ESTIMATION OF THE PROBABILITY OF DEFAULT BASED ON RELEVANT ECONOMIC AND FINANCIAL INDICATORS

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Abstract: *The credit risk is one of the main banking activity risks, with direct impact on the bank performance. Approaches based on internal rating models introduced by the Basel II agreement allow banks to use their own estimates for credit risk quantification, with direct effect on capital adequacy. This study aims to develop a scoring model for quantifying the probability of default dependent on the non-performing loans rate evolution based on quantitative information and determination of the power of prediction to determine non-reimbursement situations. Also, it was considered the determination of some qualitative variables impacting on the reimbursement capacity of companies. The financing sources, in essence, in-house or attracted, condition the profitability of any business and influence the financial position of the company, both in the short and long term. This study aims at an understanding of the inter-conditioning relationship between the financing sources, profitability and default risk. The estimation of the default probability is the first step to determining and assessing the credit risk. Major issues in the estimation of the default probability are generated by the limitation of the required information. The approach based on internal rating models relies on the accuracy of the default probability estimation.*

Keywords: *probability of default; financial performance; credit risk; qualitative variables; macroeconomic environment; credit scoring.*

JEL classification: *J08.*

1. Introduction

In the current financial conditions, banks must be prepared to promote change. One area that requires special attention and priority in action is the stronger link between the capital of a bank and the risks it can take, to prove that it is a stable, efficiently run financial institution.

The credit risk is one of the main risks to the banking business and its management has a major impact on the bank performance.

The Basel Committee proposes three basis methods to be used by the banks to compute the credit risk:

- The average external rating of the counterparty;
- The credit card models estimation;
- The calculations based on historical data or rating categories related to the bank's loan portfolio.

Basel II provides banks with a wider range of options for determining the capital requirements for the credit risk coverage. The three proposed approaches have varying degrees of complexity, giving banks the opportunity to choose one of the options according to their needs, the risk profile and the strategy of the national supervising authorities.

2. Literature Review

In the series of problematical approaches on the topic dealt we find inquiries on the validity and quality of information sources used as support for the performance analysis, and query about the instruments used in the analysis (financial or non-financial indicators), in the context of information asymmetries and governance issues.

Integrated accounting information have been treated in numerous papers by authors such as Balakrishnan, Bartov and Faurel (2010), Hall (2010) Elbashir, Collier, and Sutton (2011), Weissenberger, Angelkort (2011), Grande, Estebanez and Colomina (2011) Soudani (2012), Kargin (2013), Gullberg (2014), Frias-Aceituno, Rodriguez-Arizaşi Garcia Sanchez (2014), Steven E. Salterio (2015).

The empirical research carried out by Jing et al. (2010) analyses the attitude of managers on information provided by the managerial accounting in the Romanian companies, and believes that the accounting information "is essential in achieving the competitive advantage throughout the lifecycle of an entity".

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The credit risk modelling and the determination of the default probability were subjects developed by many researchers, who used the linear discriminant analysis for predicting the bankruptcy of a company.

The integration of macroeconomic indicators in the analysis of the credit risk was addressed, among others, by Vitor Castro (2013), who caught the relationship between the evolution of the macroeconomic indicators and the credit risk for a number of countries - Greece, Ireland, Portugal, Spain, and Italy (GIPSI), affected by the economic and financial crisis. Using a dynamic panel approach, he noted that the credit risk is significantly affected by the macroeconomic environment: the credit risk increases when the GDP decreases, but the unemployment rate or the interest rate increases, and is positively influenced by an appreciation of the real exchange rate.

The statistical techniques were used extensively in the construction of the models of classification and credit scoring, Dănila (2012) designing a scoring model for quantifying the probability of default based on quantitative information and the determination of the power of predictively of non-reimbursement situations, with respect to the determination of some qualitative variables impacting on the repayment capacity of companies.

Masahiko Egami (2013) highlights a number of precautions to credit risk management using Levy processes, and Yunpeng Sound (2011) applied Marshall-Olkin multivariate exponential distribution on credit risk. At the same time, Montgomery, Hanh, Santoso and Besar (2005) investigated bank bankruptcies in Japan and Indonesia using the logit model, while Canbas, Cabuk and Kilic (2005) proposed an integrated prediction system combining the discriminant analysis, logit, probit and the main components analysis. A major work is provided by Konstandina (2007), who used the logit model for the classification of companies and the prediction of bankruptcy, identifying the main features of such an event.

Among the most used basic models are included the credit scoring models. These are meant to determine a correlation between the economic and financial situation of the company and the non-reimbursement cases. The financial indicators used in credit scoring are considering profitability, leverage, liquidity, debt service, etc. The variables selected are those that have discriminatory power to determine the frequency of non-reimbursement after the completion of some univariate analyses.
Basel II provides banks with a wider range of options for determining the capital requirements for the credit risk coverage. The three proposed approaches have varying degrees of complexity, offering banks the possibility to choose one of the various options according to their needs, the risk profile and the strategy of the national supervising authorities.

3. Scoring Model to Estimate the Probability of Default

Over the time, some of the largest global banks have developed sophisticated systems in their attempts to model the credit risk generated by various business lines.
In designing these models, it was considered the quantification, aggregation and management of risks by geographical area and field of activity, estimates of these models being used for risk management and business performance measurement.

3.1 Data Used

An important step in developing the scoring model for quantifying the probability of default is the data collection process. Data used to build the model referred to in this study consist of financial reports for 2014 of a number of 187 companies selected from a sample of 700 companies in the category of small and medium enterprises extracted from the TPSoft database, an online database of companies from Romania.

3.2 Selection of Variables

Exogenous variables that were considered aim at selecting some relevant financial indicators for each of the five categories (profitability, liquidity, indebtedness, interest coverage and activity) reflecting the economic and financial situation of a company (Altman et al., 2005).
First we considered selecting a total of 10 economic and financial indicators relevant to each of the five categories reflecting the economic and financial situation of a trading company, as follows:

Table 1: Indicators relevant for the economic and financial situation

Category	Indicators
Profitability	Commercial profitability (profit margin)
	Return on Equity (ROE)
	Return on Assets (ROA)
Liquidity	Current ratio
	Quick ratio
Indebtedness	Debt-to-equity ratio

Category	Indicators
	Degree of financial leverage of total assets from equity
Interest coverage	EBITDA/ Interest expenses
	EBIT/Interest expenses
Activity	Turnover/ Interest expenses

1. In order to determine the discriminatory power of each variable, univariate analyses for each of the 10 indicators were performed.
2. After the analyses, we retained in the analysis the weakly interrelated variables: return on sales, return on assets, current ratio, debt-to-equity ratio and interest coverage.

It is envisaged that the relationship between the selected variables and the frequency of non-reimbursement to be clear and viable economically, namely, that the relationship between each of the variables: the return on sales, the return on assets, the current ratio, the interest coverage and the frequency of non-reimbursement is inversely proportional, respectively, an increase of these indicators implies a lower non-reimbursement frequency, while the debt-to-equity ratio and the non-reimbursement frequency is directly proportional, an increase in this indicator implying a higher non-reimbursement frequency.

3.3 The Scoring Model

To determine the probability of default, the logit model proposed by Altman et all. in 2005 was used, as follows:

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

where:

Y_{it} – dependent variable;

X^k_{it-1} – independent variables - represent the values for the indicators selected for the i (187) companies.

The multiple correlation between variables is presented in Table 2.

Table 2: Estimation of the regression model

	Return on sales	**Return on assets**	**Current ration**	**Debt-to-equity ratio**	**Interest coverage from EBIT**
SUMMARY OUTPUT					
Regression Statistics					
Multiple R	0.1130917	0.1005618	0.6285546	0.6820124	0.0112693
R Square	0.0127897	0.0101127	0.3950809	0.4651410	0.0001270
Adjusted R Square	0.0074421	0.0047651	0.3897333	0.4597934	-0.0052206
Standard Error	0.1714525	0.1716848	0.1342109	0.1261998	0.1725486
Observations	188	188	188	188	188

The results obtained based on the logit function estimating for the 5 variables retained in the analysis (return on sales, return on assets, current ratio, debt-to-equity ratio and interest coverage) are:

Table 3: Results of the research in relation to the analysed variables

Variable	Coefficient	Std.Error	t-Statistic	Prob.
Return on sales	-0.001175	0.171453	-1.556492	0.0331
Return on assets	0.076950	0.171685	1.382168	0.1867
Current ration	-0.020558	0.134211	11.05134	0.0242
Debt-to-equity ratio	0.133928	0.126200	12.75244	0.0154
Interest coverage from EBIT	-1.881640	0.172549	-0.154115	0.8776

Considering that the result obtained for the *"return on assets"* variable, respectively, the plus sign obtained (an increase of this variable causes an increase in the non-performing loans rate) is not economically correct, and in the case of the *"interest coverage"* variable - the obtained probability of 0.877685 exceeds the permissible threshold of 0.05%, we considered that the model obtained cannot be revealed. So we removed the two variables from the analysis.

Using only three indicators: return on assets, current ratio, indebtedness, for estimating the multivariate logit function, the result obtained is statistically relevant, as evidenced by the values of probabilities, less than 0.05%, obtained in the three variables.

The results obtained show that between each of the indicators, i.e. return on sales, current ratio and non-performing loans rate there is an inversely proportional relationship, so as the values of these indicators are higher, the more the non-performing loans rate decreases, while between the debt-to-equity ratio and the non-performing loans rate there is a directly proportional relationship, an increase in the value of this indicator determining an increase in the non-performing loans rate, that is, the default probability.

These results are also correct in terms of economic interpretation.

Analysing the influence of indicators on the default probability, it is noted that the *return on sales* has the greatest influence on it (obtaining a higher trade margin having a positive influence on the reimbursement capacity of the company) while *debt-to-equity ratio* has a less significant influence (a high degree of indebtedness adversely affecting, but to a lesser extent the reimbursement capacity of the company).

4. Qualitative Variables and Final Rating

To achieve a performing rating system with good power of predictability, it is necessary to also include qualitative information.

For this purpose, there have been considered four dimensions that have a direct impact on the credit decision, namely: market, shareholders, management and business, choosing for consideration those qualitative variables that have a significant impact on the reimbursement capacity of the company: market share (evolution of market share), commercial risk (degree of cashing from customers and average period of cashing from customers), risk management, dependence on suppliers, dependence on customers, dependence on supply and sale markets.

Each qualitative variable is assigned a scoring, depending on the risks involved and their development. The criteria considered are:

1) *Market share* – an increase implies better positioning of the company on the market, so a lower risk;
2) *Risk management* – it is lower if the company management has a very good experience, with direct impact on the economic and financial situation of the company;
3) *Dependence on suppliers, respectively, dependence on customers* – The higher the dependence on a supplier or customer, the more the business risks increase as any risks associated therewith also spreads on the company concerned.
4) *commercial risk (degree of cashing from customers and average period of cashing from customers* – The higher the degree of cashing from customer and the average period of cashing, the higher the commercial risk.
Thus, according to the scholarly literature, it results that a dependency to a single supplier can be considered satisfactory if it is not exceeding 25% (supplier weight in total suppliers), over this value being high, and even critical if more than 50%. In the case of customers, a weight of a single customer in total turnover of no more than 20% is considered satisfactory, above this level being high and critical above 40%.
The scoring of each variable depending on the risks involved is presented in Table 4.

Table 4: Scoring qualitative variables

No.	Qualitative variables (X_i)	Values	Score
1.	Market share	Increase	3
		Stagnation	2
		Decrease	1
2.	Risk management	Low (very good experience)	3
		Medium (good experience)	2
		High (questionable experience)	1
3.	Dependence on suppliers	Critical (weight in total suppliers of a single supplier >50%)	0
		High (25% - 50%)	1
		Satisfying (5% - 25%)	2
		Low (< 5 %)	3
4.	Dependence on customers	Critical (turnover weight to a customer >40%)	0
		High (turnover weight to a customer: between 20%-40%)	1
		Satisfying (turnover weight to a customer: between 5% - 20%)	2
		Low (turnover weight to a customer <5%)	3
5.	Degree of cashing from customers - GIC	Low (GIC > 90%)	3
		Medium (70% < GIC ≤ 90%)	2
		High (GIC ≤ 70%)	1

No.	Qualitative variables (X_i)	Values	Score
6.	Average period of cashing from customers – PMIC	Low P PMIC ≤ 30 days	3
		Medium 30 < PMIC ≤ 60 days	2
		High PMIC > 60 days	1
Total score			$\Sigma\ Xi^{6}i=1$

For qualitative variables, there have been considered three risk categories: 1 - low risk, 2 - medium risk, and 3 - high risk. Depending on the score obtained, the corresponding degrees of risk are:

Table 5: The risk degrees of qualitative variables

Risk degrees	
1	13 – 18 points
2	6 – 13 points
3	< 6 points

The final rating shall be determined by correlating the financial rating with the risk degrees corresponding to the qualitative variables.
Thus, by summing the points obtained by customers for each indicator the total score is to be obtained, based on which classification into a performance category is made, as follows:

Table 6: Categorization by creditworthiness

Category	Score	Category definition
A	80-100 points	STANDARD
B	60-79 points	UNDER OBSERVATION
C	40-59 points	BELOW STANDARD
D	20-39 points	UNCERTAIN
F	<20 points	LOSS

It was considered the design of a sufficient number of rating classes within that range to avoid excessive concentration of debtors under a particular rating class.

5. Conclusion

The scoring model obtained, which is based on quantitative information (indicators of creditworthiness on return on sales, liquidity and debt-to-equity ratio), has a good power of determination of the default probability, which means that, based on only quantitative information (economic and financial data), it is possible to realize a scoring system for companies with a good power of predictively of non-reimbursement situations.
To achieve a rating system that accurately reflects the probability of default, it is necessary to also include qualitative information. Based on the analysis performed, four non-financial dimensions that have a direct impact on the reimbursement capacity of companies shall be determined: *market, management, shareholders and*

business. The final rating results from the interplay of the financial rating resulted based on quantitative variables (indicators of creditworthiness according to economic and financial situations of companies) with risk degrees corresponding to qualitative variables.
The analysis conducted reveals that the influence of qualitative variables on the reimbursement capacity of the company is maximum 25%.
At the same time, a performing rating system must be appropriately validated through the collection, storage and analysis of historical data - in our opinion a great challenge for banking companies is the access to historical data, their quality and achieving some results in a relatively short period of time and at moderate financial costs.
As future lines of development, we propose:

- the use of the research results in developing the new scoring model applied to new entry firms to reduce the adversity of banking institutions in terms of lending to this business sector;
- introducing more macro variables expressing the aggregate state of the economy at different moments in time and that have an influence on the probability of default;
- the development of the macro-prudential framework and the promotion of financial stability aiming at the implementation of Basel III proposals on capital requirements (buffer capital).

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