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Financial Risk Measurement and Prediction Modelling for Sustainable Development of Business Entities Using Regression Analysis

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Abstract: The issue of the debt, bankruptcy or non-bankruptcy of a company is presented in this article as one of the ways of conceiving risk management. We use the Amadeus database to obtain the financial and accounting data of Slovak enterprises from 2015 and 2016 to calculate the most important financial ratios that may affect the financial health of the company. The main aim of the article is to reveal financial risks of Slovak entities and to form a prediction model, which is done by the identification of significant predictors having an impact on the health of Slovak companies and their future prosperity. Realizing the multiple regression analysis, we identified the significant predictors in conditions of the specific economic environment to estimate the corporate prosperity and profitability. The results gained in the research are extra important for companies themselves, but also for their business partners, suppliers and creditors to eliminate financial and other corporate risks related to the unhealthy or unfavorable financial situation of the company.

Keywords: financial risk; bankruptcy; regression model; sustainable development; Slovak enterprises

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1. Introduction

Financial risk is the possibility that shareholders will lose money when they invest in a company that has debt, if the corporate cash flow proves inadequate to meet its financial obligations. When a company uses debt financing, its creditors are repaid before its shareholders if the company becomes insolvent [1]. Financial risk is often perceived as the risk that a company may default on its debt payments. To eliminate potential financial risks and to be able to identify the level of the corporate financial health, predictions models are used, perceived as systems of timely warning of impending problems in the analyzed companies. Their task is to evaluate the financial health of the company based on selected financial indicators or other characteristics of the company or the environment in which they operate [2].

The originality of the research lies in the identification of crucial determinants in Slovak conditions than can predict either prosperity and profitability of Slovak companies or their default (bankruptcy), without regard to any sector, and thus eliminate potential financial risks threatening the company and its business partners. Determination of prosperity predictors in Slovak conditions can help form a complex Slovak multi-industry prediction model, which would be beneficial for all market subjects, as until the present time we only adopt the results of the models developed in foreign countries, the use of which in our conditions is disputatious.

The main aim of the paper is to extend the knowledge about identification and elimination of financial risks related to the unhealthy financial situation of the company, which is done by the formation of the regression model, results of which enable to estimate the profitability of the company.

The purpose of the paper is to measure financial risks considering national conditions. The research problem includes the formation of an econometric model of the corporate prosperity quantification, using the results of the regression analysis, based on the significant financial indicators identified in the multiple linear regression analysis. We consider the identification of the most significant predictors affecting the future prosperity and profitability of Slovak enterprises to be the main contribution of the paper; those are working capital, working capital to total assets ratio, current assets to total assets ratio, operating profit to total assets ratio, cash and cash equivalents to total assets ratio and current liabilities to total assets ratio.

The paper is divided into four main parts. Literature review highlights the current state of research in the field of prediction and bankruptcy models. Material and Methods depicts a brief description of business entities and financial indicators used as potential predictors in the research and specifies the methodology of the multiple linear regression. Chapter Results is focused on the description of all findings, resulting in the suggestion of the model, which estimates the corporate prosperity and profitability and thus eliminates financial risks. Discussion compares and analyses the studies and researches of other authors in the field of prediction models and emphasizes the various combinations of different financial indicators used as predictors in the models and compares the results of the realized study with results of other studies based on different calculation methods.

Literature Review

Financial risk measurement is a largely investigated research area; its relationship with imprecise probabilities has been mostly overlooked. Vicig [3] claims that risk measures can be viewed as instances of upper (or lower) previsions, thus letting us apply the theory of imprecise previsions to them. A complex approach to risk measurement in financial management is described in the work of Chobot [4,5]. Except for well-known risk measures, including value at risk [6] or coherent and convex risk measures [7], there are many others methods that authors use to measure financial risks. Su and Furman [8] apply a form of multivariate Pareto distribution to measure financial risks. Spatial financial time series models were introduced by Blasques et al. [9], Yang et al. [10] and Audrino and Barone-Adesi [11]. Kessler [12] presents an implementational systematic approach framework for risk, where the risk management target is to manage and mitigate the risk-around-loss causes. Campos et al. [13] underline the importance of innovative soft-computing techniques usage to classify correctly the default of a company by proper financial credit risk prediction. Chai and Xia [14] emphasize that to survive and develop in a drastically competitive market, business entities need to control possible financial risks and foresee their future financial development (using prediction models).

Since the first prediction model developed by Fitzpatrick [15], there have been numerous researches made and various predictors have been identified to predict the future situation of the business entities, e.g., Beaver model [16], Altman model [17], Springate model [18], Ohlson model [19], Taffler-Tisshawa model [20], Fulmer model [21], Zmijewski model [22], Horrigan model [23] etc. The accurate prediction of corporate bankruptcy for the companies in different industries is of a great concern to investors and creditors, as the reduction of creditors' risk can be possible [24]. The systematic review of bankruptcy prediction models is processed in the studies of Alaka et al. [25] or Peres and Antao [26]. The reviews show that there are two groups of popular and promising tools within the bankruptcy prediction models research area, i.e., statistical tools (multiple discriminant analysis and logistic regression) and artificial intelligence tools (decision trees, neural networks, etc.). In this study, we test the use of a quite simple classifier, linear regression approach (similar to Guo et al. [27]), for modelling the relationship between a scalar dependent variable and more explanatory variables (financial indicators) as it performs reasonably well in bankruptcy prediction, as proved by Jones et al. [28]. Regression analysis if often use for bankruptcy prediction, the realized analysis is supported by the study of Calabrese et al. [29] or latest researches in Romania [30] and Lithuania [31], which recommend regression models for bankruptcy prediction. A methodological framework of regression was used to construct predictive bankruptcy models for Asia, Europe and

America and the results verify the superiority of the global model compared to regional models [32]. Ben Jabeur [33] claims that regression model gives the opportunity to consider all the indicators in predicting financial distress. Hwang and Chu [34] propose a new procedure to estimate the loss given default using logistic regression. Li and Miu [35] establish a prediction model with dynamic loading on accounting ratio-based and market-based information using a regression approach.

In Slovak business environment, there are also a few representatives of prediction models. Chrastinová [36] and Gurcik [37] applied the methodology of financial health predictions to companies in the agricultural sector, Binkert [38] and Zalai [39] in commercial enterprises using multiple discriminant analysis. There is not any reputable prediction model in Slovakia, but several studies and researches have been developed. Kameníková [40] solved the limitations in the use of foreign models predicting the financial development of enterprises in conditions of the Slovak Republic. Lesaková [41] states that top management, based on predictions and forecasts, formulates the financial targets of the enterprise for the appropriate time horizon. Horvathova and Mokrisova [42] diagnosed business performance applying the modern financial performance assessment methods. Gundova [43] depicted the main reasons for not using foreign methods of predicting the financial situation in Slovak companies and underlined the importance of the formation of the national prediction model. The application of foreign prediction models and their modification in our conditions is searched by Adamko [44], Boda and Uradnicek [45], Hiadlovsky and Kral [46]. A method for logistic regression to assess the future corporate prosperity was in our national conditions firstly applied by Hurtošová [47]. Later, Delina and Packova [48] developed a new modified model in Slovak business environment while using regression analysis to get higher predictive performance of the model. Kovacova and Kliestik [49] intorduced a bankruptcy prediction model in the Slovak Republic using logistic regression and they proved significant classification accuracy of this model. Results of the last mentioned are significant but deeper research has to be done to develop a complex prediction model of the financial health of Slovak companies.

2. Materials and Methods

The aim is to form an econometric multi-industry model in Slovak environment to quantify the prosperity of the company in terms of the achieved economic result. For this reason, we used the Amadeus database; we chose the accounting and financial records of accounting entities operating in the territory of the Slovak Republic in the years 2015 and 2016. Companies included in the model were chosen considering the Nomenclature of Economic Activities in the European Community (NACE classification), representing a statistical classification based on a common statistical classification of economic activities in the European Union. We include the following economic categories in the model: A—agriculture, forestry and fishing; B—mining and quarrying; C—manufacturing; D—electricity, gas, steam and air conditioning supply; F—construction; G—wholesale and retail trade; H—transporting and storage; I—accommodation and food service activities; J—information and communication; N—administrative and support service activities; P—education; Q—human health and social work activities. The method of multiple linear regression was used to create the model; independent variables were calculated from the data of 2015, the dependent variable is from the records of 2016. Multiple linear regression consists of the following methodological steps:

1. Choosing a sufficiently large sample that accepts some of the rules for determining the appropriate sample size to perform the regression analysis. We used the Stepwise method, which does multiple regression several times, each time removing the weakest correlated variable. At the end, only those variables, that explain the distribution best, are left. The only requirements are that the data is normally distributed and that there is no correlation between the independent variables.

For this type of regression, at least 40 measurements should be added to each variable. We include 37 quantitative variables; the size of our sample from the database is more than 120,000 enterprises, so the sample size meets the necessary requirements.

2. The dependent variable was defined as the corporate prosperity and profitability measured by EBIT (marked as OPPL). We decided to choose the independent variables using the predictors, which are the most frequently used in the prediction models worldwide [50]. Identification of independent variables is summarized in Table 1.

Prosperity and profitability of the company in the future may be partly given by optimal values of the financial indicators [51]. Based on the calculated financial ratios we are able to classify the companies into two groups: default (unhealthy, non-prosperous) and non-default (healthy, prosperous) in the context of legislative adjustments. We consider three criteria, which have to be met simultaneously and which correspond with the default criteria determined by the Slovak legislation. If the value of the corporate solvency ratio is less than 0.4, current ratio is less than 1 and net income is negative, the company is not prosperous, if conditions are not met, the company is healthy and prosperous. Despite the fact, that the study identifies a set of explanatory variables that can help identifying the state of a company, we consider only two states of the corporate prosperity—default of non-default. We follow the Slovak Commercial Code defining the principles and economic criteria of the company in default, which were used to determine the dependent variable.

Table 1. Selected financial ratios.

Financial Ratios			
X1	Sales/Total assets	X20	Net income/Sales
X2	Current assets/Current liabilities	X21	Non-current liabilities/Total Assets
X3	Gross profit/Total assets	X22	Cash and cash equivalents/Current liabilities
X4	Net income/Shareholders equity	X23	Cash flow/Current liabilities
X5	EBITDA/sales	X24	Working capital/Sales
X6	(Non-current + current liabilities)/EBITDA	X25	Current ratio
X7	Net income/ Total assets	X26	Liquidity ratio
X8	Working capital/Total assets	X27	Return on assets
X9	Operating profit/Total assets	X28	Return on equity
X10	(Non-current + current liabilities)/total assets	X29	Shareholder liquidity ratio
X11	Current assets/Total assets	X30	Solvency ratio (liability-based)
X12	Cash & cash equivalents/Total assets	X31	Cash flow/Operating revenue
X13	Cash flow/Total assets	X32	Net assets turnover
X14	Cash flow/(Non-current + current liabilities)	X33	Interest paid
X15	Current liabilities/Total assets	X34	Gross margin
X16	Current assets/Sales	X35	Profit margin
X17	Operating profit/interest paid	X36	Net current assets
X18	Stock/Sales	X37	Working capital
X19	Cash flow/Sales		

3. Testing of Gauss-Markov assumptions: dependent and independent variables must be quantitative; the multi-collinearity condition must be complied; the outliers have to be removed; the variables must be in a linear relation (tested by Pearson correlation coefficient). We test the hypothesis of dependence between the individual independent variables and the dependent variable on the significance level of 0.05, which is compared to the critical p-value of the test of significance of Pearson correlation coefficient. Last assumption is to ensure normal distribution of model residuals that cannot be auto-correlated [52].

4. Realization of multiple linear regression and testing the significance of the individual independent variables in the model.

Multiple linear regression models the dependent variable as a linear combination of independent variables and an intercept [53]:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j \cdot x_{ij} + u_i \tag{1}$$

where:

y_i dependent variable
x_{ij} independent variable(s)
β_0, β_j unknown parameters of the model
u_i random variable

Parameters β_j are considered as unknown numerical constants, β_0 is an absolute number and, in general, β represents a slope (direction) of parameters. The parameter β_j explains the changes in the value of the dependent variable y_i, if the j-th independent variable x_{ij} changes of one unit, provided, that the values of other independent variable stay unchanged.

5. Testing the significance of the created model.
6. Write the equation of the regression model.

To provide the multiple regression analysis we used the software IBM SPSS Statistics v. 19. We consider all business entities in the database, accepting the selected sectors and their specificities, as we want to determine the general predictors to assess the future corporate prosperity of any company.

3. Results

Before the regression analysis itself, we test the mentioned Gauss- Markov assumptions. The regression analysis is very sensitive to outliers. To exclude all abnormal and extreme values, we used interquartile range, multiplied by the number 2.2, which is often used to detect outliers in the data. We modified the original database and used the remaining 105,708 enterprises in the regression model. One of the mentioned preliminary conditions is the character of dependent and independent variables, all of them are quantitative. However, it was not possible to calculate the values of some of the determined financial ratios due to missing or not available information in the Amadeus database, they had to be excluded from the regression. As a result, not 37 but 24 ratios are the proposed financial predictors. Their descriptive statistics (mean, standard deviation and coefficient of variation) are summarized in Table 2.

Table 2. Descriptive statistics of independent variables.

Independ. Variables	X1	X2	X4	X7	X8	X9	X10	X11
mean	1.92	4.41	0.14	0.09	0.15	0.14	0.51	0.76
std. dev.	3.92	7.76	1.05	0.18	0.29	0.21	0.31	0.28
var. coef.	2.03	1.76	7.50	2.00	1.93	1.50	0.61	0.37
	X12	**X15**	**X16**	**X18**	**X20**	**X21**	**X22**	**X24**
mean	0.37	0.45	9.45	5.73	−0.32	0.06	2.76	5.22
std. dev.	0.33	0.30	1560.19	1282.47	99.42	0.14	6.06	1040.72
var. coef.	0.89	0.67	165.10	223.82	−310.69	2.33	2.19	199.37
	X25	**X26**	**X27**	**X28**	**X30**	**X35**	**X36**	**X37**
mean	4.40	4.07	0.13	0.26	3.98	0.12	138.10	174.21
std. dev.	7.76	7.55	0.20	0.89	21.26	0.24	6419.88	4055.82
var. coef.	1.76	1.86	1.54	3.42	5.34	2.00	46.49	22.28

The assumption of the collinearity presents the high mutual correlation of variables. Multi-collinearity among the independent variables can cause the incorrect formulation of the model or could decrease the prediction ability of some variable. The simplest way to solve the existing multi-collinearity is to remove one of two independent variables with the mutual interdependence [54] and repeat the analysis. Table 3 shows the collinearity between the variables.

Table 3. Collinearity diagnosis.

Dimension	Eigenvalue	Condition Index	Variance Proportions						
			C	X37	X08	X11	X09	X12	X15
1	3.926	1.000	0.10	0.00	0.01	0.00	0.02	0.01	0.01
2	1.022	1.960	0.00	0.80	0.06	0.00	0.01	0.01	0.00
3	0.884	2.107	0.00	0.19	0.31	0.00	0.05	0.04	0.01
4	0.680	2.402	0.00	0.00	0.12	0.00	0.42	0.00	0.11
5	0.366	3.276	0.00	0.00	0.08	0.01	0.48	0.17	0.17
6	0.077	7.119	0.53	0.00	0.25	0.04	0.02	0.46	0.70
7	0.044	9.447	0.46	0.00	0.19	0.95	0.00	0.33	0.00

The collinearity diagnostics follows several important values to reveal the problems with multi collinearity-the eigenvalue, the condition index and the variance inflation factor. The resulting values of eigenvalues are different from 0 (and are not close to 0), indicating that the predictors are not intercorrelated.

The condition index is computed as the square root of the ratios of the largest eigenvalue to each successive eigenvalue. When two or more of the supposedly independent variables are correlated, the condition index for each will be above one. Values of one are independent; values of greater than 15 suggest there may be a problem, while values of above 30 indicate a serious problem. The resulting values of the condition index confirm that there are not any multi collinearity problems.

The variance inflation factor (VIF), calculated in Table 4, measures the impact of collinearity among the variables in a regression model. It is always greater than or equal to one. There is no formal VIF value for determining presence of multicollinearity; however, values that exceed 10 are often regarded as indicating multicollinearity. Based on the results in the model it can be concluded, that there is no multicollinearity symptom, as all values are between 1 to 10.

Table 4. Collinearity measured by VIF.

		Collinearity Statistics	
Model		Tolerance	VIF
6	Constant		
	X37	0.997	1.003
	X08	0.631	1.585
	X11	0.529	1.891
	X09	0.869	1.150
	X12	0.406	2.465
	X24	0.755	1.324

Gauss- Markov assumption of a liner relationship between variables claims that it is necessary to have individual independent variables in a linear relation to the dependent variable. The existence of linearity is determined by the Pearson correlation coefficient, Table 5. Indicative limits to determine the dependence by Pearson correlation coefficient in this study are (in both positive and negative relationships) [53]:

$0 < |r| \leq 0.3$ weak dependence
$0.3 < |r| \leq 0.8$ medium dependence
$0.8 < |r| \leq 1$ strong dependence

Table 5. Pearson correlation matrix.

prosperity	**X1**	**X2**	**X4**	**X7**	**X8**	**X9**	**X10**	**X11**	**X12**	**X15**	**X16**	**X18**
	−0.001	−0.008	0.005	0.008	−0.003	0.006	−0.001	−0.026	−0.024	−0.011	0.002	0.001
	X20	**X21**	**X22**	**X24**	**X25**	**X26**	**X27**	**X28**	**X30**	**X35**	**X36**	**X37**
	0.000	0.020	−0.011	0.002	−0.008	−0.009	0.007	0.005	−0.003	0.007	0.477	0.624

Values 0.000 means the figure is too small for three decimal place representation. It is clear, that there is a weak linear dependence between the independent variables and the dependent variable, except for X36 and X37 where their mutual relation with the dependent variable is described by the medium dependence.

We test the hypothesis of mutual dependence between the individual independent variables and the dependent variable on the significance level of 0.05, which is compared to the *p*-value of the test of significance of Pearson correlation coefficient, Table 6.

Table 6. *P*-value of Pearson correlation coefficient.

prosperity	**X1**	**X2**	**X4**	**X7**	**X8**	**X9**	**X10**	**X11**	**X12**	**X15**	**X16**	**X18**
	0.356	**0.013**	0.090	**0.021**	0.224	0.064	0.403	**0.000**	**0.000**	**0.002**	0.271	0.383
	X20	**X21**	**X22**	**X24**	**X25**	**X26**	**X27**	**X28**	**X30**	**X35**	**X36**	**X37**
	0.486	**0.000**	**0.002**	0.270	**0.013**	**0.009**	**0.042**	0.100	0.194	**0.027**	**0.000**	**0.000**

Based on the data shown in Table 4, we found that the p-value is higher than the significance level of some independence variables, so we claim that there is not any dependence between these independent variables and the dependent variable. However, Pearson correlation coefficient shows weak but existing linear dependence between these independent variables and the dependent variable, we decided to include these variables in the model of the corporate prosperity estimation. Considering the independent variables X2, X7, X11, X12, X15, X21, X22, X25, X26, X27, X35, X36 and X37, the *p*-value is lower than the level of significance, so we claim that there is a dependence between the individual independent variables and the dependent variable.

Gauss- Markov assumptions mentioned in the methodological part were fulfilled (the assumption of normal distribution and autocorrelation can be tested after the model formation) and the multiple linear regression can be performed.

Stepwise method of the regression analysis eliminates the multi-collinearity problems, constructs different models and shows statistics for each model, composed of different sets of variables. These models are the combinations of independent variables that best explain the dependent variable. Table 7 depicts the significant variables of the model.

Table 7. Variables entered/removed.

Model	Variables Entered	Variables Removed	Method
1	X37	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
2	X08	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
3	X11	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
4	X09	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
5	X12	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
6	X15	.	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100).
Dependent Variable: OPPL			

The regression analysis reveals that the model includes six statistically significant independent variables, which best explains the variability of the dependent variable considering the order, in which they were added into the model. The multi-industry model of the corporate prosperity quantification in conditions of Slovak enterprises consists of these predictors: working capital, working capital to total assets ratio, current assets to total assets ratio, operating profit to total assets ratio, cash and cash equivalents to total assets ratio and current liabilities to total assets ratio.

It is interesting to compare the results of Pearson correlation coefficient with the results of the relevant independent variables according to the regression analysis. In most cases, both analysis provide the same results, i.e., if the results of Pearson correlation coefficient indicates to reject a significant relationship between the variables, the regression analysis often proves the same. The difference was only in the case of the independent variables X_8 and X_9, which the regression analysis considered to as significant attributes affecting the value of the corporate prosperity and profitability. The overall correlation between the variables left in the models (we consider six models) and the dependent variable is shown in Table 8, which portrays particular steps of addition or subtraction of variables from the set of explanatory variables based on some pre-specified criteria.

Table 8. Quality of the regression model (Model summary).

	Predictors in the Model	R	R Square	Adj R Square	Std. Error	Durbin-Watson
1	Constant (C), X37	0.624	0.389	0.389	2562.368	
2	C, X37, X8	0.625	0.390	0.390	2559.914	
3	C, X37, X8, X11	0.625	0.390	0.390	2559.385	
4	C, X37, X8, X11, X9	0.625	0.391	0.391	2558.734	
5	C, X37, X8, X11, X9, X12	0.625	0.391	0.391	2558.664	
6	C, X37, X8, X11, X9, X12, X15	0.625	0.391	0.391	2558.469	1.999813
	Dependent Variable: OPPL					

R squared presents the percentage of the variation in the dependent variable that is explained using the independent variables included in the model. The model 6, which includes all the relevant model predictors, explains 39.1% of the variation in the dependent variable. Adjusted R-squared indicates how well terms fit a curve or line, but adjusts for the number of terms in a model, in our case 39.1%.

Table 9 presents the linear regression equation coefficients for the various model variables.

Table 9. Coefficients of the models.

		Unstandardized Coefficients		Standardized Coefficients		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
6	Constant	265.557	33.305		7.973	0.000
	X37	0.505	0.002	0.625	211.843	0.000
	X08	−427.954	41.398	−0.038	−10.338	0.000
	X11	−138.346	47.360	−0.012	−2.921	0.003
	X09	284.326	50.352	0.018	5.647	0.000
	X12	−156.817	45.620	−0.016	−3.437	0.001
	X24	−125.806	36.777	−0.012	−3.421	0.001

The significance (Sig.) should be below the significance level 0.05 to consider all predictors significant for the model. All independent variables are below the determined significance level and thus may be used as relevant predictors in the multi-industry model. The statistical significance of the model is proved by the F-test (Table 10).

Table 10. Statistical significance of the final regression model (*F*-test).

Model	DF	Sum of Squares	Mean Squares	*F*	Sig.
Regression	6	2.845×10^{11}	4.914×10^{10}	7507.453	0.000
Residual	105,700	4.757×10^{11}	6,545,762.407		
Total	105,707	7.602×10^{11}			

The result value of the calculated F statistics is again compared to the significance level of 0.05, and as it is below the determined level, we can conclude that the model is statistically significant.

Gauss-Markov assumption of normal distribution and autocorrelation applies to model residues can be tested after the regression. Within the regression analysis, emphasis is given on the normality of residues. If the residues were not normally distributed, the results could be inaccurate. Central limit theorem guarantees that the violation of the normal distribution in large sample sets ($n > 100$) does not have critical consequences [55]. Autocorrelation was tested by Durbin-Watson test, its value 1.9998 (see Table 7) is compared with the critical value and thus we do not reject the null hypotheses that the residuals are not auto-correlated.

The final notation of the model of the prosperity quantification, based on the corporate profitability, in conditions of the Slovak enterprises is:

$$\begin{aligned} corporate\ prosperity &= 265.557 + 0.505X_{37} - 427.954X_{08} - 138.346X_{11} - \\ &+ 284.326X_{09} - 156.817X_{12} - 125.806X_{15} \end{aligned} \tag{2}$$

The multi-industry model of the corporate prosperity and profitability shows, that the value of the intercept is the limit value, which means, that if all financial ratios are zero and the company has the value of the corporate prosperity equal or less than the constant, the future prosperity and profitability of the company is bad, it is non-prosperous. In that case, its business partners have to consider their cooperation in the future or take measures to eliminate or prevent the financial risks. It the value of the corporate prosperity is higher than the constant the company is considered profitable in the future. Ceteris paribus, the value 0.505 X37 means that if the value of the working capital increases/decreases by one measure unit, the value of the corporate prosperity increases/decreases of 0.505 €. The value 427.964 X8 presents that if the value of the working capital to total assets ratio increases/ decreases by one measure unit, the value of the corporate prosperity increases/decreases of 427.954 €. The value 138.346 X11 determines that if the value of current assets to total assets ratio increases/ decreases by one measure unit, the value of the corporate prosperity increases/decreases of 138.346 €. The value 284.326 X09 means that if the value of the operating profit to total assets ratio increases/ decreases by one measure unit, the value of the corporate prosperity increases/decreases of 284.326 €. The value 156.817 X12 presents that if the value of the cash and cash equivalents to total assets ratio increases/ decreases by one measure unit, the value of the corporate prosperity increases/decreases of 156.817 €. In addition, the value 125.806 X15 states that if the value of the current liabilities to total assets ratio increases/decreases by one measure unit, the value of the corporate prosperity increases/decreases of 125.806 €.

Given that the coefficient of determination of our model is 39.1% we can describe only slightly more than 39% of changes in the value of corporate prosperity. The remaining changes in the prosperity value may be caused by other, and also non-measurable, factors that we were not able to quantify and measure or by other factors that may not be related to prosperity and profitability of the Slovak companies. Based on the results of the multiple linear regression analysis we can identify the financial predictors, which play a crucial role in the process of the corporate prosperity quantification and financial risks identification, those are: working capital, working capital to total assets ratio, current assets to total assets ratio, operating profit to total assets ratio, cash & cash equivalents to total assets ratio and current liabilities to total assets ratio.

To verify the prediction ability of the estimated model, we use Equation (2) to predict the future corporate prosperity, which was compared with the real values of the dependent variable OPPL(0 is for prosperous companies, 1 for the non-prosperous ones). The results are portrayed in Table 11.

Table 11. Prediction ability of the model (classification results).

			0	1	Total
Non-prosper. real	**0**	**count**	46,153	30,152	76,305
		%	60.5%	39.5%	100.0%
	1	**count**	13,284	16,119	29,403
		%	45.2%	54.8 %	100.0%
Total		**count**	59,437	46,271	105,708
			56.2%	43.8%	100.0%
58.91 % of original grouped cases correctly classified					

It is obvious that the formed model of the corporate prosperity identified correctly 60.5% of prosperous companies and 54.8% of non-prosperous companies, which corresponds to the weak level of the coefficient of determination. The total prediction ability of the model is 58.91%, which Hampel and Klepáč [56] classify as an acceptable prediction ability.

4. Discussion

The financial risk measurement and prediction modelling for sustainable development of business entities using regression analysis proved, that the predictors of the model are acceptable to be used to predict the future prosperity of Slovak business entities. However, its prediction ability is not sufficient, which is the consequence of the method used. The same database of companies was used to predict the future development of companies by multiple discriminant analysis, logistic regression. The overall classification ability of the model formed by the multiple discriminant analysis is 73%; however, the more important information is the correct classification of non-prosperous entities, which is at the level of 93% [57]. The results of the logistic regression model claim, that the overall percentage of correct classification is slightly above 79%, with more than 84% of non-prosperous companies correctly classified [58]. Significant results were proved also in the study of Rohacova and Kral [59], who used data envelopment analysis to predict the corporate failure.

The wide usage of the Altman model as a measure of a financial distress of strength in the economic and financial research points out that it is widely accepted as a reasonable, simple and consistent measure of the distressed entity at risk [60]. Thus, this model was tested in the conditions of Slovak business environment. In the research of Adamko and Svabova [61] Altman model was tested on the data of Slovak entities; the prediction ability of the model is 88.17%. Comparing the results of the studies realized in the Slovak business environment and based on different calculation method, it is clear, that the prediction ability of the latest Altman model slightly outperforms the other methods used. However, it has to be emphasized, that the informative value of some indicators of Altman model are significantly different in the economy with developed capital market and in the economy with less developed market, which is the case of Slovakia as the market does not reflect the expectations of the capital market.

Despite the fact that the companies in the database differ widely in their capital structure, firm size, access to external finance, management style, number of employees, the risk of financial failure can be modelled using the same set of independent variables for both prosperous and non-prosperous companies, which is confirmed by the study of Gupta et al. [62]. This knowledge leads to the identification of factors, which are significant enough to manage financial risks, and to affect the profitability and prosperity of the company. A similar research was conducted by Faltus [63], his research was aimed at finding the optimal default prediction model for Slovak companies using the logistic regression, and Guo et al. [27], who used linear regression models and introduced a new parallel maximum likelihood estimator for multiple linear models fitted on the bankruptcy data.

Sharifabadi et al. [64] in their study of the impact of financial ratios on the prediction of bankruptcy of small and medium companies suppose the current assets to total assets ratio and operating profit to total assets to be the important indicators. Tian et al. [65] consider in their study 39 financial and market variables as candidate bankruptcy predictors, 85% of them are similar to independent variables used in our study. The most significant variables included in more than 5 models were recognized in the study of Bellovary et al. [66]. According to the results of this study, the predictors left in our model are significant variables included in many models worldwide. Current ratio appears in 51 prediction models, current assets to assets ratio in 10 and operating profit to total assets in 9, both working capital to total assets ratio and working capital in 7 models.

Ravi Kumar and Ravi [50] analyzed 62 prediction models and ranked most significant explanatory variables. Four out of six predictors used in the model are in the list of the most important explanatory variables; operating profit to total assets, ratio of current assets and total assets, current liabilities to total assets ratio and working capital to total assets.

The results of the study of 47 prediction models provided by Dimitras et al. [67] summarize the number of countries and number of models that include particular financial ratios. They identified 18 significant explanatory variables used in the prediction models worldwide. In the model, four of them are included: working capital ratio used in 5 countries and 16 models, current assets to total assets (6 countries and 12 models), operating profit to total assets (4 countries, 11 models) and net current liabilities to total asset (3 countries, 9 models).

Kliestik et al. [68] determined currently most commonly used explanatory variables and the number of studies in which they are included. Three ratios included in our model are from the list: current assets to total assets, operating profit to total assets and current liabilities to total assets. Moreover, the use of specific explanatory variables was revealed in the models of Visegrad countries [69].

In the study of Mihalovič [70], author focuses on the comparison of overall prediction performance of the two developed models, discriminant analysis and logistic regression, in conditions of the Slovak Republic and he reveals the most significant predictors net income to total assets, current ratio and current liabilities to total assets

Considering the studies on the most commonly used variables of the prediction models we can claim, that the statistically significant variables in the model of corporate prosperity belong to the group of variables, which are accepted by experts in this field. Mousavi et al. [71] conclude that the choice and design of independent variables and their nature affect the overall performance of the model. It is obvious that there are significant differences among variables used in various models and that for different countries with different type of economy should be developed a unique model with appropriate variables. The predictors identified in the study may be further applied in the formation of the complex prediction model in conditions of the Slovak Republic.

5. Conclusions

The bankruptcy prediction modelling helps predict the financial distress of companies. The importance of the area is underlined by the fact, that the information about the future corporate prosperity eliminates potential financial risks and enables to evaluate the financial health of the company based on selected financial indicators or other characteristics of the company or the environment in which they operate.

Realizing the multiple regression analysis, we identify the statistically significant determinants that affect the future financial development of the company and thus we form a regression model to estimate the corporate prosperity and profitability. As the statistically significant predictors were determined seven financial ratios: working capital, working capital to total assets ratio, current assets to total assets ratio, operating profit to total assets ratio, cash and cash equivalents to total assets ratio and current liabilities to total assets ratio. These factors are significant enough to manage financial risks and to affect the profitability and prosperity of the company and can be later used in the model to predict the default of Slovak companies.

The multi-industry model of the corporate prosperity and profitability perceives the value of the intercept as the limit value, which means, that if the company has the value of the corporate prosperity equal or less than intercept value, there is a thread of financial problems in the future. Moreover, the corporate business partners have to consider their cooperation with the company in the future or take measures to eliminate or prevent the financial risks. The model has some limitation that is to be mentioned, and it is the low value of the R square (39.1%) which means, that there is a space for unknown and unmeasurable changes than can have some impact on the corporate prosperity and insufficient total prediction ability (58.91%). The choice of the method of linear regression may not be perceived positively, but despite that fact, we were able to identify crucial predictors to be used in the further research and also to quantify the future prosperity of the entities in the database. The further research with the same data revealed that it is more appropriate to use either the multiple discriminant analysis or the logistic regression to predict the future prosperity of any company.

The main aim of the paper was to extend the knowledge about identification and elimination of financial risks related to the unhealthy financial situation of the company. The results gained in the multi-industry model are extra important for companies themselves, but also for their business partners, suppliers and creditors to eliminate financial and other corporate risks related to the unhealthy or unfavorable financial situation of the company.

The formation of the complex prediction model in the economic conditions of the Slovak Republic is still missing, and thus the results of our research may be used to determine the financial ratios that can be, based on the future detailed research, used as the predictors of the Slovak prediction model.

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