Global Crisis Effects on Romanian Credit Risk Evaluation Models

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Abstract

The effects of the global crisis can be noticed in all the economies around the world and statistic indicators reveal the fact that Romania has become one of its victims starting with the last quarter of 2008. Its consequences have different ways of manifestation, varying from one domain to another.

Economic analysts have discussed possible causes of the recession and many of them consider the failure of the loan market as the main responsible for these events. The paper aims to analyze the way in which Romanian credit risk evaluation models are affected by the new economic environment. The importance of this topic is highly relevant as the risk of granting credits is the most important risk in the banking system and the accuracy of the selection process directly influences the institution's performance.

The main dilemma is to decide whether to grant or not a credit to a customer. The question that appears is whether the decision instruments used before the crisis are still efficient.

Firstly, the authors present the Romanian loan market features under crisis conditions by analyzing some statistics recently computed by The National Bank of Romania. The main conclusion is that indicators reveal an important decrease in credit volume, explained by a changed behavior of the lenders and consumers during the last quarter of 2008.

Some important theoretical aspects related to credit scoring evaluation are introduced through the presentation of few of the most important types of credit scoring models used around the world. A particularization for the Romanian case is made as the paper briefly characterizes the background in which the study takes place.

Then a statistical model is designed with the help of regressions and the importance of the feature selection is discussed. The model is applied for two data sets dating from before and after the Romanian manifestation of the crisis. Therefore, a conclusion is drawn that under economic recession the companies tend to have a different behavior which leads to the necessity of redesigning classical credit scoring models in order to include new features that illustrate the status of the economic environment.

Keywords: crisis, credit, model, impact, risk

JEL Classification: *C30, C44, C52, C51, G21*

Efectele crizei globale asupra modelelor de evaluare a riscului la acordarea de credite din Romania

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Rezumat

Efectele crizei globale se fac resimtite in toate economiile de pe Glob si indicatorii statistici releva faptul ca incepand cu ultimul trimestru al anului 2008, Romania a devenit si ea una dintre victimele recesiunii. Consecintele sale au diferite modalitati de manifestare ce variaza de la un domeniu la altul.

Analistii economici au discutat posibile cauze are recesiunii si multi dintre ei au considerat esecurile inregistrate pe piata creditelor ca principala sursa de pornire. Lucrarea de fata isi propune sa analizeze modul in care modelele de evaluare a riscului la acordarea de credite folosite in Romania sunt afectate de noul mediu economic. Importanta acestui subiect este crescuta intrucat riscul de acordare a creditelor este cel mai important risc din sistemul bancar si acuratetea procesului de selectie influenteaza in mod direct performanta institutiei.

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Principala problema consta in luarea deciziei de a acorda unui client un anumit credit. Intrebarea care apare este daca vechile instrumente de decizie isi pastreaza eficienta.

Autorii prezinta principalele trasaturi ale pietei de credite din Romania prin analiza unor indicatori calculati recent de Banca Nationala a Romaniei. Principala concluzie este aceea ca cifrele releva o descrestere importanta in volumul de credite acordate, comportament justificat de comportamentul modificat al intitutiilor de credit si clientilor in timpul ultimului trimestru al anului 2008.

Cateva aspecte teoretice importante relevante pentru evaluarea la acordarea de credite sunt introduse prin prezentarea celor mai importante modele folosite pe glob. O particularizare pentru cazul Romaniei este facuta deoarece lucrarea isi propune sa schiteze cadrul in care studiul a fost facut.

Un model statistic este construit cu ajutorul regresiei si sunt discutate cateva aspecte legate de importanta procesului de selectie. Modelul este aplicat pentru doua seturi de date anterioare si ulterioare manifestarii crizei. Concluzia care se desprinde este aceea ca in timpul recesiunii economice companiile au un comportament care conduce la necesitatea de a reconstrui modelele clasice de credit scoring pentru a include noi trasaturi capabile sa ilustreze starea mediului economic.

Cuvinte cheie: criză, credite, model, impact, risc

Clasificare JEL: *C30, C44, C52, C51, G21*

1. INTRODUCTION

We are the eye-witnesses of a global economic crisis that has contaminated more and more countries, producing incredible cases of bankruptcies and provoking a metaphorical "earthquake" for the traditional theories. Although having a short delay when compared to the first effects noticed in the American case, the crisis has also affected the Romanian economy, starting with the last quarter of 2008. Its consequences are multiple and we can deduce them at every step we take during our daily life.

The authors focus on the crisis effects over the loan market. Many studies around the world reflect the hypothesis according to which the loan market is the starting point for the current crisis. The huge amount of granted loans that proved to be unsuccessful cases in the end led to a lack of liquidities and generated the current economic crisis.

Consequently, banks try to find different types of methods that ensure their protection against unsuccessful cases and minimize the assumed risks. One alternative can be the risk based pricing: customers who are thought of as more likely to default on their loans are requested to pay higher interest rates in order to compensate banks for the increased risk. Advocates of this system believe that it would be unfair to globally raise interest rates as this would also lead to the penalization of low-risk borrowers who are unlikely to default. Opponents give social arguments: they consider that the practice tends to disproportionately create capital gains for the affluent while oppressing the poor classes with modest financial resources. Some organizations, such as *The Association of Community Organizations for Reform Now* (ACORN) consider risk-based pricing to be unfair in principle. Lenders contend that interest rates are generally set fairly considering the risk that the lender assumes, and that competition between lenders will ensure availability of appropriately-priced loans to high-risk customers. Still others feel that while the rates themselves may be justifiable with respect to the risks, it is irresponsible for lenders to encourage or allow borrowers with credit problems to take out high-priced loans. Although applied in many domains, such as bond markets, the insurance industry and in the stock market or in many other open-market venues, this practice is considered controversial in the case of consumer loans. Other ways of improving credit risk evaluation models are represented by the acquisition of new models, tools that are able to prove their efficiency under crisis conditions.

The main question that arises is whether these investments are necessary for the Romanian case too. This paper will prove that the traditional econometric models which are used by the great majority of the Romanian banks can easily fail when the economic environment features change.

The European Commission spring forecast, recently presented in Brussels (May 2009) notes that Romania's economy got worse compared to the January 2009 forecast. The Commission reveals that Romania will not register an economic growth in the following two years: for 2009 the economy will register negative indicators of -4% and in 2010 -0%. In January the Commission estimated a 1.75% increase in 2009 and 2.5% in 2010. Unemployment rates will increase to record values in 2009 and 2010, from 5% to 8%.

Consequently, it is generally accepted that Romania is affected by crisis and our goal is to study the influences over the loan market.

2. LITERATURE REVIEW

A lot of research has been done as many scientists have invented and tried to apply different types of risk evaluation models. Each of them was characterized by a more or less complex structure and, to resume, we could say that all the studies revealed the fact that the same model gives different results and has to be modified when environmental conditions change.

One example of credit risk evaluation model is *Data Envelopment Analysis (DEA)* which, unlike the traditional statistic methods (discriminant analysis, logit models and neural networks) does not require a priori information (MIN, H., JAE and LEE, YOUNG-CHAN, 2008). The advantage brought by this model is evident if we take into account the fact that one of the main problems in the way of an efficient credit risk evaluation is represented by the lack of historical data concerning the analyzed customer.

The oldest method used is *Linear Discriminant Analysis (LDA)* which was introduced for the first time in 1936 by Fisher (in the article *The Use of Multiple Measures in Taxonomic Problems*). The method brings as a main instrument the Linear Discriminant Function (LDF). This is a method used in statistics and machine learning to find the linear combination of features which best separate two or more classes of objects or events. The resulting combination may be used as a linear classifier or, more commonly, for dimensionality reduction before later classification. In the case of credit risk evaluation models, this instrument can be used to classify clients into successful or unsuccessful ones. This classification is based on each profile’s features and the process is closely related to ANOVA (analysis of variance) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. In the other two methods however, the dependent variable is a numerical quantity, while for LDA it is a categorical variable (*good* or *bad* client).

The main weakness of this method consists of the supposition that there is a linear dependency among the input and output variables, fact which is not true for most of the practical cases. At the same time the class means and covariances are needed, but not known. In many cases they are estimated from the training set. It has to be mentioned that although the estimates of the covariance may be considered optimal, this does not mean that the resulting discriminant computed with these values is optimal in any sense, even if the assumption of normally distributed classes is correct.

Another domain where LDA is applied on a large scale is in bankruptcy prediction. This domain is very similar to risk evaluation as the goal is to decide which firms enter bankruptcy and which of them survive. Despite limitations including known nonconformance of accounting ratios to the normal distribution assumptions of LDA, Edward Altman's 1968 model is still applied by many applications.

Researchers have also introduced the usage of the artificial intelligence specific instruments: *Artificial Neural Networks (ANN) - Probabilistic Neural Networks* or *Multi-layer feed-forward nets*. It has been noticed that the evaluations registered good results when it comes to customers that fail and are correctly classified (this is a very important aspect: it is more important to have a high performance in the correct classification of bad clients than in the correct classification of good clients (the risk of not granting a credit to a customer evaluated with a higher risk than the real one)).

The most difficult aspect in the application of neural networks in the credit scoring evaluation process is the difficulty of explaining the algorithm that gives the decision of accepting or rejecting certain customers. DEA requires only the input and output data sets in order to compute the credit score. It is computed as a ratio between total output and total input. Consequently, the observed units are classified and an efficiency border is drawn, while the efficiency degree of the new units is going to be established depending on their position related to the efficiency border.

Another method introduced for the first time in 1984 is the CART method (*Classification and Regression Tree*) and it consists of the building of a maximal tree that contains all the units of the training set and can be divided into several trees out of which the most efficient one is chosen through cross-validation methods.

In 1991 the MARS model *(Multivariate Adaptive Regression Splines)* appeared for the first time bringing the advantage of being combined with neural networks. The algorithm has two steps: firstly, a high number of basic functions are built, out of which some are going to be eliminated in the order of the least contributions (the cross validation method).

Case Based Reasoning (CBR) is a model that has the goal to learn from practical failure cases and tries to build a pattern based on which to classify the new customers.

According to Agnar Aamodt and Enric Plaza (1994), case-based reasoning has been formalized for purposes of computer reasoning as a four-step process:

1. **Retrieve:** Given a target problem (the decision whether to grant or not a credit to a potential customer), retrieve cases from memory that are relevant to solving it (all the client profiles that are similar with the applicant). A case consists of a problem, its solution, and, typically, annotations about how the solution was derived.
2. **Reuse:** Map the solution from the previous case to the target problem. (If the previous customer was granted a loan and was successful in reimbursing it, than the new client should also be accepted). This may involve adapting the solution as needed to fit the new situation, as the new customer has some characteristics that are different from the old case. For example the environment conditions can change: although the client can be considered to be in a situation of apparent financial stability, the economic crisis diminishes its strength and should be taken into account.
3. **Revise:** Having mapped the previous solution to the target situation, test the new solution in the real world (or a simulation) and, if necessary, revise. Suppose that the client defaults, the old solution has to be modified in order to prevent future mistakes.
4. **Retain:** After the solution has been successfully adapted to the target problem, store the resulting experience as a new case in memory.

The RCSM model (*Reassigning Credit Scoring Model*) is an algorithm made of two steps : the classification of the applicants in « good » or « bad » cases and the redistribution of the « good » cases that have been incorrectly classified as « bad ». in order to prove the model's efficiency, researchers have tried to apply this algorithm on a data set related to credit cards. (Chun-Ling Chuang and Rong-Ho Lin, 2008)

During the first phase the algorithm uses MARS in order to reduce the number of input nodes from the ANN (Artificial Neural Networks) and simplify the networks. The simplified neural network (a backpropagation network characterized by an unique input tier, a hidden tier and one output tier) is used for the classification of the applicants into good or bad customers. The customers considered to be “bad” are going to be reassigned through the CBR method, by identifying the similarities existing between them, on one hand, and the good practical cases, on the other hand. The application has to search in the data base for those cases that present a series of similarities with the new applicants. If the new applicant’s profile approaches more the successful cases than the failure ones, the person is reclassified as a “good” one and the loan is granted. The similarity is measured through the “distance” between the two cases, by using the nearest neighbor approach.

Other examples of credit risk evaluation models described in the scientific literature are:

- Multi Criteria Decision Making
- Recursive Partitioning Algorithm
- Mathematical Programming Approaches
- Logistic Regression Analysis (LRA)
- fuzzy algorithms
- Multivariate Conditional Probability Model
- k-NN

3. A CREDIT SCORING METHODOLOGY

The process of scoring a loan applicant involves several steps that have to be followed in order to obtain a method of estimation for the risk associated with the case:

STEP 1:

The observation data set is selected (the selection of those loan applicants for which there is a high possibility to find values for all the characteristics that could influence the associated risk)

STEP 2:

The identification of the potential characteristics for each candidate (factors: income, age, accommodation, marital status, etc.)

STEP 3:

The selection of the final characteristics (instruments: regressions - econometric tool used in order to test whether the chosen variables are significant for the result - and domain experts). The result is a data set that contains the most representative indicators. It has to be mentioned that the indicators can be input indicators (previous loans, liquidities, buildings, etc.) or output indicators (in the case of the companies, one can take into consideration whether the company finances itself from its own sources or its ability to pay interests from its own incomes).

STEP 4:

The computation of credit scores as a result of the chosen model.

STEP 5:

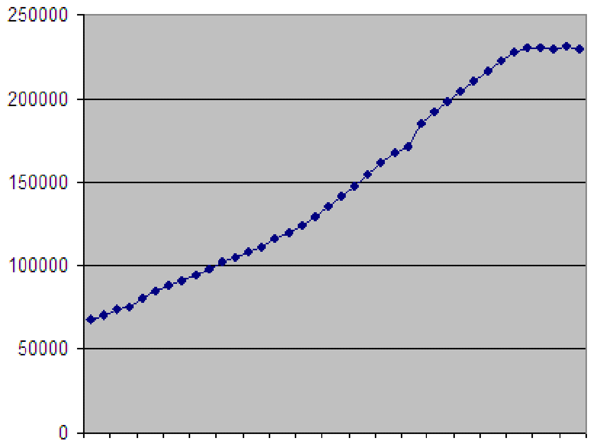
The validation of the results with the help of regression (the chosen indicators represent the independent variables and the result is the dependent variable), the discriminant analysis (in order to quantify the performance of this classification method) and practical failure cases. It is interesting to analyze whether the results correspond to the results given by other classification methods.

STEP 6: The choice of the final credit scoring method.

4. THE STATUS OF THE ROMANIAN LOAN MARKET

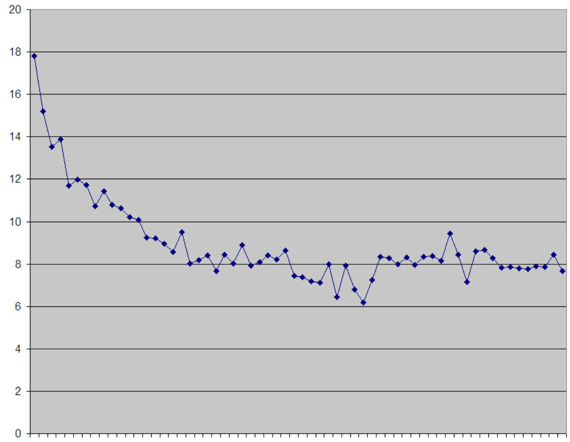
According to the reports of the National Bank of Romania (BNR), the loan requirements have become more restrictive during the end of 2008 and the beginning of 2009. For example, the last quarter of 2008 has been characterized by an increased rigidity of the credit institutions when it comes to granting credits to their applicants. This behavior can be explained through the easy observation that the economic environment has been affected by recession conditions and credit institutions and other organisms in the financial system have adapted their offer to the new economic features. The statistic analysis reveals the fact that credit terms have maintained their trend in the sense that they became more and more rigid, while the trend has proved to be more alert during the last term of 2008 and the first two months of 2009. The risks associated with companies have been perceived as increasing, including corporations. These evolutions are correlated with the reactions observed in the "euro area", where this negative reaction in relation with credit risk has started to develop at the end of 2007.

Graph 1 presents the monthly evolution of the amounts granted by credit institutions in Romania, according to their reports to BNR. It is very easy to notice that the amounts have been constantly increasing for as long as the crisis wasn't perceived in Romania, but starting with the last quarter of 2008, credit institutions became more restrictive. Consequently, the total amount has remained constant or even decreased from one month to another.



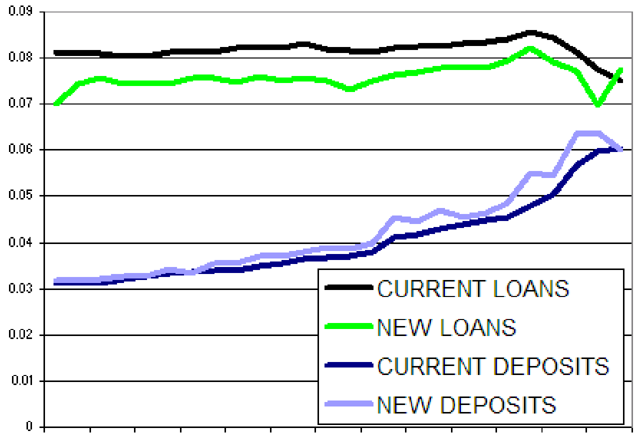
Graph 1. Total amount of loans granted from Jan 2006 until Feb 2009 (mil RON)

Another aspect that is worth being emphasized is the evolution of the ratio between unsuccessful loans and the total number of granted loans (**Graph 2**). The data set is monthly recorded between Jan 2004 and Feb 2009. While the ratio has remained approximately constant during the last quarter of 2008, a big increase has been recorded in January 2009, followed by a huge decrease during the next month. This can be explained by the fact that every time the number of defaulted credits increases very much, credit institutions become more restrictive with their clients. Consequently, the graph illustrates the fact that every increase in the ratio it is followed by an immediate decrease, so that the general trend is maintained approximately constant through the credit institution's politics.



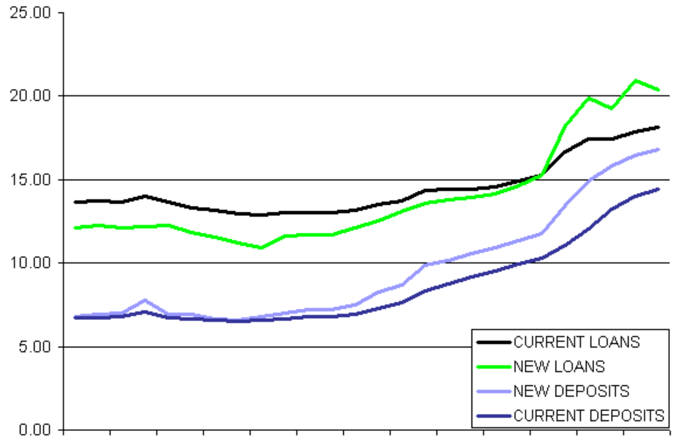
Graph 2. The ratio between unsuccessful customers and total number of credits (%).

If we analyze the evolution of interest rates for loans and deposits, we can easily notice the fact that interest rates for current loans in euro have significantly decreased during the first months of 2009, while interest rates for current term deposits have generally increased as banks' policy has been generally one of encouraging people to bring liquidities to the bank. (**Graph 3**)



Graph 3. Interest rates' evolution for loans and term deposits in Euros

On the other hand, the same analysis can be carried out for interest rates for loans and deposits in RON (**Graph 4**). It can be easily noticed that new loans and deposits have higher interest rates than current ones. This can be seen as a monetary policy that aims to encourage customers to trust the national currency and to use it more often in their financial transactions so as to determine a depreciation of euro related to RON.



Graph 4. Interest rates' evolution for loans and term deposits in RON

At the same time, one of the most important economic events is the approval of the loan that Romania wanted to obtain from The International Monetary Fund. Many analysts consider that this huge amount of money is going to bring some changes in the politics practiced on the loan market. A big part of the loan has its final destination in The National Bank of Romania reserves. Therefore, the national bank will benefit from a strengthened "belt" that will give it the possibility to relax the minimum obligatory reserves that it requires from the other banks. The minimum obligatory reserves have represented an instrument that The National Bank of Romania has used in order to control the number of grated loans. At the moment, the minimum obligatory reserve rate for foreign currency passives is 40%. Therefore, for each euro that banks grant as a loan to their clients, the financial institution has to pay approximately 0.7 cents. By reducing the minimum obligatory reserve, a considerable amount of liquidities are allowed to reenter on the financial market.

The major conclusion that can be drawn after analyzing different type of reports and figures is that the economic environment has changed as a consequence of the recession and financial institutions need to redesign their credit scoring evaluation models and to find more efficient tools of implementing them. The next section builds a simplified econometric model which is meant to prove the crisis effects over the prediction instruments' accuracy.

5. THE MODEL

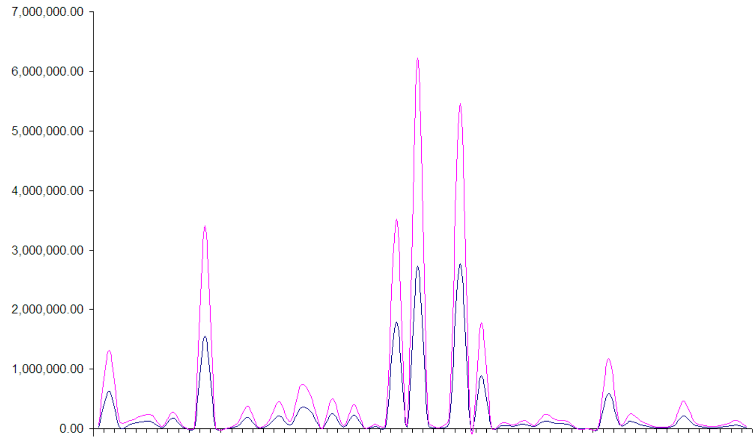
In order to obtain a practical result that confirms the impact of the changes in the economic environment over the estimation precision of a classical credit scoring model, we decided to build a simplified model designed for several companies that activate on the Romanian market. As the Romanian banking sector is characterized by the usage of traditional statistical methods rather than expert systems based on neural networks or case based reasoning, we used traditional econometric tools (multiple regression) in order to build our research model. The main data source was represented by the financial statements published by different companies, statements that are available at the Ministry of Finance and some of the information on The Bucharest Stock Exchange.

The two data sets contain the same features of the same potential customers (62 units) recorded at two different moments in time: at the end of the second quarter, when the economic recession impact was not perceived in Romania and fourth quarter of 2008, when the recession is admitted. Therefore, the information reflects the status at the middle of 2008 (30.06.2008) and at the end of the year (31.12.2008).

The initial data set included multiple variables out of which the most representative ones are going to be selected through an appropriate technique: total debts, turnover, net income, indebt degree (total debts/capital), liquidity index (current assets/current debts), economic profitability (net income/turnover or total revenues) and PER (closing price of the bond/Earnings per Share).

The authors assumed that net income is a characteristic that could be used to estimate a company's financial stability and ability to pay back its debts, including loans. Therefore the goal is to determine which variables have a significant influence over the net income and which their coefficients are. This is the first step towards building a credit scoring model as the different scores associated to variables in the credit scoring models are derived from the coefficients estimated through regression.

Before running the regressions a descriptive analysis was carried out in order to compare the values of the chosen variables at the middle and the end of 2008.



Graph 5. The value of Total Debts at 30.06.2008 (blue) and 31.12.2008 (pink).
Data Source: KTD Investments, financial statements

A general observation would be that total debts have increased during the second half of 2008. This is explained by the economic crisis effects that have been perceived during this period and can be considered as an indicator of financial instability.

Several previous studies proved the impact of the efficiency of the feature selection process on the quality of the results obtained by applying a risk evaluation model. Whenever trying to build a new evaluation model, one deals with the problem of choosing from a large number of potential variables (customer's financial performance, environmental features, etc.). The goal is to select the optimal (necessary and sufficient) number of features used to build a client's profile.

The risk of including irrelevant and redundant variables together with relevant variables is quite high in the domain of credit risk evaluation as the amount of data that a financial institution obtains from a potential client is quite large and it is difficult to establish linear relationships among variables. Therefore, by including too many features one can obtain spurious results as some features don't bring new information and their redundancy may lead to irrelevant estimations, while to few variables can bring insufficient information for taking a good decision.

There are three regular approaches for feature selection – *filter-based, wrapper-based and embedded-based* ones (Huang, 2003). The filter approach elects relevant features before the classification algorithm is applied. Therefore, this approach is a general feature selection method independent of classification algorithms. On the other hand, the wrapper approach includes a target classifier as a black box for performance evaluation. In other words, a computation-intensive evaluator is performed many times on candidate feature subsets to choose relevant features. The embedded approach is the inherent ability of a classification algorithm; i.e., feature selection is occurred naturally as a part of learners. More modern algorithms that combine different classical methods have been recently introduced. For example, Chia-Ming Wang and Yin-Fu Huang (2009) built an evolutionary-based feature selection approach with new criteria for data mining and applied it on credit approval data.

The authors tried to build different regression models and variables were eliminated and introduced according to the significance of their coefficients. In order to run the regressions the data sets were imported in Eviews 6.0 and coefficients were estimated under different scenarios, by applying Ordinary Least Squares.

The most significant regression model was obtained when choosing capital, total debts and turnover as independent variables and net income as dependent variable. The regression model was applied for both data sets.

An observation has to be made here: it can be noticed that the p-values (probabilities that express the significance of the influence of selected variables over the dependent variable) are still quite high and their values could be diminished. This is due to the fact that the regression model includes only three independent variables, while there are others that also influence the probability to return the loan. By adding other features, p-values will decrease and the model's efficiency will increase.

Table 1. Results for 30.06.2008 and 31.12.2008 regressions of net income

Variable	Coefficient 30.06.2008	p-value	Coefficient 30.06.2008	p-value
CAPITAL	0.000751	0.0000	0.001783	0.0000
TURNOVER	0.051040	0.0157	-0.141287	0.0195
TOTAL DEBTS	-0.096196	0.0010	-0.043378	0.0110

Both the regression models have high R^2 values (0.93 and 0.91) and low p – values of the F statistics (0.0000), facts that prove the models are correctly built. The most important observation that can be made by analyzing the results is that the relevancy of the selected variables decreases during the second half of the year. The capital remains the most significant feature for both data sets, while the p-value for turnover increases from 0.0157 to 0.0195 and the one for total debts increases from 0.0010 (30.06.2008) to 0.0110 (31.12.2008).

In conclusion the factors tend to lose their significance and there is a need to reanalyze and potentially redesign the credit scoring models.

6. CONCLUSIONS AND FUTURE WORK

Our paper analyzed the current status of the Romanian loan market and presented different types of results that prove the manifestation of economic crisis and its impact over the loan market. A short study was carried out in order to practically prove the decrease in efficiency that characterizes the traditional credit scoring methodologies.

At the same time the paper presented a literature review by emphasizing some of the most important advantages and disadvantages of the existing credit scoring models. The main conclusion was that the quality of the obtained results is directly influenced by the environment characteristics.

Consequently, models should take into account variables that quantify the stability and strength of the economic environment and the main goal is to build such a model. Another interesting feature is the dynamic character of variables' values. In time, the customer's profile can change and the initial risk evaluation can lose its consistency. Therefore, we should also find a method to quantify this dynamic aspect and to include its value in the risk model.

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