

Predictive Model for Measuring Sustainability of Manufacturing Companies

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crossref <http://dx.doi.org/10.5755/j01.ee.26.4.11480>

The article describes the construction of a predictive model of corporate sustainability, the DA_{CSI} Index, for measuring sustainability. The aim of the paper is to propose a predictive model DA_{CSI} Index based on economic I_{Ecoi} and non-financial indicators I_{ESGi} and appropriately selected predictive models DA_{Eco} and DA_{ESG} for manufacturing companies according to CZ-NACE classification. Predictive models were developed with the use of Multiple Discriminant Analysis (MDA). MDA results showed that the inclusion of non-financial indicators did not result in any significant changes in the classification of companies into individual groups compared to classification on the basis of economic indicators only. From MDA results it also follows that the statistical significance of non-financial indicators is low, but they signal a causal relationship between individual economic and non-financial indicators of sustainability. The results also showed that the predictive model DA_{CSI} Index, composed of economic indicators, environmental indicators, social indicators and corporate governance indicators has a much higher accuracy than the predictive model composed of economic indicators only. The essential conclusion of our research into corporate sustainability measurement is that the traditional performance assessment using economic indicators no longer suffices and does not reflect current performance of the company from the long-term perspective, and it is therefore necessary to include both economic and non-financial indicators into the predictive model DA_{CSI} Index. And the predictive model DA_{CSI} Index is just the type of model that will provide relevant information about the company's sustainability status to both the owners and investors.

Keywords: Sustainability Measurement, Predictive Model, Multiple Discriminant Analysis, Indicators, Economics, Environmental, Social, Corporate Governance, Performance.

Introduction

Success of any company depends nowadays on the extent to which it capitalizes on its competitive advantage, and that is when sustainable development comes to the fore.

The concept of sustainable development encompasses a series of sub-activities and tasks that are being gradually implemented and achieved. This is an incremental system, which, at every moment of its existence, sets out from what has already been created (Soppe, 2009).

In the context of sustainable development, there is a need for economic as well as non-financial indicators that would be able to measure corporate sustainability. They are, in particular, multivariate models using such indicators that have a specific weight assigned to them. Comprehensive corporate performance is then expressed as a composite indicator that is able to measure corporate sustainability.

Composite indicators have also been developed at the level of business entities, particularly in the area of finance, to evaluate their financial standing, i.e. models of Financial standing, or models attempting to identify the risk of bankruptcy, i.e. bankruptcy models. Composite indicators designed to assess the financial stability of the company or assess the likelihood of bankruptcy of the company are presented as predictive models.

The aim of the paper is to present a construction of a predictive model DA_{CSI} Index for measuring sustainability of companies from the manufacturing industry that supports decision-making of owners and investors. The methods section defines individual stages in the construction of the predictive model DA_{CSI} Index, which is built on the methodological approach of the draft of the predictive model DA_{Eco} utilizing economic indicators I_{Ecoi} and the predictive model DA_{ESG} utilizing environmental, social and corporate governance indicators I_{ESGi} . The empirical analysis is based on descriptive statistics, univariate and multivariate analyses.

Predictive models DA_{Eco} , DA_{ESG} and DA_{CSI} were determined by methods Discriminant Multiple Analysis. The basis for the predictive model DA_{CSI} Index is the determination of the economic, environmental, social and corporate governance indicators. Economic indicators can easily be obtained from financial statements, and these are defined by the choice from among the indicators of profitability, financial stability and productivity, and cash flow-based indicators. The environmental, social and corporate governance indicators include data that are both quantitative and qualitative in nature, and are derived from findings obtained in previous research conducted between 2011 and 2014, and from documents of international institutions such as GRI, CFA Institute, EFFAS, IFAC and ASSET4. The hypothesis tested attempts to find out whether

the inclusion of non-financial indicators will cause changes in classification into groups (0 - sustainable, 1 - unsustainable) compared with classification based solely on economic indicators. The testing showed that there are no significant changes in the classification into groups (0 - unsustainable, 1 - sustainable) between the predictive model *DA_{CSI} Index*, which includes non-financial indicators, and the predictive model *DA_{Eco}*. Although the inclusion of social and corporate governance indicators causes some reclassification, the groups are almost identical with the original groups formed with the use of economic indicators only. In empirical research, the predictive model *DA_{CSI} Index* was compared with the predictive model *DA_{CSIB}*, where the financial standing index *IB* is used instead of index *DA_{Eco}*, the results are substantially identical.

The conclusions of empirical research indicate that the predictive model *DA_{CSI} Index* for measuring the sustainability of companies through economic and non-financial indicators is necessary because measuring the performance of companies using financial indicators is nowadays insufficient. The predictive model *DA_{CSI} Index* exhibits higher reliability than the predictive model *DA_{Eco}*. The predictive model *DA_{CSI}* includes both economic indicators: *I_{Eco1}*; *I_{Eco2}*; *I_{Eco4}*; *I_{Eco6}*, non-financial indicators: (*I_{En1}*; *I_{En7}*; *I_{Soc5}*; *I_{Cg2}* and environmental and social information *I_{Cg3}*. Thus constructed predictive model *DA_{CSI} Index* evaluates companies on the basis of purposefully selected set of economic and non-financial indicators. The results of predictive model *DA_{CSI} Index* can help owners, investors and managers assess whether the company is heading towards sustainability or unsustainability.

Predictive models based solely on financial indicators have been studied since 1930 to the present day by a number of foreign and domestic authors. The authors of the most famous predictive models include (Altman, 1968), who presented his linear discriminant model in 1968, (Ohlson, 1980), who introduced his logit model in 1980, and (Zmijewski, 1984), who developed probability of bankruptcy probit models. Pioneers in evaluating the financial health of Czech companies are Mr. and Mrs. Neumaier with their IN indices (Neumaier & Neumairova, 2002, 2005). The models based on financial indicators suffer from many shortcomings, because of their reliance on historical data, their focus on only short-term goals, but the main problems are their apparent lack of connectedness to strategies, their frequent non-transparency and unreliability. To avoid those shortcomings, non-financial indicators come increasingly to the fore, which are included in the construction of predictive models, or predictions are based solely on examining these variables.

The Conceptual Framework

Predictive models are nowadays useful predictive tools. Authors of predictive models often use financial indicators as a starting point. Financial indicators are actually a measure of the company's success and reflect the company's performance. For that reason, most economists base their corporate predictive models on a financial analysis and strive to create a suitable setup of individual financial indicators that would unambiguously define the degree of the company's financial stability. The best known of the bankruptcy models used in

practice are Beaver profile analysis, Altman models, Taffler model, Beerman Discriminant Function, Zmijewski's model and Ohlson's model.

The financial standing models include Kralicek Quick Test, Tamari's model, Index of Financial Standing (IB), Rudolf Doucha's set of balance analyses, IN indices, and others. Financial standing indicators reflect the quality of the company based on its performance, and are oriented to owners and investors. In their literature overview of predictive models, (Altman & Narayanan, 2002) listed 43 works from 22 countries, and they specified the prediction method and the input data used, how the groups were defined and what results were achieved. Another literature review is included in the study by (Bellovary *et al.*, 2007), and it gives a brief description of 165 corporate predictive models that were published between 1966 and 2005. According to (Declers *et al.*, 1992), predictive model should include indicators based on gross added value, which increases model reliability. Values of such indicators, however, differ considerably between different sectors, which should be taken into account. In addition to financial ratios, (Becchetti & Sierra, 2003) include indicators reflecting customer concentrations, the presence of competitors and technical efficiency in the model. (Xu & Wang, 2009) complemented their model based on ratio indicators with technical efficiency calculated by means of data envelopment analysis (DEA).

Predictive models based only on financial indicators suffer from many shortcomings, and therefore also non-financial indicators attract more and more attention and are included in the construction of predictive models, or predictions are based solely on examining these variables. The most widespread and elaborate system of evaluation by means of financial and non-financial indicators is the Balanced Scorecard (BSC) developed by (Kaplan & Norton, 2000). A number of other authors (Lau & Sholihin, 2005; Fernandes *et al.*, 2006; Prieto & Revile, 2006; Wier *et al.*, 2007; Cardinaels & van Veen-Dirks, 2010; Fulop *et al.*, 2014) also pursued the topic of comprehensive assessment of corporate performance through a system of financial and non-financial indicators, but the practical application of these systems of indicators remains a problem because there is no uniform approach to identification, classification, measurement and evaluation by means of financial and non-financial indicators.

(Pollak, 2003) developed a well-known predictive model that uses both financial and non-financial indicators for corporate evaluation. (Argenti, 1976) constructed a non-financial predictive model suitable for internal analysis. His model was designed on the basis of non-financial indicators that diagnosed shortcomings and signs of corporate failings. The model is based on numerical scoring of individual factors, with the sum of points representing the final "score. (Ittner *et al.*, 2003) examined in their study the relation between satisfaction measurement system, economic performance, and two general approaches to strategic performance measurement: greater measurement diversity and improved alignment with firm strategy and value drivers. They found that the results are associated with higher satisfaction and performance of the share markets. (Grunert *et al.*, 2005) confirmed that the models that include both

financial and non-financial indicators show higher reliability in predicting bankruptcy compared to models that are based solely on financial indicators. (Altman *et al.*, 2010) studied models made up of both financial and non-financial indicators (related to the audit, the size and age of the company). They came to the conclusion that the addition of these non-financial indicators improved the reliability of the model by 13 %.

Recently, there has been a growing interest in the use of financial and non-financial indicators for the measurement of sustainable corporate performance. The issue of sustainability at the corporate level and its relation to performance is dealt with by a number of foreign and domestic authors (Kristensen & Westlund, 2004; Rutkauskas *et al.*, 2014). A number of concepts, tools and indicators has been developed that focus on measuring and reporting sustainability, but there is no such thing as a uniform approach to measuring sustainability.

Research Methodology

The authors dealt with the construction of a composite indicator for sustainability measurement, the Corporate Sustainability Index (CSI), in 2013 and 2014. They used the principal component analysis (PCA) to determine the CSI, and the OECD Composite Indicators Methodology (Nardo, 2005; OECD, 2008) to construct it. The principal component analysis procedure has a number of advantages but also disadvantages. The fundamental disadvantage of the PCA procedure is that weights are calculated on the data from each particular year. Composite indicators whose weights are annually recalculated cannot be compared.

The study of predictive models for company financial stability assessment offers itself as an appropriate approach to the design of corporate sustainability indicators comparable in time. Although predictive financial models are criticized for their inaccuracy by many authors, a majority of authors nevertheless agree that their accuracy is essentially sufficient (Lacher *et al.*, 1995). (Balcaen & Ooghe, 2007) reached a most interesting conclusion with respect to models when they compared selected models based on discriminant analysis and models based on logistic regression. They found that model accuracy is more affected by indicators included in the model than by the method by means of which the model was derived. (Wu *et al.*, 2010) compared the original Altman model with models whose design was not based on discriminant analysis (e.g. Ohlson's logit model). The comparison showed that the Altman model is less reliable in comparison with other models. (Russ *et al.*, 2009) see the major drawback of Altman's Z-score in its orientation to manufacturing companies.

The construction of the predictive model of corporate sustainability, the *DA_{CSI} Index* – is based on empirical research divided into three stages. The first stage is devoted to the methodology for the classification of companies based on economic indicators *I_{Ecoi}* by selecting a suitable predictive model *DA_{Eco}*. The second phase deals with the methodology for the classification of companies based on the evaluation of non-financial indicators *I_{ESGi}*, which cover the areas of environmental, social and corporate governance indicators for the predictive model *DA_{ESG}*. The third phase is devoted to the methodology for comprehensive

classification of companies based on economic (*I_{Ecoi}*) and non-economic (*I_{ESGi}*) indicators for the construction of the *DA_{CSI} Index*, i.e. the predictive model.

An analysis of Czech companies showed that financial stability is predominantly assessed on the basis of predictive models, i.e. models developed by (Neumaier & Neumaierova, 2002, 2005). These models were developed using the Multiple Discriminant Analysis (MDA).

The material for empirical research into *non-financial indicators* for corporate sustainability measurement came from findings from previous research in the years 2011-2014 (Kocmanova, 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. The most important institution dealing with sustainability and indicators is the Global Reporting Initiative (GRI), which has set up a reporting framework and a set of environmental, social and economic indicators (GRI, 2013). Another institution is the CFA Institute, which has created a manual for investors (Schacht *et al.*, 2009). The European Federation of Financial Analysts Societies (EFFAS) has set up ESG performance indicators for industries, and is currently considering ways of integrating ESG indicators into investment decisions. The International Federation of Accountants (IFAC) has prepared an overview of performance metrics and KPIs for ESG performance indicators.

Results and Discussion

Empirical research is aimed at companies from the manufacturing industry according to CZ-NACE classification with over 250 employees. The analyzed period was 2008–2012. The analyzed of 88 companies from the manufacturing industry according to CZ-NACE classification Manufacture: 10 - of food products, 11 - of beverages, 13 - of 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. The construction of the predictive model of corporate sustainability, the *DA_{CSI} Index* is based on the determination of the predictive model *DA_{Eco}* from economic indicators *I_{Ecoi}* and the predictive model *DA_{ESG}* from non-financial indicators *I_{ESGi}*.

For the construction of predictive models *DA_{Eco}*, *DA_{ESG}* and *DA_{CSI} Index*, the Multiple Discriminant Analysis was used. The general equation of discriminant:

$$Y = a_1X_1 + a_2X_2 + \dots + a_pX_p \quad (1)$$

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

Discriminant analysis undertakes to calculate the value of the discriminant function, on the basis of which entities are assigned to the primary class (Anderson, 2007). The SPSS 22.0 software was used for the MDA application.

The first step in the analysis is to decide what criterion will be taken as an explained variable, or, rather, how individual groups will be defined. For a definition of groups

in the case of companies, the criterion are prospering companies, i.e. companies that made profit in three consecutive years, and their return on equity in the last year was higher than 8 % (this indicator is crucially important for the owners of the company because it measures the profitability of invested capital), and others are considered failing companies.

Appropriate explaining variables that affect the value of the explained variable must then be selected. Economic

indicators I_{Ecoi} for the predictive model DA_{Eco} are ratios selected from a broad group of indicators used in predictive models. They are divided into groups, i.e. into profitability ratios, financial stability indicators, productivity indicators and a cash flow-based indicator. In the construction of the predictive model for measuring corporate sustainability, the eleven I_{Ecoi} ratios can be replaced with the Index of Financial Standing (IB), or some other models, IN indeces, etc. in Table 1.

Table 1

Economic Indicators and Index of Financial Standing

Ecoi - Economic indicators	Index of financial standing (IB) (German model)	
IEco1- EAT / SF (ROE)	+ 1,5 * CF / L	
IEco2 - EBIT / A (ROA)	+ 0,08 * A / L	
IEco3 - EAT + IP / NCL + SF	+ 10 * EBT / A	
IEco4 - EBIT / S (ROS)	+ 5 * EBT / T	
IEco5 - SF + NCL / A	+ 0,3 * St / T	
IEco6 - CF / A	+ 0,1 * T / A	
IEco7 - VA / OR	Prospering companies	
IEco8 - OR / A	IB ≥ 3	
IEco9 - L / SF	extremely good economic situation	
IEco10 - A / L	2 ≤ IB < 3	
IEco11 - VA / CE	very good economic situation	
	1 ≤ IB < 2	
	good economic situation	
	0 ≤ IB < 1	
	problematic economic situation	
	Failing companies	
	-1 ≤ IB < 0	
	poor economic situation	
	-2 ≤ IB - 1	
	very poor economic situation	
	IB < - 2	
	extremely poor economic situation	
<i>A_Total assets, VA_Value added, SF_Shareholders Funds, IP_Interest paid, CF_Cash flow, L_Total liabilities, CA_Current Assets, OR_Operating Revenue, T_Turnover, NCL_Non Current Liabilities, S_Sales, St_Stocks,CE_Cost of Employees</i>		

Methodical approach in the first stage of calculating the predictive model DA_{Eco} . The predictive model is comprised of 11 economic indicators I_{Ecoi} . Indicators that exhibit collinearity have been discarded. To increase the statistical significance (discriminating power) of economic indicators, an analysis of outliers, data normality and correlations between indicators was performed. In the case of non-normality, indicators are transformed. In the next step, MDA is applied to economic indicators I_{Eco3} , I_{Eco5} , I_{Eco7} , I_{Eco8} , I_{Eco9} , I_{Eco10} , I_{Eco11} , which are gradually eliminated and the model are recalculated after individual indicators have been removed. Wilks' Lambda indicates the significance of the discriminant function, the model explains 50,1 % of the variability, it is the inverse to canonical correlation. The discriminant function suitable for differentiating between groups of companies:

$$DA_{Eco} = -1,761 + 11,628I_{Eco6} - 0,007I_{Eco2} + 0,048I_{Eco4} + 0,030I_{Eco1} \quad (2)$$

and explains 88,4 % differences between companies in the two defined groups.

DA_{Eco} values less than -1.153 rank the company among Group 0 (failing) companies, DA_{Eco} values greater than 0.830 rank the company among Group 1 (prospering) companies. DA_{Eco} from the interval <-1,153; 0,830 > do not give unambiguous information on which group the company belongs to. Economic indicators that enter the predictive model DA_{Eco} : I_{Eco1} - EAT / SF = ROE; I_{Eco2} - EBIT / A = ROA; I_{Eco4} - EBIT / S = ROS; I_{Eco6} - CF / A in (Figure 1) and (Figure 2).

The primary classification reveals a moderately "skewed" division into groups, with Group 1 companies being more numerous. It is clear that high values of the variable I_{Eco6} - CF / A, which, based on the analysis

performed helps best to explain the division into groups, move observations closer to Group 1. The decisive indicator I_{Eco6} is the most influential and measures how much profit a company can make for ever unit of total assets (invested capital). Other important variables are profit ratio / profitability. These indicators are designed to reflect the company's ability to utilize its assets or sales, to make profit. It can be expected that the assignment of a company to the group of "prospering companies" will be positively dependent on each of the indicators included in this group. The extent to which they all together contribute to the division into groups can only be verified by a multivariate analysis.

The direction of the effect of other variables, I_{Eco4} - EBIT / S, pushes companies towards Group 1. This indicator measures the profitability (effect) of sales and allows us to estimate how effectively a company operates, how it controls its costs and what position the company has on the market from the success of its products' point of view. A negative value of the indicator I_{Eco2} - EBIT / A moves companies closer to Group 0. This indicator should be considered a basic measure of the profitability of the total resources invested in the business, and thus it reflects the overall efficiency of the company, its overall earnings power. The extreme value of this indicator is based on the requirement for a positive effect of financial leverage.

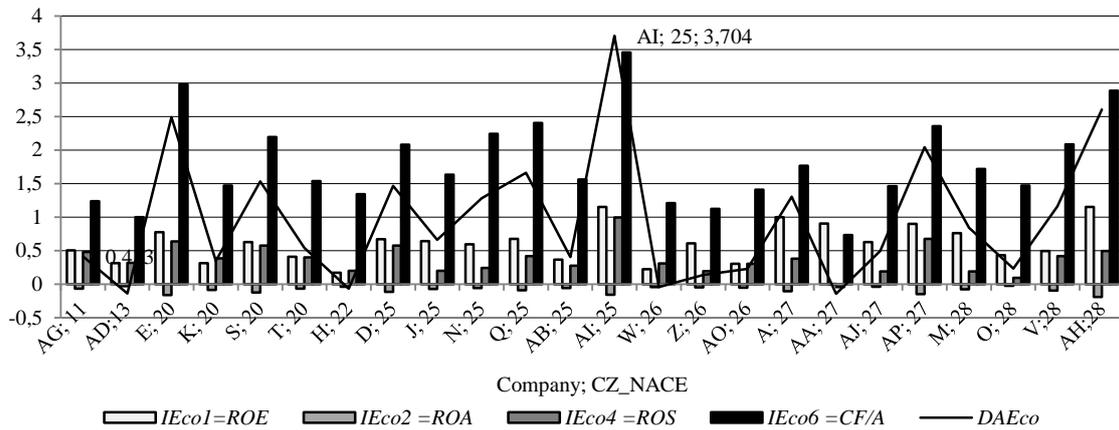


Figure 1. Prospering Companies According to Discriminant Analysis DA_{Eco}

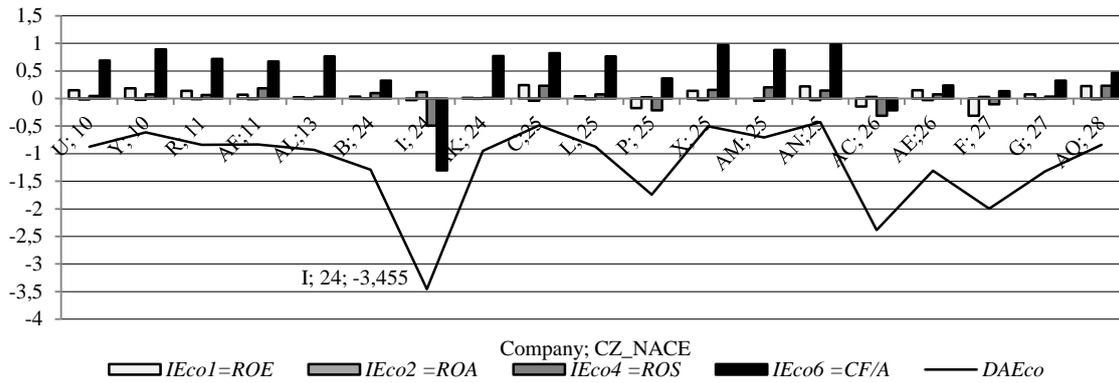


Figure 2. Failing Companies According to Discriminant Analysis DA_{Eco}

I_{Eco1} - EAT / SF: this indicator assesses the return on the investment the owners made in the company. The indicator is crucial for company owners because it measures the profitability of the invested capital. For creditors, this indicator has a supportive role. The extent to which a company increases the value of its equity provides information also about the possible extent of external capital appreciation. The extreme value is similar as in the previous indicator. In the second stage, the predictive model DA_{ESG} , was determined from environmental, social and corporate governance indicators I_{ESGi} ; these are used in the construction of the DA_{CSI} Index measuring corporate sustainability. To

calculate the predictive model DA_{ESG} , 17 I_{ESGi} indicators were used: seven environmental indicators I_{Envi} , six social indicators I_{Soci} and four corporate governance indicators I_{Cgi} (Table 2). The use of MDA requires that groups are defined and companies divided into effective and ineffective, which is accomplished by Data Envelopment Analysis. Transformation is applied on individual I_{ESGi} indicators with the aim to change their distribution so that it gets closer to normality. Transformed of the indicators I_{En1} , I_{En2} , I_{En3} , I_{En4} , I_{En5} , I_{Soc1} , I_{Soc2} , I_{Soc3} , I_{Soc6} , I_{Cg2} , I_{Cg3} , I_{Cg4} were gradually removed and the model recalculated after each indicator removal.

Table 2

Non-financial Environmental, Social and Corporate Governance Indicators I_{ESG}

Environmental group ($j=Envi$)	Social group ($j=Soc$)	Corporate governance group ($j=Cg$)
I_{Eni} - Environmental indicators	I_{Soci} - Social indicators	I_{Cgi} - Corporate governance 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 [yes = 0,52; no = 0,48]
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 [yes = 0,64; no = 0,36]
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 [yes= 0,72; no = 0,28]
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_{En5} - Total annual consumption of water / Added value [m ³ /year/EUR]	I_{Soc5} -Wage costs / Added value [%]	
I_{En6} - Total annual production of waste / Added value [t/EUR]	I_{Soc6} - Education and training expenditures / Added value [%]	
I_{En7} - Total annual production of hazardous waste / Added value [t/EUR]		

Source: Kocmanova et al., 2014

The discriminant function suitable for discriminating groups of companies:

$$DA_{ESG} = -5,728 + 0,490I_{En6} + 0,250I_{En7} + 4,419I_{Soc4} + 1,297I_{Soc5} + 26,319I_{Cg2} \quad (3)$$

and explains 65,9 % of differences between companies in the two defined groups. DA_{ESG} values less than - 0.426 identify companies that belong to Group 0 (ineffective companies), DA_{ESG} values greater than 0,465 point to a similarity with Group 1 companies (effective companies). DA_{ESG} values from the interval $\langle -0,426; 0,465 \rangle$ do not give

unambiguous information on which group the company belongs to.

For MDA purposes, non-financial environmental, social and corporate governance indicators are divided into indicators I_{ji}^+ , whose increasing value has a positive impact on corporate sustainability, and indicators I_{ji}^- , whose increasing value has a negative impact on corporate sustainability.

The resulting positive / negative impact of indicators on corporate sustainability for the prediction model DA_{ESG} : I^-_{En6} ; I^-_{En7} ; I^+_{Soc4} ; I^+_{Soc5} ; I^+_{Cg2} (Figure 2) and (Figure 3).

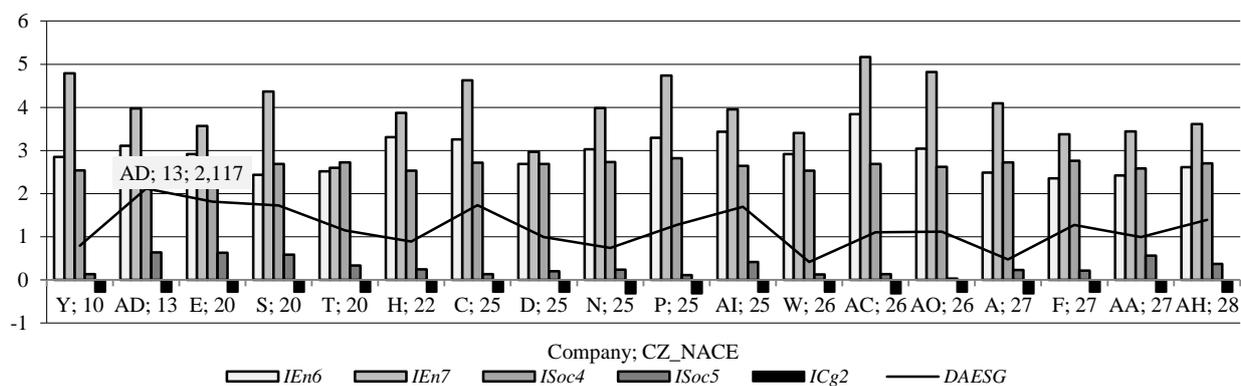


Figure 3. Effective Companies According to Discriminant Analysis DA_{ESG}

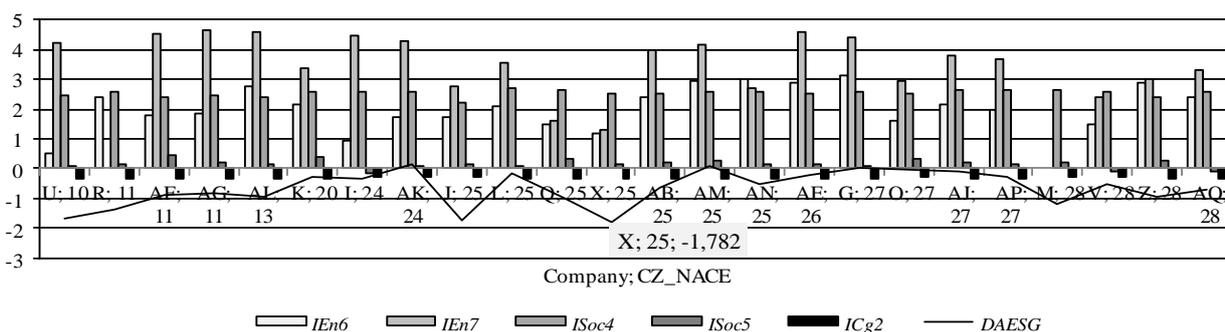


Figure 4. Ineffective Companies According to Discriminant Analysis DA_{ESG}

For a classification of companies into effective and ineffective, the decisive environmental indicators for industrial companies are: I^-_{En6} and I^-_{En7} . Social indicators I^+_{Soc4} , i.e. payroll productivity, and I^+_{Soc5} , i.e. labour productivity are also important for industrial companies. The indicator I^+_{Cg2} , i.e. corporate governance transparency towards employees, does not manifest itself as a decisive factor. It is very interesting to note that social indicators such as I_{Soc1} , I_{Soc2} , I_{Soc3} and I_{Soc6} do not have a significant effect on the overall evaluation of companies.

Methodological procedure in the third stage is based on the use of MDA and on testing the hypothesis whether selected non-financial indicators of the prediction model DA_{ESG} can "explain" the classification into groups (0 or 1) on the basis of financial variables.

HYPOTHESIS: Classification based on economic and non-financial indicators must result in the same (almost the same) classification as the previous one based on economic indicators only.

MDA is again comprised of economic indicators from DA_{Eco} , i.e. I_{Eco1} ; I_{Eco2} ; I_{Eco4} ; I_{Eco6} , to which DA_{ESG} non-financial

indicators, i.e. I_{Eni} , I_{Soci} and I_{Cgi} , were added gradually. Using MDA, transformed of the indicators I_{En2} , I_{En3} , I_{En4} , I_{En5} , I_{En6} , I_{Soc1} , I_{Soc2} , I_{Soc3} , I_{Soc4} , I_{Soc6} , I_{Cg1} , I_{Cg4} , I_{Cg5} were gradually removed and the model recalculated after individual indicators were removed.

The model explains 75,5 % variability, it is the inverse to canonical correlation. The discriminant function suitable for discriminating between groups of companies:

$$DA_{CSI} = -0,045 + 14,483I_{Eco6} - 0,011I_{Eco2} + 0,048I_{Eco4} + 0,031I_{Eco1} + 3,138I_{Cg3} - 0,095I_{En7} + 1,058I_{Cg2} - 0,011I_{En1} - 2,304I_{Soc5} \quad (4)$$

and explains 97,6 % of differences between companies in the two defined groups.

DA_{CSI} values under -1,435 signal that the company belongs to Group 0 (companies not heading towards sustainability), while DA_{CSI} values greater than 1,076 point to a similarity with companies in Group 1 (companies heading towards sustainability). DA_{CSI} values from the interval $\langle -1,435; 1,076 \rangle$ do not give unambiguous information about the company's sustainability status (Table 3).

Table 3

Predictive Models DA_{Eco} , DA_{CSIB} and DA_{CSI} Index for Manufacturing Companies According to CZ-NACE Classification

Company	CZ_NACE	Group	DA_{Eco}	Group	DA_{CSIB}	Group	DA_{CSI}	Company	CZ_NACE	Group	DA_{Eco}	Group	DA_{CSIB}	Group	DA_{CSI}
AI	25	1	3.690	1	2.881	1	3.920	AG	11	1	0.396	0	-0.532	1	-0.290
AH	28	1	2.590	1	2.784	1	2.795	C	25	0	-0.503	1	-0.071	1	-0.297
V	28	1	1.145	1	2.878	1	2.363	Y	10	0	-0.635	0	-0.623	0	-0.406
E	20	1	2.479	1	3.024	1	2.112	O	28	1	0.214	0	-0.590	0	-0.407
Q	25	1	1.645	1	1.636	1	2.011	L	25	0	-0.894	1	-0.293	0	-0.461
D	25	1	1.454	1	2.189	1	1.950	AK	24	0	-0.972	0	-0.519	0	-0.614
AP	27	1	2.028	1	1.935	1	1.738	AL	13	0	-0.948	0	-0.708	0	-0.784
M	28	1	0.825	1	1.172	1	1.580	AN	25	0	-0.446	0	-0.900	0	-0.791
A	27	1	1.287	1	0.990	1	1.502	AA	27	1	-0.168	0	-1.615	0	-0.812
J	25	1	0.641	1	0.819	1	1.244	AQ	28	0	-0.859	0	-0.984	0	-0.886
S	20	1	1.520	1	1.382	1	1.043	AD	13	1	-0.159	0	-1.112	0	-0.959
N	25	1	1.261	0	-0.500	1	0.832	G	27	0	-1.342	0	-1.003	0	-1.011
AO	26	1	0.210	1	0.487	1	0.785	R	11	0	-0.858	0	-0.810	0	-1.065
AJ	27	1	0.476	1	-0.108	1	0.784	U	10	0	-0.893	0	-1.240	0	-1.449
AB	25	1	0.388	1	0.394	1	0.687	AM	25	0	-0.720	0	-1.732	0	-1.603
T	20	1	0.524	1	0.613	1	0.656	F	27	0	-2.018	0	-1.715	0	-1.988
W	26	1	-0.059	1	0.948	1	0.394	AE	26	0	-1.327	0	-1.431	0	-2.115
Z	26	1	0.117	1	-0.235	1	0.239	AF	11	0	-0.855	0	-2.096	0	-2.218
K	20	1	0.331	1	1.642	1	0.107	P	25	0	-1.764	0	-2.536	0	-2.383
H	22	1	-0.083	1	0.487	1	0.079	I	24	0	-3.484	0	-3.202	0	-2.998
X	25	0	-0.522	1	0.546	1	-0.004	AC	26	0	-2.406	0	-2.393	0	-3.280

The predictive model DA_{CSI} Index encompasses economic indicators, i.e. I_{Eco1} - EAT / SF; I_{Eco2} - EBIT / A; I_{Eco4} - EBIT / S; I_{Eco6} - CF / A, as well as non-financial indicators, i.e. I_{En1} - cost of environmental investments / added value; I_{En7} - total annual production of hazardous waste / added value; I_{Soc5} - added value / payroll expenses; I_{Cg2} - environmental and social information; I_{Cg3} - code of ethics. The testing of the hypothesis demonstrated that the inclusion of non-financial indicators did not result in any significant changes in the overall evaluation. Although

some adjustments in classification occurred after social and corporate governance indicators were included, the groups formed were nevertheless still comparable with the original groups created from only economic indicators. To some extent, this result was expected. The spider charts below show predictive models DA_{Eco} and DA_{CSI} Index (Figure 5) and predictive models DA_{CSIB} and DA_{CSI} Index (Figure 6). It is also possible to replace IB with some other indices of financial standing, e.g. indices models IN, Z-Score, EVA, etc.



Figure 5. Predictive models DA_{Eco} and DA_{CSI} Index for manufacturing companies according to CZ-NACE classification
 a) companies heading towards sustainability (Group 1); b) companies not heading towards sustainability (Group 0)

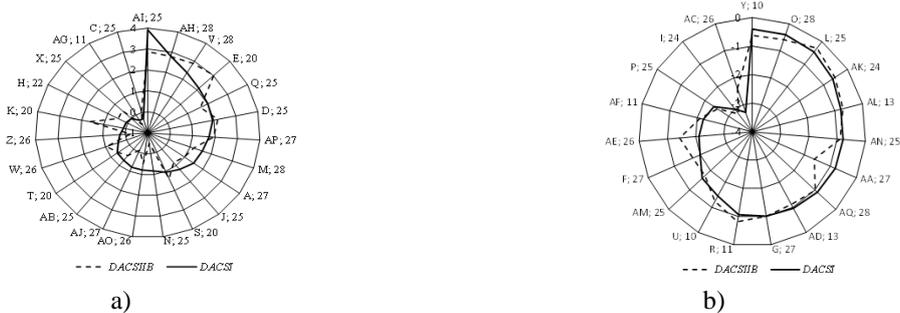


Figure 6. DA_{CSIB} and DA_{CSI} Index for manufacturing companies according to CZ-NACE classification
 a) companies heading towards sustainability (Group 1); b) companies not heading towards sustainability (Group 0)

It follows from MDA results that the statistical significance of the effect of non-financial indicators is relatively small, except for those that indirectly characterize the company's economic efficiency. They are the social indicator, which characterizes the company's financial situation in terms of its employees, i.e. labour productivity - added value / payroll expenses, and the code of ethics, an index that also affects employees. Environmental indicators attest to their relationship with economic indicators, the main one is the indicator 'cost of environmental investments / added value'. Basically, non-financial indicators are insignificant in terms of statistical tests, and their inclusion does not alter significantly the company's classification performed solely on the basis of economic indicators. This can be due to small informative power of the indicators used.

More interesting results could be obtained if the evaluation included more observations. Evaluation of selected indicators represents the most complicated and problematic part of the entire comprehensive evaluation design. Financial indicators can easily be objectively evaluated on the basis of financial statements. Non-monetary indicators include data of both quantitative and qualitative nature, whose inclusion into the overall evaluation will help fulfil one of the basic objectives, i.e. the construction of a uniform system for the evaluation of corporate sustainability measurement (i.e. of the financial health and credibility of industrial companies). It follows from the results of the empirical research that the predictive model *DA_{CSI} Index* for measuring the sustainability of companies through financial and non-financial indicators is indispensable because the traditional financial analysis of companies focusing solely on economic indicators is now obsolete. Other significant conclusions regarding the inclusion of non-financial indicators in forecasting models are corroborated by research results reported by (Cardinaels & van Veen-Dirks, 2010; Bhiman *et al.*, 2010) The conclusion that an inclusion of non-financial indicators into the predictive model improves model reliability has also been reported by (Altman, Sabato & Wilson, 2010).

Conclusions

The article describes the construction of the predictive model *DA_{CSI} Index* for companies in the manufacturing sector as defined by CZ-NACE classification. A literature review revealed that attention is paid to both financial and non-financial indicators that can simultaneously integrate economic, ownership, organizational, social and environmental aspects. The importance of the predictive model lies

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in its ability to indicate whether a company is moving towards sustainability. The predictive model may influence decisions affecting the company's long-term strategy and can demonstrate the company's approach to comprehensive performance evaluation as well as integrated sustainability reporting.

The predictive model *DA_{CSI} Index* represents a composite indicator that has been constructed using the Multiple Discriminant Analysis.

Corporate evaluations that focus only on financial aspects are very one-sided and are now obsolete, and corporate evaluations are therefore being extended to also include other approaches. The basis of the predictive model *DA_{CSI} Index* is the determination of financial and non-financial indicators. First, economic indicators were determined from the group classification into profitability indicators, indicators of financial stability, productivity indicators and indicators based on cash flows. For the predictive model *DA_{Eco}*, four economic indicators which entered into the model *DA_{CSI} Index* were selected by means of MDA. To compare the reliability of the model *DA_{CSI}*, results were compared with the use of the IB index of financial standing. The graphical representation using spider charts shows that the results of the model *DA_{CSI}* in both versions are almost identical, even in terms of the division of companies into groups.

The predictive model *DA_{CSI} Index* can facilitate decision making of owners, potential investors, managers, and can also be useful as the initial composite indicator for integrated reporting. The purpose of the predictive model is to provide a simplified and quantified expression for a more complex composition of several indicators, and also to explain why companies with good economic results may not be sustainable.

The predictive model *DA_{CSI} Index* offers the possibility to easily compare the performance of one company with other companies in the group. Above all, it is one of the ways of constructing a necessary tool for measuring corporate sustainability that will make it possible to evaluate the company's commitment to the principles of sustainability.

Acknowledgement

This paper is supported by the grant No. 14-23079S Measuring Corporate Sustainability in Selected Sectors of The Czech Science Foundation.

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The article has been reviewed.

Received in April, 2014; accepted in June, 2015.