9. CREDIT RISK MODELING FOR COMPANIES DEFAULT PREDICTION USING NEURAL NETWORKS

Alina Mihaela Dima[1]
Simona Vasilache[2]

Abstract

The paper assesses the business default risk on a cross-national sample of 3000 companies applying for credit to an international bank operating in Romania. The structure of the sample replicates the structure of the general population of companies in Romania. Based on their past credit history, we have distributed the companies in seven classes plus the default, using and adapting the Standard & Poor's categories: AAA (1020 companies, 34%) – no risk; AA (279 companies, 9.3%) – minimal risk; A (906 companies, 30.2%) – low risk; BBB (201 companies, 6.7%) – moderate risk; BB (123 companies, 4.1%) – acceptable risk; B (111 companies, 3.7%) – high risk; C (105 companies, 3.5%) – very high risk and D (255 companies, 8.5%) – default. We have then, estimated the one-step transitions probability for downgrading for one year, based on the present category, loan amount, size of company and sector of activity. Thus, although the approach is bottom-up and unconditioned, focusing on the companies, we have included the economic context, taking into account the type of company and the economic sector. We have performed the estimations first using logit regression, and then ANN (Artificial Neural Networks), and compared the results with Standard & Poor's transition matrix for 2010. The results were compared in terms of predictive power, and arguments were given for choosing an ANN design.

Keyword: credit risk, neural networks, regression, business of banking, prediction model

JEL Classification: G21

[1] *The Bucharest University of Economic Studies, E-mail:* alinamihaeladima@yahoo.com
[2] *The Bucharest University of Economic Studies, E-mail: simona.vasilache@gmail.com*

I Introduction

The recent trend of economic globalization and the volatility of financial market have made credit risk management take a focus in finance. The field of credit risk and corporate bankruptcy prediction gained considerable momentum (e.g., Bharath and Shumway, 2008; Matoussi, 2010) due to increased competition in the field and the challenges of the present financial crisis. Credit risk is one of the main risk factors for commercial banks that affects the banks' ability of sustainable operation.

Competition in the banking sector typically is seen as detrimental to financial stability. The basic idea is that when banks compete intensely for deposits, interest rates fall and their franchise value is eroded. Banks then have less to lose from a default and their incentives to take on risk increase. This argument has been very important in shaping banking regulation around the world. For instance in the form of competition and merger policies. A recent influential paper by Boyd and De Nicoló (2005) has challenged this view. Boyd and DeNicoló consequently argue that the lending market should be central to future models of bank stability. The paper written by Wagner (2010) extends the analysis of the lending channel.

Thus, borrowers are implicitly assumed, through their influence on the risk of firms, to have complete control over the riskiness of banks. Wagner argues that, while borrowers may determine the riskiness of their firms, it is banks that decide how much risk they ultimately want to take on. Wagner introduced in a model with a lending channel the possibility for banks to select among different types of borrowers. Thus, they essentially allow for both a risk choice of borrowers, as in Boyd De Nicoló (2005) argues, and a risk choice for banks. They find that this alteration reverses the stability effect of the lending channel. Wagner (2010) has shown that when banks have control over their risk-taking, the stability impact of lending market competition may be reversed. This is because banks have an optimal amount of risk they want to hold and thus want to offset the impact of safer borrowers on their balance sheet by taking on more risk. Since competition in the loan market at the same time erodes banks' franchise values, they even want to overcompensate the impact of safer borrowers causing their risk-taking incentives to increase.

To clarify how banks actually underwrite loans, Uchida (2011) employed unique data on small and medium-sized enterprises (SMEs) in Japan obtained from the Management Survey of Corporate Finance Issues in the Kansai Area in June 2005. In this survey, a responding firm (borrower) answers questions on the extent to which its main bank focuses on (or emphasizes) 22 firm characteristics when the bank underwrites its loans. This information enabled measurement of the emphasis that banks place on their screening process. On balance, they find that the three most important factors when banks screen borrowers are their relationship with the borrower, the strength of the borrower's financial statements, and the collateral and/or guarantee pledged. It is interesting that these correspond respectively to soft information, hard information, and collateral/guarantees, all considered important factors when banks screen loans. They also are consistent with the classification of lending technologies in Uchida (2011), i.e., relationship lending, financial statement lending, and fixed asset lending.

Banks' increasing dependence on asset securitization makes it essential to study the relationship between asset securitization and banks' risk exposure. Wu et al (2011) examined that relationship for a sample of U.S. bank holding companies over 2002–2007. The objective was to see whether market participants actually understood the risks associated with asset securitization and priced them properly during the period. The result confirmed the general belief that larger banks tend to have higher systematic risk and lower idiosyncratic risk because of diversification.

Festic et al. (2010) analyzed the relationship between the nonperforming loans ratio and macroeconomic/banking sector variables as a source of systemic risk in order to assess the banking sector's vulnerability to bad-loan performance at a macroeconomic level in the five EU New Member States (NMSs). In this study, they demonstrate that the credit/asset ratio contributes to an increase in the dynamics of the NPL ratio within the observed economies. Their estimates for the Baltic States, Bulgaria, and Romania therefore support the hypothesis that the growth of credit might harm banking performance—most likely due to soft-loan constraints (conditioned by the growth of available finance) and the overheating of economies. The results also imply that gross fixed capital formations in the selected economies contribute to an increase in economic activity and lower NPL ratios.

Lately, countries like Romania, as a new EU member state, seem to capture more attention since the credit risk analysis is also influenced by country risk. The EU regulations and directives, plus the Basel requirements, reshaped the financial structure as well as prudential and regulatory environment. However, they are considered more risk sensitive than other member countries within the financial crises since they experienced spectacular increase in credit growth in recent years, but also due to the questioned stability of their political and economic environment. Banking institutions should find innovative methods and solutions to assess their vulnerability to larger and diversified borrower profiles and also credit constraints.

Thus, we perform an empirical analysis using data from a banking institution operating in Romania with foreign private capital. We have used databases with 3,000 companies that originated from various countries that have credit relationships with the bank. The use of data is appealing because it allows examining not only how the banking institution attributes a rating but also how it decides on upgrades and downgrades of the borrowers in order to minimize the risk according to some variables (size of the company, delay in payments, extent of the amount approved). The sample of companies used in our analysis is large enough to make our prediction model and results obtained relevant for this type of analysis. Moreover, studies on banking in Central and Eastern European countries (CEE) lack this type of analysis.

As far as the empirical modeling choice is concerned, we use logit regression and neural network forecasting, in order to compare the Bayesian approach with the MLP (multilayer perceptron) model, and use the second to correct some of the drawbacks of the first (see Atiya, 2001, Zhang et al., 1999, for detailed parallels of the two methods in credit risk analysis). Previous studies have only used Bayesian approaches or neural network models to distinguish defaulters from non-defaulters. We repeat the analysis several times, on matched samples, in order to estimate transition probabilities from each class to each other. This is a more nuanced approach to credit risks, presuming that non-defaulters do not become defaulters overnight, and this forecasting instrument enables the bank to take required measures in due time.

Regulation effectiveness and credit risk analysis are important long-run determinants for risk prediction and banking failure. By using the appropriate instruments, the overall stability is enhanced. Our research yields its benefits in the context of financial crisis, when risks incurred by the banks diversify and intensify. Based on a focused literature analysis, aiming to identify the newest and most relevant pieces of research in the field, the statistical analysis provides the banking sector with instruments at hand for mitigating credit risks and enriches scientific literature with a situational analysis of a country in transition, more and more dependent on reliable crediting processes.

The paper is organized as follows. II gives an overview of the credit risk assessment and related literature. Section III explains our methodology. Section IV reports the analysis and prediction results. Section V concludes.

II. Credit risk assessment

Credit risk assessment is performed through the development of models usually based on a classification approach, in order to distinguish potential defaulters from non-defaulters (Dima, Vasilache, 2009). In the literature, many reasearchers try to identify the determinants of bank risk-taking revealing conflicting predictions and results.

Based on the correlation between credit risk and asymmetric information, authors as Blackwell and Kidwell (1988), Booth (1992) and Blackwell and Winters (1997), Buser et al. (1981), Benston (1983), Goodman and Santomero (1986), Kane (1987), Merton (1977), Jensen (1986), Stultz (1990), Kahane (1977), Kim and Santomero (1988), Koehn and Santomero (1980), Saunders et al. (1990) and Galai and Masulis (1976) identified the main risk-taking factors as moral hazard, leverage, ownership structure, risk preferences, and regulatory actions.

Using different combinations of credit risk, interest rate risk, and financial leverage in their models, Berger and DeYoung (1995) and Kwan and Eisenbeis (1997), Gehrig (1998) and Winton (1999), proposed a different methodology based on the structural relationship between bank risk-taking and efficiency.

Irrespective of these conflicting opinions, information play an important role in credit decizion (Jeonk, 2001; Almazan, 2002); Hauswald and Marquez, 2003); Hauswald and Marquez, 2006; Yasuda, 2005; Kenneth and Ramirez, 2008 and Altman,1968), and access to the information and technological development of intermediaries influence specialization in lending (Altman et al.,1977).

In the literature about risk evaluation, traditional statistical and econometric techniques like linear discriminant analysis models and multiple logistic regression models (Altman et al., 1981; Hand and Henley, 1977) have been widely used for many years to discriminate between failed and non-failed firms (Dima and Vailache, 2009). Lately, more accurate models such as logistic regression, neural networks, non-parametric methods and expert systems have been developed in the field of credit risk assessment (Giudici, 2003).

Studies aiming at developing new models that are compatible with new mathematical programming-based discriminant analysis also were conducted. While Sueyoshi (1997,

2003) tried to combine discriminant analysis and data envelopment analysis using goal programming and mixed integer programming, Loucopoulos and Pavur (1997) suggested a three-group classification model. Although there are several models and approaches in the literature, there is a consensus for "minimum deviation model" having the most significant results (Karacabey, 2003).

Factor analysis is used in most studies conducted to prevent use of another financial ratio, which repeats the information provided by a financial ratio in the model. Several studies generate factors that cover the information in the financial ratios instead of financial ratios using factor analysis (Pinches and Mingo, 1973; Johnson, 1978; Laurent, 1979; Mear and Firth, 1986; Canbas et al., 2004), which can be described as a technique that simplifies and reduces complex and numerous data available (Kline, 1994). Although factor analysis can cope with this problem, this technique causes loss of information in a specific ratio.

The limitations of the model correlated with the development in other fields have conducted to the introduction of new classification instruments. Among the new classification paradigms we can include: rule induction algorithms and decision trees (Breiman et al. 1987), neural networks (Ripley, 1996), nearest neighbor algorithms (Duda et al., 2001), fuzzy sets (Zadeh, 1965), rough sets (Pawlak, 1982), support vector machines (Vapnik, 1998), operations research methods (mathematical programming, multi-criteria decision aid) or of hybrid credit scoring models (Lee and Urrutia,1996) as mentioned also in Dima and Vasilache (2009).

Wang et al. (1999) applied neural networks to credit risk assessment for the first time in China. The results demonstrate that the effectiveness and robustness of neural network are better than discriminant analysis. Zhang et al. (2003) researched neural networks and proved that they perform in credit risk assessment with high precision.

In 2007, Doumpos and Zopounidis conducted the first study within the field of credit risk analysis, exploring a combination model based on popular statistical and machine learning classification methods, including discriminant analysis (linear and quadratic), logistic regression, classification and regression trees (CART algorithm), nearest neighbors algorithms, probabilistic neural networks, and support vector machines.

Several other studies used survival time analysis to predict bank failure (Whalen, 1991; Henebry, 1997; Laviola et al., 1999) based on the application of a Cox Proportional Hazards model, Bharath and Shumway (2004) employed a time-dependent proportional-hazards model to evaluate the predictive value of the Merton (1974) structural model and Fantazzini and Figini (2004) used the Random Survival Forests. The findings of Fuertes and Kalotychou (2006) demonstrated that the logit model in terms of forecasting performances is a preferred alternative to more sophisticated competing models, confimed later on by Ishwaran and Kogalur (2007).

Other prediction models have been criticized for using only one technique, for being nonsystematic, or for non-specific results. To overcome this problem, Galindo and Tamayo (2000) used a multi-strategy approach including statistical regression (probit), decision-trees (CART), neural networks, and k-nearest-neighbors on the same data set.

Albu et al. (2014) used the Arma-Garch model to estimate the impact of banking policies on credit risk, concluding that the effect of the easing policies was substantial. Hung et al. (2013) used ordered probit models to test the relationship between credit rating and other financial ratios obtaining positive and negative and positive correlations.

Originally, many algorithms and statistical methods were used by reseachers and their use has been applied to many business applications. In the economic field, most studies have been concerned with neural networks. Compared to other prediction models, neural networks are more helpful in the decision process as they maintain or improve the success rate of credit decisions (Matoussi, 2010)

The next section presents the methodology of our analysis based on neural networks. We used this type of method because it is innovative and also because it allows us to train a predictive model for the data, clearly outlining the errors and emphasizing the nonlinear connection between parameters of the credited businesses and defaulting behavior in relation with the bank.

III. Methodology

The objective of the paper is to estimate the one-step transition probability of downgrading for companies applying for credits. We build a credit behaviour predictive model for companies credited by banks, as we correlate the downgrading risk, as dependent variable with: 1. company size 2. sector of activity 3. loan amount, 4. credit performance class (from AAA to C). The research thus is useful for credit institutions in selecting their clientele and deciding on the credit limit to be offered, and on how strict the conditions should be. Predictive models allow for dynamic understanding of behavioral change in companies, in relation to the crediting bank, in a period of high instability and risks.

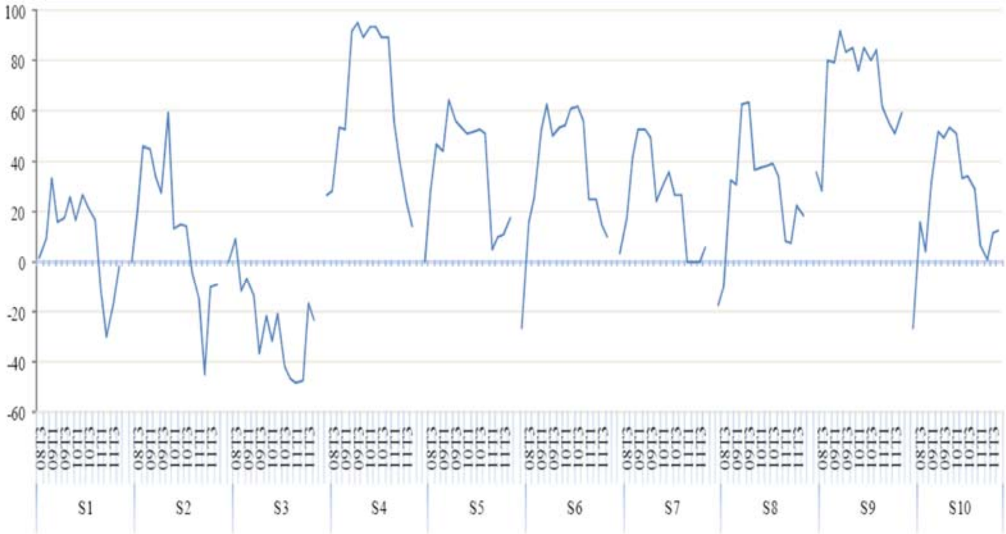
We have used a sample of 3,000 companies operating on the Romanian market and applying for credits during *2006*–2008. This period was chosen because it represented the boom of credit demand on the Romanian market. The independent variables considered were: 1. company size 2. sector of activity 3. loan amount, 4. credit performance class (from AAA to C). The dependent variable was the one-step transition probability for downgrading, expressed as 1 – the company will be downgraded; 0 – the company will not be downgraded.

The companies were classified in SMEs and large enterprises based on the European criteria (see http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition/index_en.htm). This may be considered a limitation of the study as, according to the BASEL II Agreement for SMEs (www.sme-basel2.com), the banks do not disclose their classification criteria when granting credits and these criteria may vary among banks.

An August 2015 survey of the Romanian Central Bank concerning the crediting of non-financial companies and banks shows that the company size and the sector of activity, respectively, are important factors in credit behavior prediction, as shown in Figures 1 and 2 below:

Figure 1

The evolution of the credit risk on economic sectors

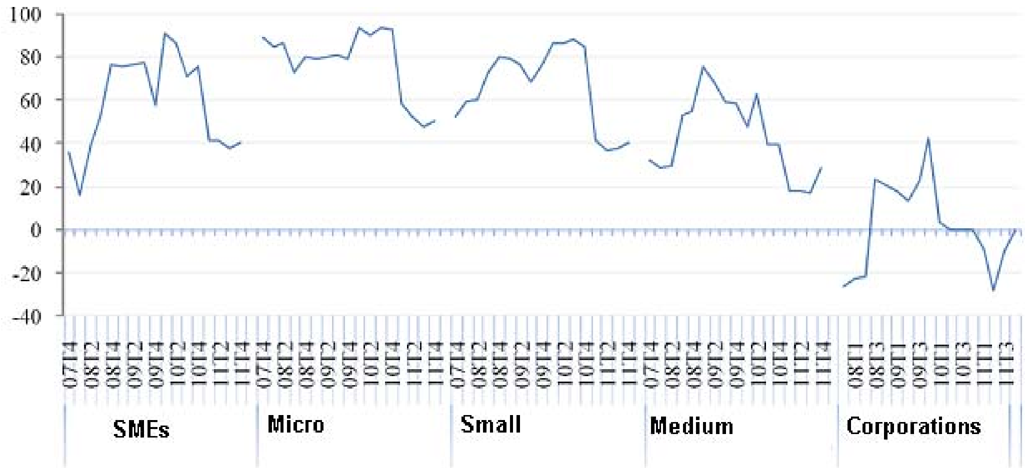


S1 = agriculture, S2 = industry, S3= energy, S4= constructions, S5 = trade, S6 = tourism, S7= transport and communications, S8 = financial intermediation, S9 = real estate, S10 = other.

Source: Romanian Central Bank Survey on Crediting of Non-financial Companies and Population, August 2015, p. 7

Figure 2

The evolution of the credit risks on types of companies



Source: Romanian Central Bank Survey on Crediting of Non-financial Companies and Population, August 2015, p. 8

The companies in our sample were 5% corporations, 17% medium size companies, 28% small companies and 50% micro enterprises. It may be seen that the majority of the pool of applicants is represented by micro enterprises, which are also seen, according to the graph above, as having the most unfavorable evolution of risks. Also, 72% of the companies in the sample operate in the trade and other services category, having also an increased risk. Thus, we consider that the structure of the sample reflects the sensitive issues in credit analysis, presently. We have assigned 1 for companies in the sectors at risk, and 0 otherwise. Also, we have assigned 1 to microenterprises and 0 otherwise. The amount was categorized as follows: 1 – for under 50.000 euro, 2 – 50.000 – 100.000 euro, 3 – 100.000 – 150.000 euro, 4 – 150.000 – 200.000 euro, 5 – over 200.000 euro.

From this sample, 1400 companies were, previously, clients of the bank, while the rest are prospective clients.

Delay was considered on a scale from 1 (less than 30 days of delay), to 7 (more than 180 days). The categories were separated by a fixed interval of one month of delay. The categories were considered based on the previous evaluations of the bank (credit history), on a scale from 1 (lowest credit quality) to 7 (highest credit quality), and 0 = default, on a structure replicating the classical Standard and Poor's matrix with seven categories, from AAA to CCC and D for default.

We have used logistic regression to estimate the probability of downgrading (0 or 1), based on the four independent variables mentioned (company size, sector of activity, loan amount, credit performance class - from AAA to C). The size of the sample reduces the risk of overestimation, making the logit regression fit for the analysis. We have also trained, based on a training sample 700 companies which had modified their status (one-step downgrading), a multilayer perceptron (MLP), which is classically used for credit risk prediction (Atiya, 2001; Lu, 2010; Mittal et al., 2011), but not, to our knowledge, for estimating downgrading probability.

The comparative results of the two analyses are presented in the following section.

IV. Results and discussions

We have run logistic regression on a random sample of 1400 companies who were clients of the bank for training the model. The model was then tested on the unselected companies, and then used to classify the 1600 prospective customers.We have computed pseudo-R^2 for our regression modell, whose value is 0.78, showing that the model is fair in predicting data.

Table 1

Variables in the equation

		B	S.E.	Wald	df	Sig.	OR	95,0% C.I.for EXP(B)	
								Lower	Upper
Step 1a	sector	-.192	.030	42.427	1	,000	,825	,779	,874
	size	-.059	.022	7.448	1	,000	,941	,904	,984
	amount	.019	.005	14.226	1	,000	1,020	1,009	1,030
	class	1.152	.019	64.818	1	,000	4,164	4,122	4,208
	Constant	-1.791	.297	36.483	1	,000	,166		
a. Variable(s) entered on step 1: sector, size, amount, class.									

All the four explanatory variables selected are well chosen for the analysis, as all contribute significantly (sig under 0.05 threshold) to the model.

The corresponding fitted model is logit (p) = -1.791 + (- .192 * a) + (- .059 * b) + (.019 * c) + (1.152 * d), where a is the size of the company, b is the sector of activity, c is the amount of credit applied for, and d is the credit performance class. This model can be used to predict the behavior of the 1600 prospective clients. Prospective clients are firms intending to apply for a credit, which are selected from the general population based on the existing customer profile. The downgrading probability is estimated by the previously trained model.

It may be seen that, according to this model, the previous class in which the company was placed is the most important predictor. Its odds ratio shows that, for instance, for companies in the AA class, as compared with companies in AAA class, all other characteristics-the same, the odds to be downgraded are about four times higher. Microenteprises have a 20% higher probability of being downgraded, as compared to the other categories of companies, and companies operating in sectors considered vulnerable have a 10% higher probability of being downgraded.

Table 2

Classification table

	Observed		Predicted					
			Selected Cases			Unselected Cases		
			Previously downgraded		Percentage Correct	Previously downgraded		Percentage Correct
			No	Yes		No	Yes	
Step 1	Previously downgraded	No	676	44	93.9	286	28	91.1
		Yes	132	124	48.4	70	38	35.2
	Overall Percentage				82.0			76.8
c. The cut value is .500								

We took into consideration the AUROC computed based on the classification table (area under the ROC curve) whose value is of 0.77 (with 95% confidence interval., between 0.68 and 0.82). The model can be considered fairly good for predicting data, having an accuracy level of 77%, that means is makes true guesses in about three cases out of four. It may be seen that the model is much better at predicting non-downgraded customers than downgraded customers. Thus, it is likely to give high Type I errors (classifying downgraded as non-downgraded), being less sensitive. . For the bank, it is dangerous to misclasify risky companies as being companies without risk, because these companies are the potential defaulters. If they are not properly filtered, and are still given credits, the risks for the bank rise. This is the reason why we consider the logit regression estimate to be not entirely adequate, in this case.

In the second credit risk modelling, for the same set of data, we have used an ANN tool, the multilayer perceptron training.

Table 3

Case processing summary

		N	Percent
Sample	Training	2265	75.5
	Testing	735	24.8
Valid		3000	100,0%
Excluded		0	
Total		3000	

We have assigned 2265 cases to the training sample (in-sample, used for model building), and 735 cases to the testing sample (in-sample, used for model testing).

Table 4

Model summary

Training	Cross Entropy Error	196.626
	Percent Incorrect Predictions	17.6%
	Stopping Rule Used	1 consecutive step(s) with a decrease in error less than .001
	Training Time	00:00:01.686
Testing	Cross Entropy Error	74.746
	Percent Incorrect Predictions	20.3%
Dependent Variable: previously downgraded		
a. Error computations are based on the testing sample.		

As it can be seen, the percent of incorrect predictions is roughly comparable, for the training sample and for the testing sample, meaning that the model is fairly good. Its performance may be improved by considering a larger sample and analyzed over a longer period of time. Still, economic instability and changes in the banking sector, over longer periods of time, may annul the benefits of a larger data set.

The classification of the training and the new cases is shown in Table 5:

Table 5

Classification of the cases

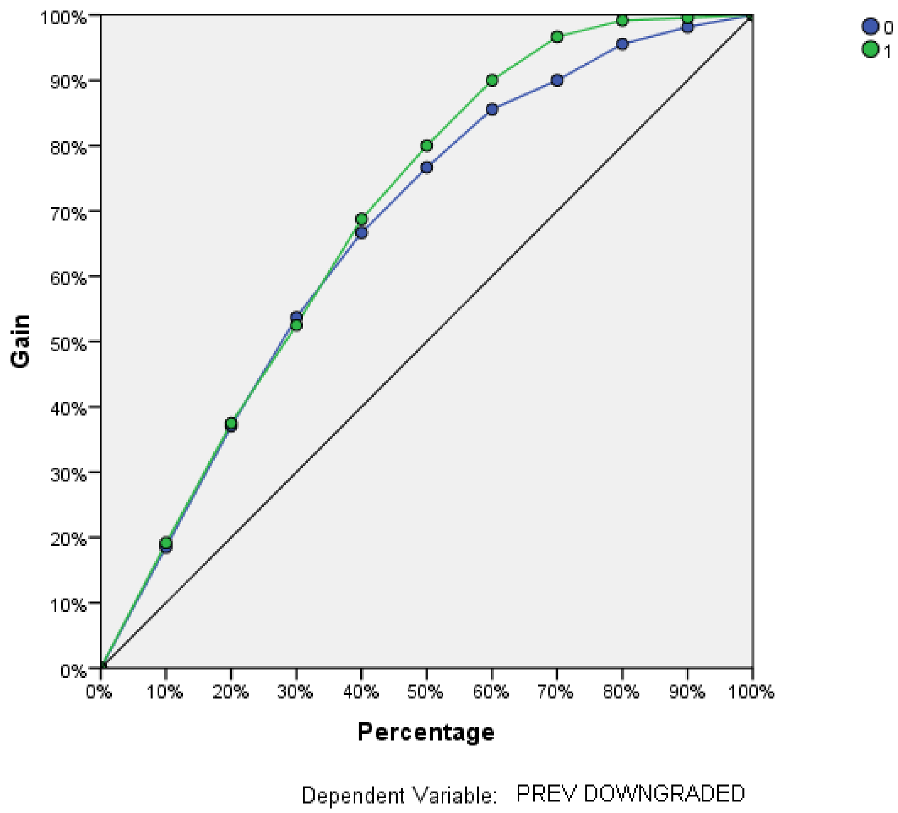
Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	1550	131	92.2%
	Yes	269	315	54.0%
	Overall Percent	80.3%	19.7%	82.4%
Testing	No	493	65	88.3%
	Yes	84	93	52.6%
	Overall Percent	78.5%	21.5%	79.7%
Dependent Variable: Previously downgraded				

The model classified correctly 1550 out of 1681 companies not having been downgraded, previously, and only 315 of 584 companies having been downgraded. However, its sensitivity is higher than in the case of logistic regression (54% correct predictions of downgraded companies, as compared with only 35.2, in the previous model). For the testing sample, the percentages are roughly the same, with a slight decrease in both specificity (classifying non-downgraded companies correctly), and sensitivity (classifying downgraded companies correctly). This means that the model works well on new data, also.

The AUROC (area under the ROC curve) gives the accuracy of the model, which in our case is .868 (the model predicts correctly the probability to be downgraded in 86.8% of the cases analyzed). The cumulative gains chart is presented in Figure 3:

Figure 3

The cumulative gains chart



The cumulative gains chart summarizes the gains obtained with the use of the model. The green curve is the curve obtained using the model to predict the companies which will be downgraded, while the baseline is obtained by applying a random selection. The applicants are distributed by deciles, and prioritized in decreasing order of their credit quality. If the bank targets only the first 30% of its applicants, in terms of credit quality, it may keep the risk of downgrading at around 50% (equal probability for an applicant to be a good borrower or not to be a good borrower). Obviously, it is the banks' decision, considering the economic context and adjacent factors which may be taken into account, if it wants to decrease its number of applicants, in order to diminish risks. Considering the economic crisis and the changes in the crediting criteria, it seems that this was the option actually adopted by most of the banks.

Conclusions

Our research, based on a rather large sample of companies applying for credit to the same bank, with whom some had previous crediting relations, and some not, confirmed our hypothesis that neural networks estimates are better than Bayesian estimates also in predicting probabilities of transition, not only probabilities of default. Our main contribution to literature resides in categorizing the companies on classes of credit quality and directing our analysis not straightly to the default situation, but taking into account the transition probabilities from one class to another.

In particular, we focused on the one-step transition probability for downgrading, which we considered to be an alarm signal for the bank, in reconsidering its relationship with the respective customer. Our results may orient the bank in projecting its risk related strategy, while trying to maintain a convenient number of credit applicants.

The limitations of the research emerge from the company-focused approach, which doesn't take into account environmental factors (although we included data related to the sector of activity of the companies, additional input variables can be added). Also, we took into account only one bank, while a comparative perspective, including multiple banks, would be beneficial.

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