Utilization of multidimensional methods for corporate sustainability

Alena KOCMANOVA, Marie PAVLAKOVA DOCEKALOVA
Brno University of Technology, Faculty of Business and Management,
Department of Economics, Brno, Czech Republic

and

Petr NEMECEK
Tomas Bata University in Zlín, Faculty of Management and Economics,
Department of Management, Zlín, Czech Republic

ABSTRACT

The article is focused on the use of multivariate methods for creating the Corporate Sustainability Index (CSI) predictive model for measuring sustainability of industrial companies according to CZ-NACE, and on comparing these methods. The goal of this article is to propose a suitable *CSI* predictive model and to determine which financial and non-financial indicators can most influence a company tending to sustainability. To determine the CSI_{LA} predictive model, the Logistic Regression is used, and to determine the CSI_{MDA} model, the method of Multiple Discriminant Analysis. However, based on the theoretical analysis of each method it is necessary to state that the methods cannot be unequivocally compared, even though each of these methods identified similar significant financial and non-financial indicators, coefficients and tests, which are interpreted analogically in the methods and are created in different ways. The results of the comparison of the methods for determining the predictive model *CSI* show that the logistic regression seems to be the best, which has a high percentage of correctly classified companies based on the calculated probability; in this case, the Gini index is also highest. The resulting classification of companies into different groups in comparing these two methods underwent significant changes as opposed to the classification of the companies according to the Data Envelopment Analysis method. The conclusions of the research of measuring the sustainability of the company show that currently - in addition to financial indicators - also non-financial indicators must be included in predictive models, namely the environmental indicator, the social indicator and the corporate governance indicator. It means that for the companies it has become a necessity to build a unified system for measuring sustainability of a company; this requirement has been confirmed also by managers of companies.

Keywords: predictive models, multivariate methods, performance, sustainable corporate performance index, financial and non-financial indicators

1. INTRODUCTION

The term sustainable development was not used until the late 1980s when it appeared for the first time in the publication [1], also known as the Brundtland Commission Report. The result of the work of the Commission established by the United Nations was the setting up of the "global agenda for change" in the concept and practice of development, when the report pointed to the need to re-assess our way of life and governance [2]. The aim of national and international institutions is to ensure cooperation in individual fields of sustainable development, create concepts, indicators and models for its measurement OECD, UN, WBCSD, GRI, IFAC, and others.

The theme of composite indicators and the creation and validation of quality of life and sustainable development indicators at three hierarchical levels (global, national and regional) were examined by [3]. Another example of a composite indicator can also be the Summary Innovation Index used in EU member states to evaluate their innovation performance, which is updated annually [4]. Most of these authors determine their composite indicators at the macroeconomic level.

To evaluate the financial situation of a company, predictive models are used, which consist of a single summary indicator - a composite indicator. Predictive models therefore rank among summary indexes of company evaluation. Their goal is to express the overall financial and economic situation of the company using a single number. Models are compiled mainly on the basis of mathematical and statistical methods, with the use of discriminant analysis, logistic or probit analysis, and on the basis of practice from the analysis of companies and neural networks. The best known multivariate model is the Altman Z-Score, then for example the Taffler model, the Beerman discriminant function, and the Index of Credibility. Mathematical and statistical methods are sometimes combined with expert evaluation, by which expert systems are created, which provide overall assessment of a company using a multi-criteria assessment.

The aim of this article is to use multivariate methods for creating the predictive model *Corporate*

Sustainability Index (CSI) to measure the sustainability of a company and their comparisons. The predictive model constructed in this way will evaluate the company on the basis of a purposefully selected set of non-financial and financial indicators. Non-financial indicators are in a causal link to the sustainability of the company expressed in financial indicators (for example ROE, ROA, ROCE, etc.). For creating the predictive model, the Logistic Regression a Multiple Discriminant Analysis is used; their suitability, accuracy and reliability is assessed. The results of the predictive model should allow informing about the direction to sustainability or about an unsustainable company.

2. THE CONCEPTUAL FRAMEWORK

Many experts have been engaged in the prognosis of the future development of the company, and compiled both successful and unsuccessful predictive models. The work of American economists Beaver and Altman are considered the beginning of scientific work on this topic. Since the 60s of the 20th century, countless models were created anticipating the financial distress of the company. Bankruptcy predictors were not created only at universities and research institutions, but also in banks or for use by public authorities.

According to the way of use, company predictive models and early warning systems can be divided into bankruptcy and credibility models.

There are foreign bankruptcy models, which use various financial ratios and predict insolvency or bankruptcy of a company in advance. Among them there is, for example, the known model of Professor Altman, Z-score models [5]. British scientist Richard Taffler proposed a model on the basis of Altman's model for the analysis of British companies; this model was subsequently supplemented and improved. It uses 80 ratio indicators in analyzing bankrupt and solvent companies [6].

In practice, other bankruptcy models are used, such as the Beaver profile analysis 1966, the Beerman discriminant function, the Springate model, Zmijewski the Ohlson model. Bankruptcy models belong to the *ex ante* analysis; its goal is to prolong the current situation into the future, predict how the company will develop in the next 3 to 5 years, and point out in advance a possible threat to financial health.

Predictive models include, for example, Kralicek rapid test, Tamari model, Index of bankrupty, Rudolf Doucha's system of balance analyses, Grünwald index of credibility and others. Mr and Ms Neumaier with their IN indexes were engaged in the evaluation of financial health of Czech companies [7].

At present, nobody seems to be able to determine exactly how many models, whether based on a Logit model, Probit model or on multiple discriminant analysis have been formed and actively used. Known predictive models, which consist also of non-financial indicators, are - for example - the model of the assessment of companies created by Argenti, or by H. Pollak.

Authors [8] analyzed the relationship between selected indicators and the probability of bankruptcy on the data of Portuguese joint-stock companies. The analysis included 11 financial ratio indicators, and 2 non-financial indicators (size and age of the company). Among others, they came to the conclusion that there is a positive correlation between the size of the company (the value of total assets) and the probability of bankruptcy. The most widespread system of the evaluation of companies by financial and non-financial indicators is the Balanced Scorecard (BSC) system by authors [9], or the model of the European Foundation for Quality Management - EFQM, and the Malcolm Baldrige model.

In the Czech companies, no known system of evaluation using financial and non-financial indicators is concretized, but as stated by it is necessary to use also non-financial indicators in evaluating the company. Predictive models are very often criticized by several authors [10], [11], [12] because of their inaccuracy, but despite this, they are exploited to the full; on the other hand, several authors also came to the conclusion that their accuracy is basically sufficient.

For comprehensive evaluation of the company performance using a system of financial and non-financial indicators, there is no uniform approach of identification, classification, measurement and evaluation; the problem is especially the practical use of these systems of indicators.

It seems that to measure the sustainability of a company, it could be quite convenient to use the knowledge from the construction of predictive models evaluating the financial stability of companies, and to use the Logistic Regression method and the comparison with the Multiple Discriminant Analysis method.

3. REASERCH METHODOLOGY

An important prerequisite for the *CSI* predictive model must be suitability, accuracy and reliability of the method and indicators selected. In modelling the *CSI* predictive model of measuring the company sustainability, the *Logistic Regression* and the *Multiple Discriminant Analysis* methods are used.

Models of the discrete binary option, which Logistic Regression belongs to, is based on the principle of regression. The Logit analysis is thus only one of the regression techniques, very often used in econometrics; it is used to analyze relationship dependencies between several explanatory and one explained variable.

For predicting the bankruptcy of the company, Ohlson introduced a Logit model [13]. This Logit model also has its downsides. It is mainly its high sensitivity to multi-collinearity and outlying or missing values [14]. Author [15] created Probit models of probability of bankruptcy. There are significantly fewer studies using Probit models as compared to Logit models.

On the basis of Logistic Regression and on the basis of the Logit model in 2010, Altman in cooperation with the group RiskMetrics developed Z-metrics models. These models are the result of previous development of Z score models and responses to the economic crisis and predictive ability of the models. They are designed for large listed companies, large unlisted companies, and small listed companies in the US and Canada, as well as for large and small companies outside the US and Canada. [16].

Regression models are used for the specification of functional relationships and analyzing dependencies between one explained (endogenous) variable and one or more explanatory (exogenous) variables. In the regression equation, a dependent variable is the function of independent variables and of the random component.

If random variable is marked y, observed quantities $X_{1,2,\dots,}X_k$, and random component ε. Then the general functional relation for the regression equation can be written as follows:

$$Y = f\ (X_{1,}X_2, \dots \dots . . X_k, \epsilon) \tag{1}$$

The first phase of determining the predictive model $\boldsymbol{CSI_{LA}}$ measuring the sustainability of the company, the Logistic Regression method is used. The Logistic Regression can be used in the case when the dependent variable is not continuous to modelling the dependency between the explained variable and the explanatory variables. If we have a binary dependent variable, which assumes values 0 and 1, Y = 1 if phenomenon J occurred in the monitored record, and Y = 0 if the non J phenomenon occurred. The aim of the binary logistic regression is to estimate the probability that the record belongs to one of two categories of the dependent variable. However, it is not possible to estimate the probability of Y = 1, because then the values predicted by the equation:

$$P(Y = 1) = \alpha + \beta_1 X_1 + \cdots + \beta_K X_k \tag{2}$$

may not assume values between 0 and 1. The probability of the phenomenon, however, can only assume values <0;1>. This drawback can be eliminated by replacing the probability of the phenomenon with the chance of the phenomenon. The chance that phenomenon J occurred is expressed in the following equation:

$$chance(Y = 1) = P(Y - 1)/[1 - P(Y = 1)] \tag{3}$$

The chance assumes positive values including zero. By transforming relation (3) to the natural logarithm of the chance whose values assume both positive and negative values, so this way resolves the issue of predicted values from the equation in relation (2), which may assume values from $(-\infty;+\infty)$. Logit is defined as follows

$$\mathrm{logit(Y)} = \frac{\mathrm{lnP(Y{=}1)}}{\mathrm{ln(1{-}P(Y{=}1)}} \tag{4}$$

The regression equation is then as follows

$$logit(Y) = \alpha + \beta_1 X_1 + \cdots + \beta_K X_k \tag{5}$$

For interpretation, probabilities and chances are easier to understand, and therefore more suitable than logits. [17], [18].

The second phase deals with the methodical procedure for classifying companies by evaluating non-financial indicators based on non-financial indicators I_{ESGi} (environmental, social, corporate governance) and financial indicators I_{Ecoi} by selecting an appropriate prediction model CSI_{MDA} *using the Multiple Discriminant Analysis (MDA) method.*

The general discriminant analysis equation [19].

$$Y = a_1X_1 + a_2X_2 + \dots\dots\dots + a_pX_p \tag{6}$$

where $a_1, \dots a_p$ are coefficients of discrimination and $X_1, \dots Xi_p$ are selected independent variables that best explain the division into groups.

The third phase is the methodical approach for comprehensive classification of companies on the basis of the prediction model. Gini index can be calculated using the following relation[20].

$$Gini = 2\ x\ AUC - 1 \tag{7}$$

where AUC (Area Under Curve) is the value under the ROC curve. The index assumes values between 0 and 1; the more its value is closer to 1, the better the discriminant function separates unsustainable companies from sustainable companies.

The basis for the empirical research of *economic indicators* includes both foreign predictive models, but also domestic predictive models. The material for empirical research into *non-financial indicators* for corporate sustainability measurement came from findings from previous research in the years 2011-2014, when environmental, social and corporate governance performance indicators were determined on the basis of theoretical knowledge gained from documents and guidelines of international institutions [21].

4. RESULTS AND DISCUSSION

The predictive model *CSI* of measuring sustainability uses a specific probability model, such as the *Logistic Regression* method and the *Multiple Discriminant Analysis* method. The model focuses on a representative sample of Czech processing industry companies according to CZ-NACE with more than 250 employees, and with implemented ISO 14 000 or EMAS systems. The period analyzed was 2008 - 2013. The sample surveyed includes 56 companies with economic indicators (the AMADEUS database) and 56 companies with non-financial indicators (a survey in the company); the companies involved are the companies of processing industry according to CZ-NACE Manufacture: 10 - of food products, 11- of beverages, 13 - textiles, 20 - of chemicals and chemical products, 22 - of rubber and plastic products, 24 - of basic metals, metallurgical processing of metals, 25 - of fabricated metal products, except machinery and equipment, 26 - of computer, electronic and optical equipment, 27 - of electrical equipment and 28 - of machinery and equipment. A research sample consists of 56 companies with economic indicators (AMADEUS database) and 56 companies with nonfinancial indicators (survey company), research is focused on manufacturing companies.

The structure of the prediction model *CSI* measuring the company sustainability is based on a determined economic indicators $I_{Ecoi,}$ and non-financial indicators $I_{ESGi,}$, which were established by research in 2014 [21], [22].

Eleven economic indicators $I_{Ecoi,}$ are included in the predictive model; indicators that show multi-collinearity are excluded. To increase the statistical significance (discriminant capability) of economic indicators, an analysis of outliers is carried out, as well as the normality of data and correlation between the indicators. Economic indicators I_{Ecoi} are ratio indicators selected from a broad group of indicators used in predictive models: the profitability indicators, indicators of financial stability, indicators of productivity, and an indicator based on cash flows.

Non-financial indicators of environmental, social and corporate governance, the I_{ESGi} indicators, enter the structure of the predictive model *CSI* measuring the company sustainability. For calculation, 17 ratio indicators I_{ESGi} are used: seven environmental indicators I_{Envi}, six social indicators I_{Soci}, and four corporate governance indicators I_{Cgi}, see Tab. 1.

Table 1 Financial $\boldsymbol{I_{Ecoi,}}$ and non-financial environmental, social and corporate governance $\boldsymbol{I_{ESGi}}$ indicatos

Environmental group (j=Envi)	*Social group (j=Soc)*	*Corporate governance group (j=Cg)*	*Economic group (j=Eco)*
***I_{Eni}* - Environmental indicators**	***I_{Soci}* - Social indicators**	***I_{Cgi}* - Corporate governance indicators**	***I_{Ecoi}* - Economic indicators**
I_{En1}- Non-investment expenditures for the protection of the Environment /Added value [%]	I_{Soc1}- Monetary support of local community and gifts to municipalities / Added value [%]	I_{Cg1} - Collective agreement [ano = 0,52; ne = 0,48]	I_{Eco1}- EAT / SF (ROE)
I_{En2}-Total emissions to air / Added value [t/EUR]	I_{Soc2}- Number of women / Average number of employees [%]	I_{Cg2} - Reports from environmental and social areas [ano = 0,64; ne = 0,36]	I_{Eco2} - EBIT / A (ROA)
I_{En3}- Total greenhouse gas emissions / Added value [t/EUR]	I_{Soc3}- Number of terminated employments / Average number of employees [%]	I_{Cg3} - Code of ethics [ano = 0,72; ne = 0,28]	I_{Eco3} - EAT + IP / NCL + SF
I_{En4}- Total consumption of renewable energy /Added value [GJ/EUR]	I_{Soc4} - Wage costs / Average number of employees[EUR/Number]	I_{Cg4} -Total financial value of remunerations to Board of Directors and Supervisory Board / Added value [%]	I_{Eco4} - EBIT / S (ROS)
I_{En5}- Total annual consumption of water / Added value [m³/year/EUR]	I_{Soc5} -Wage costs / Added value [%]		I_{Eco5} - SF + NCL / A
I_{En6}- Total annual production of waste / Added value [t/EUR]	I_{Soc6} - Education and training expenditures / Added value [%]		I_{Eco6} - CF / TL
I_{En7}- Total annual production of hazardous waste / Added value [t/EUR]			I_{Eco7} - VA / OR
			I_{Eco8} - OR / A
			I_{Eco9} - TL / SF
			I_{Eco10} - A / TL
			I_{Eco11} - VA / CE
A_Total assets, VA_Value added, SF_Shareholders Funds, IP_Interest paid, CF_Cash flow, TL_Total liabilities, CA_Current Assets, OR_Operating Revenue, T_Turnover, NCL_Non Current Liabilities, S_Sales, St_Stocks,CE_Cost of Employees			

The methodical procedure of the first phase of the calculation of predictive model CSI_{LA} using Logistic Regression.

Hypothesis H_0: The use or predictive models for measuring sustainability does not contribute to the company's directing towards sustainability.

The first step of the analysis is to decide what criterion will be considered as a variable to be explained, or how individual groups will be defined. For the use of the methods, groups are defined, companies are divided into effective and ineffective, and the *Data Envelopment Analysis* method is used. The effective company (Y=1) is selected as the variable to be explained (dependent), other companies as ineffective (Y=0). When designing a predictive model, all financial $\boldsymbol{I_{Ecoi,}}$ as well as non-financial $\boldsymbol{I_{ESGi}}$ indicators are included in the analysis. Non-financial indicators are divided into indicators Iji^+, whose increasing value has a positive impact, and indicators Iji^-, whose increasing value has a negative impact on the sustainability of the company. Gradually, indicators are phased out starting with the least statistically significant ones I_{Eco2}, I_{Eco4}, I_{Eco6}, I_{Eco7}, I_{Eco8}, I_{En2}, I_{En3}, I_{En4}, I_{En5}, I_{Soc1}, I_{Soc3}, I_{Soc4}, I_{Soc5}, I_{Soc6}, I_{Cg1}, I_{Cg2}, I_{Cg3}, I_{Cg4}. After each elimination, the logistic regression is recalculated. Based on the Omnibus test, we reject hypothesis $H_{0,}$ Sig.= 0.000. According to the Nagelkerke R^2 test, the model captures 40.7% variability of the dependent variable.

The regression equation has the following form:

$$logit(sustainability) = -7{,}722 + 0{,}503 I_{Eco1} - 0{,}559 I_{Eco3} - 4{,}740 I_{Eco5} - 1{,}303 I_{Eco9} - 4{,}559 I_{Eco10} + 0{,}363 I_{En1} + 1{,}309 I_{En6} + 0{,}129 I_{En7} + 0{,}603 I_{Soc2}$$

The equation in the case of exposed estimated coefficients (using the chance):

$$chance(CSI_{LA} = 1) = P\left(\frac{sustainability=1}{sustainability=0}\right) = P\left(\frac{majority1}{majority\ 0}\right) = 0{,}000 + 1{,}654 I_{Eco1} + 0{,}572 I_{Eco3} + 0{,}009 I_{Eco5} + 0{,}272 I_{Eco9} + 0{,}010 I_{Eco10} + 1{,}438 I_{En1} + 3{,}703 I_{En6} + 1{,}138 I_{En7} + 1{,}827 I_{Soc2}$$

Significance tests of individual independent indicators based on the Wald criterion show significances at the level of $\alpha = 0{,}05$ only in financial and non-financial indicators I_{Eco1}, I_{Eco3}, I_{Eco5}, I_{Eco9}, I_{Eco10}, I_{En1}, I_{En6}, I_{En7}, I_{Soc2}. When assessing values of regression coefficients, in this case positive values of coefficients indicate a direct dependency between the value of the particular indicator and the chance that the company is sustainable. The discriminatory power of the model given by the category of the dependent variable, "*the company does not tend to sustainability*", 75.5% of companies are classified correctly; 74.7% of the companies are classified correctly to the category "*the company tends to sustainability*". Overall, the model was able to classify 75.1% at the 95% significance level.

Methodologically the procedure of the second phase of the calculation of the predictive model CSI_{MDA} using *Multiple Discriminant Analysis*. Into the MDA, financial I_{Ecoi} as well as non-financial I_{ESGi} indicators are included, which are gradually phased out I_{Eco1}, I_{Eco2}, I_{Eco3}, I_{Eco4}, I_{Eco5}, I_{Eco7}, I_{Eco8}, I_{Eco9}, I_{Eco11}, I_{En4}, I_{En5}, I_{Soc1}, I_{Soc2}, I_{Soc3}, I_{Soc4}, I_{Soc5}, I_{Soc6}, I_{Cg1}, I_{Cg3}, I_{Cg4} after each elimination, the model is recalculated again. Wilks' Lambda indicates the significance of the discriminant function, the model explains 76.3% of variability; it is an inversion to the cannonical correlation.

The discriminant function has the following form:

$$CSI_{MDA} = 0{,}019 + 0{,}179 I_{En7} - 0{,}476 I_{Eco10} - 0{,}399 I_{Cg2} + 0{,}327 I_{En6} + 0{,}169 I_{En2} + 0{,}183 I_{En3} - 0{,}246 I_{Eco6} + 0{,}456 I_{En1}$$

and explains 70.9% differences between the companies in both defined groups. Values $CSI_{MDA} < -0{,}588$ refer to the belonging of the company to group 0 "*the company does not tend to sustainability*", values $CSI_{MDA} > 0{,}523$ define the companies in group 1 "*the company tends to sustainability*". Values CSI_{MDA} from interval $< -0{,}588; 0{,}523 >$ do not give clear information about the belonging to one of the groups. Financial and non-financial indicators I_{Eco6}, I_{Eco10}, I_{En1}, I_{Eco2}, I_{Eco3}, I_{En6}, I_{En7}, I_{Cg2}. enter the prediction model CSI_{MDA}.

The quality of the models is evaluated using the ROC curve and numerical characteristics of these curves, see Fig. 1 and Fig. 2.

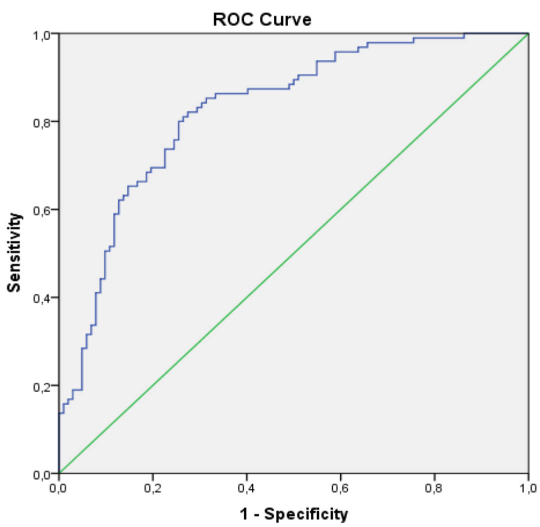

Figure 1 ROC curve of regression model

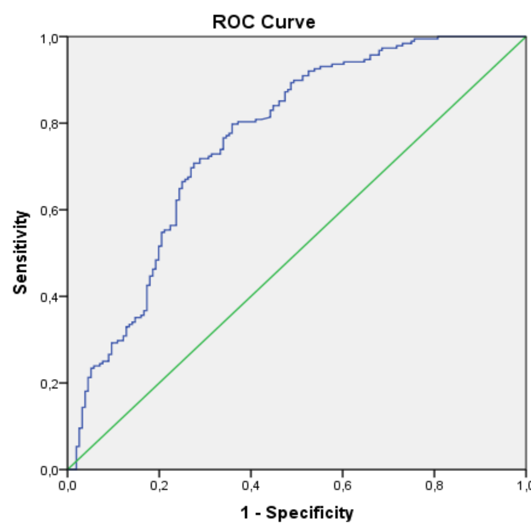

Figure 2 ROC curve of discriminant model

The area under the curve of the regression model AUC = 0.826, Gini = 0.652, of the discriminant model AUC = 0.763, Gini = 0.526. Fig. 1 reveals that companies tending to sustainability are included out of 83 % (of the regression model), but at the same time, out of 35 %, companies are also included that do not tend to sustainability. Companies tending to sustainability are included out of 76 %, but at the same time, 47 % of companies are also included, which do not tend to sustainability, see Fig. 2.

In the following Tab. 2, values of prediction models according to *Logistic Regression and Multiple Discriminant Analysis* are calculated, including their inclusion in the groups for selected companies of processing industry according to CZ_NACE for 2011.

On the selected sample of companies of the processing industry according to CZ_NACE, it can be deduced that by comparing predictive models CSI_{LA}, CSI_{MDA} and including the companies into groups (1 = the company tends to sustainability, 0 = the company does not tend to sustainability), reclassification occurred even when compared with original groups formed by the *Data Envelopment Analysis method*.

By comparing these methods it can be stated that the inclusion of selected companies of the processing industry on the basis of estimated probability (in case of logistic regression) and the score (in case of discriminant analysis), the logistic regression model is able to correctly classify most companies 75.1 %, in terms of discriminant analysis 70.9 %. Last but not least, the methods can be compared using the Gini index. The more its values is closer to 1, the better sustainable companies were segregated from unsustainable companies; the value for the logistic regression is 0.652, for the discriminant analysis 0.525.

Table 2 Comparison of predictive models $\boldsymbol{CSI_{LA}}$ using *Logistic Regression*, and $\boldsymbol{CSI_{MDA}}$ using *Multiple Discriminant Analysis*

Company	CZ_NACE	Predicted for DEA	Predicted probability	Predicted group	Predicted Group for Analysis 1	Discriminant Scores from Function 1 for Analysis 1	Company	CZ_NACE	Predicted for DEA	Predicted probability	Predicted group	Predicted Group for Analysis 1	Discriminant Scores from Function 1 for Analysis 1
			Logistic Regression		Multiple Discriminant Analysis					Logistic Regression		Multiple Discriminant Analysis	
AM	26	1	0,982	1	1	1,008	AF	28	1	0,495	0	1	-0,039
AH	28	1	0,907	1	1	0,455	M	25	0	0,490	0	1	0,144
AT	27	1	0,894	1	1	0,486	AY	13	1	0,468	0	1	-0,138
A	27	1	0,851	1	1	0,355	K	22	0	0,462	0	0	-0,667
J	27	0	0,841	1	1	-0,255	G	25	0	0,401	0	1	-0,265
AR	25	0	0,838	1	1	-0,173	AA	20	0	0,376	0	1	-0,218
D	25	1	0,812	1	1	0,111	BE	27	0	0,355	0	1	0,627
AG	10	1	0,809	1	1	0,367	AD	26	0	0,341	0	0	-0,641
AU	28	1	0,779	1	1	0,993	AB	10	0	0,329	0	1	0,049
X	25	0	0,773	1	1	0,434	U	22	0	0,291	0	0	-1,161
B	24	1	0,751	1	1	0,395	O	25	0	0,260	0	1	0,013
AI	27	0	0,713	1	1	0,585	AP	11	0	0,259	0	1	0,762
R	25	1	0,701	1	1	1,155	AO	11	1	0,195	0	1	1,138
BG	28	1	0,683	1	1	1,196	T	26	0	0,193	0	1	1,179
AL	13	1	0,678	1	1	0,461	S	27	0	0,160	0	1	0,384
AC	28	1	0,674	1	1	-0,176	W	25	0	0,158	0	0	-1,106
Y	11	1	0,672	1	1	1,248	F	27	0	0,113	0	1	0,131
BD	26	1	0,648	1	1	0,049	Q	28	1	0,110	0	1	0,328
AJ	25	1	0,644	1	1	0,125	N	20	0	0,084	0	0	-1,711
AS	28	0	0,600	1	1	-0,096	AV	24	0	0,076	0	0	-0,461
BC	25	1	0,593	1	1	0,986	E	26	0	0,039	0	0	-2,276
P	28	1	0,578	1	1	1,199	AE	25	0	0,036	0	0	-2,486
AQ	28	1	0,535	1	1	-0,166	C	24	0	0,011	0	0	-1,562

*CZ_NACE : 10 - Manufacture of food products, 11- Manufacture of beverages, 13 - Manufacture of textiles, 20 - Manufacture of chemicals and chemical products, 22 - Manufacture of rubber and plastic products, 24 - Manufacture of basic metals, metallurgical processing of metals, 25 - Manufacture of fabricated metal products, except machinery and equipment, 26 - Manufacture of computer, electronic and optical equipment, 27 - Manufacture of electrical equipment and 28 - Manufacture of machinery and equipment.

** Group 1 "*the company tends to sustainability* "; Group 0 "*the company does not tend to sustainability* "

It can be stated that the better method is the logistic regression - by 0.126. Based on the calculated correlation characteristics, it can be stated that the best method for measuring sustainability is the logistic regression, which has the highest value of the Gini index and the greatest percentage of correct classification of the companies.

The results of the predictive models indicate that the statistical significance of the impact of non-financial indicators is essentially small, corporate governance indicators were statistically insignificant. Environmental indicators describe the relation to economic indicators; this mainly includes the indicator I_{Enlg1} *(*Cost of environmental investments / Added Value). For the classification of companies, environmental indicators are decisive: I_{Enlg6}, and I_{Enlg7} for industrial companies. In terms of statistical tests, environmental non-financial indicators are significant, and their inclusion substantially changes classification of companies in comparison with the *Data Envelopment Analysis* method, see Tab. 2. The results show that evaluation to measure the sustainability of a company and the corresponding choice of financial and non-financial indicators must be determined by the purpose for which the assessment is conducted.

Predictive models for measuring sustainability of companies using financial and non-financial indicators are necessary, primarily because currently the evaluation based on financial indicators is no longer sufficient. These findings can be identified also with the results of researches [8], [23].

5. CONCLUSIONS

The article deals with the construction of predictive models CSI for companies in the sector of processing industry according to CZ-NACE. The importance of predictive models is important for owners and investors - whether the company tends to sustainability. Predictive models can influence decision-making relating to the long-terms strategy of the company, and can also show how the company approaches the comprehensive performance assessment.

Predictive models *CSI* represent a composite indicator, which was constructed using the methods of *Logistic Regression and* Multiple Discriminant Analysis.

To confirm the null hypothesis, it was proven that the use of predictive models for measuring sustainability of companies will not contribute to the tending of the company towards sustainability. Based on the results, this hypothesis can be rejected. Predictive models were able to classify more than 70 % of the companies. The basis of predictive models is to determine financial and non-financial indicators.

It can be concluded that predictive models for measuring sustainability, regardless of using which method they were created, will never be able to predict the direction of sustainability with probability 1, i.e. 100%, because they are dependent on what development and requirements for financial and non-financial indicators there will be in the changing global environment. However, if the company implements new information into the already created models, it will be able to assess the direction of the company towards sustainability with sufficient accuracy.

ACKNOWLEDGEMENTS

This paper is supported by the Czech Science Foundation. Name of the Project: Measuring Corporate Sustainability in Selected Sectors. Registration No. 14-23079S.

REFERENCES

[1] G. H. Brundtland. “Our Common Future*”*, Oxford: Oxford University Press, 1987.

[2] OECD. “Handbook on Constructing Composite Indicators. Methodology and User Guide”, 2008..

[3] P. Mederly, J. Topercer, P. Nováček, P. “Indikátory kvality života a udržitelného rozvoje – kvantitativní, vicerozměrný a variantní přístup”, Praha: Univerzita Karlova, CESES, 2004.

[4] M. Sajeva, D. Gatelli, S. Tarantola, H. Hollanders. “Metodology Report on European Innovation Scoreboard 2005”, European Commission, Enterprise Directorate-General, 2005.

[5] E. I. Altman. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The* **Journal of Finance**, Vol. 23, No. 4, 1968, pp.589–609.

[6] J. R. Taffler, “Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data”. **Journal of the Royal Statistical Society,** Vol. 145, No. 3, 1982.

[7] I. Neumaierová, I. Neumaier. “Index IN05”. In **Evropské finanční systémy,** Brno, Česká republika: Masarykova univerzita, 2005, pp.143–148.

[8] A. Bhimani, M.A. Gulamhussen, S.D. Lopes. (2010) “Accounting and non-accounting determinants of default: an analysis of privately-held firms“, **Journal of Accounting and Public Policy**, 29 (6). 2010, pp.517-532.

[9] R. S. Kaplan, D. Norton. “The Strategy Focussed Organisation*”,* HBS Press, USA, 2000.

[10] K. Keasey, R. Watson. „Financial distress models: a review of their usefulness“, **British journal of Management,** 1991, Vol. 2, No. 2, pp. 89–102.

[11] E. Eisenbeis. „Pitfalls in the application of discriminant analysis in business“. **Journal of Finance,** 1977, Vol. 32, No. 3, pp. 875–900.

[12] S. Mcleay, A. Omar. „The sensitivity of prediction models to the non-normality of bounded an unbounded fi nancial ratios“, **British Accounting Review**, 2000, Vol. 32, pp. 213–230.

[13] J. A. Ohlson. “Financial Ratios and the Probabilistic Prediction of Bankruptcy”, **Journal of Accounting Research,** 1980, Vol. 18, No. 1, pp. 109–131.

[14] S. Balcaen, H. Ooghe. “35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems”, **The British Accounting Review,** 2006, Vol. 38, pp. 63–93.

[15] M. E. Zmijewski.”Methodological Issues Related to tne Estimation of Financial Distress Prediction Models”, **Journal of Accounting Research**, 1984, Vol. 22, No. 4, pp. 59–82.

[16] D. Dluhošová, Z. Zmeškal. “Z-Metrics metodology and Altman rating models evolution”, In 8th International scientific conference Financial management of firms and financial institutions, 2011, pp. 1-11.

[17] D. W. Hosmer, S. Lemeshow. „Applied Logistic Regression“, John Wiley & Sons, Inc., Hoboken, New Jersey, 2000, pp. 383.

[18] S. W. Menard. „Applied Logistic Regression Analysis“. SAGE Publications, Inc., Thousand Oaks, CA, 2001, pp. 110.

[19] R. A. Fischer. "The use of multiple measurements in taxonomic problems." Annals of Eugenics, Vol. 7, pp. 179–188.

[20] A. Field. “Discovery Statistic Using SPSS”. SAGE Publications Inc., Thousand Oaks, CA, 2009, p. 856.

[21] A. Kocmanová, I. Šimberová. “Determination of environmental, social and corporate governance indicators: framework in the measurement of sustainable performance”, **Journal of Business Economics and Management,** 2014, Vol. 15, No. 5, pp. 1017–1033.

[22] A. Kocmanová, M. Pavláková Dočekalová, P. Němeček. „Sustainable Corporate Performance Index for Manufacturing Industry“, In **The 18th World Multi-Conference on Systemics, Cybernetics and Informatic,** 2014. pp. 1-6.

[23] E. Cardinaels, P. M. G. van Veen-Dirks. “Financial versus non-financial information: The impact of information organization and presentation in a Balanced Scorecard”, **Accounting, Organizations and Society,** 2010, Vol. 35, pp. 565–578.