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Published online: 23 Jan 2018.

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Insolvency prediction model of the company: the case of the Republic of Serbia

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ABSTRACT

In this article, the authors analyse the existing foreign insolvency prediction models of the company and on the basis of the sample of solvent and insolvent companies they aim to develop a new model to predict insolvency of a company by binomial logistic regression (LR), which will be suitable for the business environment in the Republic of Serbia. The research seeks to determine statistically most important financial ratios in predicting insolvency of Serbian companies. As a result of research, a model for the prediction of bankruptcy was created, which accurately classifies 82.9% of solvent ('healthy') Serbian companies and 93.3% of Serbian companies which have undergone bankruptcy proceedings (Serbian insolvent companies), while the average (total) accuracy of the prediction model is 88.4% of the cases.

1. Introduction

In the literature, terms such as insolvency, failure and bankruptcy are usually used interchangeably. Insolvency (Šverko Grdic, Radolovic & Bagaric, 2009) is an inability to pay, i.e., it is a situation in which a company or other legal bodies or individuals are not able to settle the due payment obligations in terms of their maturity. The failure of the company from the economic point of view (Duvnjak, 2008) represents a situation where the rate of return on invested capital is continuously decreasing; from the legal point of view, it is the failure of the company which is equal with the bankruptcy of the company, whereas from the standpoint of management this can deteriorate the effectiveness of the company that may further jeopardise its long-term survival on the market.

Prediction of financial distress is a significant issue for managers, shareholders, creditors, government, auditors, suppliers, employees and other entities. Bankruptcy prediction models can be developed to provide an early signal of a significant bankruptcy risk, and to indicate companies facing potential bankruptcy. Developing bankruptcy prediction models from financial ratios by applying different methods, such as multiple discriminant analysis (MDA), logistic regression (LR), probit analysis, artificial neural networks (NN) and other

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methods is a widely used approach in literature. Numerous researchers around the world concluded that: (1) bankruptcy prediction models can often accurately predict the potential economic and financial problems in the operations of the company a year before the opening of bankruptcy; (2) the bankruptcy prediction models progressed through the utilisation of even more advanced techniques, based on data mining, intelligence modelling techniques and artificial NNs; and (3) each of bankruptcy prediction models has its advantages and disadvantages. Despite the popularity of the MDA in constructing failure classification models, questions are raised regarding the restrictive statistical requirements imposed by this model. Therefore, logit analysis and NNs are used to develop alternative models as warning signals for bankruptcy. Contributions of this study are reflected in: (1) improving the methodology of forecasting the bankruptcy risk of companies in transition economies; (2) determining the financial ratios that have the greatest significance in predicting the probability of bankruptcy of a company in the Republic of Serbia; and (3) determining the reliability and the accuracy of prediction model created in the classification (prediction) of companies.

The objective of this research is to develop an appropriate model for predicting (in) solvency of the companies in Serbia. The article is organised as follows. After introductory remarks and historical background of the insolvency prediction models, the necessity of developing insolvency prediction models of companies at the national level is explained. In the third part of the article, used methodology, a research hypothesis, a suitable sample and the selected financial data for the development of insolvency prediction models of a company in the Republic of Serbia are presented. The fourth part presents the results of an empirical research. The final part includes concluding remarks and a list of references.

2. Research background

2.1. Necessity of implementation of insolvency prediction models

The global slowdown in economic activity caused by the global financial crisis had a negative impact on the economies of developed countries and developing countries, including the Republic of Serbia (Andrić & Vuković, 2012; Bešlić & Bešlić, 2013; Jakšić & Vuković, 2012). Low competitiveness, low level of utilisation of production capacity due to the lack of working capital, the decline in domestic and foreign demand, increasing insolvency of companies, a reduction in the employment rate and reduced export are just some of the consequences of the global financial crisis, with a negative impact on the companies' performances (business losses, inefficient management, inadequate financial policy and organisational structure, etc.). This has led to increased exposure of companies from the Republic of Serbia to a bankruptcy risk. At the end of February 2011 (Nikolić, Vučković, & Ivković, 2011) there were 66,255 business entities in the Republic of Serbia that had blocked bank accounts with a total overdue of $287.6 billion of Serbian dinars (RSD). Given the importance of this issue to the national economy, the objective of this article is to develop a prediction model based on financial ratios by using a binomial LR.

Bankruptcy proceedings arise from the insolvency of a company, as the debts of the company exceed its assets and cannot be settled even if all the assets of the company are sold. Insolvency of the company does not necessarily lead to bankruptcy because it can be recognised in a timely manner, so measures for restructuring the company can be taken.

Insolvency, which is reflected in the large number of blocked companies with fewer assets than liabilities, cannot be solved if there is not effective implementation of the provisions of the Bankruptcy Law (which came into force in early 2010 in the Republic of Serbia), in the domain of automatic activation of bankruptcy. In 2012, bankruptcy proceedings in the Republic of Serbia are automatically opened against companies whose accounts have been continuously blocked for a year.

Table 1 provides an overview of the insolvency of companies in Central and Eastern Europe in 2013.

2.2. *Historical background of insolvency prediction models*

The first researchers who investigated financial risk were: Fitz Patrick, Beaver, Deakin, Edmister, Brigs and McLennan, Gentry, Newbold and Whitford and Garcia, Calvo and Arcues. Beaver (1966) developed a parametric statistical model to predict financial distress of a company by using the information in the financial statements by applying the techniques of data analysis of one variable (univariate technique). He pointed out that the analysis by using financial ratios can be useful in predicting business success or failure, solvency or insolvency and bankruptcy of the company. After Beaver (1966), Altman (1968) also made a significant contribution to the development of models in order to predict insolvency. Altman developed a statistical model predicting the insolvency of the company by the technique of MDA. He pointed out that the prediction of the probability of bankruptcy of the company, in addition to the use of the individual (partial) financial ratios, i.e., ratios based on financial information of great significance, can be done by synthetic (aggregate) financial ratios which are the weighted sum of several financial ratios, including the well-known Altman Z-Score ratio. Such models belong to the microeconomic approach to predict the financial distress of the company.

These results are consistent with the results of the previous research (e.g., Alihodžić, 2013; Muminović, 2013; Pavlović, Muminović, & Cvijanović, 2011a, 2011b, 2012) which

Table 1. Insolvency of companies in Central and Eastern Europe in 2013.

	Total insolvencies		Of which bankruptcies		Dynamics total insolvencies		Total number of active companies	Insolvency rate
	2013	2012	2013	2012	2013/2012	2013/2012	2013	2013
Bulgaria	834	601	646	580	38.8%	20.4%	400,000	0.21%
Croatia	3186	3033	787	630	5%	174.2%	150,000	2.02%
Czech Republic	10,653	8045	5496	3770	32.4%	26.1%	1,471,000	0.72%
Estonia (2)	514	495		146	3.8%	−20.5%	139,000	0.37%
Hungary	13,489	22,840	n.a. (1)	22,644	−40.9%	11.95	595,000	2.27%
Latvia	818	883	612	875	−7.4%	7.2%	229,600	0.36%
Lithuania	1517	1400	1429	1278	8.4%	10%	90,800	1.67%
Poland	883	877	718	711	0.7%	21.3%	1,795,000	0.05%
Romania	27,145	25,842	n.a. (1)	n.a. (1)	5%	20.2%	421,900	6.44%
Serbia	8498	8333		2647	2%	−43.8%	111,700	7.61%
Slovakia	507	452	394	362	12.2%	−9.6%	540,000	0.09%
Slovenia	994	980	944	n.a. (1)	1.4%	39.2%	185,500	0.54%

Where: (1) data which is not published in the public sources; and (2) data published in 2013 by Coface Company due to lack of official data.
Source: Sielewicz, 2014

show that the existing predictive models (for example, Altman's Z-score model, Taffler's Z-score model, Sandin & Porporato's model, Zmijewski's model and Kralicek DF ratio) are not accurate in predicting bankruptcy of companies in the Republic of Serbia, as socio-economic, institutional and other operating conditions are significantly different than in countries where these models were developed. Besides, a large number of methodologies for predicting bankruptcy in the international framework were developed at a time when the economic and financial crisis was not present. Therefore, it is necessary to develop a model which could be specifically applied to a prediction of bankruptcy of companies in Serbia.

3. Research methodology and hypothesis

Different methods to develop models of bankruptcy prediction of companies are applied all over the world. The most commonly used are: (1) LR (Jakubík & Teplý, 2008); (2) discriminant analysis (Stroe & Bărbuţă-Mişu, 2010; Zenzerović, 2009); and (3) neural network (Ecer, 2013), etc. The reasons for the wide use of LR models according to Masten and Masten (2012) are: (1) is relatively easy to understand; (2) available in most software packages; and (3) fairly robust (strong, powerful) and reliable tool for predicting the financial problems of the company. Ebrahimi and Nikbakht (2011) showed that their LR model developed on a sample of companies listed on the stock exchange in Tehran for the period between 2001 and 2009 is more superior in predicting the bankruptcy of the company than Altman's (1968) model, Ohlson's (1980) model, Zmijewski's (1984) model and Shumway's (2001) model. While comparing standard tools for predicting bankruptcy of the company (Kaczmarek, 2012; Zenzerović & Peruško, 2006), which include models of MDA and LR models with the new generation of models such as artificial NNs, fuzzy logic, decision tree and genetic algorithm, it has been concluded that MDA and LR models require lower costs and the results are easier to interpret and compare, so they are more often applied in practice.

Taking into account the results of previous studies, the hypothesis (H) is defined as follows:

> **H:** *By using a binomial logistic regression based on financial ratios, it is possible to predict (in) solvency of the company in the Republic of Serbia.*

Taking into account the papers of other authors who have developed models for the prediction of bankruptcy, we decided in our study to analyse the application of binomial LR. In binary LRs (Ohlson, 1980) predicted (expected) values of the dependent variable *y* for a given value of the independent variable denoted with E(*y*|*x*) can only have value in the interval [0,1] regardless of the value of the regression ratios and the independent variables, which can be achieved by the following regression equation:

$$\text{Logit Score} = \text{P (Score)} = P_i\left(y\right) = \frac{e^{y_i}}{1 + e^{y_i}} = \frac{1}{1 + e^{-y_i}}, \tag{1}$$

where is: $y_i = \beta_0 + \beta_1 {}^* x_i + \varepsilon_i$ or $y_i = \beta_0 + \beta_1 {}^* x_{1i} + \beta_2 {}^* x_{2i} + ... + \beta_k {}^* x_{ki} + \varepsilon_i$

or

$$y_i = F\left(w_i\right) = \frac{1}{1 + e^{-w_i}}, \tag{2}$$

where is: $w_i = \beta_0 + \beta_1 {}^* x_i + \varepsilon_i$ or $w_i = \beta_0 + \beta_1 {}^* x_{1i} + \beta_2 {}^* x_{2i} + ... + \beta_k {}^* x_{ki} + \varepsilon_i$

Where: e – natural logarithm, e=2.718281828459; P_i $(y = j)$ – probability that the company i will reach the state j; j – state (j = 0,1,2, ..., n), state 0: solvency (no bankruptcy, financial stability) and state 1: insolvency (bankruptcy); y_i – dependent variable is modelled as a function of the constants, independent variables and standard error of the LR model, i.e., a variable called LR describing the linear combination βx; β_0 – constant, $\beta_1, \beta_2,..., \beta_\kappa$ – regression ratios of the independent variables to estimate each state j; $x_1,..., x_{ki}$ – value of the independent variable, and a set of k independent variables (financial ratios) x for the company I; *Logit score between 0 and 1* – expresses the risk of a company that is associated with the likelihood that a company will go bankrupt within a period of one year; w_i – is a linear function of financial ratios $w_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} +...+ \beta_k x_{ki}$ in the equation $y_i^* = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} +...+ \beta_k x_{ki} + \varepsilon_i$; ε_i – *standard error of logistic regression (logit) model*; $y_i = 0$ – solvent company i, i.e., 'healthy' company, if $y_i^* \le 0$; $y_{i=}1$ – insolvent company i, i.e., company in bankruptcy, if $y_i^* > 0$; F (.) – logistic distribution; F(w_i) – expected probability of bankruptcy of company i which is restricted to the interval [0,1].

The LR model is a type of model of conditional probabilities (Omelka, Beranová, & Tabas, 2013) which can be used to estimate the probability of business failure (bankruptcy) of the company on the basis of its specific characteristics, monitoring the solvency of the company by the bank, creditors, regulators and auditors. An LR model may also be useful for owners/managers in order to timely predict the financial problems that can lead a company into bankruptcy. Prognostic probability that a company will be solvent and will continue to operate indefinitely (Zenzerović & Peruško, 2009) is used when deciding if the sample units belong to a particular group or population of financially 'healthy' companies or companies in bankruptcy, so that the predictive probability of each company is compared with a pre-defined critical value of the probability of financial distress (insolvency, bankruptcy). The critical point (Zenzerović, 2011), or the value of the probability of financial distress can be set to 0.5 or, if necessary, can be increased. Hypothetical (general) rules of inference is that if the prognostic probability P (y=0) is equal to or less than 0.5 as the critical value, the company (the unit of observation) is classified into the groups of solvent companies ('healthy' companies). Otherwise, if the predictive probability P (y=1) is greater than 0.5 as the critical value, the company is classified in the group of insolvent companies (companies in bankruptcy). The accurate prediction is implied: $y=$**0**, if $F \le F^*$ and $y=$**1**, if $F > F^*$, where F^* is probability being treated as a threshold of correct predictions (Nojkovic, 2007; Xie, Zhao, Jiang, & Zhang, 2013), and its value is usually 0.5. However, deviations from this hypothetical rule have been observed in practice. Shumway points out that the corporate failure models are the most accurate in predicting bankruptcy if used data from the financial statements of companies for a period of one year before the bankruptcy proceedings (Altman, 2002).

Since a binomial LR involves two possible outcomes – bankruptcy or survival of the company, in Serbia the following codification is used the following codification – 0 for solvent companies and 1 for insolvent companies. Various financial ratios calculated according to financial statements are used as independent variables. LR, as a procedure for creating the model, allows the division of the sample into the part for model development and the part for testing of the model (cross-validation procedure). Among the authors who deal with this problem, we can find the distribution of the sample in the ratio 70%:30% (Bunyaminu & Issah, 2012) and 80%:20% (Bartual, Garcia, & Moya, 2013). In our study, the 70%:30% ratio is used, given that it is frequently used in the previous empirical studies

(70% development and 30% validation data sets). The research on insolvency of companies in Serbia will be performed by SPSS (Statistical Package for Social Sciences), version 20.0 (IBM SPSS Statistics 20.0).

3.1. Sample selection

The main aim of this article is to develop a prediction model which will produce the highest accuracy in predicting the insolvency of companies in the Republic of Serbia. It is assumed that the information in the financial statements of the sample companies in Serbia is valid and reliable, so estimation of insolvency is objective. The sample of 126 companies (small, medium and large manufacturing companies) was divided into two groups for development of the prediction model using the LR in Serbia (Table 2): the pattern of development of a model which contains 70% of the cases (86 cases) and sample to test the model containing the remaining 30% of cases (40 cases). Therefore, the first part of the sample of 126 companies is used for development of the prediction model and other part is used for testing the prediction model.

The sample of companies for the development of the model consists of two groups of companies: insolvent and solvent companies. For research purposes, insolvent companies have been considered as companies in which bankruptcy proceedings started in period within one year. Solvent companies are, therefore, companies in which bankruptcy proceedings did not start within one year. Due to the fact that a large discrepancy between the two groups of companies (Masten & Masten, 2012) may result in a higher probability of correct classification of a group, in this study a sample of insolvent companies that was randomly selected has been expanded with an equal number of solvent companies. The appropriate pattern for the development of models of the 86 cases, therefore, include the financial statements for the period between 2010 and 2011 for two groups of companies in the Republic of Serbia: the first group consists of 43 insolvent companies (companies which were not subject to bankruptcy proceedings during one year) while the second group consists of 43 solvent companies.

In order to obtain an answer to the question of whether the model developed to predict bankruptcy in the Republic of Serbia has the capability for generalisation, i.e., whether it can be applied to other data outside of the sample, the testing sample of the prediction models includes 40 new companies outside of the initial sample for model development (20 insolvent companies and 20 solvent companies). The selection of companies which are in bankruptcy or not has been made randomly according to the availability of financial reports from the website of the Business Registers Agency of the Republic of Serbia. The date of the bankruptcy proceedings and the availability of financial statements has been

Table 2. Sample for developing and testing the model Case processing summary.

Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	86	68.3
	Missing Cases	0	.0
	Total	86	68.3
Unselected Cases		40	31.7
Total		126	100

Source: Authors, SPSS output.

checked for each company. The sample does not include banks, insurance companies and other legal entities, due to their specific operations and financial reporting.

3.2. The selection of financial ratios for the development of insolvency prediction model

Bellovary, Giacomino, and Akers (2007) in their review of the empirical studies on the development of models for predicting financial distress (bankruptcy) of the company from 1930 onwards concluded that the most common financial ratios pointing out the potential risk of financial distress (bankruptcy) of the company (Omelka et al., 2013) are as follows: (1) Net Gains/Total Assets (in 54 prediction models); (2) Current Liquidity Ratio (in 51 prediction models); (3) Working Capital/Total Assets (in 45 prediction models); (4) Retained Earnings/Total Assets (in 42 prediction models); (5) EBIT/Total Assets (in 35 prediction models); and (6) Revenues from Sales/Total Assets (in 32 prediction models), etc.

The choice of financial ratios used in the development of models to predict insolvency of a company in Serbia was based on: (1) popularity of financial ratios in the literature; and (2) highest importance of financial ratios that have been best at predicting the probability of insolvency of the company in the previous empirical research. Initial insolvency prediction model includes 24 financial ratios. Table 3 gives an overview of the ratios used in the development of models to predict insolvency of a company in the Republic of Serbia.

There are several techniques for LR (Pallant, 2009) which are used to test the predictive power of sets or blocks of independent variables and which allow entry of independent variables into the regression model, and some of them are: (1) Forced Entry Method; and

Table 3. The overview of variables (financial ratios) used for the development of insolvency prediction model of the company in the Republic of Serbia.

Group of ratios	The name of the ratio and its calculation
Liquidity Ratios	a) Ratio of Current (General) liquidity = Current Assets/Current Liabilities
	b) Ratio of Accelerated (Rigorous) Liquidity = (Current Assets – Inventories)/Short-Term Liabilities
	c) Ratio of Financial Stability = Fixed assets/(Long-Term Liabilities + Equity)
	d) Net Working Capital/Total Assets = (Current Assets – Short-Term Liabilities)/Total Assets
Leverage Ratios	a) Debt Ratio (of Financial Leverage) = Total Liabilities/Equity
	b) Ratio of Self-Financing = Equity/Total Assets
	c) Indebtedness Factor = Total Liabilities/(Net Income + Depreciation Costs)
	d) Coverage Level I = Equity/Fixed Assets
	e) Coverage Level II = (Equity + Long-Term Liabilities)/Fixed Assets
	f) Coverage of Interest Costs = EBIT/Interest Costs
Activity Ratios	a) Total Assets Turnover Ratio = Total Income/Average Value of Property
	b) Working Capital Turnover Ratio = Sales Income/Average Value of Current Assets
	c) Inventory Turnover Ratio = Sales Income/Average Value of Inventories
	d) Receivables Ratio = Sales Income/Average Value of Receivables
Economy Ratios	a) Sales Effectiveness = Sales Income/Sales Costs
	b) Effectiveness of Continuous Operations = Business Income/Business Costs
	c) Effectiveness of Financing = Finance Income/Finance Costs
	d) Effectiveness of Total Business Operations = Total Revenue/Total Expenditure
Profitability Ratios	a) Net Profit Margin = Net Income/Total Revenue
	b) Gross Profit Margin = Gross Profit /Total Revenue
	c) Rate of Return on Total Capital (Rate of Return on Assets, ROA) = Operating Profit/Average Value of Assets
	d) Rate of Return on Equity (ROE) = Net Income/Average Value of the Equity
Other Ratios	a) Net Cash Inflow (Outflow) from Regular Activities/Total Assets
	b) Solvency Ratio = Operating Assets/Total Liabilities

Source: Authors.

(2) Stepwise Methods of Gradual Statistical Regression: Forward Selection and Backward Elimination, such as: Forward: conditional; Forward: LR; Forward: Wald; Backward: conditional; Backward: LR and Backward: Wald that allow placing a large group of potential predictors, from where the subset with the highest predictive power is selected. These techniques are considered particularly useful since they select variables based on a formal test, called the likelihood ratio test, and they avoid the multicollinearity problems that may arise with the inclusion of a number of highly correlated variables in a multivariate model (Charitou, Neophytou, & Charalambous, 2004). For the purposes of our study, we applied a stepwise statistical regression – Forward: LR method for the selection of independent variables models. Removing the independent variables in the model is based on the Likelihood Ratio Test. In LR the following models are examined:

$$P_i(Bankruptcy) = \frac{e^{y_i}}{1 + e^{y_i}} = \frac{1}{1 + e^{-y}i} \tag{3}$$

Where:

$$y_i = \beta_0 + \sum_i^{24} \beta_i * x_i + \varepsilon_i; x_i = financialratios$$

Stepwise regression analysis (Xie et al., 2013) is used to remove independent variables which are insignificantly linear with the dependent variable. In this way, remained independent variables are significant to the dependent variable and multicollinearity is removed.

4. Results and discussion

4.1. The design of insolvency prediction model in the Republic of Serbia

The developed LR model should include only those independent variables $x_1, ..., x_{\kappa i}$ that are important for predicting the insolvency of the company. By applying statistical procedures to a model design, the LR model is generated after five iterations (Table 4), which included following five ratios (out of initial 24 financial ratios): (1) Net Working Capital/Total Assets; (2) Ratio of Self-Financing; (3) Working Capital Turnover Ratio; (4) Effectiveness of Total Business Operations; and (5) Net Cash Inflow (Outflow) from Regular Activities/Total Assets.

According to calculated regression ratios for each of the included predictors the following binomial LR model to predict insolvency of the Republic of Serbia is designed:

Table 4. Variables (financial indicators) that are in step 5 of gradual (stepwise) statistical regression included in insolvency prediction model of the company in the Republic of Serbia Variables in the Equation.

		B.	S.E.	Wald	df	Sig.	Exp(B)
	Net Working Capital/Total Assets	3.938	1.066	13.646	1	.000	51.334
	Ratio of Self-Financing	2.768	1.217	5.173	1	.023	15.933
	Working Capital Turnover Ratio	.927	.309	8.985	1	.003	2.526
Step 5	Effectiveness of Total Business Operations	3.777	1.465	6.643	1	.010	43.680
	Net Cash Inflow (Outflow) from Regular Activities/Total Assets	−5.664	3.401	2.773	1	.096	.003
	Constant	−5.167	1.879	7.561	1	.006	.006

Source: Authors, SPSS output.

$$Logit\left[p(x)\right] = Ln[\frac{p(x)}{1 - p(x)}] = -5,167 + 3,938 * X_1$$
$$+ 2,768 * X_2 + 0,927 * X_3 + 3,777 * X_4 - 5,664 * X_5 \tag{4}$$

Where:

x_1 = Net Working Capital/Total Assets;

x_2 = Ratio of Self-Financing;

x_3 = Working Capital Turnover Ratio;

x_4 = Effectiveness of Total Business Operations;

x_5 = Net Cash Inflow (Outflow) from Regular Activities/Total Assets.

As one can see from the equation of LR of the analysed model, variable Net Cash Inflow (Outflow) from Regular Activities/Total Assets has a negative regression ratio β_5 (B = - 5.664), which means that an increase in the value of the independent variables reduces the probability of occurrence of insolvency of the company. Other independent variables have positive regression ratios $\beta_1,..., \beta_4$ (regression ratios $\beta_1,..., \beta_4$ have positive sign), which means that increasing the value of the independent variables (financial ratios) increases the likelihood that there will be insolvency of the company.

The developed LR model to predict insolvency of the Republic of Serbia is clearer if it is given in the following equation:

$$P_i = P\left(y = j\right) = p(x) = \frac{e^{(-5,167 + 3,938*X1 + 2,768*X2 + 0,927*X3 + 3,777*X4 - 5,664*X5)}}{1 + e^{(-5,167 + 3,938X1 + 2,768*X2 + 0,927*X3 + 3,777*X4 - 5,664*X5)}}$$
$$= \frac{1}{1 + e^{-(-5,167 + 3,938X1 + 2,768*X2 + 0,927*X3 + 3,777*X4 - 5,664*X5)}} \tag{5}$$

4.2. Reliability assessment of the insolvency prediction model in the Republic of Serbia

There are various statistical procedures for evaluating the adequacy of the created LR model, and some of the most important methods are: Omnibus Test (Goodness-of-Fit Test), Pseudo Data Values R^2 (Cox & Snell R^2 Test and Nagelkerke R^2 Test), Wald Test, Hosmer-Lemeshow Test and Classification Table.

4.2.1. Omnibus test

Omnibus test can be used in checking whether the LR model is good or not. This test (Pallant, 2009) is called Goodness-of-Fit, i.e., how well the LR model predicts results, and how well this model accurately predicts the risk of a company. Goodness-of-fit test is based on the chi-square distribution and it tests the null hypothesis if the reasonable step is to add independent variable in the equation of the LR model; in other words, it tests the null hypothesis (**H0**) against the alternative hypothesis (**HA**), wherein the hypotheses are defined as follows:

H0: Logistic regression model is well fitted;

HA: Logistic regression model is not well fitted.

Table 5 shows the results of the set of predictor variables. This table shows consecutive incremental steps of gradual LR (a step is an improvement measure for predictive power of the LR model from the previous step), when each independent variable is added or removed,

Table 5. Omnibus test for ratios of the model Block 1: Method = Forward Stepwise (Likelihood Ratio).

		Chi-square	df	Sig.
Step 1	Step	36.984	1	.000
	Block	36.984	1	.000
	Model	36.984	1	.000
Step 2	Step	13.650	1	.000
	Block	50.633	2	.000
	Model	50.633	2	.000
Step 3	Step	7.656	1	.006
	Block	58.289	3	.000
	Model	58.289	3	.000
Step 4	Step	5.567	1	.018
	Block	63.856	4	.000
	Model	63.856	4	.000
Step 5	Step	3.584	1	.058
	Block	**67.440**	5	**.000**
	Model	**67.440**	5	**.000**

Source: Authors, SPSS output.

Table 6. Summary statistics of the model.

Step	−2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	82.052	.350	.466
2	68.402	.445	.594
3	60.747	.492	.657
4	55.180	.524	.699
5	**51.595**	**.544**	**.725**

Source: Authors, SPSS output.

creating a variety of the prediction models. The significance column (Sig.) in this table is the probability of obtaining the values of Chi-squared.

If the value of Sig. is less than .05, it is statistically significant and the null hypothesis (**H0**) that the LR model is well fitted is acceptable. For the LR model obtained in the fifth step Chi-square is 67.440 with 5 Degrees of Freedom (df) and the probability is p < .05.

4.2.2. Pseudo data values R^2

The usability (validity) of an LR, and how much of the variance of the dependent variable explains the model is measured by the pseudo R^2 data values, including the most common application of Cox & Snell R^2 test and Nagelkerke R^2 test. The measures of pseudo R^2 (Braun, Muller & Schmeiser, 2013) range from the minimum of 0 to the maximum of approximately 1, wherein values greater than .4 indicate that the LR model is well-fitted. Ideally, if the R-squared is 1, it means that the predictors fully explain the dependent variable and in the future we can accurately determine the value of the dependent variable only on the basis of predictors. In Table 6, the values of Cox-Snell R-Square (R^2) and R-Square Nagelkerke (R^2) are .544 and .725 respectively, meaning that the LR model as a whole, i.e., a given set of predictor variables, explains between 54.4% and 72.5% of the variance of the dependent variable.

Comparing obtained LR models from the previous step with the LR model obtained in the fifth step, it can be noticed that the LR model obtained in the fifth step has most interpreted variations, so it is the most representative.

4.2.3. Wald test

The statistical significance of regression ratios in the LR model, and the significance of each predictor (variable) in the LE model (Suzić, 2007) can be tested by the Wald test. Wald test is used to show whether an independent variable has a statistically significant effect on the dependent variable, i.e., whether the interaction effect exists or not. If the significance (Sig.), i.e., p value of Wald test of statistics of individual independent variable is less than the level of confidence (significance) α = 5% (.05) then there is rejection of the null hypothesis (**H0**) that the regression ratio is zero (β=0) and the independent variable contributes significantly to the predictive capabilities of the model (the independent variable is statistically significant; the independent variable has a significant contribution to the prediction; the effect of the interaction is significant) and therefore it is included in the model (Zenzerović, 2011).

Table 7 presents data on the contribution or importance of each predictor variable in the model for the prediction of insolvency in Serbian companies.

Table 7. Variables in the equation of the model to predict insolvency of a company in the Republic of Serbia.

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Net Working Capital/Total Assets	3.993	.860	21.532	1	.000	54.191
	Constant	.310	.276	1.261	1	.261	1.363
Step 2[b]	Net Working Capital/Total Assets	3.351	.927	13.067	1	.000	28.533
	Effectiveness of Total Business Operations	3.077	1.009	9.304	1	.002	21.696
	Constant	−2.335	.961	5.903	1	.015	.097
Step 3[c]	Net Working Capital/Total Assets	3.466	.930	13.876	1	.000	32.005
	Working Capital Turnover Ratio	.584	.237	6.072	1	.014	1.794
	Effectiveness of Total Business Operations	2.557	1.013	6.372	1	.012	12.893
	Constant	−2.719	1.001	7.386	1	.007	.066
Step 4[d]	Net Working Capital/Total Assets	3.414	.918	13.817	1	.000	30.391
	Ratio of Self-Financing	2.377	1.088	4.776	1	.029	10.777
	Working Capital Turnover Ratio	.795	.278	8.183	1	.004	2.213
	Effectiveness of Total Business Operations	3.373	1.290	6.832	1	.009	29.152
	Constant	−4.458	1.576	7.999	1	.005	.012
Step 5[e]	Net Working Capital/Total Assets	**3.938**	1.066	13.646	1	**.000**	51.334
	Ratio of Self-Financing	**2.768**	1.217	5.173	1	**.023**	15.933
	Working Capital Turnover Ratio	**.927**	.309	8.985	1	**.003**	2.526
	Effectiveness of Total Business Operations	**3.777**	1.465	6.643	1	**.010**	43.680
	Net Cash Inflow (Outflow) from Regular Activities/ Total Assets	**−5.664**	3.401	2.773	1	**.096**	.003
	Constant	**−5.167**	1.879	7.561	1	**.006**	.006

[a]Variable(s) entered on step 1: Net Working Capital/Total Assets.
[b]Variable(s) entered on step 2: Effectiveness of Total Business Operations.
[c]Variable(s) entered on step 3: Working Capital Turnover Ratio.
[d]Variable(s) entered on step 4: Ratio of Self-Financing.
[e]Variable(s) entered on step 5: Net Cash Inflow (Outflow) from Regular Activities/Total Assets.
Source: Authors, SPSS output.

4.2.4. Hosmer-Lemeshow test

Hosmer-Lemeshow test is applicable only for models with binary outcomes. It shows how close they are to the observed (actual) and predicted (expected) frequencies. This is the most reliable test of the quality of the prediction model. The Hosmer-Lemeshow test (Pallant, 2009) is a test based on the calculation of λ^2 observed (actual) and predicted (expected) value of the dependent variable of the LR model. It compares the original variables and prediction, i.e., if there is a statistically significant difference between them. The null hypothesis

Table 8. The Hosmer-Lemeshow test.

Step	Chi-square	df	Sig.
1	6.644	8	.576
2	11.050	8	.199
3	20.289	8	.009
4	6.712	8	.568
5	**10.826**	8	**.212**

Source: Authors, SPSS output.

to be tested is whether there is a significant difference between the examined number of observations that belong to specific groups of one variable and the expected number of observations that are based on certain hypothetical (theoretical or empirical) values. In our case, the claim that the model to predict insolvency of a company in the Republic of Serbia is good is checked by the Hosmer-Lemeshow test. P-value (probability of significance, Sig.) and Chi-square statistics with 8 degrees of freedom (df) is shown in Table 8.

The Hosmer-Lemeshow Goodness-of-Fit test is interpreted differently from the previously considered Omnibus test. The small value of Hosmer-Lemeshow test statistics indicates that the model is good and a large value of Chi-square statistics indicates that the model is not well-adapted by data and that there is a major discrepancy between the observed and the expected frequency. The Hosmer-Lemeshow test (Zenzerović & Peruško, 2009) is a ratio of good prediction of significance greater than .05. If Hosmer-Lemeshow test showed significance (sig.) greater than .05, there is no rejection of the null hypothesis (**H0**) that there is no significant difference between the observed and predicted values of the dependent variable model, i.e., a model to predict insolvency of a company in the Republic of Serbia well-fitted and good since the observed (actual) and predicted values of the dependent variable models coincide. This does not mean that the model explains much of the variance of the dependent variable, but only that it does it to a considerable extent so that the model is statistically significant and convenient with regard to the given data. The results of the analysis in Table 8 shows that the value of Chi-square (χ^2) statistics is 10.826 with significance of .212, and it leads to the conclusion that the model for the prediction of insolvency of the company in the Republic of Serbia is in accordance with the data, that is, the observed (actual) and predicted (expected) frequencies do not differ significantly. Thus, this logistic prediction model is good (supported).

4.2.5. Classification table

The results of fitted LR model can be represented by a classification table, which is the result of crossing the original variable (resulting variable) and prediction (dichotomous variables whose values are derived from the estimated logistic probability). This is a simple tool that shows how the model is a good predictor of the dependent (resulting) variables. When it comes to categorical data, cross-tabulation is used.

Table 9 shows how accurately the developed model predicts a category for each tested case. This table shows the accuracy of the classification model, i.e., the percentage of correct predictions of the model with the critical value (F*) of .5. In the predicted classification table based on training sample and validation sample 0.5 is used as cut-off. On the diagonal of the classification table is the number of correctly classified observations, as predicted and the actual groups are equal. Outside the diagonal of the table there is the incorrect (wrong)

Table 9. Classification table of the model.

			Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			Bankruptcy		Percentage Correct	Bankruptcy		Percentage Correct
Observed			0	1		0	1	
Step 1	Bankruptcy	0	32	9	78	16	6	72.7
		1	6	39	86.7	3	15	83.3
	Overall Percentage				82.6			77.5
Step 2	Bankruptcy	0	33	8	80.5	18	4	81.8
		1	5	40	88.9	2	16	88.9
	Overall Percentage				84.9			85
Step 3	Bankruptcy	0	34	7	82.9	20	2	90.9
		1	4	41	91.1	3	15	83.3
	Overall Percentage				87.2			87.5
Step 4	Bankruptcy	0	33	8	80.5	20	2	90.9
		1	4	41	91.1	4	14	77.8
	Overall Percentage				86			85
Step 5	Bankruptcy	0	**34**	**7**	**82.9**	**20**	**2**	**90.9**
		1	**3**	**42**	**93.3**	**5**	**13**	**72.2**
	Overall Percentage				**88.4**			**82.5**

[a]The cut value is .500.
[b]Selected cases validate EQ 1.
[c]Unselected cases validate NE 1.
Source: Authors, SPSS output.

classification number of classified observations, given the predicted and actual group. The classification table (2x2 classification table, table of cross-classification, classification matrix) shows four cases (Zenzerović, 2011): (1) D – the number of correctly classified (predicted) solvent, or 'healthy' companies (34); (2) C – the number of incorrectly classified solvent, or 'healthy' companies (7); (3) B – the number of incorrectly classified insolvent companies, or companies in bankruptcy (3); and (4) A – the number of correctly classified insolvent companies, or companies in bankruptcy (42). A classification table (Table 9) indicates how well the model predicts bankruptcy. The sample has been randomly split into a model fitting sample and a validation sample.

The classification table consists of i rows and j columns that correspond to the categories, while the fields of the table correspond to the possible outcomes. In the classification table, two columns are intended for the values of the dependent variable (the values obtained by the model), whereas the two rows are used for observed (actual) values of the dependent variable. When the model is perfect, in the diagonal of the classification table there will be the number of correctly classified cases and the average (total) percentage of correctly classified (predicted) cases will be 100%. Pacey and Pham (Gepp & Kumar, 2012; Hu & Sathye, 2015) who state the following major problems with LA models: (1) arbitrary estimation of cut-off values; (2) assumption of equal misclassification costs in model estimation stage; and (3) bias in the selection of samples for model estimation. The developed insolvency prediction model in the Republic of Serbia classifies correctly 82.9% of solvent ('healthy') companies and 93.3% of insolvent companies from the sample for model development (fitting sample), and 90.9% of solvent companies and 72.2% of insolvent companies in the test sample (validation sample). The LR model with predictors in Serbia accurately classifies (predicts) 88.4% of the cases from the sample for model development (the average [overall] accuracy of the prediction model) and 82.5% of the cases from the test sample (see

Table 9). Therefore, it seems that strong deviations from normality of data (Situm, 2014) are influencing the estimation procedure of LR and are affecting the classification accuracy of logistic functions. Also, the unequal distribution between bankrupt and non-bankrupt firms seems to influence the classification results of model. Nevertheless, the classification accuracy could have been optimised by using normally distributed data, but this was not possible due to the lack of sufficient data. This confirms results from prior research (Situm, 2015) that models classified recovered firms into insolvent firms based on the type II errors obtained. The explanatory variables (financial indicators) do not appear to have the relevant information required to clearly distinguish between the two types of firms. This study leads to the conclusion that accounting ratios alone are not able to sufficiently describe the two defined states of this study, which is a similar result to prior research. Many prior studies (Hu & Sathye, 2015) have used financial variables as the major predictors of corporate financial distress. Recent studies, however, contend that non-financial variables and macroeconomic variables also need to be considered for financial distress prediction. Back P. for example, used only non-financial variables in the financial distress prediction model and found that the model has better predictive ability than does a model that includes only financial variables. Foster found that multivariate models that include macroeconomic variables and financial variables have better financial distress prediction ability than does a model that includes only financial variables.

The training set (Xie et al., 2013) is used to acquire the parameters of forecasting models and the testing set is used to measure the forecasting performance of forecasting models. It can be concluded that the performance of the prediction model developed depends on the sample size for model estimation, given that the classification accuracy of the model to predict bankruptcy of a company in the Republic of Serbia is better when it comes to the sample for model development which includes 86 commercial companies than on the test sample which is less than the sample for model development (40 of companies). This is confirmed by the results of empirical research Hauser and Booth (2011). The classification accuracy of the validation sample was only 5.9% less than that of the model fitting sample (88.4% and 82.5% respectively) (see Table 9). Thus, it can be concluded that the model was valid and can be replicated.

The developed LR model (Hassani & Parsadmehr, 2012; Zenzerović, 2011) can make a mistake in predicting (overlooking) the insolvency of the company in two ways: (1) it can classify the insolvent company (companies in bankruptcy) into the group of companies with a low risk of insolvency, which is a type I error (1 – ratio of sensitivity); and (2) it can be classify the solvent company (a company that is not in bankruptcy) into a group of companies with a high risk of insolvency, which is a type II error (1 – specificity ratio). Higher specificity and sensitivity are an indication of a good fit of the model. In our case, the type I error (fitting sample) is: 100%−93.3% = 6.7% or B/(B+A)*100=3/(3+42)*100=6.67%, the type II error (fitting sample) is: 100%−82.9% = 17.1% or C/(D+C)*100=7/(34+7)*100=17.07%, while type I error (validation sample) is: 100%−72.2% = 27.8% or B/(B+A)*100=5/(5+13)*100=27.78% and type II error (validation sample) is: 100%−90.9% = 9.1% or C/(D+C)*100=2/(20+2)*100=9.09%. Since the type II error (Ming-Chang & Li-Er, 2015) only creates a lost opportunity cost from not dealing with a successful business, for example, missed potential investment gains, therefore type II error is more important than type I error. The objectives of predictive of accuracy should be to reduce type II error while keeping type I error. The comparison of the LR model on fitting and validation sample, no matter to

the overall prediction accuracy, type II error, show that the LR model (validation sample) is lower than the LR model (fitting sample), while type I error is higher.

By comparing the accuracy of the classification of the developed model to predict insolvency of a company in the Republic of Serbia with the classification accuracy of prediction models that were developed in Croatia, such as: (1) model of Ivičić and Cerovac (Ivičić & Cerovac, 2009), which correctly classified 74.9% of solvent ('healthy') Croatian companies that regularly pay liabilities when due and 71.2% of Croatian companies which fail to meet their liabilities when due; (2) model of Pervan and Vukoja (2011), which accurately classified 80.8% of solvent ('healthy') Croatian companies and 85.9% of Croatian companies which started bankruptcy proceedings (insolvency); and (3) model of Šarlija and Jeger (2011), which correctly classifies 78.9% of solvent ('healthy') companies and 63.63% of companies that do not regularly pay outstanding liabilities, it can be noted that our developed model is more accurate in predicting the insolvent companies, or companies that have started bankruptcy proceedings (classification accuracy of 72.2%) and solvent ('healthy') Serbian companies (classification accuracy of 90.9%).

The basic measures for goodness-of-fit are general ratios of how well the model agrees with the data. Assessing the effectiveness of models for predicting bankruptcy of the company (Pallant, 2009) was performed using the following measures:

1. Sensitivity is the percentage share of the group with test characteristics (problem with bankruptcy) that the model accurately identified is calculated using the following equation:

$$Sensitivity\ (\%) \ = \ A/(B+A) * 100 \ = \ 13/(5+13) * 100 \ = \ 72.2\% \qquad (6)$$

Where: A – number of correctly classified (predicted) insolvent companies (companies in bankruptcy) and B – the number of incorrectly classified insolvent companies (companies in bankruptcy);

2. Specificity, or determination of the model is percentage of the group that does not have examined features (no bankruptcy problems) that the model accurately identified, classified (true negative) is calculated using the following equation:

$$Specificity(\%) = D/(D+C) * 100 = 20/(20+2) * 100 = 90.9\% \qquad (7)$$

Where: D – number of correctly classified (predicted) solvent, or ('healthy') companies and C – he number of incorrectly classified solvent, or ('healthy') companies;

3. The negative predictive value is percentage of cases that the model classifies as they do not have examined features, and that it is not really noticeable in that group. This value is calculated using the following equation:

$$Negative\ predictive\ value\ (\%) \ = \ D/(D+B) * 100 \ = \ 20/(20+5) * 100 \ = \ 80.0\% \quad (8)$$

Where: D – the number of correctly classified (predicted) solvent, or ('healthy') companies and B – the number of incorrectly classified insolvent companies (companies in bankruptcy);

4. The positive predictive value is percentage of cases that the model classifies as having examined features, and it is indeed noticeable in the group. This value is calculated using the following equation:

$$Positive\ predictive\ value\ (\%) \ = \ A/(C+A) * 100 \ = \ 13/(2+13) * 100 \ = \ 86.7\% \quad (9)$$

Where: *A* – number of correctly classified (predicted) of insolvent companies (companies in bankruptcy) and *C* – the number of incorrectly classified solvent, or ('healthy') companies;

5. The general efficiency of the model is calculated by the following equation:

$$
\begin{aligned}
\textit{General efficiency of the model } (\%) &= (A + D)/(A + B + C + D) * 100 \\
&= (13 + 20)/(13 + 5 + 2 + 20) * 100 \\
&= 82.5\% \, (10)
\end{aligned}
$$

(10)

Where: *A* – number of correctly classified (predicted) insolvent companies (companies in bankruptcy); *B* – number of incorrectly classified insolvent companies (companies in bankruptcy); *D* – number of correctly classified solvent, or ('healthy') companies and *C* – the number of incorrectly classified solvent, or ('healthy') companies.

5. Conclusion

One of the prerequisites for continuous operations of companies is a regular settlement of liabilities. The insolvency risk is a characteristic for all companies that do not have the financial means to settle obligations to suppliers, shareholders, creditors, employees, government and other entities. Modern models of analysis of financial statements successfully measure changes in the financial health of the company. Most existing models for predicting insolvency (bankruptcy) of the company are based on financial ratios and the information in the financial statements. Accounting information given in the financial statements allows not only an analysis of the past, but the prediction of future performance of the company.

In developing the prediction LR model in Serbia the financial ratios from the following groups are used: liquidity ratios, leverage ratios, activity ratios, economy ratios, profitability ratios and others. Empirical research results support the hypothesis that on the basis of financial ratios we can shape the LR model as a useful tool to predict (in)solvency of the company in the Republic of Serbia. Variables that give a statistically significant contribution to the predictive capabilities of the models in Serbia are as follows: Net Working Capital/Total Assets (X_1); Ratio of Self-Financing (X_2); Working Capital Turnover Ratio (X_3); Effectiveness of Total Business Operations (X_4) and Net Cash Inflow (Outflow) from Regular Activities/Total Assets (X_5).

The developed predictive LR model classifies correctly 82.9% of solvent ('healthy') Serbian companies and 93.3% of insolvent Serbian companies (Serbian companies that have started bankruptcy proceedings within one year) from the sample for model development (fitting sample), and 90.9% of solvent companies and 72.2% of insolvent companies in the test sample (validation sample). The LR model with predictors in Serbia accurately classifies (predicts) 88.4% of the cases from the sample for model development (the average [overall] accuracy of the prediction model) and 82.5% of the cases from the test sample. Applying the developed LR model to predict insolvency of a company in the Republic of Serbia different users of financial information might *ex ante* obtain information as to whether there is a possibility that the company will not continue to operate under the assumption of going concern (a continuity of business operations).

Our results are encouraging and should be validated by a larger sample size. Future research is also needed to investigate why selected financial ratios are related to bankruptcy prediction. Also, it would be interesting to analyse additional model variables which are not

derived from financial statements (such as industry benchmarks, market variables, macroeconomic variables, etc.), in order to test their incremental contribution to an improved model performance and classification accuracy. Future work should also be directed to development of failure prediction models for other sectors, apart from manufacturing. This could be especially useful for banking sector since this model could be used as a supplement to the stress tests.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Alihodžić, A. (2013). Testiranje primene Kralicekovog DF pokazatelja na Beogradskoj berzi [Testing of Kralicek DF ratios on Belgrade Stock Exchange]. Bankarstvo, 3, 70–95. Retrieved November 26, 2013, from http://www.ubs-asb.com/Portals/0/Casopis/2013/3/UBS-Bankarstvo-3-2013-Alihodzic.pdf

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), 589–609.

Altman, I. E. (2002). Corporate distress prediction models in a turbulent economic and Basel II environment, 1–31. Retrieved June 2, 2014, from http://pages.stern.nyu.edu/~ealtman/Corp-Distress.pdf

Andrić, M., & Vuković, B. (2012). Reflections of the crisis on the corporate operational performance of Serbian industrial companies. *Strategic Management, 17*(3), 21–28.

Bartual, C., Garcia, F., & Moya, I. (2013). Default prediction of Spanish companies. *A logistic analysis, Intelektinė Ekonomika-Intellectual Economics, 3*(17), 333–343.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71–111.

Bellovary, J., Giacomino, D., & Akers, M. (2007). A review of going concern prediction studies: 1976 to present. *Journal of Business & Economics Research, 5*, 9–28.

Bešlić, D., & Bešlić, I. (2013). The impact of global economic and financial crisis on financial position of the enterprise from Serbia. In *Proceedings: Entrepreneurship: Economic development & finance – 2nd International Conference – Employment, education and entrepreneurship – (ZOP 2013)* (pp. 399–419). Belgrade: Faculty of Business Economics and Entrepreneurship.

Braun, A., Muller, K., & Schmeiser, H. (2013). What drives insurers' demand for cat bond investments? Evidence from a Pan-European survey. *Geneva Papers on Risk & Insurance – Issues & Practice, The International Association for the Study of Insurance Economics, 38*(3), 580–611.

Bunyaminu, A., & Issah, M. (2012). Predicting corporate failure of UK's listed companies: Comparing multiple discriminant analysis and logistic regression. *International Research Journal of Finance and Economics, 94*, 6–22.

Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review, 13*(3), 465–497.

Duvnjak, V. (2008). Utvrđivanje uzroka i pokazatelja poslovnog neuspjeha [Determining the causes and ratios of business failure]. *Acta Economica, 6*(9), 139–157.

Ebrahimi, K. A., & Nikbakht, N. (2011). Comparing bankruptcy prediction models in Iran. *School of Doctoral Studies (European Union) Journal*, 24–31. Retrieved February 5, 2013, from http://www.iiuedu.eu/press/journals/sds/SDS_2011/BME_Article3.pdf

Ecer, F. (2013). Comparing the bank failure prediction performance of neural networks and support vector machines: The Turkish case. *Economic Research-Ekonomska Istraživanja, 26*(3), 81–98.

Gepp, A., & Kumar, K. (2012). Business failure prediction using statistical techniques: A review. *Faculty of Business Publications, 1*(1), 1–25. Paper 675.

Hassani, M., & Parsadmehr, N. (2012). The presentation of financial crisis forecast pattern (evidence from Tehran stock exchange). *International Journal of Finance and Accounting, 1*(6), 142–147.

Hauser, P. R., & Booth, D. (2011). Predicting bankruptcy with robust logistic regression. *Journal of Data Science, 9*, 565–584.

Hu, H., & Sathye, M. (2015). Predicting financial distress in the Hong Kong growth enterprises market from the perspective of financial sustainability. *Sustainability, 7*, 1186–1200. doi:10.3390/su7021186

Ivičić, L., & Cerovac, S. (2009). Procjena kreditnog rizika poduzeća u Hrvatskoj [Credit risk assessment in Croatia]. *Financijska teorija i praksa, 33*(4), 385–413.

Jakšić, D., & Vuković, B. (2012). Uticaj krize na manipulisanje finansijskim izveštajima [Crisis impact on financial statements]. 16th Congress of Accountants and Auditors of the Republic of Srpska – Proceedings: Banja Vrućica.

Jakubík, P., & Teplý, P. (2008). The prediction of corporate bankruptcy and Czech economy's financial stability through logit analysis, *IIES Working Paper Series, 19*, 1–19.

Kaczmarek, J. (2012). Construction elements of bankruptcy prediction models in multi–dimensional early warning systems. *Polish Journal of Management Studies, 5*, 136–149.

Masten, A. B., & Masten, I. (2012). Predicting bankruptcy with semi-parametric single-index model. *Ekonomska istraživanja – Economic Research*, *25*(1), 121–133.

Ming-Chang, L., & Li-Er, S. (2015). Comparison of wavelet network and logistic regression in predicting enterprise financial distress. *International Journal of Computer Science & Information Technology, 7*(3), 83–96.

Muminović, S. (2013). Revaluation and Altman's Z-score – The case of the Serbian capital market. *International Journal of Finance and Accounting, 2*(1), 13–18.

Nikolić, I., Vučković, V., & Ivković, B. (2011). Stanje nelikvidnosti i analiza predloga zakona o sporazumnom finansijskom restrukturiranju privrednih društava [Non-liquidity state and analysis of the draft of law on consensual financial restructuring of companies]. *Industrija/Industry, 4*, 181–191.

Nojkovic, A. (2007). Modeli diskretne zavisne promenljive: Pregled metodologije i primenjenih istraživanja [Models of discrete dependent variable: Overview of methodology and applied research]. *Ekonomski anali, 52*(172), 55–92.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), 109–131.

Omelka, J., Beranová, M., & Tabas, J. (2013). Comparison of the models of financial distress prediction. *Acta Universitatis*, *61*(7), 2587–2592. Retrieved December 28, 2013, from http://acta.mendelu.cz/pdf/actaun201361072587.pdf

Pallant, J. (2009). *SPSS: Priručnik za preživljavanje* [SPSS: Guide for survival]. Belgrade: Mikro knjiga.

Pavlović, V., Muminović, S., & Cvijanović, M. J. (2011a). Adekvatnost Taffler-ovog modela za predikciju bankrotstva srpskih kompanija [Appropriateness of Taffler model for predicting bankruptcy of Serbian companies]. *Industrija/Industry, 4*, 57–70.

Pavlović, V., Muminović, S., & Cvijanović, M. J. (2011b). Application of Sandin&Porporato's bankruptcy prediction model on Serbian companies. *Industrija/Industry, 2*, 1–13.

Pavlović, V., Muminović, S., & Cvijanović, M. J. (2012). Adequateness of applying the Zmijewski model on Serbian companies. *Industrija/Industry, 40*(3), 25–39.

Pervan, M., & Vukoja, B. (2011). Prediction of company bankruptcy using statistical techniques – Case of Croatia. *Croatian Operational Research Review (CRORR), 2*, 158–168.

Šarlija, N., & Jeger, M. (2011). Comparing financial distress prediction models before and during recession. *Croatian Operational Research Review (CRORR), 2*, 133–143.

Sielewicz, G. (2014). CEE Insolvencies: 2013 was a challenging year for companies in Eastern Europe. *The coface economic publications – Panorama, Coface*, 1–26. Retrieved May 10, 2014, from http://www.coface.com/News-Publications/Publications/CEE-Insolvencies-2013-was-achallenging-year-for-companies-in-Eastern-Europe

Situm, M. (2014). Inability of gearing-ratio as predictor for early warning systems. *Business Systems Research, 5*(2), 23–45. doi:10.2478/bsrj-2014-0008

Situm, M. (2015). Recovery from distress and insolvency: A comparative analysis using accounting ratios. *Proceedings of the 6 589 TH GCMRM 2015,* 589–606. Retrieved March 15, 2016, from

file:///C:/Users/Windows7/Downloads/Situm%202015%20%20Recovery%20from%20distress%20and%20insolvency.pdf

Stroe, R., & Bărbuţă-Mişu, N. (2010). Predicting the financial performance of the building sector enterprises – Case study of Galati county (Romania). *The Review of Finance and Banking, 2*, 29–39. Retrieved February 8, 2013, from http://www.rfb.ase.ro/articole/A3-Stroe.pdf

Suzić, N. (2007). *Primijenjena pedagoška metodologija* [Applied pedagogical methodology]. Banja Luka: XBS.

Šverko Grdić, Z., Radolović, J., & Bagarić, L. (2009). Solventnost poduzeća u Republici Hrvatskoj i u Europskoj uniji. *Ekonomski pregled, 60*(5–6), 250–266.

Xie, G., Zhao, Y., Jiang, M., & Zhang, N. (2013). A novel ensemble learning approach for corporate financial distress forecasting in fashion and textiles supply Chains. *Mathematical Problems in Engineering,* 1–9.

Zenzerović, R. (2009). Business financial problems prediction – Croatian experience. *Ekonomska istraživanja – Economic Research, 22*(4), 1–16.

Zenzerović, R. (2011). Credit scoring models in estimating the creditworthiness of small and medium and big enterprises. *Croatian Operational Research Review (CRORR), 2*, 143–158.

Zenzerović, R., & Peruško, T. (2006). Kratki osvrt na modele za predviđanje stečaja [Short retrospection on bankruptcy prediction models]. *Ekonomska istraživanja – Economic Research, 19*(2), 132–151.

Zenzerović, R., & Peruško, T. (2009). Ocjenjivanje pretpostavke vremenske neograničenosti poslovanja u tranzicijskom okruženju – empirijski nalazi u Republici Hrvatskoj [Evaluating the assumption of going concern in a transitional environment – Empirical findings in Croatia]. *Ekonomski Pregled, 60*(7–8), 348–368.