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Credit Risk Assessment under Basel Accords

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Abstract. *Credit risk represents one of the most critical risks associated with the banking sector, having a direct impact on the banking institutions' overall performance. As of today, such institutions can access a wide range of methods and systems for assessing credit risk, with direct impact on their capital adequacy ratios. Approaches based on internal rating models, as introduced by Basel II, allow banks to utilize their own methods to quantify credit risk, essential to the risk-weighting of their assets and therefore to the measuring of the capital requirements.*

This paper addresses a potential scoring model in order to quantify the default probability, based on quantitative information and forecasting of potential default scenarios. Qualitative variables have also been considered in order to generate higher prediction accuracy.

Keywords: scoring model; default probability; logit model; qualitative variables; credit risk.

JEL Code: G24.
REL Code: 11C.

1. Introduction

Under the current market conditions, deriving from the global financial crisis, the banks have to pay special attention to getting prepared in order to promote and implement a large number of required changes. One of the top priority areas should be the connection between the bank's capital structure and size and the amount of risk which can be taken in order to maintain the requirements for a stable and efficient institution.

It is well known that credit risk represents the most critical risk associated with the banking sector, also having a direct impact on the banking institutions' overall performance.

Basel II offered the banking institutions a wide range of approaches for assessing credit risk, with direct impact on their capital adequacy ratios. The three approaches under Basel II are varying in terms of complexity; however the banks have the possibility to choose one such approach, based on their risk profile, internal requirements and requirements of the local and regional supervision authorities.

The standardized approach represents a more complex version of Basel I, through allocating various risk weights to each asset class (both on balance sheet and off balance sheet assets), depending on counterparty and collateral quality as indicated by rating agencies and similar institutions.

Internal ratings approach (IRB) allows a more detailed classification of risks, based on internal rating systems established by each credit institution. The banks are using their own estimations with respect to the probability of default (PD). When it comes to the loss given default (LGD) or exposure at default (EAD), the banks are using data provided by financial services authorities (Foundation IRB) or own estimations (advanced IRB). It is clear that the accuracy of such models depends on the quality of assessing the probability of default.

Nowadays some specialists are discussing if the new methods applied to credit risk have really improved the regulatory framework or they have actually contributed to the current financial crisis, given the fact that banks were allowed to use their own predictions and models for assessing credit risk and set up their capital adequacy ratios accordingly (Ranjit, 2009, p. 3). Despite these concerns, Basel III does not bring substantial changes regarding the approach to credit risk.

Within this broader context, I am proposing a scoring model to quantify the probability of default based on quantitative variables (financial ratios) relevant to such scenario. I have also considered qualitative variables which have a direct impact on the reimbursement capacity of a borrower. I have used data collected from a Romanian banking institution pertaining corporate borrowers.

2. Estimating the probability of default

Estimating the probability of default is the first step toward quantifying and evaluating the credit risk within IRB. At this stage the major challenges appear from lack of data in the collection process.

Basel Committee defined three major methods to be used for calculating the PD:

- Average external counterparty rating;
- Estimation through the employment of various models on credit risk;
- Estimation based on historical data and ratings allocated to the assets in the bank's balance sheet.

Devising relevant models in order to quantify the PD has been a constant topic for modern researchers, i.e. Beaver (1966 and 1968) and Altman (1968) studies on using linear discriminant analysis to predict a company's default. Currently there are several other models dedicated to such predictions.

The structural models are based on Merton Option Pricing Model and regard the borrower's capital as on option on its assets. The default appears when the market value of the borrower (depending on both value and volatility of its shares) reaches a certain default barrier.

Fundamental models are estimating the PD based on certain variables extracted from the borrower's financials and are used primarily for unlisted companies, for which there is no publicly available market value.

Within the above mentioned category of models there are three sub-categories:

- Macroeconomic models – assessing PD based on the overall economy status (useful especially for calculating PD with respect to various economic sectors);
- Credit scoring models – based on financial and accounting data of borrowers;
- Rating based models.

The credit scoring models are most widely used; they are based on several financial ratios with respect to the borrower's profitability, liquidity, debt multiples, debt service etc. A correlation is built between the borrower's financials and probability of its default. Such models are using techniques derived from statistics (i.e. linear discriminant analysis devised by Beaver and Altman) and econometrics to determine the PD. There are also alternative approaches based on non-parametric methods: neural networks, fuzzy algorithms, K – nearest neighbor. There is a lot of debate in this respect – despite several studies (Galindo & Tamayo 2000, Caiazza 2004) suggesting that non – parametric models generate more accurate predictions, other studies (Altman, Marco, Varetoo, 1994, Yang, 1999) prove otherwise.

Linear discriminant analysis is based on the hypothesis that there are two types of companies – in default and not in default. The associated function is:

$Z = v_1x_{1,j} + v_2x_{2,j} + \dots + v_n x_{n,j} = V^TX_i,$

in which:

v_j, $j = 1,\dots,n$ – coefficients;

$X_{j,i}$, $j = 1,\dots,n$ – financial ratios.

The coefficients are selected in order to maximize the following function:

$F = [\, V^T(\mu_F - \mu_{NF}.)\,]^2 / V^T \Sigma V,$

in which

μ_F si μ_{NF} are reflecting the average financial ratios for companies in default and companies not in default and Σ – the covariance matrix

After defining coefficients v_i, $i = 1, \dots, n$, the function can be used to determine the status of a borrower – in or not in default: if $V^TXi + \alpha < 0$ – the company is in default, where α is a constant reflecting historical data on defaults.

Z – score models reflect in an indirect way the default probability.

Such probability is calculated as follows:

$p_F(X_i) = 1 / [1 + \exp(V^T X_i + \beta)],$

in which:

$\beta = \alpha + \log(p_{NF} / p_F);$

p_F and p_{NF} – probability of default/non default.

Altman's Z – score method is the most known application of the credit scoring for predicting bankruptcy.

The Z score function (Altman, 2000) is:

$Z = 0{,}012X_1 + 0{,}014\,X_2 + 0{,}033\,X_3 + 0{,}006X_4 + 0\,{,}999X_5,$

in which:

X1 = Working Capital/Total Assets;

x_2 = Retained Earnings/Total Assets;

x_3 = Earnings Before Interest and Taxes/Total Assets;

x_4 = Market Value of Equity/Total Liabilities;

x_5 = Sales/Total Assets.

Econometric models are mostly based on logit and probit functions; nevertheless the specialists are recommending the logit models as the best technique to determine the default probability. Ohlson (1980) and Platt & Platt

(1990) are considered the pioneers of logit models. Laitinen (1999) used automatic selection processes to determine the variables used in linear and logic models.

The most popular application based on logit model is Moody's KMV EDF RiskCalc Model, which indicates the expected default frequency (EDF) for analysed companies, based on their financials, through the following formula:

$$EDF = F\left(\Phi\left(\sum_{i=1}^{N} \beta_i T_{i}(x_i) + \sum_{j=1}^{K} \gamma_j I_j\right)\right)$$

in which:

xi, i=1,..., n – financial ratios;

Ij j=1,...,K– variables associated with economic sectors;

Φ = normal distribution;

F, T = nonparametric transforms.

The logit model represents a direct method for predicting bankruptcy.

3. Scoring model for predicting defaults

Given the information presented so far, I will present a scoring model for quantifying the default probability

3.1. Data collection

In my opinion data collection represents one of the most critical issues associated with the implementation of an accurate rating system. In this respect, the following factors have to be considered: easy access to raw information, the data quality and accuracy and process management.

Easy access to raw information – given the high volume of data, the systems have to allow its processing (reading, writing and updating) with minimum human intervention.

Data quality and accuracy – high quality systems have to be capable to identify and "repair" missing or inaccurate information, to identify ways to improve data collection, to reduce redundancy, to capture and integrate information collected from several sub – systems.

In order to build my model I have used data representing financials of 317 corporate borrowers, selected from a number of randomly generated 1000 such borrowers (SMEs), clients of a Romanian bank. Out of the 317 analysed borrowers, 58 have defaulted during the last year (1), giving an NPL ratio of 16,6%, in correlation with the overall NPL ratio for this borrowers segment (SMEs).

The selection process was based on economic sectors (see Figure 1), mirroring the distribution across the entire loan portfolio; the start-up and real estate clients were excluded as not relevant.

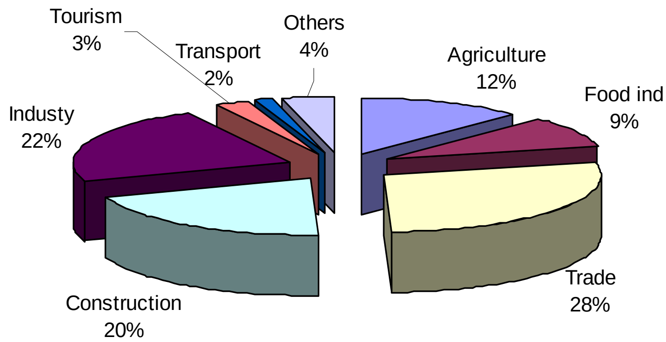

Figure 1. *Economic sectors distribution of analysed companies*

3.2. Selection of Variables

The exogenous variables used in this analysis are exclusively of a quantitative nature – ratios and indicators pertaining the evolution of the company's financials.

As a first step, I have selected 14 relevant financial ratios across five major categories (according to Altman et al., 2005), as in Table 1.

Table 1

Category	Ratio
Profitability	Profit Margin
	Return on equity (ROE)
	Return on assets (ROA)
	Return on investment (ROI)
Liquidity	Current ratio
	Quick ratio
Debt	Debt ratio
	LT debt to equity
	Debt to equity
Debt service	EBITDA Coverage
	Interest Coverage
Activity	Asset turnover
	Accounts Payable Turnover
	Accounts receivable / debt

In order to assess the discriminatory power of each variable, I have prepared univariate analyses for each of the 14 indicators (Fernandes, 2005). Following such analyses, five of the variables present weak correlations between themselves: profit margin, ROA, current ratio, debt ratio and Interest coverage. I have considered that the relationship between the selected variables and expected default frequency has to be clear and economically viable:

- Profit margin, ROA, current ratio and the interest coverage are in inverse correlation with the EDF;
- Debt ratio has a positive correlation with EDF.

Figures 2-6 are showing the relationship between EDF and each considered variable(2).

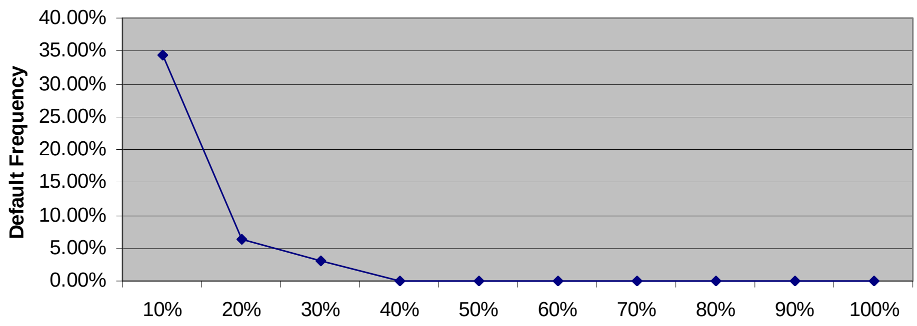

Figure 2. *Univariate relationship between profit margin and default frequency*

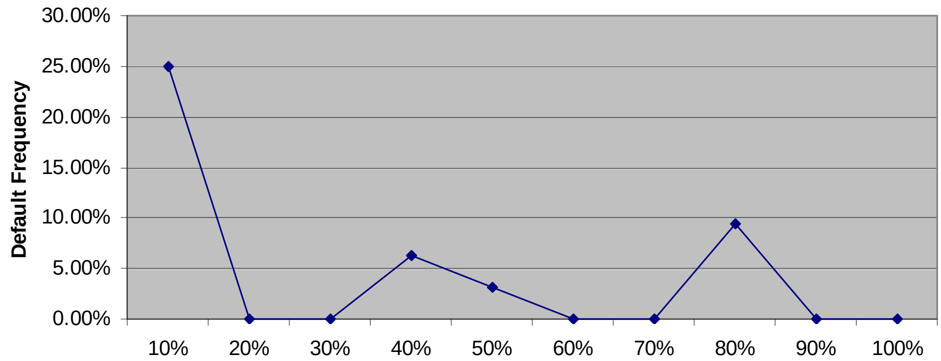

Figure 3. *Univariate relationship between ROA and default frequency*

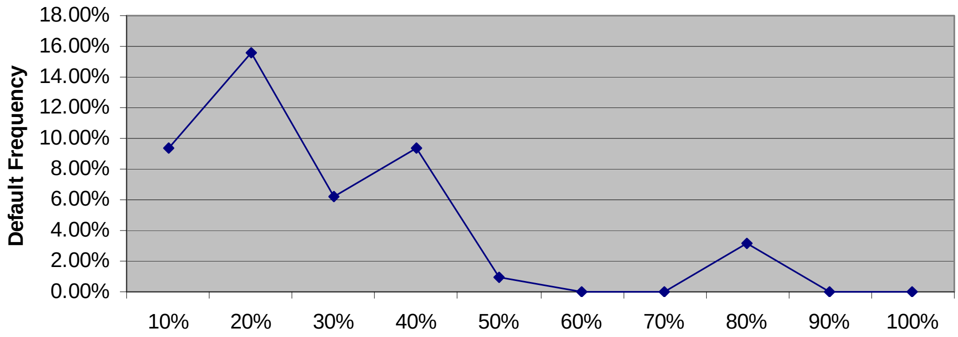

Figure 4. *Univariate relationship between current ratio and default frequency*

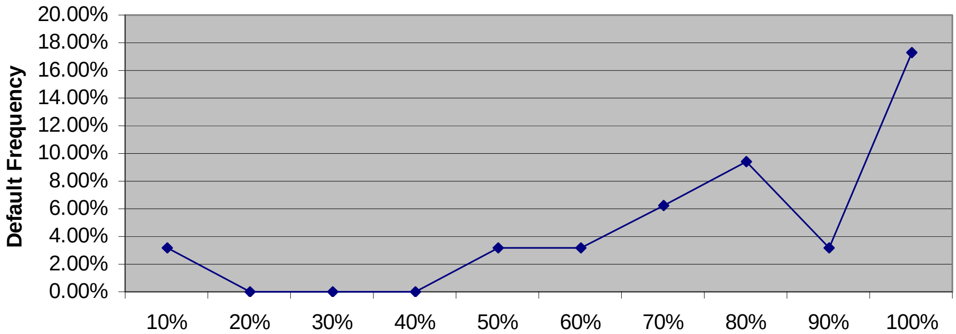

Figure 5. *Univariate relationship between debt ratio and default frequency*

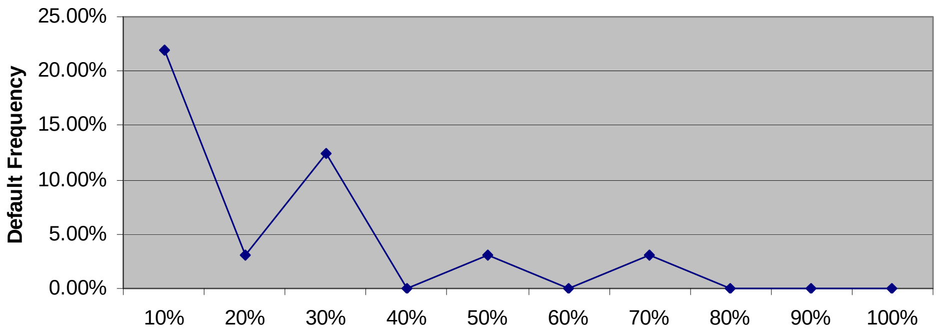

Figure 6. *Univariate relationship between interest coverage and default frequency*

3.3. Scoring model

A logit model was used to determine the probability of default (Altman et al 2005):

$$Y_{it} = f\,(\beta_k, X^k_{it-1}) + e_{it},$$

in which:

Y_{it} – dependent binary variable – default and non–default scenarios;

X^k_{it-1} – independent variables – financial ratios values for each analysed borrower.

The logit function results, based on the five selected variables/financial ratios (V1- Profit margin, V2 – ROA, V3 – Current ratio, V4 – Debt ratio, V5 – Interest coverage) are as follows:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
V1	-0.312407	0.089443	-3.492818	0.0005
V2	0.067621	0.058591	1.154121	0.2485
V3	-0.034178	0.013798	-2.476983	0.0132
V4	0.000295	0.000175	1.683654	0.0922
V5	-0.053892	0.116278	-0.463480	0.6430
C	-1.224376	0.944995	-1.295644	0.1951

Considering the fact that the V2 (ROA) results are positive (which means that an increase of the value of this variable will imply an increase of the PD), which is incorrect from an economic point of view, and the fact that the probability associated with V5 (0.643) exceeds 0.05%, this model cannot be considered relevant and the two variables were eliminated.

Using only three ratios (V1 – Profit margin, V3 – Current ratio and V4 – Debt ratio) within the logit model, the following results were obtained:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
V1	-0.274833	0.069655	-3.945653	0.0001
V3	-0.034467	0.013765	-2.503992	0.0123
V4	0.000322	0.000164	1.963116	0.0496
C	-1.004333	0.891212	-1.126930	0.2598
Mean dependent var	0.044164	S.D. dependent var		0.205784
S.E. of regression	0.155796	Akaike info criterion		0.209707
Sum squared resid	7.597226	Schwarz criterion		0.257137
Log likelihood	-29.23849	Hannan-Quinn criter.		0.228653
Restr. log likelihood	-57.36402	Avg. log likelihood		-0.092235
LR statistic (3 df)	56.25106	McFadden R-squared		0.490299
Probability(LR stat)	3.71E-12			

The above results are statistically relevant (the probabilities associated with the three variables are lower than 0.05%). Also the results show that between each of the V1 and V3 variables and the default probability there is an inverse correlation and a positive one in case of the V4 variable, which is economically correct.

Analysing the impact of the variables over the default probability, it is obvious that there is a significant influence on this probability deriving from profit margin (V1), while the influence of debt ratio (V4) is much weaker.

To verify the model's accuracy I have considered the discriminatory power (capacity to determine on an ex-ante basis the default situations) through a ROC curve – relationship between the percentage of defaulted companies correctly identified and percentage of non-defaulted companies incorrectly identified.

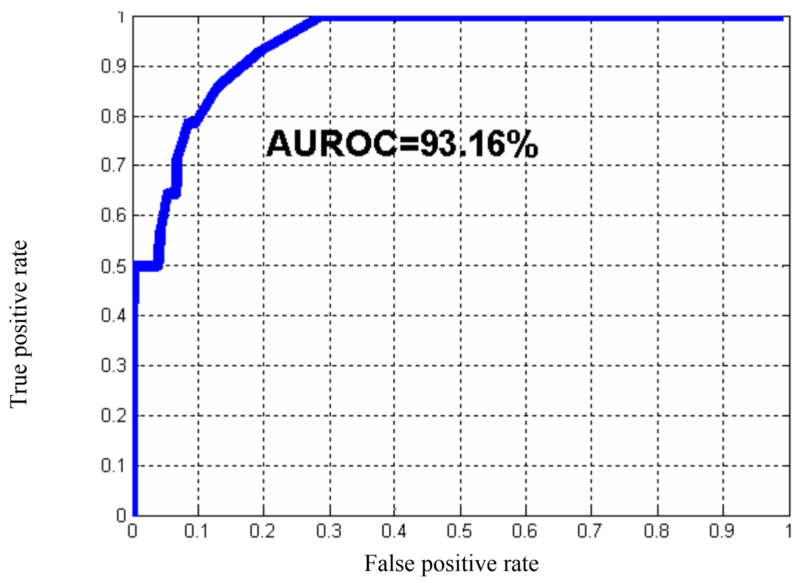

Figure 7. *ROC curve*

As shown by the above graph, the ROC curve confirms the fact that the model correctly quantifies the default probability – AUROC is 93.16%.(3)

3.4. Interpreting the results

The main finding of this analysis is that using exclusively quantitative information (financial ratios) it is possible to build a scoring system which offers accurate predictions. Based on such system, rating categories will be put in place through dividing the obtained scorings into the required number of classes (such number will be based on the Basel II provisions – minimum 7 classes for non-default borrowers and one for default borrowers, to avoid excessive concentration into one rating class).

4. Qualitative variables and final rating

As recent literature demonstrate (Lehmann, 2003) the next step in building a high quality ratings system, able to provide accurate predictions, is to include the qualitative variables. In this respect I have considered 4 factors with direct impact on any credit decision: the market, the shareholders, the executive management and the business. Based on observations on a number of 2,800 corporate borrowers (SMEs) out of which a number of 460 defaulted within 12 months, I have determined the following relevant qualitative variables:

- Market share;
- Shareholders risk;
- Executive management risk;
- Dependency on suppliers;
- Dependency on clients.

I have allocated for each qualitative variable a certain scoring based on the relevant risks and their past evolution:

- Market share – negative correlation with the risk level (an increase of the market share means a better position on a market, so a lower risk);
- Executive management risk – negative correlation with the quality of the executive management involved in this area or any other areas with impact;
- Shareholders risk – negative correlation with the level of involvement of the shareholders (i.e. shareholder loans, dividends allocated for future investments);
- Dependency on suppliers and clients – positive correlation with credit risk. The dependency on one supplier is considered standard if it does not exceed 25% out of total suppliers (critical at over 50%). Also, the dependency on one client is considered standard if it does not exceed 20% out of total clients (critical at over 40%).

The scoring for each qualitative variable based on the credit risk impact is presented in Table 2.

Table 2

Scoring for quantitative variables

No.	Qualitative variable (X_i)	Value	Score
1	**Market share**	Growth	3
		Stagnation	2
		Decrease	1
2	**Executive management risk**	Low (high quality of management)	3
		Medium (standard quality)	2
		High (low quality)	1
3	**Shareholders risk**	Low	3
		Medium	2
		High	1
4	**Dependency on suppliers**	Critical (one supplier >50% of total suppliers)	0
		High (25% - 50%)	1
		Good (5% - 25%)	2
		Low (< 5 %)	3
5	**Dependency on clients**	Critical (one client >40% of total clients)	0
		High (20%-40%)	1
		Good (5% - 20%)	2
		Low (<5%)	3
Total			$\sum_{i=1}^{5} X_i$

For these qualitative variables I have used three credit risk classes: 1 – low risk, 2 – medium risk and 3 – high risk, generating the following score brackets:

Credit risk	
1	11 - 15 points
2	6 - 10 points
3	< 6 points

Final rating is determined through performing a correlation of the financial rating (quantitative) with one of the credit risk brackets for qualitative variables. The analysis shows that the impact of the qualitative variables on a borrower's capability to maintain a proper debt service stands at a level of 25% (with 75% deriving from quantitative aspects). Consequently, in building the credit risk matrix it has to be taken into consideration the fact that following the introduction of qualitative variables, the final rating could be up to two classes, above or below the financial (quantitative) rating.

5. Conclusions

A scoring model based exclusively on quantitative information (profitability, liquidity and debt service ratios) offers a good prediction capability of credit default events, a fact also shown by the ROC analysis and an AUROC level of 93.16%.

However, in order to increase the accuracy of any rating system based on the above model, I personally consider as necessary in practice to split the system into two separate systems dedicated to trade and non-trade companies, each system employing relevant ratios for each type of company.

To further increase the rating system's accuracy qualitative variables have to be inserted; in this respect I have determined four such variables - Market share, Shareholders risk, Executive management risk, Dependency on suppliers and clients. The final rating is based on both quantitative (financial ratios) and qualitative (score brackets) variables, but its accuracy is always highly dependent on the quality of the historical data collection and processing.

In this respect I consider that one of the major challenges of the Romanian financial institutions in implementing an accurate rating system is represented by the availability and ease of access (within a short period of time and with minimal costs) of historical data.

However a good risk management strategy has to be always certified by practice and continuous monitoring and improvement of the performance of a rating system is mandatory, especially considering the critical aspects associated with wrong credit decisions.

Notes

(1) Based on Basel II definition –payment default of over 90 days.

(2) Data in ascending order based on the variable's value and for each period the DF has been calculated as number of defaults divided by total number of analysed borrowers.

(3) The accuracy of a diagnostic test is good if AUROC >80%.

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