Lending Process for the SME Segment. The Findings and Experience from the Czech and Slovak Banking Sectors.

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Summary

Small and medium enterprises (SME) fulfil important tasks in an economic system. However, these companies have limited access to credit resources comparing to big companies. The aim of this article is thus to define the possibilities of lending process improvements based on an analysis of the significance of Internal Rating Models (IRM). Resulting from the data obtained in our research, a custom IRM for the SMEs segment has been created, testing its quality and defining its limitations as well. In this process, the quadratic discriminant analysis (QDA) has been used. Moreover, the article also examines the opinions of the banking sector professionals on the quality and accuracy of the IRM currently used in Czech and Slovak banks. Finally, our own innovative methodological proposal for the lending process management for SMEs is introduced. A model of the lending process has been designed to ensure optimization of credit decisions, a reasonable rate of effectiveness of lending practices and a reasonable rate of individual commercial banks approach to the SME segment. Carrying out the research, the qualitative as well as the quantitative methods were used. The results have shown the level of IRM accuracy in the mentioned banking sectors is at approximately 80%. Therefore an optimisation of the lending process could lead to additional interest incomes for banks.

Keywords: commercial banks, SME credit risk, internal rating models, loan processing.
JEL codes: G21

The issue of credit risk for small and medium-sized enterprises (SME) is being widely treated in the theoretical field of research and practical applications in the process of credit risk management in commercial banks.

Internal models for credit risk assessment of a client are an important part of credit risk management process in a commercial bank. These models have developed dynamically in the last few years and have become an essential part of the assessment of credit risk in banks. The banking practice itself, however, points out that it is important to incorporate these models in an appropriate form for the loan process in commercial banks.

In this article, the role and the importance of internal rating models (IRM) in the commercial banks´ lending process is examined. Based on qualitative and quantitative analysis, there are proposals and suggestions made for optimizing the parameters of a commercial bank's credit policy. Given the importance of SMEs in the economic system and their persistent problem of a limited access to financial resources, it is considered to be very important to address this issue.

1. Theoretical background

Small and medium-sized companies face many inconveniences comparing to large companies. The disadvantages in the area of financing are affected primarily by fewer options to finance, especially for individual entrepreneurs. Here the main funding source is a self-financing. As for the external capital, the most important is a bank loan and a supplier credit. The fact that SME represent relatively higher cost of lower volume of loans and higher risk for a lender (a bank) implicates that these companies do not belong to the most popular clients of bank institutions. Other disadvantage in this area is that small and medium-sized companies do not have high volumes of intangible and tangible fixed assets as a result of depreciation what reduces the space for continuous reinvestment.

In this context, Dierkes, Erner, Langer and Norden (2013) state that companies in the SMEs segment are smaller, have higher information opacity, carry greater risk and are more dependent on a commercial credit and a bank loan.

Internal models for credit risk assessment of a client represent a significant and important part of credit risk management in commercial banks.

Internal rating systems are used to quantify the credit risk of individual borrowers. The credit rating score is assigned to individual borrowers by using different methods and indicates the level of credit quality. The validation of the rating system is closely linked to the validation of other risk parameters that are derived from the rating provisions of Internal Rating Based Approach of Basel II and which largely determine the amount of required equity. The aim of internal rating models is to estimate risk parameters such as Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD) and Effective Maturity (M) which are based on the quantitative and qualitative variables. (Deutsche Bundesbank, 2003)

Internal rating of a client is assigned by the bank according to its risk characteristics and risk characteristics of the contract which is based on specific rating criteria from which estimated PDs are derived. As a part of the credit approval process, each borrower is assigned to a rating class with a specific PD assumed by a bank. The rating of the client determines their access to credit resources and their cost.

In the theory, there are various approaches to credit risk management of SMEs.

According to Neuberger and Räthke (2009), the relationship between a bank and a client is determined by the credit techniques which can be classified either as the relationship lending or the transactional lending. The relationship lending is primarily based on soft information (personal characteristics, quality of the management in the company, business strategy, ownership structure etc.) that the bank acquires in the direct contact with the client, in the local territory and on the base of the long-term observations of the company’s performance. The transactional lending is based on the hard data (the quantitative data), such as return on equity, profitability, operating cash flow, interest coverage, liquidity etc. Ono and Uesugi (2009) indicate that the relationship lending is common mainly in lending to small businesses, because these typically rely on bank loans which represent a very important part of their financial needs and at the same time tend to be informationally opaque. In this context, authors highlight the importance of the collateral, which is a common tool in the credit process between banks and small companies around the world. In the context of information asymmetry between banks and credit applicants, the collateral can be seen as an option for reducing the problem of an improper selection and the moral hazard.

According to Internal documents of the largest Slovak bank, there exist some rules generally applied within the rating process, such as the smaller the company, the more important the soft information is. Personal characteristics of the owner of a certain SME are also essential in relation to the financial performance of the company, which determines the level of credit risk in the SMEs segment. (Belás, Cipovová, Novák, Polách, 2012) Witzany (2010) states that the accounting data have low explanatory power in relation to SMEs and that an expert system is very important in the rating process. In this context, Altman, Sabato and Wilson (2010) reported that the use of non-financial variables of function of default signals significantly improves the quality (predictive power) of rating models.

In the document of the European Committee (2007), 75 % of the total number of large and medium-sized banks in the survey of McKinsey & Company state that the current level of debt of SMEs is considered as the most important quantitative factor of internal rating; 50 % of the banks give equal importance to the indicators such as liquidity and profitability. From the wide range of possible quality factors, around 50 % of medium-sized and large banks give high or very high priority to the quality of management of SMEs. Other factors resulting important according to the mentioned survey are the market situation of SMEs and its legal form. Furthermore, the qualitative factors have a greater influence on the rating in case of larger SMEs and larger loans. In case of start-up companies, the weight of these factors represents 60 % of the overall rating. In case of companies with a sufficiently long business history (minimum 2 years), the weight of qualitative indicators is significantly lower and represent only 20-30 % of the overall rating.

Figure 1 represents a diagram of a typical loan process used in the Czech and Slovak commercial banking.

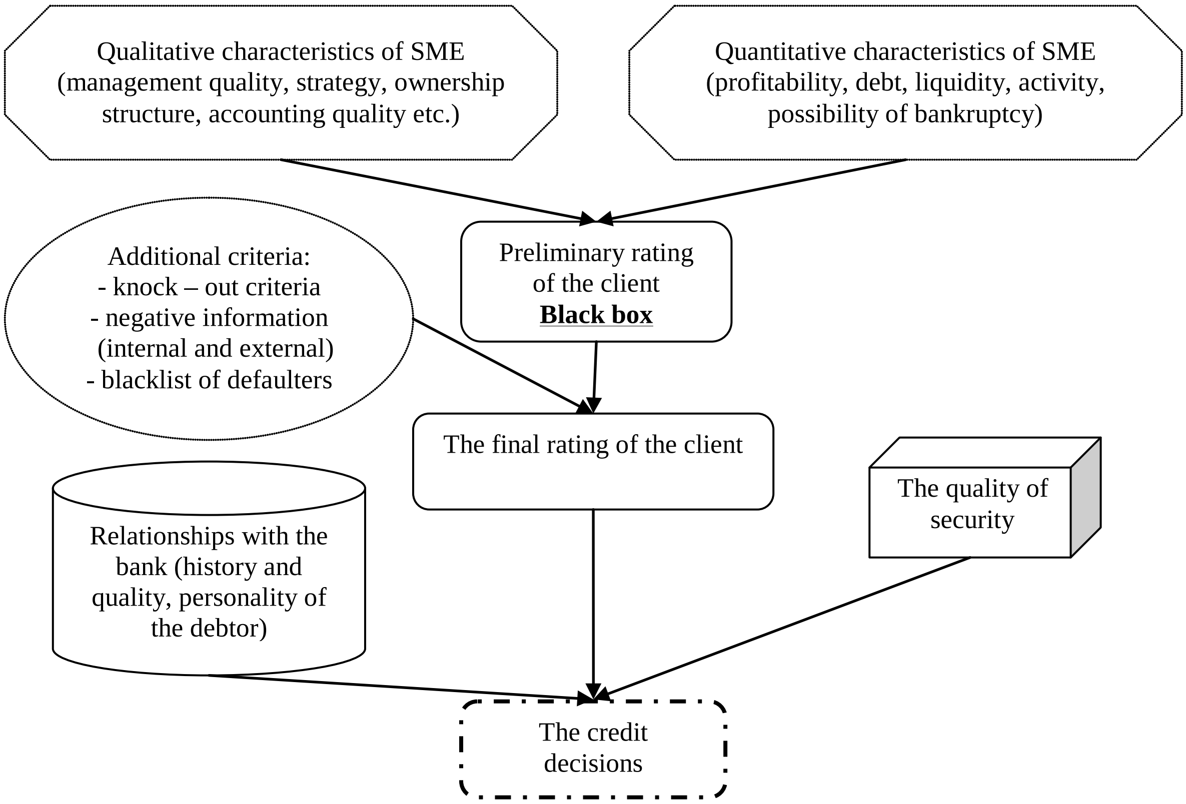

Fig. 1. The Scheme of a Typical Rating Process in the SME segment. Source: Internal documents of a bank, corrected

The quantitative factors (profitability, level of debt, liquidity, level of activity, possibility of bankruptcy) and the qualitative factors (personal characteristics of the owners, quality of management, business strategy, owner structure, accounting accuracy etc.) enter the model of the preliminary rating. The bank, on the basis of this data, calculates the preliminary rating. The calculation method itself is a secret for clients and the credit specialists in the bank, often called a Black box. This rating tends to be a vital (frequently the dominant) criterion for the final credit decision. If the client obtains a good rating at this stage, they continue to next phase which includes comparing with the Knock-out criteria. These criteria filter out the clients with debts towards the state, social and health insurance institutions, the clients in bankruptcy or liquidation and tax dodgers. The result of this filtering is the final rating of the client. If this final rating is positive, the bank takes into account previous experience with the client and the quality of collaterals (such as fixed and current assets, stock, securities, receivables etc.) in the final credit decision.

The mentioned credit rating process, however, has its numerous weaknesses. This article deals above all with the role and significance of IRM models of commercial banks in their loan processes.

2. Objectives and Methodology and Data

The aim of this article is to define the possibilities of improvements in the loan process of commercial banks on the basis of analysis of the role and significance of the IRM in the process of credit risk management in the SME segment.

In this context, the status, importance and shortcomings of internal rating models of commercial banks in relation to credit risk measurements have been analysed. Consequently, own internal rating models and own methodological proposal for the management of the lending process are presented.

The criticism of internal rating models is focused on various aspects of their operations. In practice, a perfect rating system does not exist (Deutsche Bundesbank, 2003). Their explanatory power in relation to the assessment of the quality of a client and its risk profile is significantly limited.

The quality and accuracy of internal rating systems are different. The current models to measure the credit risk are not perfect and do not give substantially reliable results. In this context, Kuběnka and Králová (2013) indicate that the inaccuracy of the model in predicting a financial distress is 27.5 % and the success rate to classify a financially healthy company into the group of prosperous ones represents 89.2 %.

In our previous research (Belás, and Cipovová, 2013), the accuracy and quality of a certain IRM was experimentally verified. We found out that model used by a large Czech bank does not have the sufficient quality as it evaluates an excellent company as a negative one and at the same time it evaluates a company even after various negative changes in the financial performance with the same rating. The model proved to be 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 (loss-making firms).

All the theoretical knowledge mentioned above combined with our own previous research and consultations with the loan specialists from the Czech and Slovak commercial banks lead us to formulate the following hypothesises:

H1: Less than 50% of the loan specialists in the Czech and Slovak banking sector know the weights within IRM used in their banks.

H2: IRM have a dominant position in the loan process of banks. If the results of IRM are negative for a client, the bank does not make a loan.

H3: IRM have a limited accuracy. The average level of IRM accuracy in the Czech and Slovak banking sector is lower than 80% according to the estimation of the loan specialists.

H4: The accuracy of our own IRM is lower than 80%.

In our research, the proceeding was as follows:

Through a structured interviews there have been investigated the role of IRM in the credit policy of commercial banks and their degree of accuracy. The data was obtained from the bank personnel, in details, 10 bank managers and credit specialists working in Czech commercial banks and 10 managers and specialists working in Slovak banks were addressed. In the Czech Republic, the managers included in the research were employers of the five biggest banks which represent approximately 70% of the market. In Slovakia, the managers worked for three medium-sized and seven large banks, representing 75% of the total loan market.

The sample of respondents is considered to be representative for the following reasons: the staff engaged in this research represents the leading commercial banks of the Czech Republic and Slovakia; the banks apply unified credit policy which means that if a representative of a bank has indicated a certain fact this can be applied throughout the entire bank (eliminating the need for a large number of respondents) and the banks consider their IRM as a subject of business confidentiality, which they do not inform the public about so any quantitative research with a large sample of respondents is excluded.

At the same time, our own IRM has been created. In this process the quadratic discriminant analysis (QDA) was used. Input data for the creation of the model were drawn from a professional search database of companies Albertina. It is appropriate to emphasize the fact that there exist various types of approaches to evaluate a default (default means a liquidation of the company or delay of loans' repayment within a period of more than 90 days etc.). In this case, default of the company was understood as the bankruptcy or liquidation of the company.

First of all, the data passed through an adjustment selecting only complete, relevant and not extreme data which enhanced no distortions of the analytical calculations and degradations of the statistical methods. The result was the creation of two sets of data. The first set contained the input data of the years 2010 and 2011, which consisted of 393 companies (42 defaulted companies). This data set was used for the so-called "learning model". The second set contained the input data of the year 2012, which consisted of 320 companies (14 defaulted companies) and was used within model testing. Based on the literature research and consultations with experts, following parameters of the financial performance of the company have been selected and have served for the calculation of the Probability of Default (Table 1).

Tab. 1: Selected Parameters of the Financial Performance for IRM.

Parameter (customize labelling for the input into IRM)	Equation
Return on assets (ROA)	EBIT/Assets

Turnover of assets (TA)	Revenues/Assets
Current ratio (CR)	Current Assets/Current Liabilities
Interest coverage (IC)	EBIT/interest expense
Financial Leverage (FL)	Assets/Equity

Source: own source

The creation of the model was carried out in the R program. The data uploading was performed through the Notepad ++ program. The rating model was created on the data of the years of 2010 and 2011. Therefore the data of the year 2012 has been used for testing of the model in order to avoid so called "overfitting" of the model.

Consequently, an own model of lending process in SMEs segment was created. The basic criteria of the model of the lending process in relation to SMEs were determined as follows:

- Optimisation of credit conditions, i.e. maximum rate of provided loans at an acceptable risk level (our intention is to set up the lending process so that a bank can eliminate the consequences of the error of the first kind to the maximum extent; respectively errors which may arise from other inaccuracies of IRM. This process should take place in a close and intense communication with the client).
- Appropriate level of the efficiency of the credit processes through the quantification and optimisation of operating costs in the context of an individual approach of SMEs.
- Appropriate level of an individual approach to SMEs through the optimal level of knowledge of individual clients and its business parameters; the decentralization of competencies of banks' managers (for example, we suggest to assign different level of a relevant competencies to banks' managers for the approval of the limited volume of corporate loans, for the approval of exemptions beyond of standard credit processes and decisions on specific levels of credit risk; part of these rules should also represent a regular monitoring as an application of these rules to business processes because of some risks' increase of credit losses) and the creation of other methodologies.

In this process, qualitative as well as quantitative methodologies have been used. The implementation of qualitative research methods allow to define the essential determinants of the examined systems, processes and approaches of the credit risk management, existing links, connections and key factors of the success. The quantitative research methods allow to measure and exactly compare the process and its results with the similar processes and results.

In the process of creation of an innovative model of the loan process, the loan documents of three commercial banks have been examined and two IRM used by commercial banks in the Czech Republic have been analysed.

3. Results and Discussion

The results of investigating the role and significance of IRM in the lending policies of Czech and Slovak banks are represented in the Tables 2, 3 and 4.

First of all, the Table 2 shows to what extent the surveyed loan specialists know the weights of certain factors within the IRM of their banks. The aim was to find out if the IRM is a Black-box or not.

Tab. 2: The level of knowledge of the weights within the IRM by loan specialists.

Do the loan specialists in your bank know the weights of the factors within your rating model?	ČR	SR	Index ČR/SR
1. yes	0	4	0.000
2. no	9	6	1.500
3. I do not know	1	0	-

Source: own source

The H1 was confirmed. Our research has proved that less than 50% of loan specialists in the Czech and Slovak banking sector know the weights of single factors within the IRM used by their banks. According to the interviews with the loan specialists, the level of knowledge of the IRM parameters is low which confirmed our assumption that the inner part of the IRM is a Black box. The findings of our investigation imply these weights are a trade secret for each bank. Our next question to the loan specialists was if they find this approach correct in the relation to SME. Their opinion was clear: the potential knowledge of weights of criteria within the IRM could be abused by loan applicants.

Behr and Güttler (2007) state exactly the opposite. These authors see the solution in companies that understood banks' approach within the evaluation of creditworthiness and moreover they were able to evaluate their expected probability of default (PD) using a rating model. This fact could help firms to understand their position from the bank's point of view. This fact would also lead to providing necessary documents about themselves for better assessment of their creditworthiness and it would lead to the possibility of further negotiations between the bank and the company about credit conditions. According to authors, the knowledge of own PD allows to increase the transparency in the credit process as well as it allows potential use for searching of external funding sources. Providing SMEs have knowledge about their creditworthiness, they may affect management decisions in favour of new sources of external funding due to the expanding range of financing options. Our research has shown the average level of knowledge of the weights of criteria within the IRM was 43.89% in the Czech Republic and 48.12% in Slovakia.

In this context Ozdemir (2009) declare that the validation of IRM is not a backstage problem and is almost useless if it is aimed only at the technical tests of performance and its results fall mostly in the validation group. From the organisational and commercial reasons, rating models are frequently misused. To understand where the error occurred and how to fix it means for banks to ensure the connections between the validation staff and other employees, i.e. create the right mix of professionals in the validation group being able to communicate with the others in the banking jargon.

The optimal validation of IRM, besides the commonly defined requisitions, has to take into account the quality of the commercial relations as well as their organisation, management, relevant setting of the selling competencies and has to be supported by high level of banking staff qualifications (Speth, Šebo, and Kováč, 2010).

In the Table 3 we state the results of our investigation on the importance of the IRM in the loan process of banks.

Tab. 3: The IRM Importance in the Loan Process.

What weight do the results of the corporate client's rating have in the loan process of your bank?	CZ	SK	Index
1. Dominant – if a client fails in the rating, the loan would not be granted in any case	0	8	0.000
2. Substantial – if a client fails in the rating, the possibilities of granting a loan are extremely limited	8	2	4.000
3. Important – the client rating is considered as an important part of the loan process, but the quality of security instruments, quality of relationships with the customer or other factors may change the results of the rating	2	0	-
4. It has no weight	0	0	-
5. Other evaluation	0	0	-

Source: own source

The majority of the surveyed managers in the Czech Republic and Slovakia have confirmed the dominant or substantial position of IRM in the loan process, i.e. if a client fails the rating process, they will not be provided a loan at all or with considerable problems. We found out significant differences in the perception of the IRM importance between the Czech Republic and Slovakia. In details, the requirements of Slovak commercial banks seem to be stricter than the requirements of their Czech counterparts.

However, according to the discussions with Czech companies from the SME segment, the assessment of the employees of commercial banks is too optimistic. For instance, only 4% of Czech entrepreneurs and 2% of Slovak entrepreneurs included in our research stated the banks fully accept their financial needs. H2 was confirmed in Slovakia and was not confirmed in the Czech Republic.

We present the research results of the evaluation of IRM accuracy in the Table 4.

Tab. 4: Accuracy of the IRM Models Used.

How accurate are the internal models used at your bank?	CZ	SK	Index
1. 81% and more	4	7	0.571
2. from 70 to 80%	0	3	0.000
3. from 50 to 69%	0	0	-
4. less than 50%	0	0	-
5. I do not know	6	0	-
Average value in %	85*	82	-

Source: own source

*note: calculating the average value we used the level of 85% for the first interval

The most popular opinion among our respondents in the Czech Republic and Slovakia is that the IRM models used are very accurate as the majority of them evaluate their accuracy at the level of 80% or more. However, the results from the Czech Republic are skewed as the majority of the respondents could not evaluate this accuracy.

H3 was not confirmed. The average value of the IRM accuracy estimated by loan specialists was 85% in the Czech Republic and 82% in Slovakia. This hypothesis was reconfirmed by another question (Do the loan specialists of your bank define the rating model as excellent?). The Czech respondents stated yes in 50% of cases, no in 30% of cases and 20% could not answer. The results differed in Slovakia, where 30% stated yes and 70% declared no in this question. Consequently we assume the IRM used by commercial banks have certain weaknesses.

Another step in our research was to create our own IRM. The result of the process was the creation of IRM with the usage of the statistical method of QDA which successfully categorises firms with a success rate of more than 88 %. Although it is represented by a high success rate, this probability is not appropriate to assess the terminable ability of this model and therefore in the Table 5, type 1 and 2 error for a more precise analysis of the model can be found.

Type 1 error (known as alpha), is such an error where the company is assessed as the default company, but in fact it is a non-default company. Type 2 error (referred to as beta) is such an error, where the company is considered as a non-default model, but in fact it is the default company.

Tab. 5. Type 1 and 2 Error of the Own IRM.

	Non-default companies - 0	Default companies - 1
Non-default companies - 0	280	25
Default companies - 1	11	3

Source: own source

The created model correctly classified 280 from the sample of 319 companies, but it achieves a high type 1 error. Here are some discussions if this difference represents really a non-default company as shown the data from the year 2012. Because although it may not be a default company according to the banks´ IRM, its financial performance can be so bad that it has been correctly assigned as the default one by our model. Another possibility is that the model incorrectly assessed the financial health of the company. It can be assumed that the minimum of 20% of these companies are incorrectly assessed by this model.

The value of individual parameters for default and non-default companies is shown in the Table 6.

Tab. 6: The Average Values of Financial Indicators.

	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 source

We define the weaknesses of our model as follows: the IRM is created from a set of financial values, which includes only two previous years. The model does enter any long-term data, any business strategy, and any prospects for the future. Secondly, it is based on the definition of default as a bankrupt or liquidation of the company.

On the other hand, our model shows certain strengths. It is fully functional from a theoretical point of view; it is easily applicable which leads to an immediate decision about the company´s default and can be helpful in quantitative decision making. Secondly, it achieves high theoretical prediction capabilities. Moreover, this IRM takes into account the update of data which is user-friendly and finally, it represents a way to reduce costs associated with rating systems management.

Afterwards, the created model was verified on the real economic data from the Czech business environment. To do so, the professional database of companies, Albertina, was used. The results of this verification are the object of the Table 7.

Tab. 7. The Results of Own IRM Verification Test.

	Non- default companies - 0	Default companies - 1
The original data set	0	101
The probability of appearance in the population	0 %	100 %
Missing data loss		64
The final number of companies tested in the model		37
Model validation		
Default companies - 1	**23**	**14**
The real data classification accuracy		37,84 %

Source: own source

The H4 was confirmed. The verification of the model showed that our model was able to correctly evaluate as default ones only 14 of 37 of such companies. The accuracy of the model is thus only 37.84%.

The IRM used by commercial banks have a variety of limits. Tőzsér (2010) states that in the context of the world financial and economic crisis, the criticism of risk management models continually resounds in academic circles. The stable operation of financial systems then represents, if not impossible, at least a very complex matter. This is due to the imperfection of the current risk measurement models which give very unreliable results. In these days, the vastly increased application of the statistical models to measure and predict the risk even itself contributes to the growth of endogenous risk of the system. These statistical models promote pro-cyclical changes in financial leverage of banks, thereby contributing to pro-cyclical tendencies of the entire financial system.

The models for credit risk management are therefore largely pro-cyclical (Mileris, 2012) which means that these models are usually very mild in the good times and in the worst period of the economic cycle, they are too hard. As a result, they may paradoxically worsen the development in the banking sector.

Besides, credit risk management models represent an effort to accurately define the complex economic processes through mathematical or statistical models. These models, despite their highly sophisticated approaches, tend to fail and cannot accurately show the complexity of the economic system, which is determined by some significant non-quantifiable variables (attitudes, expectations, preferences of individual economic entities, etc.). (Belás, 2013) We can say that it was justified that with the use of statistical methods it is not possible to create an indicator that produces a general forecast relevant to enterprises in the SME sector. (Szeverin and Koloszár, 2014)

Mitchell and Van Roy (2007) reported that 20% of companies that had been evaluated by different models had vastly different ratings. One model assessed them as bad clients while another model assessed them as good clients. The results of our previous research confirmed that our model had failed to assess the financial health of a company properly. Comparing the resolution of the model and the real data on the default of the tested companies, it was found out that our model had wrongly evaluated more than 20 % of the companies in the SME segment. (Belás, Cipovová, 2013)

Szeverin and Koloszár (2014) declare the complex statistical solutions will not surely reach the aims of an accurate evaluation of the financial health of a company themselves. There is a need for an experienced expert´s competence.

The above mentioned facts point to the need of an appropriate use of IRM in commercial bank lending process because the bank can lose a significant amount of revenue due to a missing credit given to a good client (Type I error).

While in case of a Type II error the bank may compensate the loss of income by realizing some kind of hedging, in the event of an error of the first kind the loss of income is a non-recoverable one.

In this context, it is necessary to define a comprehensive approach to credit risk management of the client, which is based on the creation of an approach that will ensure a fair and effective assessment of the possibilities, abilities and willingness of a client to return the borrowed money to the bank in the agreed mode.

Our theoretical contribution is that it is necessary to incorporate Negotiation procedure I and Negotiation procedure II to a standard loan process (Figure 1).

In case of a negative outcome of the preliminary rating of the client, it is proposed to apply Negotiation procedure I under which the bank should obtain information to verify or modify the results of the preliminary rating. If this procedure ends up in a negative result, the loan process will be ended. If the result is positive, the bank continues in the lending process. The proposed process should allow the removal or abrasion of the sharp edges of the rating process in the context of defined limits and limitations of quantitative rating and incorporate in the loan process positive personal characteristics of the owners of the company or positive historical experience with this firm.

In case of a negative result of the analysis, it is suggested to hold Negotiation procedure II. The financial analysis should be seen also as one of the processes that can help quality credit decisions, but its results do not guarantee anything (successful development of the company in the past does not automatically mean a successful future).

In this context, Pavelková and Knápková (2005) define several weaknesses of a financial analysis. The financial analysis provides important and useful information about the company management. Nevertheless, it represents various limitations as an analytical method what requires a special attention and common sense of the analysts working with it. The most problematic matter is the relevance and informative power of financial statements. The internationally most recognised accounting principle is to create a reliable image of the reality. Despite all the efforts to complete this requisite, it is necessary to admit some limitations of creating this reliable image. The most significant are historical orientation of accounting and inflation influences. The historical accounting does not take into account the price changes of the assets in the market, ignores the cash unit purchasing power changes and thus skews the earnings of the accounting period. Secondly, the solid differences in the accounting methods and thus problems to obtain comparable companies for the benchmarking are other obstacles of the objective results of a financial analysis.

Moreover, even more serious could be the deliberate editing of the financial statements mostly because of the so called tax optimisation. Besides the optimisation within the existing rules, there can be also examples of such an editing which goes far behind law (effort to pay lower taxes, to influence investors in financial markets etc.). The common practice in the banking sector is that a company realises a tax optimisation and afterwards it hands in a credit application. Having problems to get a loan, it often admits it has edited the financial results deliberately. Such situation significantly complicates the correct evaluation of the company´s creditworthiness.

In case of negative or inconclusive results, a bank’s analyst must consider the significant determinants of the financial analysis in the context of credit risk. Let´s assume a company reports an annual decrease in sales, but also achieves higher profit compared to the previous period. Does it mean that the company is deteriorated or is it in danger of a collapse? Or does the company sell products or services with a higher added value or significantly streamline its operations? A similar situation may occur in the area of corporate assets, inventories, receivables and equity. The situation has to be treated differently if the company retains a high proportion of the profit to the equity each year and if the company distributes annually neither achieved profit nor retained earnings. If the company’s equity is growing despite the losses, what could this mean? Is it an attempt to save the company, do the owners invest into the company increasingly larger amount of capital or are there any speculative reasons?

The process of the financial analysis, despite its primary exact character, requires a certain amount of imagination, professional knowledge and experience of this process from the side of a credit analyst. For example, the same numbers may lead to the different results or indicators of profitability if a company is subjectively biased by the massive tax optimization. Paradoxically, if the business grows too quickly, the risk of growth management grows too. The company could face the problems to handle the enormous personnel, managerial, capacity or logistical growth in relation to management of customers, or in the area of complaints. Consequently, there are numerous factors that need to be considered in an assessment of the future financial health of a company.

4. Conclusion

The aim of this article was, on the basis of an analysis of importance and position of IRM in the credit risk management in the SME segment, to define the possibilities to improve the loan process in the mentioned segment which would appropriately react to the financial needs of SME and evaluate correctly their creditworthiness.

The theoretical analysis and the practical verification of the quality of the internal rating models developed by us have shown that these models are of limited quality and introduce a range of open problems.

The credit rating models are important for commercial banks, but they should not have a function of a credit machine because they fail when using insensitively or may not respond flexibly to complex business processes and the specifics of the business environment. As a result, the bank is losing its sales opportunities and the companies do not have enough money for their own development.

Due to this reason we have introduced an upgraded model of the lending process in the SME segment, which should bring an optimisation of the credit decisions, a reasonable degree of the efficiency of the lending practices through the quantification and an optimisation of operating costs in the context of an individual approach to SMEs. It is assumed that at least 20 % of companies have been incorrectly assessed by the IRM model, which means that with the proper use of our methodology in the loan process, the bank can give out significant amounts of safe loans.

Our theoretical contribution is to incorporate two new processes to the standard loan procedure: Negotiation procedure I and Negotiation procedure II. These procedures would ensure the correct interpretation of the economic performance of SMEs and remove the information asymmetries in the credit process as the bank would be able to understand the client's credit quality at a substantially higher level.

In the next phase of our research we would like to focus on the quantification of the effects of our model on the financial performance of commercial banks.

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