The study of risk determinants and the impact on enterprise value Credit risk for Romanian SMEs

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ABSTRACT

The purpose of this paper is to study the determinants of credit risk for Romania SMEs and their impact on value. The first reason behind the choice of this theme was that SMEs are an important component of the development of any economy, named *the blood of the economy*. The second reason was that in terms of credit risk SMEs are different from large corporations, are riskier taking any financial impact on the market. We used a sample of listed companies that were financially healthy and insolvent enterprises. The sample was comprised of 903 enterprises which had turnover of 50 million Euros maximum accepted for SMEs and the time horizon is 5 years from 2010 to 2014.

In the first part we made an overview of the existing models for credit risk, indicators that can measure the value of the company and the determinants of credit risk identified in the literature.

In the second part of the paper we showed qualitative factors and quantitative, the analysis techniques used for work, reminiscent here of principal component analysis to identify gross credit risk factors, stepwise logistic regression and finally a simple regression to study the relationship between factors and enterprise value. We also explained the nature of data and the training model database.

In the third part we combined data from the first two parts, with two directions: one for qualitative and quantitative data.

So we made two prediction models, the first model referring to a year before the event. Determinants of credit risk were EBITmargin, Liquidity ratio, DTS_CapProp (leverage1) EBITDA_ChD. These factors were statistically significant and respected the influence of recommended literature. The regression model was built on the strength of their global forecast 89.3%. The majority of the factors, apart from EBITDA_ChD have revealed that influence the value of the company. For the second model - five years before the event I followed the same steps and had resulted as drivers EBITmargin, Currentratio, CA_AT, LogcCA and DT_CapProp or leverage2. Its power was 81.9%. The models were validated afford that these factors may also apply to other companies that were not part of the database, the percentage is even greater determination towards development models.

As can be seen from the factors influencing the specific credit risk of Romania SMEs, these factors are part of the most important groups of factors: liquidity, profitability, solvency activity, but the degrees of influence differs from studies conducted in other countries.

JEL codes: G17, G21, G32, G33

Key words: credit risk, Tobin's q, SME, prediction model, principal component analysis

INTRODUCTION

The risk is the cornerstone of most influences on financial behavior any undertaking. With increasing globalization, diversity and complexity of the activities of businesses, attention is channeled to risk management that impacts the enterprise and not least on its value. Then identifying and managing risk factors is of great importance especially after the economic and financial crisis which was based on poor management of corporate loans.

The theme of this work is to study the determinants of credit risk for SMEs in Romania and their impact on value. The first reason behind the choice of this theme was that SMEs are an important component of the development of any economy, is called blood of the economy. The second reason was that in terms of credit risk of SMEs differ from large corporations, are riskier taking any financial impact on the market. Finally, addressing this issue is a challenge to future research that seeks to find viable solutions to the problems and competent Romanian enterprises. The importance of credit risk, knowing and understanding the determinants is a topical issue of great pragmatism.

Thus to achieve the objectives we had three research plans:

- establishing credit risk factors specific to SMEs
- developing the credit risk forecast model
- identify factors and study the impact on the firm value

In order to identify credit risk factors, creating a predictive model of credit risk and ultimately study the impact of credit risk factors on the value of Romania SMEs , we used a sample of listed companies that were healthy in terms of financial and business insolvency. The sample was comprised of 903 enterprises which had a maximum turnover accepted for SMEs of 50 million Euros, analyzed time horizon being 5 years starting with 2010 up to 2014.

The steps we have pursued during the three research plans were: compiling a comprehensive database; Descriptive-comparative analysis of the main financial indicators of firms,identifying and structuring factors determined based on the analysis of significance tests; econometric analysis of the determinants, creating statistical models based on factors identified; validation of models; studying the impact of credit risk factors on the value of the compan

Starting from the three lines of research, the work comprises four sections. The first section is structured and reconstituted originated credit risk, presented some of the literature, one that led to the research, being mentioned the most important studies on credit risk, factors to measure the enterprise value. The second section is found behind the methodology of determining factors, indicators are presented and forecast models, techniques used. The third section contains the database and the manner of its construction. In the last section combines the previous sections, the results of the study, formulating interpretations and conclusions are realistic.

In conclusion, in this study we wanted to identify the specific determinants of credit risk of Romania SMEs. After setting these factors, I made two prediction models (for one year and five years) credit risk through stepwise logistic regression. Subsequently we compared the two periods to see if selected factors are relevant for the two periods considered. Finally based on specific credit risk factors identified have studied the relationship between them and value companies.

LITERATURE REVIEW

SMEs and credit risk in the literature

SMEs have become an important component of any economy, is appointed by the European Commission (2011) "blood of the economy. Thus SMEs are considered the engine of the economy due to relatively simple structure, the enterprise can respond rapidly to these changes in economic conditions, but they differ from country to country (Altman, Sabato (2007))[1] . SMEs are carcaterizate by the number of employees, the level of sales, total net assets. In the European Union SMEs are classified as enterprises with fewer than 250 employees and annual turnover of less than EUR 50 million, as stated by Altman et al (2007). But it must be borne in mind that these companies are characterized by a financial gap because many have limited access to external financing sources.

Dierkes et al. (2013) [2]revealed that most SMEs are smaller, rikier and more dependent on bank loans and these companies have less cash flow internally to fund their activities and also faces a high information asymmetry. Neuberg & Rathke (2009)[3] analyzed SMEs financing and concluded that these enterprises are characterized by moral hazard, and this because their access to finance is limited. So SMEs are characterized by information asymmetry and credit risk.

In terms of credit risk, SMEs are different from large corporations in this regard Dietsch and Petey (2004) [4] analyzed a set of SMEs in Germany and France. They concluded that SMEs are riskier than large companies and because of this credit risk factors affecting different. SMEs are dependent on credit, have few ways to finance and, also have low credit ratings. These companies are sensitive to changes in the economic climate, and in this case these companies must be specific models for identifying credit risk

The first study took into account credit risk modeling for SMEs was conducted by Edmister (1972)[5] . He analyzed 19 financial ratios in the period from 1954 to 1969 and multivariate discriminant analysis was used to predict credit risk with regard to small companies. Despite the importance of this segment to the economy, credit risk analysis was not until the introduction studiatat towards Basel rules (Claessens et al., 2005) [6]. Recently, this topic is enjoying a growing interest high (historical and cultural reasons are debated by Claessens et al., 2005). Berger & Frame (2005) [7] analyzed the effects on credit scoring. They analyzed companies with turnover of up to 250,000 euros showing that banks that use credit scoring in the decision increased loans in this segment. Also they sublinitt that SMEs are more risky than large corporations because of

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1 Altman, EI, & Sabato, G. (2007) Credit Risk Modelling for SMEs: Evidence from the US Market. ABACUS: A journal of accounting, finance and business studies, Volume 43, Issue 3, 332-357

2 M. Dierkes, Carsten E., T. Langer, L. Norden (2013), Business information credit and default risk of private sparing Firms. Journal of Banking & Finance 37: 2867-2878

3 Nueberger D. Rathke S. (2009), Microenterproses and multiple Relationships: The case of professionals. Small Business Economics, 32: 207-229

4 Dietsch, Joel Michel and Petey (2004), SME Exposures Shoud BE as Treated as Retail or Corporate Exposures? A Comparative Analysis of Default Probabilities and Asset Correlation in French and German SMEs, Journal of Banking and Finance 28

5 Edmister, R., (1972) "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction", Journal of Financial and Quantitative Analysis

6 S. Claessens, Krahnen J. and Lang WW (2005), The Basel II Reform and Retail Credit Markets, Journal of Financial Services Research, vol. 28, pp. 5-13.

7 AN Berger, Frame NH WS and Miller (2005), Credit Scoring and the Availability, Price, Credit and Risk of Small Business, Journal of Money, Credit and Banking, vol. 37 n. 2, pp. 191-222.

this and banks need to develop credit risk models specifically focused on SMEs in order to minimize the expected loss and the unexpected.

It's quite difficult to draw a fine line between traditional and new approaches in terms of credit risk as many of the good ideas from traditional models are used in new models. There are four groups of models that combine traditional approaches: expert systems, neural networks, rating system and credit scoring system.

Univariate model has a predictive calculation for a single variable (Babbie 2010) [8] . A drawback of this model is that it does not provide an overview of the situation. The first prediction model was used for the study was conducted by default and Beaver (1966) [9] . He analyzed the financial ratios on a five-year utilizatnd 79 bankrupt firms with 79 companies financially healthy. The Beaver highlighted the role of analytical indicator as a useful tool in predicting a company's problems, showing a list of indicators in the first analysis involved in prediction techniques. Beaver obtained conclusive results for a period of up to five years before actual insolvency through a univariate analysis or one-dimensional indicators being analyzed in isolation, without taking into account the links between them.

The multivariate model uses statistical techniques to use all the multiple variables (Hair et all (2007)) [10] . From multivariate pattern analysis is the discrimination whereby analyst performs a grouping variables. (Fujikoshi,Ulyanov & Shimizu, 2010) [11] . Anliza multivariate discriminant (MDA) Technical unites the multivariate discriminant analysis.

The logistic regression is a further embodiment of MDA. The regressions using several independent variables to predict a dependent variable non-metric. A variable that can have a discrete value called non-metric statistics, unlike the variable metric values spread within.

Methods for establishing the value of the company

Given the economic climate and the many problems of default (credit risk) with which companies faced was raised as a company's value can be measured in the most objective way. This represents a challenge and a concern for managers to financial analysts, but not least for investors. The literature emphasizes that there is no single indicator by which to measure the value of the company, considering performance, internal and external factors differ.

The value of a company can be determined by five methods: book value (book) value, market value (market value), the amount capitalized (capitalized value), deductive analysis (deductive Judgment) and adjusted net (Adjusted net worth). By these methods still achieving the company, but the result is different depending on the method chosen. (Thorell, 1997) [12]

The first and easiest method is applied or adjusted net book values. But this method may use different accounting rules (Goosen, Jensen & Welles, 1999) [13], and some generally accepted accounting principles, such as historical cost, can lead to values that are far from reality. There

[8] Babbie, ER (2010). The Practice of Social Research. Wadsworth: Cengage Learning

[9] Beaver WH (1996). Financial Ratios as predictors of Failure .. Journal of Accounting Research, 4 (3), 71-111

[10] F.Hair, J., Black, B. Babin, B., Anderson, RE, & Tatham, RL (2007). Multivariate Data Analysis, 6th Edition. Delhi: Pearson Education India

[11] Fujikoshi, Y., Ulyanov, VV, & Shimizu, R. (2010). Multivariate Statistics: High-Dimensional and Large-Sample Approximations. New Jersey: John Wiley & Sons

[12] Thorell, HB (1997). Musings on business performance Evaluations game. Developments in Business Simulation & Experiential Learning, 24, 12-18

[13] Goosen, KR, Jensen, R., & Wells, R. (1999). Purpose and learning benefits of business Simulations: A design and development perspectives Developments in Business Simulation & Experiential Learning, 26, 133-145.

are several parameters through which one can determine the value of a company using this method. Of these the best known is the EVA (value added).
The second method is the market value, this being the most common method in the evaluation of listed companies. There are a number of economic indicators that measure the value of a company, of which MVA (market value added) is the most used. Stewart (1991) [14] MVA defined as the excess capital in market values (both debt and equity) on the carrying amount of capital. If MVA is positive highlights that the company has created value for shareholders.

A third method is the capitalized value of future performance. Modigliani and Miller (1961)[15] showed four methods used to value capitalized and all four methods estimate the same value of the company when markets are perfect, people are rational, and the future is uncertain.
The fourth approach is the deductive. By this method, companies get a score of over a scale, then converts the result is a formula in money. This method creates an index of the performance of companies by combining the values of the accounting market. Since this method is Tobin q index representing the amount of capital relative to replacement cost (Tobin, 1971) [16] . Q is calculated as the actual amount of the company's value and total liabilities divided by total assets (representing replacement cost.

METHODOLOGY AND DATA BASE

The set of factors was determined based on the economic-financial indicators found in the literature of credit risk.

Based on the specific literature we constructed in the first phase rates regarding assets and liabilities structure, as these rates are a reflection of the company's financial info and they can be an alarm signal regarding default risk. The next step was to calculate different rates which are sorted into 7 groups: liquidity, solvency, profitability, activity, performance, quality and macro.

Thus, in Table 3.1 of the Annex are highlighted the 46 factors that were the basis for analysis.

Working method

From a methodological point of view, in order to quantify the level of influence of the above mentioned factors on credit risk and then study the impact on Tobin's q (the measure of firm value) and to highlight the causal links between specific methods I have applied specific methods regarding *qualitative analysis* – grouping, comparison in time and space, modeling using sector diagrams and bar charts and *quantitative analysis*- data homogeneity analysis, principal components analysis, stepwise logistic regression analysis, linear regression and ROC curve analysis.

Nature and source of data and selection of companies

In order to identify credit risk factors, create a credit risk prediction model and ultimately study the impact of credit risk factors on the value of romanian SMEs, we used a sample of listed companies that were healthy in financial terms and insolvent companies. Companies were selected using the Amadeus platform, collecting data from the balance sheets, profit and loss accounts, and also variables related to price and number of shares.

[14] Stewart, GB, 1991 The Quest for Value, New York: Harper
[15] Miller, MH, & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. Journal of Business, 34, 411-433

Selected companies were different in terms of size, sector of activity and age, what should be noted is that enterprises younger than 5 years (2010-2014) were not selected due to the fact the financial data for these companies would not have been available. All rates were expressed as a percentage, except for those relating to period and some qualitative factors, in order to have an overview, as recommended by the specific literature.

This sample is composed of 903 companies with different business sizes and sectors. In terms of size, considering that the analysis is focused on SMEs, we selected companies that had the 2014 turnover (the last time analysis) less than 50 million, this threshold being the maximum acceptable to classifiy a company as an SMEs. Out of the 903 selected enterprises, 796 are active and 107 are insolvent. They were sorted in two groups, constructing a dummy function, which received value 0 for the active companies and 1 for companies in insolvency.

RESULTS

Qualitative analysis database

Companies from the database were part of different business areas, and in order to facilitate the analysis method we created four large industrial groups: group 1, includes enterprises which activate in production, Group 2: comprises enterprises that have a retail activity, group 3: core business services, and group 4: wholesale. In the figure below (Figure 4.2) we plotted these four sectors with the number of businesses related default risk (1-insolvent firm, healthy-firm 0)

The credit risk forecast for SMEs - 1 year model

To determine credit risk factors for SMEs in Romania as mentioned in the methodology we have considered a number of 47 factors grouped in structure, liquidity, solvency, profitability, activity, performance and qualitative factors. The chosen factors are those that are found in the literature, but in order to determine specific factors of SMEs in Romania, we have applied several procedures in order to reduce the high number of factors.

In the first phase we identified variables with values significantly different between the two types of companies. With the help of Levene test and Anova we have reduced the number of variables.

Based on the variables identified using ANOVA we want to identify the determinants of credit risk one year before. First I investigated the presence of multicolinearity because in the presence of multicolinearity it is almost impossible to determine the real contribution and effect of each factor. In order to study multicolinearity I applied two tests (Kaiser-Meyer-Olkin, Bartlett's Test) (Table 4.1) to identify how sustainable are the variables in developing a model. Based on these test we can see that the analyzed factors are significant and factor analysis can be used.

The first specific information for the factor analysis is provided by *The total variance explained.* (Table 4.2) Using ACP method, before the extraction there have been generated 15 main components (indicators), the same as the number of variables introduced. By applying the calculation program, I requested extraction after the first rotation for eigenvalues greater than 1. As it can be seen, only the first six indicators meet the selection criteria (eigenvalues ≥1). Variances summed up for the 6 components (columns *Extraction Sums of Squared loadings)*explains 75.521% of the value of the analyzed variance. It is visible that the first factor has the greatest predictive power of 25.634%. The 6 identified components contain the factors that will be used in the credit risk forecast model. *Rotation Sums of Squared loadings* column presents the values of the 6 factors after the rotation procedure. Rotation is intended to optimize the structure of the factors. In the context of the same total variance (75.521%), we can observe a redistribution of variance explained by each indicator:through the rotation method the first three indicators lose saturation level in favor of the last three factors. Based on Table 4.3 rotation matrix components we have identified the 6 factors resulted after components analysis and their determinant factors *EBITmargin* (.911) and *Profitmargin* (0.910) for the first, the second component is explained by *Currentration* (.933) and *Liquidity ratio* (.926) which represent a part of the liquidity indicators, the third component is explained by *Leverage1 (DTS_CapProp)* (.998) and *Leverage2 (DT_CapProp)* (.998) solvency indicators, and the fourth component retains in analysis *receivables turnover (, 824) and EBITDA_Chd (.817)* activity indicators, the fifth component being explained by *log_CA (company size)* (.806) and the sixth component being explained by *Book value per share* (.711) performance indicator.

Stepwise logistic regression uses step-by-step automatic procedures starting with the selection of the strongest predictor, followed by the addition of other significant factors and removal of those that do not have impact on credit risk. The end of the analysis is summarized in Table 4.4 , where the determinants of credit risk are presented.

According to the estimated model, the β coefficients and corresponding values for the ratio of the chances of each independent variable to intervene in the evolution of the dependent variable when it changes by one unit (column *Exp (B) Table.),* one year prior to the event it can be observed that all variables included in the model are statistically significant (sig <0.005). Column B identifies coefficients (beta coefficients) associated with each predictor. Thus:

- *EBITmarg (β* = -0.224) is a variable which is part of profitability factors group and is inversely related with credit risk (PD) regarding listed romanian SMEs. This factor is a measure of profitability and a high the value can reflect better and more efficient cost management that can lead to a decrease in default risk . In other words , the chances for EBIT_marg to determine credit risk are 0.799 (e = $^{-0.224;}$ Table 4) because for every increase in this factor the chance that the company may face default risk decreases from 1 to 0.799.This is consistent with literature that states that between profitability and credit risk exists an inverse relationship (Ford, 1997). According to this relationship profitable firms are less exposed to default and distressed companies are more sensitive to the availability of internal funds represented by profit (Liu (2004), Pagliacci (2006) [18])

- *Liquid or low liquidity ratio (β* = -0.066) this factor is part of the liquidity factors being inversely related with credit risk. The chances for reduced liquidity ratio to determine credit risk are 0.066, for each point increase of this factor the chances for a company to face credit risk decreases from 1 to 0.859. Thus, such an increase in reduced liquidity leads to a decrease in the risk of bankruptcy, this being in conjunction with short-term debt, emphasizing that firms can fulfill their short-term obligations. This emphasizes the fact that when a company is no longer able to produce liquidity it has low reserves . The result is as expected, due to the fact that default risk of companies is determined by the speed with which they are able to generate liquidity. A similar result is presented by Altman (2005) who found a negative relationship between liquidity and probability of default.

- *DTS_CapProp (leverage1) (β* = 0.124) is a part of the the solvency indicators factors and has sign (+) indicating a positive correlation between this indicator and default risk. If the leverage increases by one unit then the likelihood of default risk increases from 1 to 1.132 (e

= 0.124; Table 4), credit risk increasing with approximately 13%. For Romanian SME's the increase is more pronounced than in the case of US companies as demonstrated by Ericsson, Jacobs & Oviedo (2005) [19] which showed that a 1% increase in the rate of financial leverage lead to a growth of 5-10% of the risk of default. This result is consistent with the one obtained by Westgaard and Wjit (2001) [20], Altman (2005) who also found a positive and statistically significant relationship between financial leverage and default risk. Most studies show that the level of financial leverage is directly related to enterprise value and the probability of default.

- *EBITDA_ChD (β =* -0.138) belongs to the activity indicators , its purpose being to measure the interes coverage strength. As you can see there is an inverse relationship between this factor and the risk of default. Such an increase in this factor leads to a decrease in credit risk from 1 to 0.871 or in other words a 1 percentage increase in the interest coverage power leads to a decrease in credit risk by about 12% for Romanian SME's. This level of influence is consistent with the literature. (Francesco et.al, 2013) [21] .

The study of credit risk determinants and the impact on company value- 1 year model

The company's value was measured by Tobin's Q rate as this indicator is used to explain the relationship between company capital and its overall value, and also to quanitify the relationship between management performance and investment opportunities (Chung and Pruitt, 1994). [22] This indicator is used as a proxy to measure the value of a company from an investment perspective, being the most appropriate indicator to measure the value of a company (Wernerfelt & Montgomery, 1988) [23] .The base being made up of listed SMEs, choosing this rate is justified. By definition, it is a rate between the market value of a company's assets and their replacement value.

Thus in the first phase we studied the link between the company and *PD* through simple linear regression. (Table 4.5) revealed that between enterprise value and probability of default exists an inverse relationship. Thus the literature reveals that between the probability of default and the value of Tobin's Q there is an inverse relationship as investors perceive the company as as one that does not have enough capacity to develop. (Fazzari et.al) [24] . Thus the first determinant of credit risk is a factor of profitability *EBITmargin (table 4.6)*. As you can see, there is a direct relationship between profitability and company value. The second factor is *liquidity* . As it can be seen between liquidity and value of SMEs there is a positive statistically significant relationship according to Table 4.7 Model Summary from the appendix. Companies with higher liquidity could support a relatively higher debt ratio due to higher capacity to meet short-term obligations when due. The third factor is *DTS_CapProp (leverage1)* . We can observes that between this factor and enterprise value there is a direct and statistically significant relationship, this being consistent with the theory of signal (see table 4.8 Summary Model of the Appendix). Thus, companies that issue debt send a positive signal to investors, because only companies that use debt to finance its assets are enterprises with large financial performance and future development opportunities (Rayan, 2008). [25]

The credit risk forecast model for SMEs - 5 year model

The second research was intended to determine credit risk factors for SMEs in Romania within 5 years before the event. We used the same procedure, and after principal component analysis yielded seven components: -first component is best explained by *EBITmargin* (.902) and *Profitmargin* (0.890, second is explained by *Currentration* (.951) and *Lichidity ratio*(.943), part of the liquidity factors, the third component is explained by *Leverage1 (DTS_CapProp)* (.997) and *Leverage2 (DT_CapProp)* (.997) solvency factors, fourth component is explained by Analysis *CA_AT* (.906) and *credit period* (.886) activity indicators. The factors are different from those identified for the first model, the fifth component being explained by *log_CA (company size)* (.806) and Board (0.606) qualitative factors, the sixth component is explained by *Working capital per share*(.568) performance factors and the seventh component is explained by *RcapProp* (0735) structural factors. Following the stepwise logistic regression the following equation results (Table 4.10 Annex):

- *EBITmarg* (β = -0.033) which is a variable part of the profitability factors implies that a higher the value of this factor reflects better and more efficient management of costs that leads to a decrease in default risk, being inversely related to credit risk (PD) for the case of listed Romanian SMEs.

- *Currentratio or general liquidity ratio* (β = -0.102) is a liquidity factor. Compared to the first model in which the reduced liquidty ratio resulted, in this model which included a larger time period,the results suggested that credit risk takes into consideration the general liquidity ratio of SME and not the short term one. The higher overall liquidity an enterprise has, the chances that it will face default risk decreases from 1 to 0.903

- *CA_AT or sales turnover* (β = -0.092) activity factor aims to measure business activity, and the ability of the management to cope in a competitive market. It emphasizes how a company generates income through the sales they make. Thus this factor is inversely related to credit risk, as confirmed by the literature. (Altman et.al, 2007)

- *LogCA or company size* (β = -0.236) is a qualitative factor that is inversely related credit risk. If SMEs if the size of these increases the chances that undertaking to enter into involvenţă decrease from 1-0790. This influence is confirmed by the literature. Most studies reveals an inverse relationship between company size and probability of default: the enterprise is bigger probability of default is low because it has the necessary financial and human resources to cope with shocks. Larger firms tend to be more diversified, so have a lower probability of default. SMEs larger can use their influence on financial markets and the product market. (Westgaard and Wijst 2001).

- *DT_CapProp or leverage2 (β = 0.021)* is a solvency factor. Compared to the first model which resulted DTS_CapProp, within this model which accounts for a longer period of time, the long term liabilities seem to have an impact on credit risk and not those due within one year. This result was expected. It can also be noted that between this factor and credit risk there is no direct relationship.

Regarding the impact on company value of all factors except for sales turnover had an impact on enterprises.

CONCLUSIONS AND PROPOSALS

The aim of this study was to establish the determinants of credit risk for Romanian SMEs, the development of prediction models based on determinants, and finally to study the impact of these factors on enterprise value. I have chosen SMEs primarily due to the fact that they have become an important component of the development of the Romanian economy, their number increasing on a monthly basis and secondly due to the difference between large corporations and this segment that requested for an identification of the specific factors and particular credit risk models for SMEs.

Credit risk determinants were EBITmargin, Liquidity ratio, DTS_CapProp (leverage1) EBITDA_ChD. These factors were statistically significant and respected the relationship suggested by the literature. The regression model built on their basis had a global prediction power of 89.3%. All of the factors, apart from EBITDA_ChD have revealed their influence on company value. For the second model - five years before the event I followed the same steps, the only difference being the determinant factors EBITmargin, Currentratio, CA_AT, Logcat and DT_CapProp or leverage2. The prediction power of this model was 81.9%

In future research, I propose to conduct a comparative analysis between Romania and another country in order to include macroeconomic factors because the macroeconomic environment and the conditions arising from it have an impact not only on credit risk and on the financial decisions that it implies. The inclusion of the macroeconomic factors in models induce an increase in the forecast power and accuracy of models. Also, I consider as being important in the prediction of credit risk also the inclusion of bank behavioral and psychological factors, because, inevitably, they have a big impact on business, decisions being taken ultimately by people. Also the usage of statistical models interconnected with financial analysis and accounting could set a new research direction.

References:

[1] Altman, EI, & Sabato, G. (2007) Credit Risk Modelling for SMEs: Evidence from the US Market. ABACUS: A journal of accounting, finance and business studies, Volume 43, Issue 3, 332-357

[2] M. Dierkes, Carsten E., T. Langer, L. Norden (2013), Business intormation credit and default risk of private sparing Firms. Journal of Banking & Finance 37: 2867-2878

[3] Nueberger D. Rathke S. (2009), Microenterproses and multiple Relationships: The case of professionals. Small Business Economics, 32: 207-229

[4] Dietsch, Joel Michel and Petey (2004), SME Exposures Shoud BE as Treated as Retail or Corporate Exposures? A Comparative Analysis of Default Probabilities and Asset Correlation in French and German SMEs, Journal of Banking and Finance 28

[5] Edmister, R., (1972) "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction", Journal of Financial and Quantitative Analysis

[6] S. Claessens, Krahnen J. and Lang WW (2005), The Basel II Reform and Retail Credit Markets, Journal of Financial Services Research, vol. 28, pp. 5-13.

[7] AN Berger, Frame NH WS and Miller (2005), Credit Scoring and the Availability, Price, Credit and Risk of Small Business, Journal of Money, Credit and Banking, vol. 37 n. 2, pp. 191-222.

[8] Babbie, ER (2010). The Practice of Social Research. Wadsworth: Cengage Learning

[9] Beaver WH (1996). Financial Ratios as predictors of Failure .. Journal of Accounting Research, 4 (3), 71-111

[10] F.Hair, J., Black, B. Babin, B., Anderson, RE, & Tatham, RL (2007). Multivariate Data Analysis, 6th Edition. Delhi: Pearson Education India

[11] Fujikoshi, Y., Ulyanov, VV, & Shimizu, R. (2010). Multivariate Statistics: High-Dimensional and Large-Sample Approximations. New Jersey: John Wiley & Sons

[12] Thorell, HB (1997). Musings on business performance Evaluations game. Developments in Business Simulation & Experiential Learning, 24, 12-18

[13] Goosen, KR, Jensen, R., & Wells, R. (1999). Purpose and learning benefits of business Simulations: A design and development perspectives Developments in Business Simulation & Experiential Learning, 26, 133-145.
[14] Stewart, GB, 1991 The Quest for Value, New York: Harper
[15] Miller, MH, & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. Journal of Business, 34, 411-433
[16] Tobin, J. (1971). A general equilibrium approach to monetary theory. In J. Tobin (Ed.), Essays in Economics: Macroeconomics, 1, (pp. 322-338). Chicago
[17] Dragotă, V., Dragotă, M., Obreja, L., Ciobanu, A., tattooed, L. (2007), Practical Approaches company finances, Bucharest: Irecson.
[18] Pagliacci M. (2006), "SME's and Basel 2 Challenge", Theoretical and Applied Economics, vol. 3, pp. 7-10.
[19] Ericsson, J., Jacobs, K. and Oviedo, R. (2005), The Determinants of Credit Default Swap Premia, Working Paper, Faculty of Management, McGill University
[20] Westgaard, S., Wijst, N. (2001), Default probabilities in the corporate bank portfolio: A logistic model approach, European Journal of Operational Research, 135, 338-349
[21] Francesco, D., Francesco, G., Fabrizio C. (2013), Deteriminans of SME credit worthiness under Basel rules: the value of credit history information, PSL Quarterly Review, vol. 66 n. 264 (2013) 21-47
22 Chung, KH, & Pruitt, SW (1994) A simple approximation of Tobin's q. Financial Management, 23 (3): 70-74
[23] Wernerfelt, and Cynthia A. Montgomery Briger; Tobin ' sq and the Importance of focus in firm performance; The American Economic Review; Vol. 78 (1); March 1988; pp. 246-250
[24] Fazzari, SM, Hubbard, RG (1998), Financing constraints and corporate investment. Brookings pappers on Economic Activity, 88 (1), 141-95
[25] Rayan, K. (2008), Financial leverage and firm value, Gordon Institute of Business Science, University of Pretoria.

Tabelul 3.1

FACTORI	Denumire
Structură	Rata active imobilizate, Rata active necorporale,Rata active corporale,Rata active circulante,Rata creanțe, Rata creanțe, Rata capitalurilor proprii, Rata datorii pe termn lung, Rata datorii termen scurt, Rata împrumut
Lichiditate	Cash ratio (Rata lichiditatii imediate), Liquidity ratio (Rata lichiditatii reduse),Shareholders liquidity ratio(Rata lichiditatii curente), Current ratio(Rata lichiditatii generale)
Solvabilitate	Leverage 1, Leverage 2, Rata de solvabilitate generală(Active), Rata de solvabilitate(Pasive) rata autonomiei financiare, EBITDA/Active Totale, Acoperirea dobânzilor, Durata de rotație a creditelor-furnizor
Profitabilitate	ROE,ROA, Marja EBITDA, Marja EBIT, Cash flow/Venit operațional, Valoarea intreprinderii/EBITDA, Marja Profitului, ROCE
Activitate	Viteza de rotație a activelor totale, Durata de rotație a creanțelor, EBITDA/Cheltuieli dobânzi, EBIT/Cheltuieli dobânzi
Performanță	Valoarea contabilă/acțiune, Capitalul de lucru/acțiune, Preț/valoarea contabilă, Capitalizarea bursieră/capitaluri propeii
Calitativi	Vârsta companiei,Mărimea companiei,Număr angajați,Structura boardului, Sex manager,Vârstă manager, Nivel educație board
Macroeconomici	Rata de creștere PIB, Rata inflației, Rata șomajului

Tabelul 4.1 KMO and Bartlett's Test *Sursa:SPSS*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,919
Bartlett's Test of Sphericity	Approx. Chi-Square	10298,687
	df	105
	Sig.	,000

Tabelul 4.2 Total Variance Explained ***Sursă: SPSS***

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of	Cumulative	Total	% of	Cumulative	Total	% of	Cumulative
1	3,845	25,634	25,634	3,845	25,634	25,634	3,461	23,076	23,076
2	2,012	13,411	39,045	2,012	13,411	39,045	2,056	13,704	36,780
3	1,885	12,567	51,612	1,885	12,567	51,612	2,001	13,343	50,122
4	1,412	9,417	61,029	1,412	9,417	61,029	1,393	9,286	59,409
5	1,112	7,413	68,442	1,112	7,413	68,442	1,270	8,467	67,876
6	1,062	7,079	75,521	1,062	7,079	**75,521**	1,147	7,645	**75,521**
7	,893	5,950	81,471						
8	,797	5,315	86,786						
9	,599	3,991	90,777						
10	,558	3,723	94,500						
11	,419	2,796	97,296						
12	,210	1,402	98,697						
13	,145	,967	99,664						
14	,047	,316	99,981						
15	,003	,019	100,000						

Extraction Method: Principal Component Analysis.

Tabelul 4.3 Rotated Component Matrix ***Sursă: SPSS***

	Component					
	1	2	3	4	5	6
EBITmarg	,911				,116	
ProfitMarg	,910				,118	
EBITDAmarg	,871					
Cach_Voper	,862	,106				,105
Current_ratio	,102	,933				
Lichid		,926				
Solvency_A	,120	,533		-,172	,344	-,215
DT_CapProp			,998			
DTS_CapProp			,998			
Collect_period				,824		-,128
EBITDA_ChD				,817		,157
logCA	,117				,806	,148
ROA	,480	,131			,623	-,116
Book_value	,130				-,131	,711
Board					-,213	-,698

Extraction Method: Principal Component Analysis.

a. Rotation converged in 5 iterations.

Tabelul 4.4 Variabile în ecuație *Sursă: SPSS*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	EBITmarg	,025	,003	50,877	1	,000	1,025	1,018	1,032
	Constant	2,246	,120	350,967	1	,000	9,450		
Step 2[b]	EBITmarg	,025	,004	50,821	1	,000	1,025	1,018	1,032
	DTS_CapProp	,004	,003	1,609	1	,205	1,004	,998	1,011
	Constant	2,255	,121	350,096	1	,000	9,539		
Step 3[c]	**EBITmarg**	**-,224**	**,004**	**46,662**	**1**	**,000**	**,799**	**,799**	**1,032**
	Lichid	**-,066**	**,036**	**3,237**	**1**	**,012**	**,859**	**,859**	**1,147**
	DTS_CapProp	**,124**	**,003**	**1,521**	**1**	**,008**	**1,132**	**1,132**	**1,011**
	Constant	**2,103**	**,138**	**232,141**	**1**	**,000**	**8,194**		

Tabelul 4.5 Sumar model *Sursă: SPSS*

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square	F Change	df1	df2	Sig. F Change
1	,768[a]	,589	,587	3,91395527	,009	8,026	1	901	,005

a. Predictors: (Constant), Predicted probability

b. Dependent Variable: Tobin

Coefficientsa

Model		Unstandardized Coefficients		Standardized	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,029	1,103		-,933	,001
	Predicted probability	-3,519	1,242	,094	2,833	,005

a. Dependent Variable: Tobin

Tabelul 4.6 Model Summaryb Sursă: SPSS

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square	F Change	df1	df2	Sig. F Change
1	,634[a]	,401	,400	3,91713425	,007	6,551	1	901	,011

a. Predictors: (Constant), EBITmarg

b. Dependent Variable: Tobin

Coefficientsa

Model		Unstandardized Coefficients		Standardized	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,108	,131		16,084	,000
	EBITmarg	,112	,005	,085	2,559	,011

a. Dependent Variable: Tobin

Tabelul 4.7Sumar model ***Sursă: SPSS***

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square	F Change	df1	df2	Sig. F Change
1	,895[a]	,801	,801	3,93134476	,000	,002	1	901	,007

Model		Unstandardized Coefficients		Standardized	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,071	,141		14,645	,000
	Lichid	,452	,016	,001	,039	,007

a. Dependent Variable: Tobin

Tabelul 4.8 Sumar model ***Sursă: SPSS***

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square	F Change	df1	df2	Sig. F Change
1	,736[a]	,542	,540	3,93126029	,000	,040	1	901	,002

a. Predictors: (Constant), DTS_CapProp

Model		Unstandardized Coefficients		Standardized	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,073	,131		15,840	,000
	DTS_CapProp	,491	,003	-,007	-,201	,002

a. Dependent Variable: Tobin

Tabelul 4.10 Variabile în ecuație ***Sursă: SPSS***

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 4[d]	EBITmarg	-,033	,005	40,329	1	,000	,967
	Current_ratio	-,102	,048	4,462	1	,035	,903
	CA_AT	-,092	,001	9,055	1	,003	,912
	logCA	-,236	,064	13,509	1	,000	,790
	DT_CapProp	,021	,009	7,142	1	,001	1,022
	Constant	3,689	,483	58,416	1	,000	40,021