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Credit Risk
Features of a non performing company

Coordinator:
Prof.Univ.Dr. Anamaria Ciobanu

Student:
Oniga Oana

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Abstract

Number of aplicants on loans is continously rising from one year to another. The decision to give a loan is based on developing statistical models, intuition not being enough. So looking through the economic enviroment arises the need for developing new scoring models that can predict as acurrate as posible the performance of the client and the future capacity of reimbursment. Banks are constantly looking for new ways of maximazing their profits but also they are trying to minimize theirs loss.

1.Introduction

Banks survive when there is a balance between active and passive. Loans granted will be based on the percentage of deposits. Population tends based more to consume than to save. Considering the recovering economy,it appears to have created an imbalance in the banking industry. Thus the volume of bad loans increased faster than the volume of deposits. Trying to attract new customers puts banks in the position to choose between the facilitating but also strenghten the criteria required to grant loans to customers able to refund. Hence the need to develop competent scoring model. Thus, it will need to respond to the need to invest in bank customers who are classified at the edge of risk, while managing to handle its products for the population.

This paper aims at seeking new perspectives in scoring, whose primary purpose is in constant defining new models. This is to want to create a model for financial performance of its clients to minimize risk.

The study is based on a rigorous research showing that relevant methods following analytical methods: discriminant analysis and clustering.

Present work has as a basic structure of 3 parts, the first part aims to create a framework in the context of the current financial current bank, the second part covers the theoretical and the latter includes the practice. The first part contains the first chapter in which we gathered information about the evolution of the banking system and how the trends of bank lending in Romania affected by regulations. I have also tried to highlight the importance of double reporting, both prudential perspective, RAS, and in terms of IFRS impairment losses. These are methodologies offered banks ways of hedging and classify customers as performing or underperforming.

The second part presents the general framework of risk assumed by a bank, a brief classification. The first chapter of the second part of the study creates a framework based on prevention of such risks, both the time and the importance of credit monitoring. The second chapter of the second part of the study comes to present the current state of research in the field of statistical models and results. This part of the preceding empirical part of the paper and introduces the study`s relevance in the context of previous research.

The last part of the paper contains the presentation of a statistical model. The model is based on a portfolio of a bank's corporate clients, both performing and nonperforming. Based on financial ratios resulting from the handling balance sheet and profit and loss account, we sought answers to questions like, which ones have the greatest relevance to predict loan repayment capacity. The study was conducted for 40 clients who were granted credit.

1.1 Economical and financial context

On the basis of the crisis that the global economy, we see signs of growth in the Eurozone. Year 2014 seems to be the first year that there will be positive growth after 2011 due to easing to stimulate exports and austerity measures. Even in this context, the economic recovery should be based on more extensive program of reforms to boost competitiveness. In addition, domestic demand, which played a decisive role in terms of economic growth in recent years, should improve from 2014. Austerity measures will continue to hinder growth, but their impact will be considerably less than in previous years . Relatively weak recovery, combined with the company's attempt to improve profitability and productivity, indicating that we will assist further on modest increases in unemployment in 2014. This estimate may, however, be too pessimistic. Thus, a more favorable labor market may provide a firmer recovery in consumer spending.

Companies in Romania tried continuation of adverse conditions caused by the intensity and duration of the economic contraction in Romania. Todate companies faced liquidity problems, based on supply and demand worsening ties between business sectors due to their uneven developments. In this way, commercial activities between business partners were affected by these constraints.

According Stability Report NBR companies receiving foreign direct investment had an advantage during excise duty, being employed in better conditions than the rest of the economy. They come with a plus in terms of financial and commercial structure that allows them to bear shocks more smoothly, having the ability to create added value throughout the economy (about 40%) and also make a great contribution to the realization of exports (75%).

1.1.1 Financial institutions in Romania

International financial markets situation, had a negative impact on financial stability in Romania in terms of adjustment of balance sheets by major European banking groups, resulting in reducing exposures. In this way, also affected the quality of loan portfolios, taking into account the financial situation of the customer pressure, and tighten loans. So wanting to reach a level of comfort, they provisioning level rised mainly through the central bank's decision to continue using prudential impairments.

NBR Stability Report (2010) states that "the main vulnerabilities generated by companies on the financial stability of the country are given by the ability to service the debt to the creditors of financial and payment discipline among partners."

Lending standards in the euro area and in Romania, strengthened the onset of the crisis (especially for SME), but have lost momentum over it. Also, the credit institutions in the euro area have maintained a cautious attitude towards the corporate sector, banks have resorted to a relaxation of standards for short-term loans, but continued to tighten those for long-term loans.

The main causes of the credit squeeze is about the quality of debtors: poor liquidity as a result of delays in collection, decreased interest coverage, inability to maintain a steady cash flow (decreased profitability restricting volume of credit lines due to adaptation needs financing to small workload).

Most affected by the withdrawal of funding were SMEs and micro-enterprises, as banks were perceived as the most risky in terms of credit risk. However, in this sector, there are many alternatives for financing and as such contagion lack of funding has caused negative reactions in the industry chain, generated by the SME NPL ratio exceeded 10% in June 2010, while companies Larger indicator is approx. 2.5% (estimate BNR). According to reports BNR, in 2012, SMEs have received additional funding from internal and external creditors (up 0.9%), loans from domestic banks recorded the alert dynamic (+2.5%). Instead, there were adverse developments with companies providing services that require a higher level of knowledge, which recorded a decline of 6.2% financing, while firms providing services that require a level of knowledge in May Low recorded a decrease of 0.2%.

1.2 Prudential adjustments

In order to cover the credit risk of customers showing signs of deterioration, the central bank, which is the main regulatory body of the banking industry, demands on taking precautions, they materialized through prudential adjustments calculated individually for each client of the bank. These adjustments prudential common denominator and provisions are set aside to cover the cost if a client becomes counterproductive.

Evaluation of the financial performance of a debtor person or entity, shall be according to the criteria set by the Bank based on customer classification categories of default risk. Thus, assessing financial performance in categories from A to E, a debtor person or entity is achieved by mapping between the final rating of consumer and corporate financial performance.

-Category A: good performance, allowing payment at maturity of the debt, maintaining this performance,

- Category B: good performance, but without certainty on a medium term perspective,
- Category C: satisfactory financial performance, with worsening trends;
- Category D: low financial performance and cyclical;
- Category E: loss and the inability of repayment.

Bank loans made to borrowers outside of credit institutions are classified into the following categories:standard;observation;substandard;doubtful;loss.

Customer classification is made through simultaneous application of the following criteria: debt service; financial performance;initiation of proceedings.

1.3 Impairment (IFRS)

A new reporting model, which adopts parallel banks, especially banks whose parent company has adopted such a model is the model IFRS (International Financial Reporting Standards). This model is more permissive in terms of allocation of provioane, by the fact that here there is a standard model, and the establishment of provisions may vary depending on the information received from clients and promises up to a late payment, but safe in the future.

Internal ratings (IRB) is based on the following risk indicators such as PD - Probability of default (the probability that a customer becomes unsatisfying) for a period of one year,LGD - Loss Given Default (expected loss) and is calculated as 1 recovery rate estimated, EAD - Exposure at default (credit volume with risk of default)

Using the above-mentioned indicators estimated two types of expected loss (expected loss-LG),Volume loss EL = PD x LGD x EAD ,Assumed loss percentage EL% = PDX LGD

In terms of monitoring clients there are being performed statistical scoring models to help determine the financial condition of the customer. Such scoring sites fall into the category of behavioral scoring, with monitoring role. Banks are required to conduct such annual review for each client in order to prevent credit risk, and thus may serve as new models of reimbursement for those customers, helping further work towards a future repayments. Thus protected ability to bring profit bank by keeping some clients showing signs of improvement, but that need refinancing.

2.What we know

2.1 Defining Risk

Credit risk is the risk of insolvency of the debtor, default risk and the deterioration of bank assets Risk. Bank is organized as a separate activity analysis, evaluation and monitoring of credit risk to the individual client company. There are specialized departments of the credit risk management role in minimizing credit risk and maximizing return on bank assets, with the role of ensuring observance of specific procedures for credit and credit risk and regulations.

Investment loans represent the highest share of banks. When credit is granted, the risks are automatically associated with the debtor, and is carried by non-payment at maturity.

In analyzing credit risk should be taken into account that credit risk is strongly correlated with the risk of reinvestment. A loan became non-performing întarzirea lead to reinvest funds that the bank caught the market.

Credit analysis is the assumption of credit risk, which must be determined by analyzing the bank expects earnings to be obţină.Acestea direct gains by receiving interest and related fees, or indirect, by offering new products to existing customers and performing.

Looking into the light of recent global events, the need to improve methodology to quantify the credit risk at the individual level but also at the aggregate level in order to avoid vulnerabilities banks and financial systems to various types of shocks. It is important "efficient resource allocation and risk diversification."

In terms of existing models for assessing credit risk "forecast losses on credit risk, developing advanced scoring models, and studying the necessary legistlativ influence its implementation on banking"

2.2. Scoring

In an analysis in terms of the provision of credit related risk, it is desirable to take into account the probability of default. This will perform above some correlation between the economic and financial indicators of the company.

Scoring is a term used to describe the means used by a bank (or other donor) to determine the creditworthiness of a loan applicant. Financier assesses client using specific criteria, such as age, occupation, monthly income, etc..

Seeking a broader understanding of this procs selection literature gives many definitions of community and also scoring its classification.

According to Van Gestel and Baesens, the scoring can have several meanings, analyzing in terms of the period in which the analysis takes place. Thus we have:

-Application of scoring, which takes into account the premises granted a new credit applicants. This quantifies the possibility of default by analyzing factors such as monthly income, age, occupation, the demographic;

-Scoring behavioral scoring application involves similar principles except that they apply to existing customers. This type of scoring takes into account historical data such as account operations, account balance, frequency îintarzierilor maturity approximating account and aims when the client becomes unable to pay;

Collection-scoring is used to divide customers with different levels of insolvency in groups separating those who require more decisive action by those who have not reached a critical stage. It examines the signs deducted from the remainder (past due date) and take steps to collect the debt through legal methods of enforcement of claims and then derecognition of filing the claim;

-Detection of fraud, fraud scoring models categorize customers by the likelihood that an application to be fraudulent. Such guarantees shall be reviewed revenues and conditions already promised.

Hand D. J. and WEHenley studied statistical models for classification of credit scoring applications. They concluded that there is no best method for scoring and selecting the best method of scoring and that it depends on parameters such as data structures and contextual variables. They concluded that when the data is not structured, it is best to use flexible smart structures, such as neural networks.

Thomas L. C. analyzed statistical techniques and operational research techniques used in credit scoring decisions and behavior. He also discusses the need for a scoring profit, profit level of importance that the customer can bring to the organization. He explains scoring profit as a tool that would better represent the interests of the organization, with the primary objective of profit accumulation, compared with present methods that aim rather probability measure of deviation from paying the debt. The paper concludes that the development of an information system in May qualities will enable more detailed analysis of credit and behavioral scoring, and thus the possibility of developing a scoring attract tax.

Robert B. Avery, Paul S. Calem, Glenn B. Canner, raised issues that may impact on the accuracy of scoring. They have shown the importance of taking into account the macroeconomic effects and how they can trigger the risk of default and bring errors in econometric models. This finding as well as pertinent as it is limited in terms of quantification.

March. Hybrid approach. This approach has the benefit of compensation methods based on the premise that data is processed in several ways, and so the end result comes to be tested more rigorously. Thus we find the following combinations:

- Classification + Clustering. Clustering is an unsupervised learning method that does not fails to differentiate data and supervised learning methods. Such analysis is required in advance the outcome of which is used for clustering and thus be better defined classes, with different risk of clustered data by other criteria than initially;

- Clustering + Classification. This approach uses outlier detection (values outliers) and thus exclude them from the database for further classification is one whose statistical results may have a homogeneous structure.

- Classification + Classification. This approach has the dual purpose data classification. Such classifications can narrow the results of the first variable, the second classification will be done starting from a smaller base, which can generate more relevant results. In this way it will be seen that variables do not have a high discriminatory power, and they can be excluded from the analysis.

- Clustering + Clustering. The combination of the two types of clustering techniques is used to reduce the complexity of the database. Thus the first clustering of the data will be used as a starting point for the second clustering, managed to identify the most relevant values.

Scoring method has a main objective in providing predictive models to assess the risk of failure of an enterprise. The method is based on statistical techniques of discriminant analysis. Applying this method involves observing a population of enterprises grouped in companies facing financial difficulties and healthy businesses. For each of the two groups establishes a set of indicators and then determine the best linear combination of the rates which exemplify the differentiation of the two groups of companies. Following the application of discriminant analysis, Fischer, is obtained for each firm a score "Z" linear function of a set of rates. Distribution of different scores distinguishes the healthy firms in difficulty. "Z" score assigned to each company is determined by the function:

Z = a1x1 + a2x2 + a3x3 + ... + Anxn, where:

- X represents the rates involved in the analysis;

- A is the weighting coefficient of each installment.

In economic theory were developed a series of models based on scores method, of which the best known are: The Altman; Conan and Holder model. E. I. Altman used the information obtained by studying a large sample of companies, some of which have gone bankrupt and others have survived and found that the analysis based on several variables allowed prediction of 75% of failures, with two years in advance of their .

Function determined by Altman (example):

$Z = 3.3\ x1 + 1.0\ x2 + 0.6\ x3 + 1.4\ x4 + 1.2\ x5$, where:

X1 = Current result before tax / total assets

X2 = turnover / total assets

X3 = Market capitalization / loans (long-term debt)

X4 = reinvested profit / total assets

X5 = Net current assets / total assets

Market capitalization represents the absolute size given by the product of the last class for the year ending stock and number of shares. Net current assets are the difference between current assets and current liabilities. The contents indicators that their levels are even better when recording a higher absolute value. Score "Z" are as follows:

$Z < 1.8$ - the bankruptcy is imminent;

$Z > 3$ - the financial situation is good, the banker can trust undertaking (is solvent);

$1.8 < Z < 3$ - the financial situation is difficult, visibly diminished performance and close to the threshold of bankruptcy.

3.Theory

When research a particular phenomenon will choose a population for which it is essential to extract the most relevant information in its characterization. Thus the process begins by gathering all the characteristics associated with the phenomenon, followed by statistical techniques, the study population can be analyzed by means of features that includes the largest amount of information.

3.1 Principal components analysis

Principal components analysis is a method of factor analysis which aims to reduce the complexity of the original data, highlighting and fixing model associations (correlations) between variables and latent variables also highlight behind the measured variables. The latter are called factors, which will be processed by intermediiul discriminant analysis.

Factor analysis begins by testing the correlation matrix by using statistical tests to see if there are correlations between variables large enough. Use Bartlett sphericity test, anti-image correlation matrix and Kaiser-Meyer-Olkin index (KMO) and extraction method known as the following types of analysis: principal component analysis, principal component analysis normally rank analysis and analysis correspondences.

The principal components analysis (principal component analysis) will decompose the variance across variables. The factor analysis propriuzisa (principal axis factoring) will decompose only common variance variables.

3.2 . Discriminant analysis

Discriminant analysis is a predictive classification method, which is explanatory in analyzing the data, so the model will be built through a Y variables explained more explanatory variables X1, X2,

..., Xn, quantitative or binary. The purpose of the analysis will materialize when identifying the one or more linear combinations.

Important in discriminant analysis is that the variables are not correlated. Thus, the subsequent analysis is principal component analysis, following the new data results, the new components to be used as explanatory variables.

This will take into account a lot of variables X1, X2, ..., Xn, and seeks to determine new variables C1, C2 ..., Cm, where Ci = wi1 X1 + X1 + ... + wip wi2 Xp, such that m <p These new variables are called factors or components.

If it is proposed that the new components, denoted by F (factor), to retain only what imparts common variables X, ie Xi = AI1 + AI2 F1 F1 + ... + Fm + They aim where F1, F2, ... Fm are common factors variables X, and they are the X1's specific analysis is proposed in psychology (common and specific factors analysis).

Bartlett assay tests whether the correlation matrix is estimated unit (null hypothesis), resulting in a sharp multicollinearity without specifying the variable is not correlated with other variables.

KMO (Kaiser-Meyer-Olkin) test match partial correlations between variables and variable batch factorial model.

The first factor extracted will correspond to the largest eigenvalue, the first factor extracted is the one that explains most of the variance in the observed variables. Next extracted factor explains as much of the remaining variance remained unexplained, and so on. Variance decomposition will end when the factor explains less variance than a single variable, ie when the corresponding eigenvalue factor is less than 1 (Kaiser criterion).

For this result we used the criterion Cattel (scree test). Using the graph, we can see the point of inflection of the curve, and thus will only retain their values until that point.

Confirmation of these factors will make it through the rotation factors, so that they can be substantial and theoretically interpretable.

Notice for specifying the number of discriminating variables to be taken into account using a test for nullity latest reports correlation q. For this there Wilks statistic:

Hypothesis is rejected for small values of. So Wilks statistic measures the overall power of discrimination of the new variables (axes). The lowest value recorded with greater discriminatory power axis. Those variables (axes) of discrimination which have a low discriminatory power is of no interest to be taken into account.

For discriminant axis (Z) can be interpreted in terms of statistical significance, have studied the link between them and the explanatory variables. This can be done by:

• coefficient functions, which shall read as a share of the explanatory variables in forming the axes;

• correlation coefficients of discriminant axis and each explanatory variable, which will highlight the variables that correlated best discriminant axes.

Score the completion of discriminant analysis is a method of diagnosis. The methods of calculating the scores can be used umătoarele methods: Bartlett (zero mean scores su products and minimized the sum of squared factor applied); Anderson-Rubin (scores have zero mean, unit standard deviation and are uncorrelated)

In conclusion discriminant analysis aims, namely:

• To determine the explanatory variables that contribute most to differentiating classes defined variable explained so identify explanatory variables influence the proportion of explained variation of building more linear combinations, choosing the one best.

• To build a discriminant space. If simple discriminant analysis (Y has two states) is determined discriminant Z axis explaining a unit belonging to one class or another. If multiple discriminant analysis to determine several independent linear combinations (discriminant axis) and the explanatory variables to be analyzed determined by those axes space that separates the best units studied in class by a state variable Y.

3.3. Cluster Analysis

Cluster analysis aimed at achieving classes (groups) so that observations belonging to the same class are as like each other by the values of variables while classes up to be as different. We can say that an analysis cluster involves the following two steps:

a) choice of proximity measures, namely, defining a measure of closeness between individuals based on all observed variables;

b) specification of rules for building classes so that the difference between them be as large, while individuals in the same group to be as close.

Disjoint classes analysis is a statistical technique for clustering of cases (individuals) in the class suggested by the data matrix. We distinguish:

1) Analysis of hierarchical classes (hierarhical Cluster Analysis - HCA) is a method of grouping "hierarchical" in which each class is completely contained in another class. Is not required a priori information about the number of classes, and once an individual has been assigned to a class, it will remain there. It is not recommended to be used for large databases with many individuals.

2) Analysis of disjoint classes (disjoint Cluster Analysis - DCA) is a non-hierarchical technique which uses a classification iterativă.Iniţial all individuals arbitrarily grouped into classes. Then follows a breakdown of each individual to a class based on those of respectively similaritateaindividului class. The process is iterative and terminates when you no longer find shifts between classes. The process is more efficient for large databases and for speed would require a priori knowledge of the number of classes.

3) Classification based on the average (k-mean clustering). It is a technique of classification disjoint classes, each class is obtained center "dynamic" as the average of the individuals in the class. K-mean technique aims at each iteration, reducing the variance of individuals within each class and maximize the variance between classes.

4. Case study

The case study is based on statistical evaluation based on a group of indicators, the performance of companies in terms of the bank. Thus initially charged and classification based on performance and underperforming firms, we see the ability to predict status indicators selected companies.

We selected a group of 40 observations (firms) equally divided by the degree of performance. Such observations will correspond to 20 underperforming firms and 20 observations will correspond to firms in terms of performance of the company. The objective of the case study will materialize by choosing variables that influence perfrom a company in terms of the bank.

For the study we used SPSS statistical software used. The database is built taking into account the following variables:

- Interest coverage = operating result + depreciations (EBITDA) / interest expense
- Commercial Return (%) = current year result / turnover * 100
- Return on assets after interest expense ROI (%) = current result for the year / total assets * 100
- Current Liquidity (%) = Current assets / current liabilities * 100
- Fixed assets share in total assets (%) = fixed assets / total assets * 100
- Degree of total assets financed from equity (%) = Equity / total assets * 100

- The level of funding of tangible and financial capital (%) = (equity - intangible assets) / total assets - intangible assets) * 100
- CA coating (%) = Debt - Cash and cash equivalents / turnover * 100

By testing the correlation matri, I noticed that there are variables that correlate relatively strongly with each other. The correlation test we used the Pearson correlation coefficient. In analyzing the obtained values we see that the coefficient takes values greater than 0.5 in the correlation of certain variables. Given this strong correlation degree, will continue through the reduction the degree of correlation by creating new variables using principal component analysis. Asttfel we will see what are the factors that explain variance latent common sub-sets of variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.632
Bartlett's Test of Sphericity	Approx. Chi-Square	315.067
	df	28
	Sig.	.000

Tabel 1 Testul KMO si Bartletts

Kaiser-Meyer-Olkin index (0.632) (tabel.1) is used to compare the size of the correlation coefficients observed size partial correlation coefficients. Sampling adequacy test shows that the analysis is statistically significant. Bartlett test (tabel.1) tests whether the correlation matrix is approximately uniform, which shows a pronounced multicollinearity. Value (315.067, sig. = .000) Allows us to reject the assumption that the variables are not correlated, there is a strong relationship between the data. We have a chance close to zero (Sig. = 0.000) to obtain this value of HI-square if the variables analyzed were not correlated. Thus we can conclude that there are several common factors and factor reduction will continue. We notice that the variance is divided as follows: the first factor explains 41.9%, the second 28.1%, and the third explains 15.5% of variance

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]		
Co mponent	otal	% of Variance	Cu mulative %	otal	% of Variance	Cu mulative %	Tot al	% of Variance	Cu mulative %
1	.295	41. 190	41. 190	.295	41. 190	41. 190	3.2 55	41. 090	41. 190
2	.251	28. 134	69. 323	.251	28. 134	69. 323	2.1 79	28. 244	69. 334
3	.242	15. 530	84. 854	.242	15. 530	84. 854	1.4 96	15. 520	84. 854
4	503	6.2 81	91. 135						
5	363	4.5 32	95. 667						
6	255	3.1 94	98. 861						
7	087	1.0 93	99. 953						
8	004	.04 7	100 .000						

Tabel 2 Tabel of variance

Matrix components provides variables and their contribution to the formation of each component. Data refer to initiate solutions.

From the principal component matrix for the three components we see that the first component is mainly influenced by the return on sales (0.902), interest coverage (0.811) and return on investment

(ROI) (0.730). The second component consists of the level of funding of tangible and financial capital (0.956), the level of funding of total assets in equity (0,955) and the share of real estate assets in total assets (0.611). The third component is influenced by current ichiditatea (0,667).

After observing the degree of explanation, we will rename the three components as follows Profitability ; % financing from own sources ;lichidity.

	Wilks' Lambda	F	df1	df2	Sig.
Rentabilitate	.229	127.711	1	38	.000
Grad de finantare din capital	.621	.671	1	38	.000
Lichiditate	.912	3.681	1	38	.043

Tabel 3 Test Wilks

We can see from Wilks test (Table3) discrimination power of the new variables. First, it is observed that the overall discrimination is very strong, as indicated by the table header information: Wilks's Lambda statistic has the value 0.229; 0.621; 0.912 (the statistical value is closer to zero, the power of discrimination is greater as the lambda is aporoape of one, the power of discrimination is reduced). Thus we conclude that the only variable return has a strong discriminatory power 0.299, while the level of funding and liquidity indicators have low discriminatory power, taking values close to 1. Semnficaţiei In terms of statistics, variable liquidity has a lower value 0.043 <0.05, which has a very low discriminant power.

The value of the Lambda (Table4) for the discriminant function, taking value close to 0, and the statistical significance is .000. Allowing us to conclude that this group of predictive variables will make predictions that will have a strong statistical significance.

est of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
	.174	63.350	3	.000

Tabel 4 Wilks' Lambda

To see which of the three components of the function discrminare we look at the function coefficients (tabel.14) to observe the power play in defining the variance of each outcome. Thus we see that the variable has a coefficient of 1.054 Return, The 0253 Capital Funding and Liquidity has a coefficient of 0.512. Which shows that the pointer Return will have the greatest effect on the results.

In the categories of firms, the model allows us to obtain Fisher scores that define the model for both companies and for the bad performance.

Ff0 =-4.167xRentabilitate-capital financing 3.261xGrad-1.151xLichiditate-3288

FF1 = 4.269xRentabilitate 0967 xGrad capital funding xLichiditate 1043-2759

From the classification results, we can see that the model was accurate in predicting the two classes are initially fime performance and bad companies. Thus we see in the cross-predictability we see the ability of classification. In this mode we observe that firms performing group (0), model accuracy is 95%, a single observation estimated not fall into the classification, and the cross-validation result shows 97.5% of the observations were correctly classified. Also we can see that for the group of companies performance model failed to predict the classification of 100%, so all 20 performing companies were classified using the same criteria.

The last step of the analysis is the classification of the clusters. Clusters represent a descriptive analysis method classifies objects by similatităţile casre of them, with no previous group.

Table initial cluster centers, the initial centers are presented for fiecae cluster centers and thus the coordinates in the space variables.

Cluster	1	17.000
	2	23.000
Valid		40.000
Missing		0.000

Tabel 5 Cluster

5. Conclusion

This paper aims to model the dynamics of scoring and searching for a model looking to make a contribution relevnaţi the indicators when deciding to lend to a customer. Starting from this premise, based on already indebted companies, I tried setting up a behavioral scoring model to see which indicators should be followed more closely and have a higher discriminatory power for classification decisions. However one wishes to observe and model the correlation of indicators to notice is the ideal combination when a client categorization decision as performing or non-performing.

Principal components analysis is a very useful instrument that fails while synthesising information and eliminate redundant information. After applying this type of analysis we obtained a set of new indicators that can be used on the discriminant analysis. We got 3 new inidicatori or principal components to synthesize as much information from the original. So we continued the analysis by naming these after all information they retain as follows efficiency indicators, level of funding from its own resources and liquidity. The latter being strongly correlated between them have the ability to return results as relevant.

Using these three components in discriminant analysis we observed that the set of firms originally collected, 20 and 20 bad performance test shows that the 40 companies were included in the desired class, so new components extracted were able to convey the extent of information desired each of the two classes, retaining 84% of initial value variance

By comparing the two results that return, here composed mainly of commercial profitability, return on investment and coverage of interest, have the greatest influence in discriminating result with negative senmn performing firms and firms performing good sign. The same can be observed for the liquidity and distribution of signs the same. Regarding however the extent of their funding from the degree of discrimination is changing. Analyzing these bad companies have a share close to what rentability, but if the coefficient is very small firms performances. Therefore, we conclude that this indicator is based mainly on their ability to finance capital shows that the total assets as a company does not keep within the limits of the effectiveness of this indicator, the overall situation is deteriorating. When signs of NPL firm, bank weighs the degree of financing from own sources to search for ways of debt constituted.

To confirm data after classification using cluster analysis into clusters tried to reclassify the two types of firms. Discriminant analysis was confirmed in 97% classes initially set remain largely the same. And we conclude that scores identified by discriminant analysis and cluster analysis confirmed correct.

The conclusion from studies correlated with results from the literature can be seen that there is no perfect scoring model that is universally available. Therefore it is important that each bank to develop their own models to maintain them through constant improvement. Thus they can increase their profits resulting or by promoting customers who rambusare increased capacity and on the other hand can advise customers who show signs of worsening. This creates a system that seeks more than prevent unwanted events.

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