CREDIT SCORING MODELS IN ESTIMATING THE CREDITWORTHINESS OF SMALL AND MEDIUM AND BIG ENTERPRISES

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Abstract

This paper is focused on estimating the credit scoring models for companies operating in the Republic of Croatia. According to level of economic and legal development, especially in the area of bankruptcy regulation as well as business ethics in the Republic of Croatia, the models derived can be applied in wider region particularly in South-eastern European countries that twenty years ago transferred from state directed to free market economy. The purpose of this paper is to emphasize the relevance and possibilities of particular financial ratios in estimating the creditworthiness of business entities what was realized by performing the research among 110 companies. Along most commonly used research methods of description, analysis and synthesis, induction, deduction and surveys, the mathematical and statistical logistic regression method took the central part in this research. The designed sample of 110 business entities represented the structure of firms operating in Republic of Croatia according to their activities as well as to their size. The sample was divided in two sub samples where the first one consist of small and medium enterprises (SME) and the second one consist of big business entities. In the next phase the logistic regression method was applied on the 50 independent variables – financial ratios calculated for each sample unit in order to find ones that best discriminate financially stable from unstable companies. As the result of logistic regression analysis, two credit scoring models were derived. First model include the liquidity, solvency and profitability ratios and is applicable for SME's. With its classification accuracy of 97% the model has high predictive ability and can be used as an effective decision support tool. Second model is applicable for big companies and include only two independent variables – liquidity and solvency ratios. The classification accuracy of this model is 92,5% and, according to criteria of predictive ability, it can be estimated as high. Credit scoring models represent scientifically based derived decision support tool. Their application on micro level can prevent the establishment of business relation with financially instable companies what can potentially result in losses while on macro level they can signal the forthcoming problems in economy as a whole and give the impulse for acting in appropriate direction.

Key words: *financial instability, credit scoring models, small and medium and big enterprises, logistic regression analysis*

1. INTRODUCTION

Credit scoring models have been drawing the attention by a plethora of researchers in financial and accounting area after the big economic crisis in thirties of the past century and are always becoming particularly actual in the era of recession and big breakdowns. Although the application of credit scoring models can seem universal no meter in which country one apply them, some research results indicate that their classification ability is significantly lowered for the companies that operate in the countries with lower level of economic and legal development, as well as countries with different business ethics than for the companies from the countries in which the models were derived (see Škeljo, 2000). This gave the impulse for performing broader research among the companies operating in the Republic of Croatia as a representative of the Southeastern European Countries (SEEC). Namely, SEEC have lower level of economic and legal development as well as relatively different business ethics than developed countries in which most credit scoring model was derived and the research curiosity logically imposed the need to estimate the new models that will reach better diagnostic and prognostic abilities.

Traditionally, market economies are characterized with emphasized importance of small and medium sized enterprises that employ majority of workforce. According to official data, in Republic of Croatia at the end of 2009 there were operating 91.320 enterprises among which 99,5% were SME's that employed 587.235 workers or 66,01%. If we add 92.965 crafts that are operating and employing 225.793 people, the relevance of small and medium size business is even higher. Structure of most world economies does not differ significantly from these data and the estimation is that SME's are producing 50% of the world biggest economy GDP. SME's are more risky enterprises in the business relations than big companies what indicate the need to develop appropriate tools to estimate their creditworthiness[1]. In this article the credit scoring models are derived separately for SME's and for big companies. Paper starts with research hypothesis and methodology after what the credit scoring models' estimation are presented. At the end, the models' practical application as well as some open questions is stated in order to emphasize the practical importance and possibilities of models' improvements.

2. PREVIOUS STUDIES ON CREDITWORTHINESS ESTIMATION

Scientific research on credit scoring model started after the big crisis in thirties of the past century when simpler models were derived. Application of quantitative statistical methods began some 20 years later when univariate statistics was deployed (Beawer, 1966). The biggest impulse for application of more complex statistical method known as multiple discriminant analysis was given by Edward I. Altman who developed

[1] In the first five years of doing business 40% of enterprises go bankrupt, while 10 years of operating survive only 33% of enterprises.

Z-score model using the data of U.S. companies (Altman, 1968) – the most cited credit scoring model in the literature. In his further research Altman improve his Z-score and derive another credit scoring model known as ZETA® score. Other important researchers like Deakin, Ohlson, Edmister and Kralicek used the same method but on the companies' data from other developed countries. The instability of free market economies characterized by bankruptcies make the credit scoring models always actual what resulted in growing number of researches in this area. They become very actual in Croatian economic researches too. Some of the authors that researched or are researching in the area of credit scoring models are N. Osmanagić Bedenik, L. Žager, N. Šarlija, N. Vitezić, I. Pervan, V. Belak, Ž. Aljinović Barać, B. Novak, I. Crnković, R. Zenzerović and other. The techniques that followed after the multiple discriminant analysis were linear probability models i.e. probit and logit models where logit models were found to be particularly robust and showed high predictive ability.

Further development of quantitative methods resulted in their implementation in the field of credit scoring estimation. Table 1 shows the overview of relatively new methods applied in estimating the creditworthiness of a company.

Table 1: The overview of contemporary methods applied in credit scoring estimation

Method	**Main advantages**	**Main drawbacks**	**Failure prediction models**
Survival analysis	* accounts for time dimension of failure ! * gives likely time to failure * allows for time-varying independent variables * no assumption of dichotomous dependent variable * no distributional assumptions * uses more data * allows for random censoring * easy interpretation	* not designed for classification * assumption: failing and non-failing firms belong to the same population * sample construction may affect hazard rates * requires homogenous lengths of failure processes in sample * subject to multicollinearity	Lane et al. (1986) Luoma & Laitinen (1991) Kauffman & Wang (2001)
Decision trees	* no strong statistical data requirements * allows for qualitative data * can handle noisy and incomplete data * user friendly: clear output * simple procedure	* specification of prior probabilities and misclassification costs * assumption: dichotomous dependent variable * relative importance of variables unknown * discrete scoring system * can not be 'applied'	Joos et al. (1998b) Frydman et al. (1985)
Neural networks	* does not use pre-programmed knowledge base * suited to analyse complex patterns * no restrictive assumptions * allows for qualitative data * can handle noisy data	* black box problem * can not be 'applied' * requires high quality data * variables must be carefully selected a priori * risk of over-fitting * requires definition of architecture	Odom & Sharda (1990) Cadden (1991) Coats & Fant (1991) Coats & Fant (1993) Fletcher & Goss (1993) Udo (1993) Wilson & Sharda (1994) Altman et al. (1994)

	* can overcome autocorrelation * user-friendly: clear output * robust and flexible	* long processing time * possibility of illogical network behaviour * large training sample required	Boritz et al. (1995) Back et al. (1996a) Bardos & Zhu (1997) Yang et al. (1999) Atiya (2001) Charitou et al. (2004)
Fuzzy rules based classification model	* intuitive basis	* dependence on arbitrarily ifthen rules	Spanos et al. (1999)
Multi-logit model	* considers information from several years	* assumption of signal consistency	Peel & Peel (1988)
CUSUM (cumulative sum) model	* takes account of data from present and past * short memory concerning good performances - long memory concerning bad performances		Theodossiou (1993) Kahya & Theodossiou (1996)
DEHA (dynamic event history analysis)	* sees failure as a process * allows for time-varying variables * allows for censored cases * conditional probability' feature		Hill et al. (1996)
Chaos theory model	* considers information from different times	* strong assumption: healthy firms are more chaotic	Scapens et al. (1981) Lindsay & Campbell (1996)
MDS (multidimensional scaling)	* statistical map with intuitive interpretation * robust, when outliers * deals with highly correlated data * no distributional requirements * no need for data reduction	* not dynamic * not designed for prediction * can not be 'applied'	Mar-Molinero & Ezzamel (1991) Neophytou & Mar-Molinero (2001)
LGP (linear goal programming)	* no distributional requirements * flexible	* complex	Gupta et al. (1990)
MCDA (multi-criteria decision aid approach)			Zopoudinis (1987) Zopoudinis & Dimitras (1998) Doumpos & Zopoudinis (1999)
Rough set analysis	* allows for qualitative variables * easy method * user-friendly: can easily be applied to new cases * flexible	* quantitative variables need to be recoded into discrete variables	Slowinski & Zopoudinis (1995)
Expert systems	* allows for qualitative variables * no statistical distribution requirements * user-friendly: can easily be applied to new cases	* 'predefined knowledge base' needs to be programmed * heuristics needs to be determined * time consuming, expensive * not flexible * sensitive to incomplete, noisydata or input information with errors	Messier & Hansen (1988)
SOM (self organizing	* allows to detect regions of	* requires pre-selection of a	Kiviluoto & Bergius

maps)	increased failure risk or to view the evolution of the condition of a company *the two-level SOM offers some possibilities to explore typical ‘failure paths	small set of independent variables	(1998)

Source: Balcaen, S.; Ooghe, H. (2004)

3. RESEARCH HYPOTHESIS AND METHODOLOGY

The central problem of research is to estimate the creditworthiness of SME’s and big companies in order to minimize the credit risk and improve the process of decision making when establishing a business relations in economic, legal and social surrounding of SEEC, what is the purpose of this paper. In order to solve this problem further research hypothesis was set: The combinations of financial ratios with appropriate weights can be used in estimating the creditworthiness of SME’s and big companies. The models will be derived for each group – SME’s and big companies – and they will be reliable in estimating the creditworthiness of enterprises operating in SEEC in the two years period.

In the centre of research there are financial ratios that represent the financial performance of SME’s and big companies. These ratios will be combined in order to estimate the reliable credit scoring models what is the main objective of this paper.

Scientific approach to credit scoring models derivation usually includes five steps. In the first step theoretical models have to be defined. According to aforementioned research hypothesis, theoretical models consist of 50 independent variables that will try to explain the state and movement of dependent variable i.e. creditworthiness of enterprises analyzed. Independent variables in models are most commonly used financial ratios where: six of them represent liquidity ratios, 11 solvency ratios, eight activity ratios, nine profitability ratios, five ratios that are calculated upon relation between different types of revenues and expenses and 11 ratios calculated from cash flow. Dependent variable is dichotomous where value 0 is given to firms that have low degree of creditworthiness, while those treated stable i.e. with high degree of creditworthiness had value 1. Enterprises with low degree of creditworthiness are those that went bankrupt or disclosed loss above equity in their financial statement. High degree of creditworthiness enterprises are considered to be others.

In the second step sample should be defined and data collected. Representative sample definition is one of the key elements of model quality. Starting point for sample definition was the structure of Croatian companies by size and activities. Some specific activities, like financial intermediaries were excluded from the sample according to their particular characteristics and differences from manufacturing and service activities. The proportion of companies by size is the result of analysis based on the proportion of employees that each group of companies had. Final sample included 110 enterprises where half of them were enterprises with low degree of creditworthiness and other part were enterprises with high degree of creditworthiness. It covered the activities that employed 55% of total employees, as well as 36% of total number of profit oriented companies that were operating in the period of the research. The sample of 110 enterprises was divided in two subsamples: first include small and medium enterprises, and second consist of big companies. The sample and subsamples structure is shown in table 2.

Table 2: The final sample structure

Activities	Size			Total
	Small	Medium	Big	
Manufacturing	9	16	13	**38**
High degree of creditworthiness enterprises	5	7	7	**19**
Low degree of creditworthiness enterprises	4	9	6	**19**
Building industry	10	10	10	**30**
High degree of creditworthiness enterprises	5	4	5	**14**
Low degree of creditworthiness enterprises	5	6	5	**16**
Traffic, warehousing and communications	3	11	12	**26**
High degree of creditworthiness enterprises	2	5	7	**14**
Low degree of creditworthiness enterprises	1	6	5	**12**
Hotels and restaurants	4	6	6	**16**
High degree of creditworthiness enterprises	2	3	3	**8**
Low degree of creditworthiness enterprises	2	3	3	**8**
Total	**26**	**43**	**41**	**110**

Source: Research results

Further, the data needed for calculating 50 financial ratios was obtained from two available sources: publicly disclosed financial statements on Zagreb stock exchange and database of Financial agency – company that collects data from enterprises operating in Republic of Croatia. Data regarded various positions from financial statements that were collected for the year before the enterprises went bankrupt or disclosed loss above equity. On the other side the same data for the same period were collected for enterprises considered to have high degree of creditworthiness. In the situations where enterprise that went bankrupt had loss above equity in the appropriate year, the data were collected for the year before the loss above equity was obtained.

Third step consist of selection and application of appropriate quantitative method. Binominal logistic regression analysis was used. It represents a form of regression analysis which is used when the dependent variable is a dichotomy and the independent variables are of any type. Logistic regression can be used to predict a dependent variable on the basis of continuous and/or categorical independents and to determine the percent of variance in the dependent variable explained by the independents; to rank the relative importance of independents; to assess interaction effects; and to understand the impact of covariate control variables (Garson, 2008). Its advantages are primarily in its robustness that can be seen in further characteristics:

- Logistic regression analysis does not assume linear relations between dependent and independent variables;
- Logistic regression analysis does not assume normally distributed variables;
- The subsamples or group in subsamples could be different sizes;
- Logistic regression analysis does not assume homoscedasticity.

The logarithmic form of logistic regression function is presented by equation 1.

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n \qquad (1)$$

This form could be transformed by the process of antilogarithming what will result with equation 2 that can be used to calculate the prognostic probability of credit scoring model. The prognostic probability represents the probability that the enterprise have high degree of creditworthiness. Logically, there raises the question: When one enterprise should be treated as enterprise with high degree of creditworthiness or opposite? It is generally accepted that if the prognostic probability is higher or equal to 0,5 the enterprise is treated like high degree of creditworthiness enterprise and opposite.

$$P_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n)}} \qquad (2)$$

In the fourth step statistical adequacy of the model is estimated. If the statistical parameters are appropriate the model should be theoretically examined once more (fifth step) and it can be used on real word cases. If the parameters indicate that the model is not statistically adequate, it should be theoretically reformulated and the scientific approach starts again. These last two phases in scientific approach to credit scoring models estimation are examined in the next chapter.

4.1. Credit scoring model for small and medium enterprises

Subsample of SMEs consists of 69 enterprises among which 36 of them were treated as enterprises with low degree of creditworthiness and rest of 33 companies was treated financially stable i.e. with high degree of creditworthiness.

Logistic regression analysis began with analysis of statistical relation of 50 financial ratios - independent variables with degree of enterprise creditworthiness. According to the assumption of no multicollinearity, correlated independent variables were omitted[2], as well as statistical insignificant variable i.e. variables whose significance is higher than 0,05[3]. Result is logistic function shown in equation 3 while independent variables characteristics are presented in table 3.

$$GCE_{sme} = \frac{1}{1+e^{-(-0{,}124+13{,}831WK/TA-0{,}029TL/(RE+D)+110{,}421ROA)}} \tag{3}$$

Table 3. Independent variables included in GCE[4]sme model with their characteristics

Independent variables	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	**Upper**
Working capital/Total assets **(WK/TA)**	13,831	5,362	6,654	1	,010	1015853	27,724	4E+010
Total liabilities/(Retained earnings + depreciation) **(TL/(RE+D))**	-0,029	0,013	5,262	1	,022	0,971	0,947	0,996
Return on assets **(ROA)**	110,42	39,215	7,928	1	,005	9E+047	4E+014	2E+081
Constant	-0,124	0,747	0,027	1	,868	0,884		

Source: Research results

Logistic function i.e. credit scoring model for small and medium enterprises (GCE_{sme}), includes three independent variables and constant. Independent variables are financial ratios that belong to the group of liquidity, solvency and profitability ratios what is according to expectation and research results performed among companies in developed countries.

Credit scoring model quality can be tested using appropriate tests (table 4). High significance of Hosmer – Lemeshow test indicate that the hypothesis on no difference between real and prognostic values of dependent variables could be accepted. In other words the model is statistically adequate. Parameter Nagelkerke R^2 confirms the representativeness of model. Namely, the value Nagelkerke R^2 indicate that GCE_{sme} model explain 91,4 % of variations.

Table 4. Quality coefficients for GCE_{sme} model

-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2	Hosmer-Lemesh Test		
			Hi square	**df**	**Significance**
15,372	0,685	0,914	0,420	8	1,000

Source: Research results

[2] Multicollinearity of independents is determined by analyzing the correlation of independent variables shown in pooled within-groups matrices. The independents whose correlation was higher than 0,8 were analyzed. From further analysis was excluded the independent which is expected to be less representative in estimating the particular segment of financial stability according to the experience from previous research.

[3] Statistical insignificant variables were excluded using the process of testing the hypothesis that variable's logistic coefficient is equal to 0. If the significance of independent variable is higher than 0,05 the hypothesis could be accepted and the variable will be excluded from the further analysis.

[4] GCE is an abbreviation for going concern estimation.

Next procedure in model quality estimation is calculation of its' classification ability. It was done by calculating the GCE_{sme} model values for enterprises included in subsample and their classification in the appropriate group. If the enterprise GCE_{sme} model value was lower than 0,55[5] the enterprise was classified as low degree of creditworthiness enterprise and vice versa.

Table 5. Classification results of GCE_{sme} model

Real degree of creditworthiness		Predicted degree of creditworthiness in %		
		Degree of creditworthiness		Percentage of correct classification
		Low	High	
One year period prediction				
Degree of creditworthiness in %	Low	97,1	2,9	**97,1**
	High	3,0	97,0	**97,0**
Overall classification accuracy in %				**97,0**
Two years period prediction				
Degree of creditworthiness in %	Low	48,4	51,6	**51,6**
	High	0,0	100,0	**100,0**
Overall classification accuracy in %				**73,3**

The cut value is 0,55

Source: Research results

The model classification ability was examined for two different periods: one year before the enterprise reach appropriate degree of creditworthiness and two years before. In fact, the prognostic ability of model was tested for the mentioned periods. The model overall classification accuracy in one year period is 97% what indicate its high predictive ability[6]. Predictive ability is lower in two year run. The reason for this lies in the fact that the model has low classification ability for the enterprises with low degree of creditworthiness. Namely, GCE_{sme} model correctly classified only 48,4% of enterprises while 51,6% was misclassified i.e. classified as high degree of creditworthiness. This misclassification, known as type 1 error, indicates that the GCE_{sme} model is not appropriate in creditworthiness estimation in two years run.[7] Last step in GCE_{sme} model quality examination is ROC (Receiver Operating Characteristic) curve analysis. Central role in ROC curve analysis have type 1 and type 2 errors, which represent the number, proportion or percentage of misclassified sample units, in this case enterprises, and terms of sensitivity and specificity. When estimating the

[5] Cutoff point was first set at the value 0,50. In further steps the classification accuracy was tested using cutoff points from 0,50 to 0,60. The model show the highest classification ability at cutoff point of 0,55.

[6] The conclusion on model classification ability can be done by comparing particular classification results with theoretical probability increased by 25%. Theoretical probability for two equal groups is 50%. Increasing the theoretical probability by 25% will result with 62,5% what is the cutoff point for estimating the model classification ability. In the case the groups' sizes are different, theoretical probability can be calculated by using the equation $P_{sluc} = p^2 + (1 - p)^2$ where *p* represent proportion in group 1, and *1 – p* proportion in group 2.

[7] Although the model correctly classified all enterprises with high degree of creditworthiness (type 2 error was 0%), high level of type 1 error make it risky to use. Reason for this lies in fact that costs of type 2 error are significantly lower than costs of type 1 error.

classification ability of GCE_{sme} model four possible outcomes can appear. These outcomes can be formulated in so called contingency table or confusion matrix which is shown in table 6.

Table 6. Contingency table for credit scoring model

Real degree of creditworthiness		**Predicted degree of creditworthiness in %**		**Total**
		Degree of creditworthiness		
		Low	High	
Degree of creditworthiness	Low	D – true low	C – false high (type 1)	**D + C**
	High	B – false low (type 2)	A – true high	**B + A**
Total		**D + B**	**C + A**	**A + B + C + D**

Source: Adjusted according to: www.medcalc.be/manual/roc.php (page visited: 15.08.2010.)

Sensitivity measures model classification accuracy when classifying enterprises with high degree of creditworthiness and it could be calculated using equation 4. In other words, it represents the relation of correctly classified high degree of creditworthiness enterprises with whole group of enterprises with the same degree of creditworthiness i.e. the probability that the model will correctly classify enterprise with high degree of creditworthiness.

$$Sens = \frac{A}{A+B} \tag{4}$$

Specificity, on the other hand, measure the model classification accuracy when classifying enterprises with low degree of creditworthiness i.e. the probability that credit scoring model will correctly classify low degree of creditworthiness enterprise. Equation 5 shows the way in which the specificity is calculated.

$$Spec = \frac{D}{C+D} \tag{5}$$

Table 7. Model discriminant power estimation

Proportion of area under ROC curve	**Model discriminant power**
0,50 – 0,60	Insufficient
0,60 – 0,70 (0,50 – 0,75)	Sufficient
0,70 – 0,80 (075 – 0,92)	Good
0,80- 0,90 (0,92 – 0,97)	Very good
0,90 – 1,00 (0,97 – 1,00)	Excellent

Source: Adjusted to Rozga & Simon

These two terms have the major role in calculating the area under the ROC curve which represents the discriminant power of credit scoring model.

Among authors there are different approaches in estimating the model discriminant power. Table 7 shows the intervals of proportions under ROC curve with estimation of model discriminant power of two groups of authors.

According to the results of ROC curve analysis, the GCE_{sme} model discriminant power is excellent. Namely, the proportion of area under model ROC curve is 0,992 with standard error of 0,007.

4.2. Credit scoring model for big enterprises

Subsample of big enterprises consists of 41 business entities where 22 of them was considered financially stable i.e. had high degree of creditworthiness, while the rest of 19 enterprises were those that vent bankrupt or had loss above equity, or in other words, were those with low degree of creditworthiness. The procedure of logistic regression analysis, that resulted with derivation of credit scoring model for big enterprises (GCE_{be} model shown in equation 6), was equal to that used in GCE_{sme} model derivation.

$$GCE_{be} = \frac{1}{1+e^{-(2,515+6,777WK/TA-0,218TL/(RE+D))}} \tag{6}$$

Further three tables (tables 8, 9 and 10) show the model statistics and its quality. GCE_{be} model include only two independent variables that belong to the groups of liquidity and solvency ratios. According to the value of Nagelkerke R^2 model explain 74,8% of variations what is lower than previous model, but still satisfactory.

Table 8. Independent variables included in GCEbe model with their characteristics

Independent variables	B	S.E.	Wald	df	Sig.	Exp(B)	95,0% C.I.for EXP(B)	
							Lower	Upper
Working capital/Total assets **(WK/TA)**	6,777	3,192	4,507	1	0,034	877,684	1,683	457780,3
Total liabilities/(Retained earnings + depreciation) **(TL/(RE+D))**	-0,218	0,097	5,043	1	0,025	0,804	0,665	0,973
Constant	2,515	1,068	5,546	1	0,019	12,361		

Source: Research results

Table 9. Quality coefficients for GCE_{be} model

-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2	Hosmer-Lemesh Test		
			Hi square	df	Significance
22,436	0,561	0,748	8,126	8	0,421

Source: Research results

Classification of sample units using the GCE_{be} model indicates on high level of its predictive ability. In the one year period model correctly classifies 92,5% of enterprises, while in the two years run its classification ability is lower but still on respectable 88,9%.

Table 10. Classification results of GCE_{be} model

Real degree of creditworthiness		Predicted degree of creditworthiness in %		
		Degree of creditworthiness		**Percentage of correct classification**
		Low	High	
One year period prediction				
Degree of creditworthiness in %	Low	89,5	10,5	**89,5**
	High	4,8	95,2	**95,2**
Overall classification accuracy in %				**92,5**
Two years period prediction				
Degree of creditworthiness in %	Low	78,6	21,4	**78,6**
	High	0,0	100,0	**100,0**
Overall classification accuracy in %				**88,9**

The cut value is 0,50

Source: Research results

ROC curve analysis is the last method used to estimate the model quality. The proportion of area under model ROC curve is 0,94 with standard deviation of 0,043 what indicate that GCE_{be} model discriminant power is very good or even excellent according to less restrictive criteria of estimation.

Theoretical re-examination of models derived is last, fifth step in scientific approach. The relation between independent variables and dependent variable satisfy theoretical assumption. Namely, liquidity and profitability ratios are directly related to degree of creditworthiness i.e. higher levels of these ratios imply higher degree of enterprises' creditworthiness. On the other side, solvency ratio is reversely related to degree of creditworthiness. According to aforementioned, liquidity and profitability ratios have positive, while solvency ratio negative weights in models presented.

5. CREDIT SCORING MODELS APPLICATION

Credit scoring models derived in this paper have broad area of application. Their application is particularly actual in economic moment when economies are trying to get out of recession. Nowadays economic reality faces many stakeholders with challenges in estimating creditworthiness of enterprises in which they have particular interest. Management is among first instances interested in estimating the creditworthiness of enterprise because it is responsible for managing as well as disclosing information regarding going concern assumption. Other subjects employed in enterprise and its owners are another group of subjects interested in estimating the enterprise creditworthiness. The level of creditworthiness not only indicates its ability to continue as a going concern but it reflects the level of risks enterprise is exposed to. Enterprise with high level of creditworthiness is supposed to be exposed to lower level of risks what results in more availability of funds and lower financing costs. Credit scoring models are primarily used by banks and suppliers to estimate the level of credit risk they are exposed to, but they can be used by customer too as a tool to estimate the future stability and availability of goods and services they buy from enterprise. Other important stakeholders on micro level are auditors that are responsible in estimating the quality of financial statements. Credit scoring models derived can be auditors' tool in estimating going concern assumption of enterprise audited as well as the level of enterprise's customers credit risk according to what the reality of receivables can be estimated. On macro level the credit scoring model could be used as a tool to estimate the level and trends in creditworthiness movements for particular branches and/or economy as a whole.

6. CONCLUSION

Estimating the creditworthiness of enterprises is sophisticated skill rather than combination of analytical tool developed by employment of various and complex quantitative methods. Enterprises, no matter their size, represent the complex interaction of number of factors that is impossible to count and the intensity and direction of interaction of these countless factors is especially difficult to estimate in nowadays dynamic socially economic environment. This is the reason why in estimating the creditworthiness one must start from most important variables – representatives that will give most appropriate information on level of enterprise stability. Financial variables satisfy this request and represent the starting point for creditworthiness estimation but their examination should be expanded by nonfinancial variables recognition and their importance estimation what will probably bring qualitative improvement of models derived. Another open area for research is in estimating more than just two levels of creditworthiness where multinominal logistic regression analysis could be employed.

Credit scoring models as diagnostic and prognostic analytical tools will probably find appropriate place in estimating the creditworthiness of enterprises assuring in this way appropriate resources allocation on the level of the state. Namely, by signalling the low level of creditworthiness, credit scoring models: focus the management attention on the need to make appropriate decisions, signal to enterprise owners to examine the management activities, does not allow establishing business relations with unstable enterprises and direct the auditors as well as macroeconomic management attention toward risky areas.

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