Determinants of default risk - analysis of a loan portfolio

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Introduction and summary

In the economic activity risk of failure (default) is inherent even for "giants", involving many parts and being costly, that is why the interest in studying and identifying the best forecasting model to prevent the risk is so important both to private agents and for public institutions. On the one hand the private agents are interested to have on hand a tool that enables them to take measures to prevent or correct the situation before it is too late, they are interested in a model for the prevention of bankruptcy. On the other hand the state should aim to identify firms likely to default to take corrective measures in order to prevent bankruptcy.

This paper addresses the analysis and prediction of the risk of failure (default) in the small and medium enterprises in Romania, the source of data comes from the accounting reports, balance sheet and profit and loss account as follows: the period from 2007 to 2012 for companies registered situation of default (default) and companies in the repayment situation (non-default) the fiscal year 2012 is included in the study. As the deadline for the financial statements for 2013 is 30.05.2014 I chose the most recent annual data available. Information on debt service were taken from the bank's computer system. Corporate failure is treated in this paper in terms of the bank that finances the activity of the companies and the focus is the payment behavior of their loans.

The motivation for choosing this theme touches several points, namely:

- The impact of the failure of a company, especially in the extreme situation of bankruptcy, cause loss for all parties involved, including society at large.

- This paper aims on the one hand the development of a predictive model of bankruptcy risk and its application to the bank that finances small and medium enterprises and on the other hand wants to improve the evaluation system of the companies credited.

- Testing whether the conclusions drawn in previous studies checks on SMEs that comes from emerging economies.

Literature review

Despite considerable interest in the prediction of bankruptcy, the literature does not clearly distinguish theories about this topic, but rather empirical studies that are based on a definition on failure and a set of data available. However, in terms of predicting bankruptcy can be considered as the starting point the theory of capital structure. This connection is the fact that capital structure expresses the risk for a company to be "in a better or poor balance, between capital raised and her ability to cope with the obligations under this grant (reimbursements and remuneration of capital raised) "(Stancu, I. - 2007). As you increase the indebtedness of a company its financial risk grows. The capital structure expresses the company's solvency, the ability to cope with commitments to capital providers.

Classical theory of capital structure argues that the loan has a lower cost than equity funds because it is less risky, so a moderate increase in debt can reduce the weighted average cost of capital.

Starting from a restrictive assumptions (no taxation and bankruptcy costs, a company finances its activities only with equity and long-term debt, capital market is perfect, the information is free and accessible to all), Modigliani and Miller (1958) require a new theory. In their study, the authors concluded that (1) the market value of a firm is independent of the politics of debt in the same way and WACC (weighted average cost of capital) is independent of capital structure and is equal to the cost of equity for an unlevered firm in the same risk class and that (2) the cost of equity for a company in debt is equal to the cost of unlevered equity of a company belonging to the same class of risk plus financial risk premium.

The findings radically change when Modigliani and Miller include in model the claiming that taxation will favore indebted companies compared to the unlevered, due to the deductibility of interest (on loans contracted) of operating profit that reduce income tax and thus tax savings. Thus the total cost of capital diminishes indebted company in the form of reduced taxes. It is important however to note that the tax savings are made on condition that the company makes a profit, otherwise the existence of an imbalanced company will deepen its debt and will increase the cost of capital required by investors (both shareholders and creditors). Deductibility of interest implies that financial structure is not neutral and the indebtedness to the optimal point is possible to increase the company's value. But this conclusion is less realistic as it is based on the assumption that the interest rate remains constant at all levels of indebtedness. It is known that the higher the levels of debt the higher the interest rate. To control the risk of bankruptcy administrative costs and legal costs occur (direct costs of bankruptcy) and also cost of opportunity for operating in an uncertain economic environment (indirect costs of bankruptcy).

Empirical review

The topic on corporate failure has been extensively studied. The pioneers in bankruptcy research are Ramster and Foster (1931), Fitzpatrick (1932) and Winakor and R.F. Smith (1935), the research methodology consisting primarily of comparing the financial ratios of bankrupt and non-bankrupt firms, concluding that in general the first shows the values of the indicators weaker than the 2nd category. Durand published in 1941 the first study using discriminant analysis aimed at assessing the credit risk of consumption required for the purchase of second-hand cars.

Beaver W. H. (1966) published the first study on bankruptcy prediction using discriminant analysis univariate. In 1968 Altman E.I. implements a model with a considerable impact both in financial theory and practice. Using multivariate discriminant analysis, Altman estimated parameters of a bankruptcy prediction model. Until the 80 discriminant analysis was used above all in bankruptcy analysis models. The 80 are marked by the implementation of the non-linear regression methods to estimate the discriminant function coefficients (Saretto A., 1985). After 1990 the neural networks and expert systems are used for predicting bankruptcy. Recent studies are using mostly the same basic methods and techniques, developing specific aspects and using significantly larger amounts of information than studies conducted in the last century.

According to research conducted by Akers, M., Bellovary, J., & Giacomino, D. in 2007, since 1965 until the date of the study were developed more than 165 models for forecasting failure. The paper mainly aims synthesizing, analyzing trends and highlighting studies in developing predictive models of bankruptcy. The authors rank models according to prediction method used, the number of explanatory variables, the variables most commonly used in studies and the accuracy of models. This analysis shows that the models with the highest predictive power are multivariate discriminant analysis and neural networks with 100% accuracy but neither the logit analysis is second to none, featuring a maximum accuracy of 98%. The results of this study show that the model accuracy is not guaranteed by the number of factors included in the analysis, models with two explanatory factors can be as strong as what models include 21 factors. In this example we have the most convincing study by Beaver (1966) that made discrimination between bankrupt and non-bankrupt company with an accuracy of 92% by analyzing each one explanatory variable, compared with the model developed by Jo and the authors (1997) who obtained a 86% prediction accuracy using 57 explanatory variables.

Development of the model

I constructed the endogenous variable as a binary variable taking the value of 1 for companies in default (debt service over 90 days) and 0 for companies in non-default situation.

The initial set of explanatory variables includes 13 elements, namely synthetic indicators and qualitative variables covering the criteria traditionally used in determining the creditworthiness of a debtor and its classification into a category of reliability (A, B, C, D, E).

The data used for characterizing each company contains both quantitative and qualitative. The quantitative indicators were imported directly in RStudio software. Instead, qualitative indicators are categorical variables (with several levels of values) which were coded in binary categorical variables (with two levels of values).

The preliminary analysis of the data is the first step to know the data in an attempt to extract as much information significant to support the study. The data sample is well structured in terms of both customer categories, the total number of studied companies is 121 of which 61 (50.4%) are in a state of default companies and 60 (49.6%) in the state of non-default. The analysis noted that companies that are able to repay (non-default) shows an average monthly turnover relatively low compared to companies in the category of non-repayment (default). Hence we conclude that for the sample, for a small sized company versus a large company is more easily to achieve liabilities management.

From the analysis of all characteristics included we can determine the portrait of the defaulted company: young company (under 5 years of operation) with a relatively large size, operating in sector services, led by un-experienced management, who has contracted loans in the national currency and who has not benefited from rescheduling procedure.

Comparing the average values of the numeric variables for each category of studied company I completed the sketch described above: the companies defaulted, compared with those in repayment status, have less seniority (years of operation), register a larger size (average monthly turnover of approximately 4 times higher), current liquidity ratio recorded a significantly lower (half) figure, relies on funds borrowed to finance assets (solvency registered a negative value and the indebtedness value is greater than one) and record loss.

Exploring the variables

The descriptive statistics indicates the minimum, maximum, average and quartiles for each continuous variable analyzed. To illustrate the interpretation of the information provided by these data I am using the variable that indicates the number of years the company was founded until 31.12.2012 for the companies in state of reimbursement (non-default) or the number of years after the company was founded until the declaration of default as follows:

- the youngest company in the analysis is founded half a year ago and the most experienced has a 21 years of operation;
- Quartile 1 indicates that 25% of companies included in the analysis were less than 5 years of operation (Q1 = 4.88) and quartile 3 shows that 75% of companies have less than 11 years of operation.
- Average operating age of the entire sample is 8 and half years.

From the Pearson correlation coefficient matrix it can be seen that between indicators included in the analysis there are the following correlations:

- strong correlation (correlation coefficient> 0.4) between variable Grad_indatorare and solvency, correlation which was expected since both indicators are measuring indebtedness;

- good correlation relationship between indicators of indebtedness (Grad_indatorare and Solvency) and Rata_profit as follows:

    • Rata_profit is positively correlated at a rate of 56.59% with Solvency;

    • Rata_profit is negatively correlated at a rate of 56.58% with Indebtedness;

The analysis performed on the correlation coefficients for continuous exogenous variables, it follows that the same information is contained by several indicators (especially those between which there is correlation coefficient greater than 0.04). This means that if correlated variables will be used in the same regression informational redundancy may result so that if two parameters are strongly correlated, I used in estimated regression only one of them.

Regression analysis

As an example I will interpret regression results for R1 (Logit regression containing only continuous exogenous variables: liquidity, profitability, Log.CA., Vechime_companie), as shown below:

- In logit regression we do not interpret the magnitude of the estimated coefficients but their sign as follow: a rise in the company's liquidity and age will cause a decrease in the probability that the company is in default situation (reverse relationship) while an increase in turnover will increase the probability that the company is in default situation (direct relationship). In other words, a rise in the company's liquidity and age cause the situation to be less likely to default while an increase in turnover causes the default situation to be much more probable;
- Interpretation of regression average marginal effects is both in terms of size and sign of coefficients and the change in the probability that y = 1 (the probability that the company is in default category) as a result of a unit change in the dependent variable so (results in table 5): an increase in company's age by 1 year lowers the probability of default of 2.74% while an increase of one unit of the variable Log (CA) will increase the probability of default of 10, 11%. The sign of the estimated coefficients of the regression is the same as the sign of the marginal effects.

- Odds ratio or relative risk measures the likelihood that a company will be in default (y = 1) in relation to the likelihood that the company would be able to repay his debts (y = 0). This indicator is interpreted according to the unit value as follows:
  - Indicator = 1 => the results have the same probability of occurrence;
  - Indicator> 1 => is more likely to get an Y = 1results than Y = 0;
  - Indicator <1 => is more likely to get an Y = 0 result than the outcome Y = 1;

  Thus, we can say that in the case on the variable Log (CA) is more likely that the company be in default situation (Y = 1) than in repayment situation.

  This is a less frequently calculated coefficient comparing to the average marginal effects.

- The model estimated probabilities ranges from a minimum of 4.87% to a maximum of 89.16%.

- The percentage of correctly classified companies is the prediction accuracy of the model, and in the case of the R1 we have obtained a percentage of correct classification of 66.96%. In other words, 39 companies in the category of non-default (Y = 0) and 42 companies in the default category (Y = 1) were correctly classified while 21 companies in non-defaul and 19 in default were not correctly classified. The percentage of correct classification of the model is obtained by dividing the cases classified correctly (81) the total number of observations in the sample (121).

In this case, as analyzed sample is balanced (61 companies in default and 60 in non-default), we can say that the level of 50% correct classification as a random pattern so that the percentage obtained by regression R1 is a decent one but , the higher the probability of correct classification is higher the model has a higher predictive power.

- The accuracy of the model can be measured through the McFadden's Pseudo R-squared coefficient which is not interpreted in the same way as R^2 coefficient of linear regressions (estimated by the method of least squares - OLS) where R^2 measures the proportion explained by the pattern of variability of independent variables. Such adjusted R^2 has no intuitive interpretation but the literature says that a value of this indicator between 0.2 and 0.4 is satisfactory.

Likewise following regressions were performed and the results can be found in Table 1:

1. Logit Regression only with continuous exogenous variables: liquidity, solvency, Log.CA., Vechime_companie, which I call regression R2.
2. Logit Regression only with continuous exogenous variables: liquidity, Grad_indatorare, Log.CA., Vechime_companie, which I call regression R3.
3. Logit Regression only with categorical variables: Categ_client, currency, Experience, Risc_sector_activitate, Credite_Reesalonate, Stare_legala, dagricultura, dcomert, dconstructii, dproductie, which I call regression R4.
4. Logit regression on continuous and categorical variables that emerged as significant in the regressions R1 - R4: liquids, Log (CA), Vechime_companie, experience and sector work, which I call regression R5.

Variabila independenta	R1-coef.	R2-coef.	R3-coef.	R4-coef.	R5-coef.
Lichiditate	**-0.0034 ***	**-0.0033 ***	**-0.0033 ***	-	**-0.0034 ***
Rata_profit	-0.0063	-	-	-	-
Log_CA	**0.4878 .**	**0.4935 .**	**0.4904 .**	-	0.0135
Vechime_companie	**-0.1321 ****	**-0.1287 ****	**-0.1286 ****	-	**-0.1174 ***
Solvabilitate	-	-0.0032	-	-	-
Grad_indatorare	-	-	0.0031	-	-
Categ_client	-	-	-	0.4600	-
Deviza	-	-		1.3009	-
Experienta	-	-	-	**-1.4888 ****	-0.4219
Risc_sector_activitate	-	-	-	0.2540	-
Credite_Reesalonate	-	-	-	-1.0843	-
Stare_legala	-	-	-	34.2133	-
dagricultura	-	-	-	-17.7327	-14.2200
dcomert	-	-	-	**1.5784 ***	**2.1490 *****
dconstructii	-	-	-	0.8683	0.7433
dproductie	-	-	-	-16.7196	0.0664
McFadden's Pseudo R-squared	0.1331	0.1259	0.1254	0.4472	0.2241
% companii incadrate corect de model	66.94%	67,76%	67,76%	81,81%	76,03%

Signif. codes: 0 '***'; 0,001 '**'; 0,01 '*'; 0,05 '.'; 0,1 ' ' 1

Source: own research

Conclusions

Although the results of the model can not be extended at the level of the general population as the sample is not representative, interesting conclusions were obtained in point of correlating the economic- financial indicators with the bankruptcy risk.

- regressions constructed only with continuous variables have a low level of significance, with a coefficient McFadden's R2 <0.14 (while to have a good model coefficient must register a levelbBetween 0.2 and 0.4) .
- built only categorical variables regression has a significantly higher rate, 81.81% of the observations are correctly classified by model takes McFadden's R2 register coefficient value of 0.44.
- liquidity indicators, company size (in 3 of 4 models in which indicator was used), age of the company, experience management (in model 2 in which it was used, with a significance threshold of 0.1%) and sector, stands as determinants of risk factors for default.

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