Scoring Models of Bank Credit Policy Management

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ABSTRACT – The aim of this paper is to present how credit scoring models can be used in financial institutions, in this case in banks, in order to simplify credit lending.

Unlike traditional models of credit analysis, scoring models provides valuation based on numerical score who represent clients' possibility to fulfil their obligation. Using credit scoring models, bank can create a numerical snapshot of consumers risk profile. One of the most important characteristic of scoring models is objectivity where two clients with the same characteristics will have the same credit rating.

This paper presents some of credit scoring models and the way that financial institutions use them.

KEY WORDS: credit scoring, score, probability, risk, financial institutions

Introduction

Banks are one of the most important financial institutions in the economy. Although their function has changed, loan approval is one of the most important functions of these financial institutions. For the most banks, loans form a half or more of their total asset and about 1/2 up to 2/3 of their incomes. Risk in the banking industry has tendency of concentration in credit portfolio and when the bank has to deal with those financial problems, the causes should look for in loans, primarily those which can not be paid because of bad management, bad loan policies or unexpected economy reversal. This trend is present from the beginning of world financial crises in 2008. Actually, the crisis has led to drastic decline in the economy activity, increase of unemployment, inflation and drastic decline of currency values what have resulted in huge abasement of financial system and increased risk for money laundering and financing terrorism. Large number of banks have confronted with liquidity problem and in the purpose to avoid this problem they have avoid procedures and standards for money laundering presentation and accept „dirty" money without any check.

Risk quantification is one of the main challenges in contemporary banking and finance. Banks are trying to cope with them on different ways. One of the most frequent ways is to assign different status to certain debtor. For example, default represents debtor status which denotes impossibility of debtor to fulfil its contractual obligations. A probability of default – PD denotes probability that debtor will not fulfil its obligations within one-year period. For

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avoiding such situations, respectively to mitigate credit risk, banks manage with credit risk in the way to do selection and loan approval to those clients which fulfil certain criteria. For instance, banks are using different acts such as credit scoring as statistical derived tool which assign numerical evaluation to each of input client characteristic and the sum of all numeric evaluations will be compared with the set threshold. This is where the story about credit scoring begins.

Credit scoring

A sound credit risk management is built upon a good-quality portfolio of performing assets. The pricing of the loans has to reflect the risk. A good selection strategy aims to avoid high losses. Credit scoring is a credit risk management technique that analyzes the borrower's risk.[2] The quality of the credit scores risk ranking and calibration can be verified by analyzing ex-post observed credit losses per score. Credits scores are often segmented into homogeneous pools. Segmented scores are discrete risk estimates that are also known as risk classes and ratings. Credit risk basically entails default risk, recovery risk, exposure risk and maturity. Credit scoring can be formally defined as a mathematical model for the quantitative measurement of credit (He, Zhang, Shi, Huang, 2010.). Another definition of credit scoring is: "Credit scoring is the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit."(Thomas, Edelman, Crook, 2002.). Credit scoring is not only used by banks or financial institutions. Insurance companies, telecommunication companies, companies wishing to find customers or those wishing to analyze their customer risk also can use credit scoring. Fair, Isaac and Co. in 1959 developed first credit score card for America Finance Inc. which dealt with indirect lending to car buyers. William Beaver presented first statistical model for bankruptcy prediction. He based his model on the financial ratios which are based on accounting data. The following three of 30 ratios have the best results in bankruptcy prediction:

1. Cash flow / total assets
2. Profit /total debts
3. Cash flow / total debts

For each ratio, Beaver calculated threshold so every company above that threshold is declared as potentially successful. Otherwise, company with ratio value below the threshold is declared as potentially unsuccessful. First model that uses multivariate approach was Altman's Z-Score model. This model is based on financial indicators where each of them has appropriate pounder and sum of that financial indicator is Z-score. Value of Z-score tells in which zone potential borrower will belong. First general formula of professor Altman for Z-score calculation is:

$$Z - 0,012X_1 + 0,014\ X_2 + 0,033X_3 + 0,006X_4 0,010X_5 \qquad (1)$$

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[2] Van Gestel, T. & Baesens, B. 2008. *Credit Risk Management: Basic Concepts: Financial Risk Components, Rating Analysis, Models, Economic and Regulatory Capital: Basic Concepts: Financial Risk Components, Rating Analysis, Models, Economic and Regulatory Capital.* Oxford University Press

Pounders (0,012 to 0,010) are constant based on empirical experiments. Values (from X_1 to X_5) are calculated as follows:

X_1= Working Capital/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings before Interest and Taxes/ Total Assets

X_4 = Market value of Equity/Book Value of Total Liabilities

X_5 = Sales/Total Assets

Structure for assessment and quantification of credit rating of potential borrower (company) is calculated based on following matrix:

Table 1. Zeta score model

Z score	Zone
Z < 1,81	Distress Zone
1,81 < Z < 1,99	Grey Zone
Z > 2,99	Safe Zone

There are special Altman's formulas for Z score depends on business of company.

Z score for private firms:

$$Z - 0{,}717X_1 + 0{,}847X_2 + 3{,}107X_3 + 0{,}420X_4 + 0{,}998X_5 \qquad (2)$$

X_1 = (Current Assets − Current Liabilities) / Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings before Interest and Taxes/ Total Assets

X_4 = Book Value of Equity / Total Liabilities

X_5 = Sales/Total Assets

Table 2. Zeta score model for private firms

Z score	Zone
Z < 1,23	Distress Zone
1,23 < Z < 2,90	Grey Zone
Z > 2,90	Safe Zone

$$Z = 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4 \qquad (3)$$

For non-manufacturer industrial & emerging market credits Z-model is:

X_1 = (Current Assets − Current Liabilities) / Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings before Interest and Taxes/ Total Assets

X_4 = Book Value of Equity / Total Liabilities

Classical method of granting loans depends on subjective judge of a loan officer and it consists of about 50 questions that are answered with yes or no and a loan officer subjectively interpreted information follows formal instruction and on based on that, he/she accepts or rejects the loan application. If a bank uses exclusively quantitative analysis and credit scoring, loan officer puts the requested data in the model that has score or rating as output. Based on that, decision to reject or approve credit is made.

Credit scoring in practice

Being first introduced as a handy tool for underwriting retail credit, such as residential mortgages, credit cards, instalment loans, and small business credits; credit scoring is nowadays being used to administer and follow-up default risk across the entire credit portfolio of a financial institution covering firms, sovereigns, local authorities, project finance, and financial institutions. Credit scoring is not only used by banks or financial institutions. Insurance companies, telecommunication companies, companies who want to find customers or who want to analyze their customer risk also can use credit scoring. Let us consider a simple example by using three characteristics: residential status, age and loan purpose. These are the values:

Table 3. Values for example

Residential status	Score	Age	Score	Loan purpose	Score
Owner	13	18-25	22	New car	41
Living with parents	14	26-35	25	Second hand car	33
Other specified	20	36-43	34	Other	25

- A 20-year old, living with his parents, wishes to borrow the money to buy a second-hand car. On the other hand there is a 40-year old house owner who wishes to borrow the money for daughter's wedding. The bank analysis their characteristics and gives the scores where a 20-year old will score 69 (14+22+33) and a 40-year old will score 95 (36+34+25). Some lenders operate a very strict cut-off policy. If the score is greater than or equal to the cut-off, the application is approved, if not it is declined. From this very simple example we can say that main advantages of scoring systems are:
- Quantification of risk as probability – instead of subjective judge of credit analyst we have numerical score or rating of creditworthiness;
- Consistency - two clients with the same characteristics will have the same credit rating for impartial assessment;
- Interpretability - it is possible to explain (showing the input variables of the model) that each variable effects on increasing or decreasing the likelihood default.

Figure 1. How should loan system operate VS how it often does
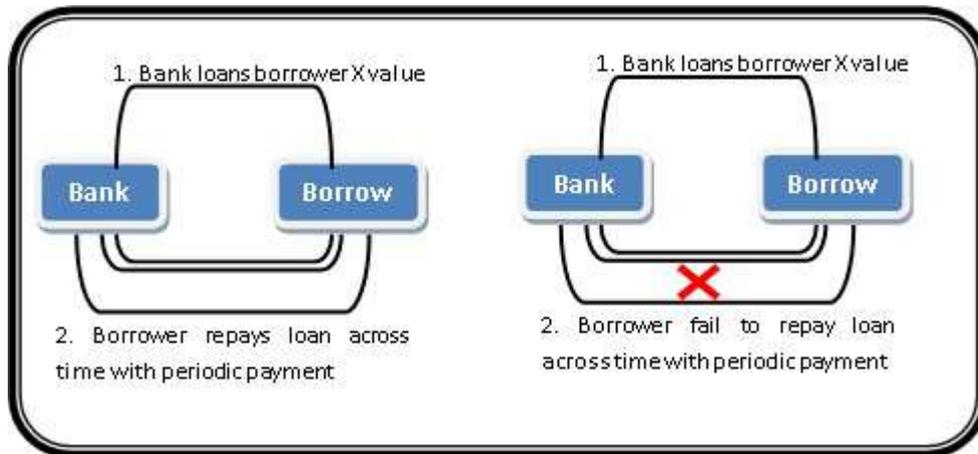
Most familiar risk metric is often the adequacy of general and specific loan loss provisions and the size of the general and specific loan loss reserve in relationship to the total exposures of the bank.[3] The most basic model of expected loss considers two outcomes: default and non-default.

- In the event of non-default, the credit loss is 0.
- In the event of default, the loss is loss given default (LGD) times the current exposure (EAD)

Credit loss distributions tend to be largely skewed as the likelihood of significant losses is lower than the likelihood of average losses or no losses. Active loan portfolio management embracing diversification of exposures across industries and geographic areas can reduce the variability of losses around the mean. Unexpected loss represents the minimum loss level for a given confidence level an alpha UL(a) is the maximum loss a bank will suffer a% of the time.[4]

Figure 2. Expected Loss[5]

Event	Loss	Probabillity
No default	**0**	**1-PD**
Default	**LGDxEAD**	**PD**

Expected Loss= (1-PD)x0 + PDxLGDxEAD = PDxLGDxEAD

The aim of the credit score model is to build a single aggregated risk indicator for a set of risk factors (Bolton, 2009). Data about scoring should be safer in order to prevent

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[3] Credit risk management. 2013. The GARP Risk Series http://www.garp.org (20.01.2013.)
[4] Credit risk management. 2013. The GARP Risk Series http://www.garp.org (20.01.2013.)
[5] Credit risk management. 2013. The GARP Risk Series http://www.garp.org (20.01.2013.)

manipulation of results creation. Because of that scoring background, mechanism and weighting of scores have to be known only to risk evaluators, software developers and system administrators.

In addition, client data have to be secured within the bank. After the introduction of standards "Basel II", credit scoring models have become mandatory. Since each bank has to assess the risk and to quantify the loss of the bankrupt debtor (Eng. LGD - loss given default), different methods and models for the prediction of bankruptcy debtors become widespread. Popular models are: Moody's *RiskCalc*, Credit Sight's *Bond Score*, Kamakura-approach, and KMV approach and Altman's *ZETA* credit scoring[6]. There are two types of credit scoring based on their construction (Bolton, 2009):

- **Generic credit scoring models** - based on exclusively credit bureau's data who have millions of data about credit past clients with a bank account. It is based on such database by applying statistical methods and artificial intelligence created by the credit scoring models, which include those borrower characteristics that best predict future behaviour in the repayment of the loan.
- **Customized credit scoring models** - based on customer information specific to providing financial institutions and they are designed specifically for each creditor. A customized scoring is a better and more appropriate tool but more costly. The advantages are that it is more accurate in comparison to the bank needs, it is difficult to implement and requires knowledge and resources in the bank.

Another possible model is called Household model. It is, in fact, a kind of scoring models and calculations by which to obtain images of the client seeking a loan. Household obtains a realistic picture of the financial situation of the client and the household in which he resides. There are two ratios that must be met:

- **Ratio 1** represents the calculation of individual creditworthiness and only takes into account individual client data,
- **Ratio 2** takes into account all income and expenditure (household), which means that it takes into account all revenues and expenditures of the entire household.

To make the loan approved both ratios must be met. In addition to these ratios in the household model client data, such as general information, then his net salary, all the other benefits that go only through a bank account, and based on the account of its corporate lending capability that ultimately has the approval or rejection of the loan, are also taken into account. Which model the bank will select (whether customized or generic), depends on a number of factors:

- **Historical experience in lending** – in order that scoring is meaningful and aligned to the needs, it is necessary that there is sufficient information on lending in the bank.
- **Preservation of data** - data on lending must be useful, in electronic form, and in a form that can be cheaply processed.
- **Information on the outcome of lending decisions** - information should be known

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[6] Sajter, D. 2009. „*Pregled osnovnih metoda i istraživanja poslovnih poteškoća uz predviđanje stečaja*", Osijek

- **Age of decisions** - decisions must be old enough to make the analysis to have the sense**.**
- **Sample size** - sample must be sufficiently large and diversified that the analysis made sense.
- **Costs** - include the development, implementation and maintenance of the model. Typically range from 30,000 to 80,000 Euros for customized models as generic models do not have these costs because they are already developed but have high fees for use.

Today in the market there are over 50 generic credit scoring systems that contain over 100 different credit scoring models. Credit scoring models have greatly facilitated work of banks. In this context, it is important to mention scoring model advantages and disadvantages. Credit scoring models have the following advantages (Šaralija, 2008):

- scoring models are objective and consistent,
- if they are well designed, they can eliminate discriminatory practices,
- they are relatively cheap,
- relatively simple and easy to interpret,
- institution is able to provide better service to its customers with faster approval or rejection of the application.

Disadvantages of credit-scoring models are (Šaralija, 2008):

- they can just automate existing practice of bank loans, but there is a little work on the elimination of bias in the process created in the past,
- models may degrade over time if the population to which the model is applied changes in relation to the original population by which the model is designed.

Credit scoring using logistic regression[7]

Firm default is an example of a qualitative response—at least if we do not look at the severity of the default in terms of recoveries. We simply observe a firm's characteristics and whether it defaults or not. Logistic regression views the probability of default as depending on a set of firm characteristics (or *covariates*). The actual response depends on a noise variable, just like the deviation of a response from its mean in ordinary regression depends on a noise variable. Specifically, let Y be the observed status of the firm at the end of some predetermined time horizon. Let $Y = 1$ if the firm has defaulted and 0 otherwise. The assumption in a logistic regression is that for each firm…

$$P(Y = 1|x_1, \ldots, x_k) = p(x_1, \ldots, x_k). \tag{4}$$

I the logit specification we use the logistic distribution function to specify probabilities, i.e. we assume that

$$P(Y = 1|x_1, \ldots, x_k) = \frac{\exp(\alpha_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}{1 - \exp(\alpha_0 + \beta_1 x_1 + \cdots + \beta_n x_n)} \tag{5}$$

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[7] Lando, D. 2004. *Credit Risk Modeling: Theory and Applications*

The model then assumes that the outcomes of different firms are independent. In a probit specification we use the distribution function Φ of a standard normal random variable to transform the regression into the unit interval,

$$P(Y = 1|x_1, \ldots, x_k) = \Phi(a_0 + \beta_1 x_1 + \cdots + \beta_n x_n) \tag{6}$$

At this point, we will focus on the logit specification because of its connection with discriminant analysis and because we have an interpretation of the β-coefficients in terms of log-odds ratios: if two firms have covariate vectors xi and x_j and we let p_i and p_j denote their probabilities of default as given by a logit specification, then we have

$$\log \frac{\frac{p^i}{1-p^i}}{\frac{p^j}{1-p^j}} = \beta'(x' - x^j), \tag{7}$$

We let y_i denote the response of the ith firm and think of $y_i = 1$ as default, then we may express the likelihood function as

$$L(\alpha, \beta) = \prod_{i=1}^{n} \left(\frac{\exp(\alpha + \beta' x^i)}{1 + \exp(\alpha + \beta' x^i)} \right)^{y_i} \left(\frac{1}{1 + \exp(\alpha + \beta' x^i)} \right)^{1-y_i}$$

$$= \prod_{i=1}^{n} \left(\frac{1}{1 + \exp(\alpha + \beta' x^i)} \right) \exp(\alpha S + \beta' SP),$$

Where we define

$$S = \sum_{i=1}^{n} y_i \quad and \quad SP = \sum_{i=1}^{n} y_i x^i. \tag{9}$$

Logistic regression is not used so much in earlier studies related to default risk is probably due to computational limitations. With modern computers and statistical software, the maximization is simple when the number of regressors is not too large.

Credit scoring using discriminate analysis

The basic assumption in a discriminant analysis is that we have two populations which are normally distributed with different means. For the purpose of default modeling we think of one group as being the firms which will survive over a relevant period of time and the other group as being those which will default.

Hence the logic is somewhat reversed compared with a logistic regression. In a logistic regression, we have certain firm characteristics which influence the probability of default.

Assume that we are given a "training sample"

$$(x_1^0,...,x_N^0) \text{ and } (x_1^1,...,x_D^1) \tag{10}$$

consisting of multivariate firm characteristics of *N* surviving firms and *D* defaulting firms. Hence, *x0 1* is a vector of firm characteristics for a firm labeled 1 within the group of no defaulted firms. Faced with a new observation *x*, our goal is to decide whether this vector of characteristics belongs to a firm which will survive or a firm which will default. We mention here two approaches to making that decision which lead to the same type of discriminant function. One uses a decision-theoretic approach and the other uses a likelihood ratio test.

If our decision rule places a firm in group 0 when its characteristics belong to the set *R0* and to group 1 when its characteristics belong to the complement *R1*, then we can compute the probabilities of the possible types of classification. Suppressing the dependence on regions, Let *p (i | j)* denote the probability of assigning a firm to class *i* when it belongs to *j*. Then

$$p(i|j) = \int_{R_i} \Phi_j(x)dx, \quad i = 1,2 \text{ and } j = 1,2. \tag{11}$$

It is shown in Anderson (1984) that the expected cost of misclassification is minimized if one uses a discriminant function of the form

$$d(x) = x^{-1}E^{-1}(\mu^0 - \mu^1) - \frac{1}{2}(\mu^0 - \mu^1)'E^{-1}(\mu^0 - \mu^1) \tag{12}$$

and assigns the firm with characteristics *x* to group 0 if $d(x) \geq logK$ and to 1 if *d(x) < logK*, where

$$K = \frac{q_1}{q_1} \frac{c(0|1)}{c(1|0)}. \tag{13}$$

In practical applications of discriminant analysis the parameters of the populations are estimated using the training sample, i.e.

$$\hat{\mu}^0 = \frac{1}{N}\sum_{i=1}^N x_i^0, \quad \hat{\mu}^1 = \frac{1}{D}\sum_{i=1}^D x_i^1, \tag{14}$$

and

$$\hat{\Sigma} = \frac{1}{N+D-2}\left(\sum_{i=1}^N (x_i^0 - \hat{\mu}^0)'(x_i^0 - \hat{\mu}^0) + \sum_{i=1}^N (x_i^1 - \hat{\mu}^1)'(x_i^1 - \hat{\mu}^1)\right). \tag{15}$$

A second approach (see Anderson 1984 for details) for classifying a new observation *x* is to use a maximum-likelihood approach. Given our sample of no defaulting firms and their characteristics and the new observation *x* first compute MLEs of μ_0, μ_1 and Σ under the hypothesis that the observation *x* is added to the sample of no defaulting firms, and then subsequently compute MLEs under the hypothesis that *x* is added to the sample of

defaulting firms. The decision with the highest likelihood wins. The outcome of this exercise is not completely satisfactory in modern risk management in which we want to be able to assign probabilities of default.

While the efficiency depends on model assumptions, a fundamental problem with the discriminant analysis is that the assumption of normality seems unrealistic for many types of characteristics that we observe. Furthermore, it is hard to imagine that if we had a very large sample of firms, we would see a two-point mixture distribution of normal. In practice, characteristics do not follow such a simple distribution. Furthermore, we cannot reasonably make default probability estimates using the model unless we are willing to specify an "overall" default probability rate. And, finally, the model is static and does not include the important information on how long a firm survives with a set of characteristics. All of this can be remedied using methods of survival analysis.

Credit scoring models for population

Loans for population can be divided into:
- Loans that are repaid in instalments - periodical payments include principal and interest.
- Credit card and other revolving loans - although some banks issue credit cards with their own logo and is supported by its own marketing efforts, most have a franchise for MasterCard or Visa.
- Loans that are not repaid in instalments - a limited number of consumers loan requests payment of interest and principal at once.

The objective of credit analysis that is conducted for the approval of consumer loans is to assess the risk associated with the loan approval. There is used 6 Cs (subjective) analysis:

1. **Character** - the character is the most important, but also the most difficult to assess.
2. **Capital** - capital refers to the ability of borrower which affects its ability to repay a loan.
3. **Capacity** - the capacity of the client's financial ability to meet repayment of the loan in addition to living costs and other obligations.
4. **Conditions** - refer to some of the economic impacts of changes on the client's ability to continue to pay.
5. **Collateral** - Collateral is important in ensuring a secondary source of payment
6. **Control**.

Using scoring models, bank puts emphasis on protection against credit risk. However it is important to note that the bank is protected against currency, interest rate and operational risk when give loans (Šehić, 2009):
- In order to mitigate currency risk bank arrange the appropriate currency clause through loan agreements,
- To protect from interest rate risk of the bank should be protected by contracting variable interest, and keep in mind that a good integration of the scoring with a basic banking system, accurate forms, contracts and billing module will avoid problems that might arise from misunderstanding about interest calculation.

- In order to mitigate operational risk of the bank, he should be protected in the scoring activities, as well as the data and specific methods for lending procedure.

Scoring for loans include recording of loans, rating of requests, which includes a credit check on the parameters and scoring the map that defines by bank, including download information from credit bureaus, and credit application resolution as the final decision in the process of loan approval. Most of the techniques that are used for the design and validation of credit rating model apply to legal persons and scoring models for individuals. Since banking is a dynamic category, with an increase in consumer loans, banks were no longer able to process a large amount of requests for loans by hand and they are all turned over the design and use of credit scoring models. Desirable Credit Scoring Model characteristics are (Econ, 2013):

1. Accuracy
2. Simplicity
3. Nontrivial
4. Feasibility
5. Transparency
6. Economic sense

Figure 1. FICO score
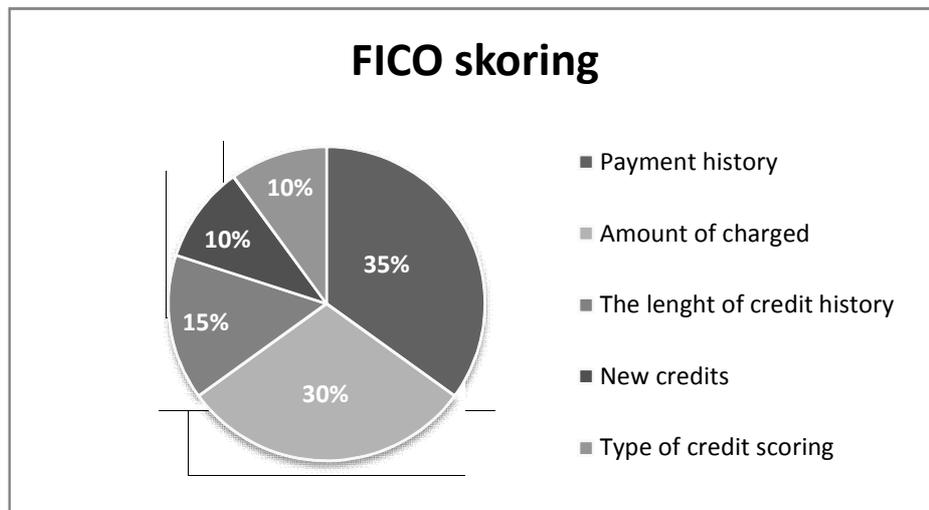
Writing about scoring and not to mention FICO is almost impossible. Specifically FICO score is still the most complete and the most common scoring for individuals, primarily in the United States. FICO model is decomposed into the following parts:

- 35% - Payment history loan account,
- 30% - the amount of debt that a customer has with its creditors,
- 15% - length of credit history or how long a person is the credit user,
- 10% - New credit (if the customer got some credits in the preceding month was :
- 10% - types of credit scoring.

The strongest accent is on the **payment history (35%).** This is logic because the first and elementary thing which a creditor wants to know about the potential debtor is how he/she services its obligations. Inside of payment history the greatest focus is on delay analysis, type and length of delay etc. FICO inside the scoring has very diversified evaluation system of every specific datum so that delay of 90 days will be more sanctioned than that with 60 days. **Amount of charge (30%)** is next important factor. Here is a thing about total debt in the country on any basis in regard to total income. FICO will take in consideration not only total ability to service plus new request, but also debt frequencies, average usage of approved request, debt ratio which is in every moment on the account. In this way, better results will have a person with higher discharged debt on one card than a person with less discharged debt on the 5 or 6 cards. **The length of credit history (15%)** is the next factor regarding the importance. The longer is the credit history, the better will be FICO result. FICO make distinction between those who have very long credit history, but in the last time they don't use loans, and those using loans for shorter time, but more frequently. **New credit** has pondered **10%** and in this case FICO observed new required debt and its characteristics and bring it into connection with historical frequencies of debt. For the example, a person who has in comparatively short period required debt on the several places is considered a risky client. The last important factor is **type of credit scoring (10%)** and the crucial question is: does the person has health credit mix by the purpose and amount. In FICO model those information which are predictors of future behaviour in the repayment of the loans are only used. If the score is larger, the risk is lower, i.e. if the score is lower, the risk is larger. It is necessary to define marginal value which divides "good" consumers from "bad" ones. FICO credit score rank is 300 to 850. 723 is the average FICO credit score and on the USA market, the average FICO score is 678. The Score of 620 or lower means that your credit is "subprime" what means that the credit will be repaid by the larger interest rate than by the one it was borrowed (Baselinemag. 2013).

Table 5. FICO Score 2005. – 2012.

	Percent of population							
FICO Score	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
300 - 499	6.6	6.5	7.1	7.2	7.3	6.9	6.2	5.7
500 – 549	8.0	8.0	8.0	8.2	8.7	9.0	8.7	8.5
550 – 599	9.0	8.8	8.7	8.7	9.1	9.6	9.8	10.0
600 – 649	10.2	10.2	9.7	9.6	9.5	9.5	10.0	10.1
650 – 699	12.8	12.5	12.1	12.0	11.9	11.9	12.1	12.2
700 – 749	16.4	16.3	16.2	16.0	15.9	15.7	15.5	16.0
750 – 799	20.1	19.8	19.8	19.6	19.4	19.5	19.4	19.0
800 - 850	16.9	17.9	18.4	18.7	18.2	17.9	18.3	18.6
TOTAL	100	100	100	100	100	100	100	100

Figure 2. FICO Score Distribution

The first two years of the recession (2008-2009) moved the scores for millions of people into the lowest (300-499) and the highest (800-850) segments of the FICO Score range. This flattening of the distribution curve peaked in 2009-2010 and has since slowly been reversing. However, the latest numbers suggest two unusual patterns in this recovery. First, the quantity of people with very low scores has continued to drop and is now well below pre-recession volumes. In 2005, 14.6% of consumers had scores at the bottom of the score range (300-549). In 2012, the corresponding figure is 14.2%, which is 0.4% lower. This means that about 800,000 fewer people have such low scores today. At the highest part of the score range (800-850), we see a similar pattern. Since 2010, the quantity of people in this range has continued to increase instead of returning to pre-recession levels. The percentage of people (18.6%) in this scoring segment is now 0.7% higher than it was in 2010, representing approximately 1.4 million more people (Bankinganalystic, 2013).

SME scoring model

Scoring models form of small and medium firms have several specificities and the most important are:

- The combination of personal loans rate of entrepreneur and financial report of his firm;
- Credit ability of small entrepreneur directly connected with his financial profile of firm owner;
- Desire and ability of firm owner to pay his personal credit is collinear with ability and desire of firm to repay business credit.

The greatest number of scoring models for firms includes financial indicators. When we talk about huge and public firms, they have structured financial reports about their operations, ventures and finances. In the SME situation is a little bit different. Actually, in the SME sometimes is hard to use financial ratios because of fact that personal activity of the owner and business activity of the firm are combined. Empirical researches Fair, Isaac and

Co. Inc. show that data which are detailed investigate and take into consideration at traditional way of evaluation don't have to be involved in future repayment definition when we talk about small firm. One of the reasons is that a smaller firm doesn't have obligations of regular reporting, and when they publish their financial reports, these don't have to be revised. Also business results of SME vary because only one huge order can completely change financial picture of business for certain period (Bohaček, Z., Šarlija, N. & Benšić, M. 2008). Necessary condition for beginning of credit rating process over SME segment is gathering and structuring data about:

1. Default of SME clients
2. Data from balance sheet and income statement – construction of financial ratio

Default variable or target variable represents key information for assessment of default probability. Based on this variable, the key information about consumer behaviour is acquired. Scoring process for SME segment can be presented as:

1. Making development sample
2. Detailed analyze and variables explanation
3. Transformation input variables
4. Estimation models' parameter
5. Review of scoring model performances
6. Implementation and monitoring of scoring model

In the process of credit activation the conditions for loan approval will be automatically checked and then the process of client request evaluation will start. As result of this procedure the total credit limit of client will be settled, as well as maximum period of the loan length, minimum percentage of insurance and maximum discount on the interest. Risk manager is responsible for request resolving and making final decision. If the request has been approved, the process will be continued with ordinary processing loan procedure; otherwise the request will be settled at state denied. Until the moment of loan request realization, request can be withdrawn. Principle "two pairs of eyes" (one operator entries request and/or confirms request acceptance and automatically starts scoring process and another evaluates scoring results and makes decision or gives recommendations) will be gained with programmatic control. Requests which have not satisfied, scoring conditions can be forwarded to resolving with positive recommendation. Scoring process is modelled by the criteria defined by the loan administrator, for each type of loan. Based on these settled criteria, scoring procedure analyzes answers to the questions given through the loan request and the data obtained from information system and based on that passes adequate assessment (Antegra, 2013). Ratios which are considered during the analysis are:

- A - activity
- C - cash flow
- G - growth
- L - leverage
- Q - liquidity
- P - profitability
- S - size
- - other

Statistical Techniques for Analyzing Defaults. While the option-based approach provides a consistent way of thinking about default probabilities and prices of corporate bonds, it seems implausible that a single value, the value of the firm's assets, is the sole determinant of default probabilities. We have seen in fact, that the liquidity of assets and restrictions on asset sales were the key factors, as well. It is not always easy to build full structural models which include all the variables that empirically influence estimated default probabilities. The intensity models that we will turn to later try to include more variables in the default pricing, typically (but not necessarily) at the cost of making their influence exogenously specified. Before we enter into these models it is natural to look at some of the dominating methods used for default probability estimation. As we will see, the most natural statistical framework for analyzing defaults is also the natural framework for linking credit scoring with pricing. The focus of this section is on model structure. No properties of the estimators are proved.

Conclusion

Standardization and better risk management is one of the purposes of scoring models. There are several reasons why banks use scoring models: first, they provide an increase in revenue because faster and more efficient process of bank lending increases competitiveness and allows a greater volume of sales; second, they are cost- efficient because of the automation of the loan approval process, it reduces the need for the number of people who work on processing the loan and finally, credit scoring models allows a better quality of portfolio and implies lower costs of provision for credit losses. Seen from this point of view we could say that scoring models have achieved the goal. Credit scoring models reduces the time it takes for a decision, on whether to approve the loan or not, from previous 12 hours to 15 minutes. This clearly indicates the importance and necessity of application scoring models in banks and also in other financial institutions which make decisions on ranking clients. Although scoring models have some deficiencies, benefits of using scoring models have greatly exceeded those deficiencies, so that in future we can expect the traditional method of granting loans to be completely replaced by scoring models.

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Skoring modeli upravljanja kreditnom politikom banaka

REZIME – Osnovni cilj rada jeste predstaviti kako kredit skoring modeli mogu biti upotrebljeni u finansijskim institucijama, u ovom slučaju u slučaju u bankama, u cilju pojednostavljenja odobravanja kredita.

Za razliku od tradicionalnih modela kreditne analize, kredit skoring modeli obezbeđuju ocenu kreditne sposobnosti klijenta na osnovu numeričkog skora koji predstavlja verovatnoću ispunjena obaveza klijenta. Upotrebom kredit skoring modela, banke mogu kreirati numerički prikaz rizičnosti klijenta. Jedna od najvažnijih karakteristika skoring modela jeste objektivnost što znači da će dva klijenta sa istim karakteristikama imati isti kreditni rejting.

Ovaj rad će predstaviti neke kredit skoring modele i način na koji ih finansijske institucije koriste.

KLJUČNE REČI: kreditni skoring, skor, verovatnoća, rizik, finansijske institucije