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Model of the loan process in the context of unrealized income and loss prevention

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Abstract. Currently, in the banking sector of the economically developed countries is possible to monitor the trend of high liquidity and the low volume of credit financing of Small and Medium-sized Enterprises (SMEs). This situation is far from ideal because the banks are losing potential revenue and the SME segment within appropriate extent cannot finance its business objectives through bank loans. The aim of the paper was to propose a model for a comprehensive assessment of the credit worthiness of the client and retrospective evaluation of bank lending in terms of unrealized income and loss prevention, resulting from the application of exit strategies in the SME segment. The aim of this article was to propose a model for comprehensive assessment of the credit worthiness of the client and retrospective evaluation of bank lending in terms of unrealized income and loss prevention, resulting from the application of exit strategies in the SME segment. Our most important finding is that there is potentially quite a large group of clients who have problems with the bank ratings, but despite the fact that the bank does not give them credit, these companies continue to remain on the market. Another important finding is that there is the possibility of improving the loan process in the SME segment. These options are incorporated in our proposal to the loan process.

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INTRODUCTION

The issue of credit risk for small and medium-sized enterprises (SMEs) is currently up to date theoretical field of research and practical applications in the credit process in order to minimize the credit risk of commercial banks and possibly increase their financial performance.

Between the academics and the professional public there have been a many years belief that SMEs have a lack of sufficient funding and that there is a need to establish mechanisms in the credit process, which would be able to allocate funds in sufficient volume for these companies (for example, Siddiquee, Islam, and Rahman, 2006), and the youngest and smallest SMEs have the worst perception of access to bank loans (Canton, Grilo, Monteagudo, and Zwan, 2013)

On the other hand, some authors, for example De la Torre, Peria, and Schmukler (2010) present the view that SME financing is a very profitable segment for the commercial banks due to intensifying competition in the other services to the corporate sectors and increased competition and the improvement of subsidiaries' lending technologies have led banks to gradually expand into the SME and retail markets. (Hass and Naaborg, 2005) According to Altman and Sabato (2007) SME segment can be profitable to invest in the banks rather than big corporate firms.

Currently in the international banking sector it is possible to monitor trends of high liquidity and low volume of credit financing of SMEs.

In this article there is examined the model of the credit process in the SME segment in the context of unrealized income and loss prevention and is presented possible loan process innovation in this segment.

1. THEORETICAL BACKGROUND

Small and medium enterprises (SMEs) fulfill important tasks in the economic system, because they create jobs, contribute to the GDP and engage in other important activities within the socio-economic system.

SMEs face many disadvantages toward large companies. Disadvantages in the area of financing are affected primarily of lesser availability options to finance especially for individual entrepreneurs. The main funding source is a self-financing. The most important borrowed capital is a bank loan and supplier credit. Relatively higher cost of lower volume of loan and higher risk of the lender do not make companies as the most popular clients of banks' institutions. Other disadvantage in the area represents the fact that SMEs do not have a high value of intangible and tangible fixed assets because of depreciation which could create the space for continuous reinvestment.

The liability is very important for lenders to borrow capital for SMEs. Since the value of fixed assets is low in the SMEs, lenders required adequate guarantee, which is usually manifested by higher interest rates. Lenders are used financial analysis to assess liability, particularly debt ratios.

The debt ratio is an basic indicator of financial analysis, which represents how much of the property is covered by foreign capital. The recommended value is 30% to 60% (Kislingerová, 2010). In business is preferred a low value debt ratio, because there is less risk of default claims. We can conclude that the higher value of total debt means higher risk for lenders. Another indicator is equity ratio, which determines the ratio of equity to company´s assets.

An important indicator for lenders is also regarded as times interest earned ratio. The time interest earned ratio indicates how many times the total income covers interest payments. The value of this indicator should be higher than 1, then the profit should exceed the interest. Lenders using this indicator to detect the resistance of debt

1.1. Credit technology for the segment of SMEs

SMEs segment by its nature is a very specific field and it needs to be treated a special way. For example, Han et al. (2012) in their survey have proven that, among other things, there are characteristics of enterprises and entrepreneurs, which should determine the financial decisions of the Bank in evaluating the applicant's credit process in the segment of SMEs.

According to Brancati (2014) the companies in the segment of SMEs have fewer possibilities to innovate and are more likely to face financial constraints, but also their innovative tendency is much more sensitive to the financial status of the company. In this sense innovation is understood as one of the main determinants of the dynamics of companies, which will strengthen the long-term growth, stimulates economic performance of the company and creates opportunities for occupying of new markets (Baregheg et al., 2009). For achievement of innovation it is necessary, however, to have free funds, which in the segment of SMEs is rather rare, and this forces companies to use foreign financial resources to ensure their own development as well as survival.

Among the experts in this field it is more likely considered that SMEs are riskier than bigger firms (for example, Luppi, Marzo, and Scorcu, 2006). Dierkes, Erner, Langer and Norden (2013) state that companies in SMEs segment are smaller, have higher information opacity, carry greater risk and they are more dependent on a commercial credit and a bank loan.

Banks lend to SMEs through the lending process technology, but they are inconsistent across the banking sector and there exists a lengthy discussion about their correct settings.

According to Neuberger and Räthke (2009), the relationship between the bank and the client is determined by the credit techniques which can be characterized as the relationship lending or the transactional lending. The relationship lending is primarily based on soft information (soft information: personal character, quality of management in the company, business strategy, ownership structure, etc.). The transactional lending is based on hard data (the quantitative data) such as: return on equity, profitability, operating cash flow, interest coverage, liquidity, etc.

According to internal documents of the largest Slovak bank, a rule applies within the rating process such as follows: the smaller the company, the more important soft information is. Personality characteristics of the owner of the company are very important in relation to the financial performance of the company, which determines the level of credit risk in the SMEs segment. (Belás, Bilan, Demjan, and Sipko, 2015)

Berger and Udell (2006) define credit technology as a unique combination of primary sources of information, auditing and internal policies, where the first role is played by set procedures, strategies and mechanisms. According to the authors, credit technologies can be primarily divided according to the type of information as per which the bank decides while granting and monitoring credit. This is a decision, based (mainly) on solid quantitative information, such as information obtained from accountancy data of debtors.

The easiness in the evaluation of such information has led to a boom of the default modeling in the evaluation of the applicant of the loan. Although the origins of the default modeling are more sophisticated methods were initiated by publishing of the seminal works of authors Beaver (1966) and Altman (1968), and just focusing on quantitative data in the credit process led to extending this approach across the banking sector, where the weight of quantitative information is at least 70% and credit rating models have taken the supreme position in the credit process.

In the groundbreaking studies mentioned in the previous paragraph, the both authors used linear discriminant analysis (LDA) to find the classification rule for dichotomous outcomes. LDA method was later extended to handle nonlinear decision boundaries by creating a quadratic discriminant analysis (QDA). With the improvement of the computational ability of computer algorithms, logistic regressions have become the preferred statistical methods for standard modeling (Homolka et al., 2014). Over time, in addition to standard statistical methods have also begun to be used other methods, in the original version they are called multi-layerperceptionneural network (MLP), self-organizing map (SOM) and support vectomachines (SVM). For greater depth in historical evaluation our readers are referred to get to know works of Ravi and Ravi (2007).

Surprisingly, most of these patterns are formed on the cross section data, and thus can be considered as only static classification models. As a class of static models Tronnberg and Hemlin (2014) consider those models that do not include the historical development of economic characteristics. If there is being used the data from the last two years (in the form of delayed variables), the research proposal does not distinguish healthy companies that go bankrupt in the next year, and therefore cannot properly describe the trajectory of decline. (Homolka et al., 2014)

A frequent problem is also the arbitrary time distribution when classification does not differentiate exactly, and this leads to an inaccurate definition of the credit worthiness of the applicant. Static rating modeling ignores the progress of the company changes over time and creates a likelihood of bankruptcy, where probability estimations are distorted and inconsistent. (Homolka et al., 2014)

Such distortion can be, and often it means, the rejection of the loan for the company, especially in the segment of SMEs.

Belás et al. (2013) shows that credit risk management models represent an effort of accurately define complex economic processes through mathematical respectively statistical models. These models despite their highly sophisticated approaches fail and cannot accurately show the complexity of the economic system, which is determined by significant non-quantifiable variables (attitudes, expectations, preferences of individual economic entities, etc.).

Quality and relevance ability of internal rating systems are different. Current models to measure credit risk are not perfect and do not give quite reliable results. Mitchell, Van Roy (2007) reported that 20% of companies that have been evaluated by different models have vastly different ratings. One model assessed them as bad clients, while another model assessed them as good clients. In this context, Kuběnka, Králová (2013) indicate that the inaccuracy of the model in predicting of financial distress is 27.5% and the success rate to classify a financially healthy of company to the group of prosperous one represents 89.2%.

According to the results of research by Belás, and Cipovová, (2013) the accuracy and quality of IRM has been experimentally verified. This model used a significant Czech bank and did not have sufficiently quality because it evaluated an excellent company as a negative one and in the same time, it evaluated various negative changes in the financial performance of the company by the same rating. The model was less sensitive to significant changes of important financial indicators that determine the loan repayment which is especially evident when assessing the profitability of different variants, respectively loss-making firms.

The survey conducted in the Czech and Slovak banks (Hlawiczka, 2014), however, showed that the results of internal rating models (IRM) have a dominant position in the credit process in these markets. If the client does not pass through the rating evaluation, he would not get a loan, respectively the possibility of obtaining a loan is very limited then. In the research conducted on the Czech and Slovak banking market, the authors in their survey have also analyzed employee satisfaction with the rating model in their bank. Bank employees have expressed that the accuracy of the rating models typically varies in interval of 70-80%, and users think about their own models as of models of an average quality. According to the author, many loan specialists admitted that due to the complexity of these rating models and low awareness of these models they are not able to determine which factor was the key factor for the refusal of the application.

These models also have their advantages. Berger and Fame (2007) report that by using credit-scoring models banks are willing to provide more loans to SMEs now, due to easier default measurement of the borrowers.

The dominance of SMEs, together with the financial system, which is characterized by low sophistication of equity and bond markets, however in the conditions of the Czech Republic and also in other countries with similar capital structure ensures that companies have virtually no access to alternative sources of funding and thus must be fully depending on their bank and the banking system in general. Then, in this sense, a wrong setting of the default modelling, as well as the entire lending process can mean significant loss to the economy.

In this context it is often being talked about credit management process based on other information, such as *qualitative information*. The emphasis here is on the need to establish close ties with the bank. The creditor may understand the needs of the client better by using a larger amount of information and longstanding relationship and with provided loans the borrower can then again overcome financial obstacles.

There have been carried out many researches on this subject, for example (Han et al., 2012; Bartoli et al., 2013 and Uchida et al., 2013), demonstrating for example the meaning of „relationshiplending". According to Behr, and Guttler (2007) relationship lending is more convenient to reduce the asymmetric information problem. Futuristic non-financial information such as management quality produces better result about the default prediction when combined with past financial information. (Grunert, Norden, and Weber, 2005)

The information about the financial situation must be evaluated in order to reflect indebtedness and liability of the companies. For detection of debt indicators in the financial analysis are important information in the financial statements, which should reflect the real financial situation of the companies. Only correctly preparation of financial statements, provides a prerequisite to the correct assessment of debt and determination of liability, which is important for creditors and also for SMEs. SMEs may modify financial statements in order to improve the financial situation of the company, that interest on borrowed capital would be as low as possible. For the lenders is important to correctly assess the financial situation, to detect possible non-payment risks associated with foreign capital. Typically banks use software products for financial analysis on which are evaluated companies. The calculated value of the indicator does not have sufficient explanatory power. Financial analysis indicators derived from the financial statements represent only one source of information. The financial statements does not provide all information to the lenders on a proper assessment of debt.

According to the research of Mudd (2012) it is more likely that the bank will invest considerable time and resources to collect qualitative information about the company in the event that the bank is: smaller and has less competition. Yet, it applies that the gathering relevant information about prospects and creditworthiness of the borrower can significantly affect the creditor's decision on whether and on what terms to grant the loan, thus regardless of the size of or the competition on the market. Long lasting relationships, for example, reduce a fixed cost of credit, as well as the amount of collateral required by the bank (Degryse a Van Cayseele 2000). This in turn reduces the probability of an adverse financial situation of SMEs and increases the willingness of the bank to encourage borrowers in the short terms in anticipation of the future profits. (Savignac, 2008).

In addition, in the research of the authors of Grunert, Norden, and Weber (2005) there could be found a support for the hypothesis that the assessment of qualitative information (mainly managerial skills and character), is significantly associated with a positive situation of the debtor. In addition, more favorable assessment of qualitative with respect to quantitative information is also associated with higher negotiating power. The most important thing is that these two results provide evidence in favor of the secondary effects of quantitative information, thus it affects not only the level of the final ratings, but it also affects credit conditions within each category rating.

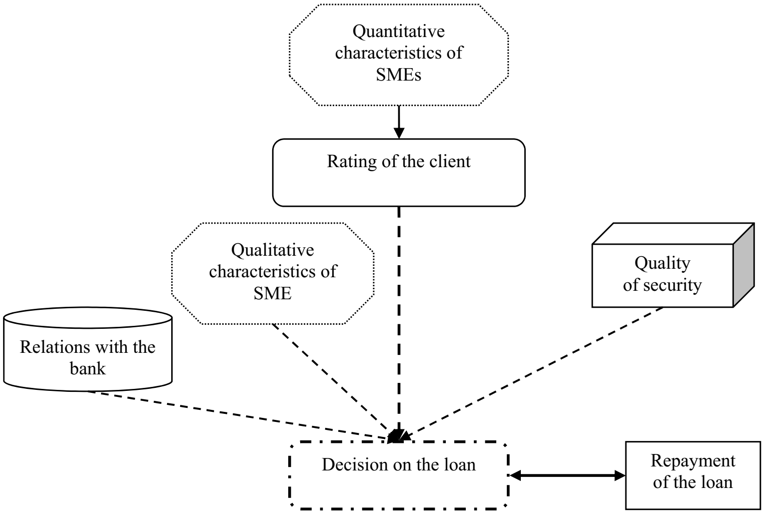
Bartoli et al. (2013) suggest that the difference between lending technologies is based on the idea that there are two types of production functions with the use of various inputs. However, the nature of the information is not exogenously fixed. In fact, the practices of lenders have shown us that it may be possible to change the nature of the information.

For this reason it should be stopped looking at a rating model in the segment of SMEs as a universal, determining element in the credit process, in which further elements of decision by its weight and the result from the IRM mainly on the basis of quantitative information is not directly KO criterion. The banks should be able to tell their customers clearly and precisely why they were rejected when applying for loans, and what the applicant might do in order to change this decision over time.

1.2. Traditional lending process in segment of SMEs

Although there are many studies that deal with the lending process, in recent years, the research is focused more on the component parts of the process, rather than the whole. For example, the study of authors Tronnberg and Hemlin (2014), who analyzed the decision of 88 banks' officials from the four largest Swedish banks while providing loans from a psychological perspective. Firstly, they found out that the loan personnel from their sample of respondents have used especially cautious thinking and less intuition in decision making. Secondly, the loan officers have more difficulty in determining which was related to qualitative information (for example, Customer Relations), than the decision, which was based on quantitative information (for example, financial information). Finally, it was found out what was the potential influence of organizational factors, such as internal decisions for lending on the final conclusion whether to provide a loan. This is a research that belongs to a series of analyzes of the effect of intuition of loan officers in providing loans where it was rather assumed that the intuition is often present at the final decisions about providing the loan. (Hodgkinson et al., 2009).

According to our knowledge, client rating based on quantitative data constitutes the major part of the loan process. A graphical representation is shown on Pic. 1.



Pic. 1. Theoretical diagram of the lending process in relation to SMEs
Source: Internal documents of the bank, adjusted.

In case if the repayment is unsuccessful, there are established penalties and default procedures are introduced; in case of success of repayment it often leads to a new loan application.

As it could be seen from the diagram, in order for the banks to be able to correctly assess the ability of the company to meet its future obligations (Degryse a Van Cayseele 2000), it does so by analyzing its financial situation and simultaneously gathering information regarding the past repayment history, if there is any. Financial institutions have large amounts of information through the provision of other services (for example, Deposit accounts and billing and payment services), from which they can draw information and thus properly assess the credit worthiness of the borrower. The banks can then use this information in the draft of a credit agreement for SMEs, as well as to adjust their overall lending process with this information.

2. METHODOLOGY

In our research the procedure was as follows: based on the processing of literature researches of relevant resources there have been defined scientific question and scientific hypotheses. Then our own research was conducted, which have focused on the quality of IRM and the quality of the risks measurement process in a commercial bank.

Research Questions (RQ) and scientific hypotheses H1, H2:

RQ: Is a standard credit process of a commercial bank in relation to SMEs segment configured properly and if there are opportunities for improvements?

H1: The accuracy of the rating based on statistical models is limited. It was assumed that the accuracy of the rating as per our model, tested on the real bank data would be less than 70%.

H2: The sum of unrealized income of the surveyed exited enterprises exceeds the losses prevented from them, and therefore the bank was too conservative. If the bank from the whole of the sample did not close the financing, it would execute additional profit.

Our own rating model was created on the base of publicly available information from the database of the companies Albertina. The model was tested on real data which was provided to us by important commercial bank in the Czech Republic.

Data had to go through adjustment, so such data to be selected that are complete, relevant and do not reach extreme values, which would distort the analytical calculations and degrade statistical methods. The result was the creation of two sets of data. The first set contained the input data for the year 2012, which comprised a total of 349 companies (35 by default). This data set was used for the so-called „learning model". The second data set was for the year 2013, comprising a total of 271 companies (14 by default), which was used to validate the model. Summary of the data is shown in the *Tab. 1.*

Tab. 1.

Classification of input data for our own IRM

Data	2012	2013
Non-default companies	314	257
Default companies	35	14
Total	349	271

Source: own processing.

Among the most commonly used approaches to estimate the probability of default remains the same model with the use of a linear probability regression, logistic regression or regression model. (Ravi and Ravi, 2007).

For the purpose of this work there was chosen statistical method of linear discriminant analysis (LDA).

IRM with the use of a linear discriminant analysis is possible for the conformity of covariance matrices C1 = C2 = C. For two classes 1,2 is the logarithm of proportion of posterior probability:

$$\frac{\ln\left(P(G=1|\mathbf{x})\right)}{P(G=2|\mathbf{x})} = \ln\left(\frac{f_1(\mathbf{x})}{f_1(\mathbf{x})} + \ln\left(\frac{\pi_1}{\pi_2}\right)\right) =$$

$$= \frac{\ln \pi_1}{\pi_2} - \frac{1}{2}(\mu_1 - \mu_2)^T C^{-1}(\mu_1 + \mu_2) + \mathbf{x}^T C^{-1}(\mu_1 - \mu_2) \quad (1)$$

When creating the model as the most important financial indicators (independent variables) there were used Return on assets (ROA), Turnover of assets (TA), Current ratio (CR), Interest coverage (IC) and Financial Leverage (FL).

For completion of the created model there was needed a back test of its functionality. This was achieved with the data for the year 2013 to avoid of the so-called "recalibrating" of the model.

Tab. 2.

Error of the 1st and the 2nd kind

	Non-default companies - 0	Default companies - 1
Non-default companies - 0	249	11
Default companies – 1	8	3

Source: own processing.

The quality of the loan decision, it was examined a sample of 21 companies that were once part of the bank's portfolio and the decision was made to terminate financing of these clients in the interval of 2008-2012. Such a character of selected enterprises is chosen so that the work was based on actual historical data. Given that these clients were financed by these bank for some time, there are documents proving the amount of revenue for these clients, loan amount, interest margins, almost all documents of changes are archived, etc. 7 of surveyed companies now either exist or are in liquidation, the remaining 14 companies are still active.

A. Unrealized bank's income

In the first step, a general model was developed to quantify the unrealized revenues of banks for operating and capital funding. For each type of financing there are created two scenarios. In the first scenario there are taken loans and services that businesses have actually used in the past. These assets are kept under the conditions of that time and extrapolated into the future, as the final date of the still operating companies considered to be 31 December 2014. For the businesses that do not exist anymore these revenues are terminated on the date when the bankruptcy appeared. Compared to them is based a scenario that has actually occurred after the exit. The difference between these two scenarios is in revenues that have not been realized due to the application of exit strategies.

The main factors entering into the model are the following: the amount of loan, the average drawdown of the loan, the interest margin, commitment fees, and the fees associated with processing the credit documentation, etc.

The limit of the credit line defines the revenue from the loan. A major role is also played by an average using of the credit line because businesses usually do not take loans normally at the rate of 100%, but on average over the given period, for example only 75%. The archives of the banks contain this value only for some companies, while no such data about other companies exists. Therefore it was taken an advantage of qualified estimation of consultants, in whose portfolio the company was.

An important factor is the interest margin of the loan and a so-called commitment fee. It is not a final interest rate for the company. It consists of the part that relates to the cost of bank for the acquisition of liquidity (for example 1M PRIBOR), additional surcharges and precisely from the interest margin. Commitment fee applies to an undrawn loan and is usually much lower than the interest rate.

With the loan there are also associated fees for processing credit documentation. This activity is very time consuming, i tis necessary to process all the relevant information about the company, its business environment and financial situation. There are analyzed both rating of the company and its „soft facts", i.e. qualitative factors that may either aggravate the financial rating or make it better. These fees are used to cover the cost of processing these documents and their amount is therefore based on the size of the company, the required loan amount, degree of clarity in the ownership structure of the company and other factors.

The procedure of quantification of unrealized revenue for commercial bank.

1. Step. Finding relevant data.

The first step was to find documents related to the given case. The archive contains the credit agreement and all amendments that regulate it and changed. From the credit proposals and other documentation there were found out the average historical loan, the required fees associated with the loan and also the amount of additional income that do not arise from the loan itself.

2. Step. Quantification of impacts: Scenario without the intervention of the risk management department.

The first scenario is a hypothetical situation, if the department of risk management has not decided on exit or worsening conditions at all and if financing that has actually existed prior to this decision, the company would be provided with a financing until today. It is therefore conceived as historical conditions, both loan volume and interest margin, etc.

3. Step. Quantification of impacts: the course of financing in reality.

The second scenario is the actual course of financing, for example, what was its real progress following the decision of the risk management department to worsen financing conditions due to increased risk, or after the decision to reduce credit exposure of bank at the client, leading up to the exit.

4. Step. Quantification of unrealized revenues.

Based on the above mentioned procedures there was calculated the height of unrealized revenue of commercial bank. In some years, this difference may be even negative, if, for example, after the decision of the risk management department to increase margins and not to so sharp reduction in loan volume, however, the sum of all years is generally positive.

B. Averted losses of the bank.

The procedure for calculating prevention of loss of the Bank was as follows.

The methodology is the following: it is taken into consideration the credit exposure scenario *„scenario without intervention risks"* at the time of the bankruptcy, from which is extracted the applied pledge value and the result for a bank means that its losses avoided. The values of applied pledges are estimated based on expert estimates of experienced banking consultants, and on the basis of what the yield pledges the Bank has really achieved in the past from these cases and even in the event of exit got a loss.

Total net unrealized revenues obtained by subtracting total avoided losses from the total unrealized revenues.

3. RESULTS AND DISCUSSION

The process resulted in the creation of the IRM using statistical methods of the LDA who successfully have classified companies from public data with a success rate of more than 90%. While analyzing the errors of the first and second kinds, then the model have correctly classified 252 companies from a sample of 271, but achieved high level of errors of the 1st kind.

In the *Tab. 3* there are shown the values of the independent variables in our own rating model.

Tab. 3.

Average values of the independent variables in our own model

	ROA	TA	CR	IC	FL
Non-default companies - 0	0,169674	1,104028	4,236315	29,65750	1,766125
Default companies - 1	-0,108725	1,647332	1,210145	-15,28758	35,63083

Source: own processing.

The test results of an own model on real data are presented in the following tables.
In Tab. 4 there is given an overview of the real data that have been used.

Tab. 4.

Overview of the real data that have been used

	Non-default companies - 0	Default companies - 1
The original data set	0	101
The probability of occurrence in the file	0 %	100 %
Loss due to missing data		64
The resulting number of firms tested in the model		37
Validation of the model		
Default companies - 1	25	12
The success of classifying real data		32,43 %

Source: own processing.

IRM, which was created by LDA method when checking for „live data" did not confirm the predictive capability. Especially when analyzing of the errors of the 2nd kind, which significantly affects the bank's credit exposure and its negative impact on the performance of the bank, see Tab. 5

Tab. 5.

Error of the 1st and the 2nd kind

	Non-default companies - 0	Default companies - 1
Non-default companies - 0		25
Default companies - 1		12

Source: own processing.

Model of a critical mass of 37 companies that have been default in the past period, has managed to select only 12 companies that would not go through a rating based on the evaluation produced by IRM. This fact highlights the importance of greater non-quantified items in ratings, such as movement in the account, the client's history etc., as well as deficiencies in the formation of IRM.

The Hypothesis 1 was confirmed. IRM confirms its predictive ability only on publicly available data, and that is from more than 90% (which is determined by statistical methods used), but its predictive ability when tested on real data proved to be very low, namely 32,43%.

The results of our model to some extent are confirmed by the views of Mitchell, Van Roy (2007), Kuběnka, Králová (2013), Belás, and Cipovová, (2013), (Hlawiczka, 2014), Grunert, Norden, and Weber (2005) and other authors.

According to Luppi, Marzo, and Scorcu (2008) profitability and bank relationship with a borrower has an inverse relationship for predicting the probability of default. A longer relationship with the bank lowers the probability of default. They have also shown that, firm size and the number of employees both the variables have an inverse relationship with the probability of default. The one interesting thing that they have pointed out, most of the SMEs in their sample has tended to extract money from the loan for their personal use, and the higher the number of money extraction for personal use the higher the possibility of default.

Similar views are presented by Psillaki, Tsolas, and Margaritis (2010), which state that the company performance is negatively related to default. By using a DEA (data evolvement analysis) they have also shown that, firm efficiency has enough explanatory power to perform better than the financial indicators. They have emphasized the non-financial information on predicting the business failures of the firm. They find that more efficient firms are less likely to fail. A 0.1 unit increase in the inefficiency score increases the probability of default on average by about 2 percent. This probability decreases to about 0.35 percent for the top quartile of the most efficient firms. They also find that, a one percentage point fall in profitability increases the probability of default by about 1 percent. Similarly, a one percentage point fall in intangible assets is expected to increase the probability of default by about 0.25 percent. Tangible assets had a negligible and insignificant effect on the likelihood of default in this industry so this variable was dropped from the regressions. We find that the solvency ratio (SR) is a poor predictor of a company's default.

In the context of IRM Mileris (2012), Tőzsér (2010), Belás et al. (2013), Horvátová (2009) state, that models for credit risk management of the client are therefore largely pro-cyclical which means that these models are usually very mild in the good times of the economy and at worst period of economic development, they are too hard as a result, may paradoxically worsen developments in the banking sector.

In general, the strength of the rating model is quite limited, below the corresponding predictive ability and to look for other ways to adjust the quality of the loan process.

In another part of our own research there were quantified the effects of selected decisions in measuring credit risk in commercial bank.

Based on the presented methodology, there have been calculated the total unrealized gains on a sample of 21 respondents from the end of the loan relationship with a non-default clients in the amount of CZK 79.859.267.

In *Tab.6* there is shown the total avoided losses which were calculated by means of the presented methodology.

Tab. 6.

Total losses avoided

Optimistic scenario	CZK 38.489.600
Neutral scenario	CZK 40.739.600
The worst-case scenario	CZK 42.989.600

Source: own processing.

In *Tab. 7* there are shown the net unrealized gains in total. The overall net unrealized gains obtained by subtracting the total avoided losses from the total unrealized gains. According to our results, on the survey sample of the bank clients by their decisions has not made additional CZK 36,9 to 41,4 million over 5-6 years, which in the opinion of the author is a significant amount.

Tab. 7.

Net unrealized gains in total

Optimistic scenario	CZK 41.369.667
Neutral scenario	CZK 39.119.667
The worst-case scenario	CZK 36.869.667

Source: own processing.

The Hypothesis 2 was confirmed. According to our results, the amount of the income of the surveyed exited companies exceeds the losses avoided by them and therefore the bank was too conservative. If the bank would not have ended financing of the entire surveyed sample, it would implement an additional profit.

It does not mean that the bank as a whole, or perhaps its risk management department was wrong. The aim was primarily to point out the fact that credit risk management might be different and especially that level of confidence of the risk management departments' decision-making from this perspective is not analyzed by anyone today as well as it is not evaluated in this way, which is a significant deficiency of the current status.

It would be appropriate to move from measuring the number of already provided bad loans as well as evaluating the correctness of rejected cases, which is interesting and important information for potential growth of performance for a commercial bank.

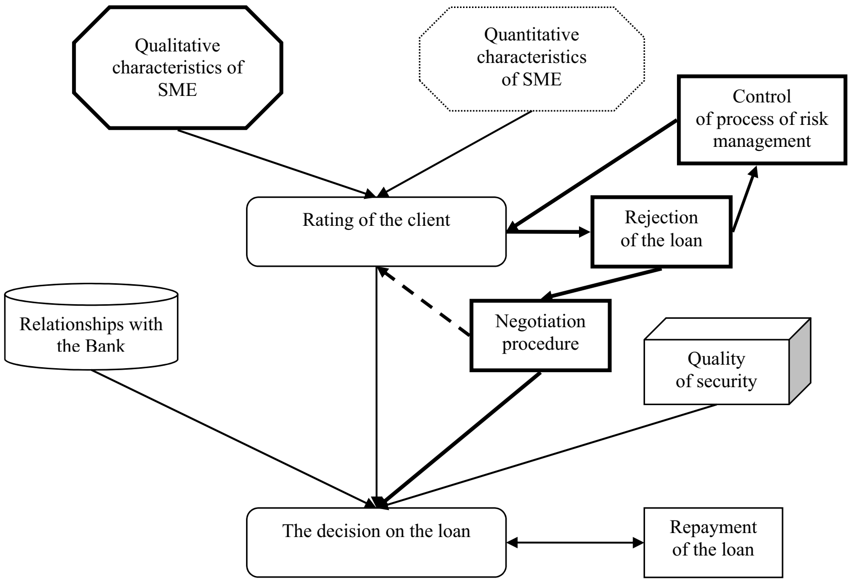
An important finding from our researches is that in managing credit risk the nature of provided pledges is extremely important. In the analysis of the default company the quality of provided collateral has appeared as critical since a certain type of collateral was almost worthless at the time of bankruptcy, while another was able to provide up to one hundred percent of the due amount. Another research observation is that if a bank has a quality pledges it is almost illogical to terminate funding when the value of the collateral several times exceeds the amount of credit exposure to the bank.

Based on the research results, our own proposal for lending process is presented in *Fig.2.*

The essential attributes of this proposal are:

1. there is highlighted the importance of qualitative factors in the process of measuring credit risk for SMEs;
2. in case of rejection of the loan because of bad credit rating of the client it is offered to the bank to re-evaluate the quality of such decision, for example, according to our model of additional income and loss prevention, the results of this control procedure may be a good inspiration for improvement of the rating process in a commercial bank;
3. in the event of rejection of the loan because of poor credit rating of the client in justified cases (the client is a longtime client of the bank and always behaved responsibly, etc.), it is offered that the bank held negotiations with the customer (negotiation procedure) to thoroughly examine the probability of default of the client.

In this context Hlawiczka, Doležal, Belás, and Cipovová (2014) state that financial analysis should be seen also as one of the processes that can help to quality of credit decisions, but the results also do not guarantee anything by hundred percent (successful development of the company in the past does not automatically mean a successful future). In case of negative, respectively inconclusive results, the bank's analyst must consider the significant determinants of the financial analysis in the context of credit risk.



Pic. 2. Proposal for innovative lending process in relation to SME
Source: own processing.

CONCLUSION

The aim of the article was to propose a model for a comprehensive assessment of the credit worthiness of the client and retrospective evaluation of bank lending in terms of unrealized income and loss prevention, resulting from the application of exit strategy in the SME segment.

The results of our research have confirmed the assumption that there are opportunities for improving the credit process for the SME segment, which is an important factor for the growth of the financial performance of commercial banks, but also for the increase of financing of these firms in the context of overall economic growth.

Our most important finding is that there is potentially quite a large group of clients who have problems with bank ratings, but despite the fact that the bank does not give them credit, these companies continue to remain on the market. In our study it was 67% of the research sample.

Another important finding is that there is a possibility of improving the loan process in the SME segment. This finding is certainly not the breakthrough in economic theory. It is rather a forgotten rule, which says that the bank has to thoroughly understand its clients.

Many banks have forgotten about this rule as they too intensively seek to standardize and automate those processes that are not actually suitable for that.

It is understood that our research has some limitations, but it may be an appropriate form of inspiration for banking theory and practice.

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