors based on information from balance sheets of the non-financial companies in our sample. The variables are divided into six major categories, namely:

1. Profitability
2. Leverage
3. Liquidity
4. Size
5. Activity
6. Debt Coverage

Each of these dimensions is (or should be) related to the probability of default. Following the traditional literature (since Fitzpatrick 1928, Beaver 1966, Altman, 1968), we use, in most cases, financial ratios as explanatory variables. This ensures that the variables are not affected by the size of companies, which was included as a separate factor. Companies' size vary by several orders of magnitude, which make figures like net income look like they are more correlated with firm size than one should expect. In addition, ratios avoid problems regarding comparisons between companies with statements denominated in different currencies. Each explanatory variable has several possible measures (EBIT or EBITDA, for example) and may be related to more than one risk factor (retained earnings / total assets is related both to leverage as to profitability).

Given the large number of variables, combinations of ratios may become numerous. This requires a method for selecting variables so that just the ratios most correlated with the probability of default are considered. Many of these ratios are highly correlated with each other, i.e., both explanatory variables behave similarly so that they are measuring the same risk factor. In order to avoid collinearity issues, when two variables showed a correlation greater than 80%, the one with the highest correlation with the other variables was discarded.

Table 2. Descriptive statistics

Variable	Minimum	Maximum	Mean	s. d.
Net Debt / EBITDA	-8.068	103.094	2.673	4.489
Interest Coverage	-24.457	1788.988	14.563	61.993
ROA	-0.947	0.585	0.038	0.082
Utilities Dummy	0.000	1.000	0.098	0.298
Liabilities /Total Assets	0.000	24.017	0.658	0.599
Size (Ln of Total Assets)	12.284	27.266	22.588	1.462

After data cleaning and the variable selection process, a candidate model with 6 ratios was estimated. Table 2 lists the descriptive statistics of the included variables:

Having identified the risk factors and selected the most appropriate variables, we proceeded to model estimation.

Step 4. Model estimation

The modeling process was carried out using R (R Development Core Team, 2009), and employed least squares methods in order to estimate the parameters.

The dependent variable was defined as the logit of the probability of default associated with ratings issued by international agencies. The logit is defined as the natural logarithm of the odds ratio: log (pd / (pd-1)), where pd is the probability of default associated with any rating. This ensures that the model predictions are within the [0, 1] range.

In addition, we have included a binary variable that serves as an indicator for utilities companies. The inclusion of this variable allows us to take into account the fact that such companies generally have guarantees or government ownership. It grants them with better credit quality on average.[2]

Also, utility firms have operational measures that hide the perils of a strict regulatory environment. Typical companies from this industry have a greater need for fixed capital, which often makes liquidity measures become negative (S&P, 2009).

The final model is given by:

[2] The dummy for utilities assigns a 0 if the firm is not an utility firm and 1 if it is a firm that is a utility firm.

Formula 1. Estimated model

$$score = \alpha + \beta_1.\frac{Net\ \ Debt}{EBITDA} + \beta_2.Ln\,Total\ Assets + \beta_3.InterestCoverage$$

$$+ \beta_4.\frac{Net\ \ Income}{Total\ \ Assets} + \beta_5.Dummy\ \ Utilities$$

$$+ \beta_6.\frac{Liabilities}{Total\ \ Assets} + \varepsilon \qquad \text{and: } PD = \frac{1}{1+e^{-score}}$$

All variables are statistically significant, and the signs of the coefficients are all in the expected direction. It is also worth reporting that the standard errors calculated for statistical inference are robust to heteroscedasticity.[3]

Table 3. Model results

Variables	Coefficient	p-value
Constant	9.9267	< 0.0001
Net Debt / EBITDA	0,0569	< 0.0001
Interest Coverage	-0,0014	0.0008
ROA	-4,4797	< 0.0001
Utilities Dummy	-0,859	< 0.0001
Liabilities /Total Assets	0,9135	< 0.0001
Size	-0,5953	< 0.0001

n=1614, Adjusted R^2=0.564, likelihood ratio test = 1345.17

Following model estimation, we proceeded to model validation.

Step 5. Model validation.

The selected model has undergone several tests to assess its ability to produce ratings close to the ratings of international rating agencies.

The ability of the model to correctly predict agencies' ratings through was tested using a method known as hit-mismatch (or hit-miss-match), following Grün et alli (2010), presented in Table 4. The method allows us to evaluate the ability of a model to correctly predict the ratings we are interested in.[4]

3 Besides the procedure described above to deal with the collinearity, we used the White´s test (1980) to deal with the presence or not of heteroscedasticity.

4 The rating obtained by the model presented here should be limited to one notch above the company´s country rating. For countries that do not have a published rating in a compatible scale, an estimated rating could be obtained using the approach proposed by Guimarães et allii (2013).

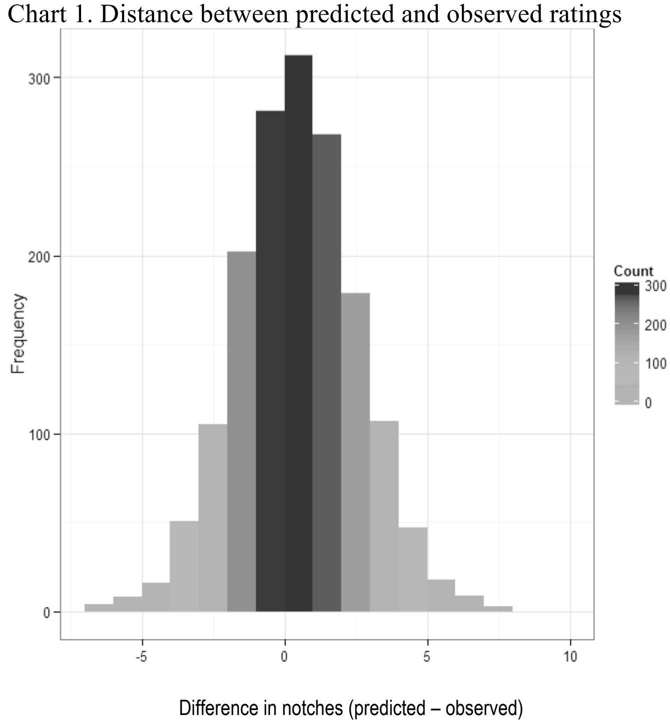
Table 4. Results summary

Distance (notches) between predicted and observed ratings	%	% cumulative
0	19.33	19.33
1	34.02	53.35
2	23.60	76.95
3	13.14	90.09

It is notable that that the estimated model has a hit rate of 90% within the 3 notches range.

In a similar fashion, we evaluated the distribution of the differences between the ratings that were estimated by the model and by those issued by international agencies. The results showed consistency between the measures; albeit the estimated model exhibits a lower output variance.

Chart 1. Distance between predicted and observed ratings



Finally, we tested the model against long-standing ones in order to compare and evaluate their performances against the gold standards provided by the ratings issued by agencies. Our references are: (i) the 4 variables Altman Z-score, also known as Z" (Altman and Saunders, 1998), (ii) the Shumway (1999) model, (iii) the improper linear model, given simply as: Y = (Net Income / Total Assets) - (Total Liabilities / Total Assets), as recommended by Schmidt (1971).

Table 5. Accuracy as measured by continuous ROC.

Model	Area under ROC curve
Altman	0.59
Shumway	0.60
Improper model	0.61
Proposed model	0.78

In order to test the proposed model against these competitors, we employed a tool known as continuous receiver operating characteristic (continuous ROC). With the help from this diagnostic test (Nguyen, 2007), it is possible to compare the accuracy of a given model against a gold standard, even if it is continuous. Values with a greater area under the ROC curve indicate higher accuracy. The tests (Table 5) allow us to claim that that the model has a good ability to discern good from bad credits, thereby being a decent proxy to the ratings from international agencies.

Conclusion

The presented model aims to produce ratings and default probabilities in the absence of a database with sufficient number of defaults. However, it is well established that rating agencies take into consideration qualitative and quantitative information on the preparation of their ratings. Notwithstanding the limitations, the model presented here, based on the shadow rating approach, performed well in-sample with an area under the Receiver Operating Characteristics Curve of 78%. Accuracy was also noteworthy, with 90% of the predicted ratings located within a distance of three notches of the observed ratings.

Finally, the presented model is easy to understand and apply, requiring only a handful of financial inputs, and is able to satisfactorily predict corporate ratings issued by rating agencies, and can be an useful tool for the assessment of corporate credit risk.

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