Credit Risk – One of Management Tools of Business Subject in the Local Conditions of the Slovak Republic

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Abstract

Operation of each business entity in the local conditions of the Slovak Republic and subsequently in global worldwide who places their products and services on the primary or secondary markets is associated risk factors, which may eventually lead to loss of market share and, in extreme cases, to default. Early quantification of appropriately selected parameters in the composition with methodology adjustment to the trends may within a reasonable period of time to predict the potential risks associated with incorrectly set parameters qualitative and quantitative parameters. Credit risk as one of the key risk borne by each business entity in a local and global context is fundamental information carrier from which they could derive other parameters of risk assessment in specific areas by targeting the production undertaking. There is a certain presumption that in the conditions of an open and export-oriented Slovak economy, relevant compiled scoring models gain a greater degree of popularity in their use by end users.

Keywords: credit risk, scoring models

JEL Classification: G17, C52, C53

Introduction

Credit risk is the most serious risk for each banking institution since loans are the main bank products. For that reason, we will focus on this kind of risk. Credit risk according to Hogan (2004) is the probability that the borrower fails to pay, thus becoming default. This may be due to change in market value, which results in changes to the solvency of the issuer or counterparty. Therefore, every responsible lender tries to predict as precisely as possible the probability of default in the loan portfolio as well as the loss given default from these failures and will also try to estimate volatility of these two indicators. Probability of Default (PD hereinafter) is a measure of the risk that the debtor is unable to pay regular instalments on time. Another significant factor is the Loss Given Default (LGD hereinafter) - loss due to default of the borrower. It represents the amount of funds that a bank or other financial institution will lose if the borrower is late in paying the loan. The structure of bank credit risks can be divided into two basic parts, transaction risk and portfolio risk. Transaction risk can be understood as the risk of over-loaning resulting from errors occurring in the approval process. This risk consists of three components: selection risk, underwriting risk, operational risk.

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1.Credit Risk and Its Relation to the Trader

The selection risk arises mainly from the selection problems regarding bank credit analysis. The underwriting risk results from current approval standards and internal policies governing the approval of specific types of loans. These include e.g. terms of credit agreements, forms and types of insurance received. Operational risk is greatly related to the possible occurrence of a fault in the internal processes of the institution. Furthermore, we can say that the portfolio risk is the risk associated with a combination of loans in the portfolio. Internal risks arise from factors that are unique to a specific borrower or a business sector or a market activity (Hogan, 2004).

Credit risk represents the largest share of the overall risk of the bank. It largely determines the basic indicators of banking activities, such as size of assets weighted by risk level, reserves level related to losses on loans, capital adequacy and, ultimately, the profitability of the bank's capital. These are basic reasons for the choice of a reliable model of credit risk management being a key strategic decision of the bank. The process of managing credit risk should be conducted on two levels. On the individual level and on the level of the overall portfolio. Management of credit risk of a particular client means assessing their creditworthiness and also a minimum required rate of return for each individual loan. In terms of portfolio credit risk management process is an assessment of the overall credit risk portfolio of bank loans as well as determining the optimal structure of the loan portfolio due to limited credit resources of the bank.

The process of credit risk management is an integral part of banking business and includes the following consecutive activities:

- assessing the "creditworthiness" of the client
- determination of the probability of failure
- a debtor internal rating assignment
- determination of losses on loans in case of default of the borrower

Based on the above mentioned indicators, the price of the loan is fixed, the credibility of the borrower and the correlation (interdependence) of assets with other borrowers in the loan portfolio is determined.

In practice, this means that we determine the risk-homogeneous groups i.e. grades. Each of them consists of a calibrated score interval from which it is possible to calculate the exact value of the PD. After completing all the previous steps you decide on the applicant loan involving impact assessment, risk indicators and actual return on the total portfolio in line with the sovereign credit policy of the bank.

The main factors that determine the success of an application for a loan is the reputation and a good name of the applicant. Dishonest applicants do not feel any moral responsibility for failing to pay their debts. Passionate, experienced and dishonest applicant can usually get a loan through misleading presentation. Due to the fact that the loan officers must divide their time among a lot of the credit relationship, they do not have time to uncover fraudsters using complex schemes. (Hogan, 2004) For this reason, credit risk modelling for pricing on riskier

clients and for its measurement throughout the portfolio is extremely important for the bank (Cisko, S. & Kliestik, T. 2013).

Information on the quality dimension is generally more difficult to access and obtain. According to Hogan (2004) the process consists of the following steps:

Gathering information and records of applicants on their financial responsibility **Revealing** the actual purpose of the funds

Identification of the risks of the applicant's business confrontation with future sectorial and economic conditions

Anticipation of the debtor expectation to pay installments on time.

Quantitative risk assessment includes (Hogan, 2004)

- the analysis of historical financial data,
- the projection of future financial results, including an evaluation of the capacity of the borrower to repay the loan on time,
- the analysis of the debtor's ability to eliminate possible sectorial and economic cyclical or unpredictable fluctuations or anomalies.

2. Credit Scoring

Due to the fact that competition in the banking market continues to expand, the bank competitiveness is influenced mainly by the factors that are able to provide clients with easily understandable and easily readable information. Such information include, for example, shortening the period for assessment and decision to grant the loan, reducing operating requirements, reducing the amount of documents when applying for a loan. Banks usually rely on a large number of customers, as well as rapid processing of their applications correlating to the maximum possible high percentage of return on loans. Reducing the execution of the request proportionally increases the risk of the client being unable to repay the loan.

To improve efficiency or the effectiveness of the customers verification process, its effective automation within the organization allowing minimizing the risk of the bank is required. This increase in efficiency is secured by a bank scoring system.

Credit scoring is a fast, accurate and stable process in the assessment of credit risk on a scientific basis. Scoring process is based on mathematical and statistical models that analyse customer information and compare the level of credit risk based on the parameters characterizing the debtor and try to assess his future conduct. (Lawrence Solomon, 2002) There are many credit scoring models, each using their own set of factors characterizing the risk involved in issuing loans.

The simplest example of a scoring model may be the sum of the different characteristics of the borrower, multiplied by specific weights and then compared with a threshold (i.e. cut-off). (The result is the amount the creditor may compare with the cut-offs and use this as a base of dividing potential borrowers to the category of "wanted" and "not wanted". At first glance the description seems quite simple, but in fact it is necessary to solve several problems hidden behind that simplicity. The first is of course the question of what qualities and weights to choose. Quality assessment and also the profitability of the use of the scoring system greatly

depend on the choice of initial data. To solve this, the problem can be approached in several ways.

The most widely used is the training set built on existing customers well known either for their either regular repayments or otherwise.

The analysis of information about potential customers starts with the collection of the credit history of other clients. Scoring system compares the current customer with those who have already been successful in obtaining a bank loan. These show signs of similarity in the spectrum of relevant endpoints.

In case the system detects that, for example, within a set of 100 customers with comparable parameters only 20 have repaid their loans, the new potential customer is denied a loan. His record will be included in the risk group and stored in the scoring system database. If the scoring system will begin to reject all customers in this group, it is possible to adjust the system's behavior manually by changing the weight of coefficients or the threshold corresponding to the current realities of the market for that subject. The sample model can also be designed for specific intervals parameters of the transaction, taking into account risk factors, for example industry or market structure.

The set of characteristics that may be associated with a delay in installments or loan defaults are different for different countries. Therefore, national, cultural and economic characteristics should be taken into account. The accuracy of prediction of the scoring system is dependent on the specificity of the sample. Therefore the model with weights and thresholds from one country cannot be moved to another one and remain effective. Even within the same bank it would be wise to apply different models to different customer groups and groups of banking products. A customer may, under certain circumstances, consider scoring model evaluation absolutely unfair, particularly in the case that he was denied the loan or in case of reduced requirements for obtaining secondary sources. This should not in any way interfere with the technocratic, emotionless evaluation of the scoring. The dynamics of the scoring models expands the possibilities of input data, which in the near future may not be limited to the exact input data, but may interfere with the level of self-perception of which given the current state of knowledge, we can only speculate.

Scoring is not only used in banks, it has found its use in many other sectors of human activity. It is used in insurance companies in evaluating candidates for life insurance and the assessment of their longevity and health or in accident insurance on the assessment of crash risk. Scoring models are also used by some logistics and shipping companies. We can claim that the use or structure of the model is greatly dependent on the ability to gain sufficient input data (Lawrence Solomon, 2002).

3. The Internal Model of Assessment of Candidates for a Loan

The internal model can be described as a set of several partial approval scoring models for personal loans and unsecured consolidation of loans. These scoring models are opted for because of their generally largest representation in the bank loan portfolio. Thus it is possible to assign to them the largest and most comprehensive volume of input data obtained.

The main prerequisite for internal models is the existence of some data or customer information collected in a specific place, i.e. where an application for a loan is submitted. Using the available data we are able to predict future behavior of customers with the same characteristics. The expected commercial purpose of the model is to monitor the process of creating personal loans and their consolidation, i.e. deciding whether to grant a loan or consolidate a loan, the risk assessment on the basis of pricing, claims management and so on.

Some examples of the input parameters of the model:

- the internal data on customer behavior
- the data from the current account,
- the history of the submitted applications,
- socio-demographic characteristics,
- the credit card transaction history.

The performance of scoring models was measured by standard metrics such as KS statistics and the Gini coefficient. The distribution of scores for the "bad" and "good" clients was also calculated. Distribution should be visually inspected for unusual fluctuations or distortions in the development and control sample. If no suspicious deformations or registered significant score concentrations are found, there is a high probability of the model to be successful.

4. Data Analysis

The basic description of data was conducted using the tools in SAS EG for descriptive statistics.

Table 1: Analysis of the internal model

GOOD	Numberco mpared	Min	1.st quartile	Median	Mean	3.st quartile	Max
0	397	657	713	749	755	790	1098
1	189254	788	882	931	934	984	1479

Source: Authors

On the basis of the observed values we can see that the scores of "good" vary in the range from 788 to 1479. This range is limited by minimum (0% quintile) and maximum (100% quintile). The average value of internal score is 934 and it is given by the sum of the score of "good" and the total number of subjects evaluated the internal model ratio. This value does not significantly differ from the median value, which is 931. This reflects an intermediate value, which means the median divides the research sample into two equal-sized halves.

Here we present other characteristics such as variance and standard deviation, which shows the diversity of individual data in the selected file.

Table 2: Analysis of the internal model second part

GOOD	Variance	SD	T-test stat	P-value	Coefficient ofvariation
0	4241,461	65,1265	231,1711	0	8,619097
1	4381,888	66,19583	6143,4	0	7,081313

Source: Authors

Variation range indicates the absolute variability of the data. As for the internal model, the range of values is 691 points, this being the difference between minimum and maximum (1479-788 = 691).

The selected file data quartile range is 102 points, which is the range of values between the lower and upper quartile (984-882 = 102), also called the interquartile variability.

The mean square deviation from the average data is determined by variance. In this case, the value is 4381,888. The value of the standard deviation - 66,19583 is obtained by extracting the root of the variance.

The value of mean and standard deviation show that 95% of data values is within the range: $934 \pm 2 \times 66,19583$. The coefficient of variation is a dimensionless number that is the ratio of the standard deviation and the mean; in this case it is 7,081313.

Conclusion

In this paper we present an audition internal prediction models implemented in local conditions Slovak economic environment, taking into account the specifics of bankruptcies in the region. Used processed data was obtained from the records of the accounts of undertakings operating in the Slovak Republic.

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References

Cisko, S. & Kliestik, T. (2013). Financny manazment podniku II, EDIS Publishers, Zilina, Slovakia.

Hogan, W., (2004). Management of Financial Institutions. 2nd ed. Milton, Qld: Wiley.

Lawrence, D. B. and A. Solomon, (2002). *Managing a Consumer Lending Business*. New York, NY: Solomon Lawrence Partners.