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I. ARTICLES

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STUDY OF THE CLASSIFICATION ACCURACY MEASURES FOR PREDICTING CORPORATE BANKRUPTCY TAKING INTO ACCOUNT CHANGES IN THE ECONOMIC ENVIRONMENT

Many types of methods for predicting corporate bankruptcy have been formulated by business theory and practice. Among them, an extensive group is composed of classification methods, which can divide companies into two groups: bankrupt and financially sound companies. The aim of the paper is to present the outcomes of the comparative analysis of classification accuracy for selected kinds of corporate bankruptcy prediction methods. While building the models, both the financial ratios of companies and the variables which reflect changes in the economic environment were taken into account. The analysis is based on data concerning companies operating in the industrial processing sector in Poland. The following four types of bankruptcy prediction methods were employed: linear discriminant analysis, logistic regression, classification tree and neural network. In order to assess the classification accuracy of a model for a training set and test set, three measures were used: sensitivity, specificity and overall accuracy. The results of the conducted empirical studies confirm the hypothesis that changes in the economic environment of companies affect their financial situation and risk of bankruptcy. The indicators of economic growth, the labour market, inflation and the economic situation were useful in bankruptcy prediction of companies operating in the industrial processing sector in Poland.

Keywords: classification model, classification accuracy, corporate bankruptcy, economic environment
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1. Introduction

Methods for predicting bankruptcy of companies are of great interest to both economists and business practitioners, those based primarily on data taken from financial statements of financially sound and bankrupt companies

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are used to predict the risk of corporate bankruptcy. If it is impossible to collect a sufficiently large set of data for a single year, a database is built on the basis of financial data from several years (e.g. Altman, 1968).

The fundamental goal of studies on predicting corporate bankruptcy is to build a model or determine decision-making rules to enable accurate forecasting. One of the possible sources of prediction errors concerning the risk of bankruptcy is the unstable nature of the economic environment (e.g. Blanchard and Johnson, 2013). On the basis of data that reflect the financial situation of companies in different years, and – consequently – under various conditions of the economic situation in a country (e.g. Trabelsi et al., 2015), the question arises as to whether a model with estimates of parameters obtained without taking into account changes in the economic environment of companies can be the basis for reliable bankruptcy forecasting.

Suggestions can be found in the literature on predicting the bankruptcy of companies for making the methods for forecasting corporate bankruptcy more dynamic. Examples include models prepared for the Italian economy on the basis of data from the period 1995-1998 (De Leonardis and Rocci, 2008) and 1999-2005 (De Leonardis and Rocci, 2014). In the paper by Pawełek et al. (2016), a methodological proposal was presented which involved the use of the interactions between qualitative variables (binary variables that identify the periods from which the financial data come) and quantitative variables (financial ratios) in predicting the bankruptcy of companies in Poland. The considerations as presented in this paper are a continuation of the research presented in the paper by Pawełek et al. (2016). An extension to the research consists in including selected macroeconomic indicators in traditional models, i.e. based solely on financial ratios. Literature on the subject presents proposals of macroeconomic indicators (e.g. Acosta-González et al., 2019; Bonfim, 2009; Crook and Bellotti, 2010; Korol and Korodi, 2010; Nouri and Soltani, 2016; Tinoco and Wilson, 2013) or market indicators (e.g. Beaver et al., 2005; Carling, 2007; Chava and Jarrow, 2004; Nouri and Soltani, 2016; Shumway, 2001; Tinoco and Wilson, 2013), the values of which reflect changes in the economic situation in a given country. Based on the results of the studies attempting to use macroeconomic indicators in models for forecasting corporate bankruptcy, it can be assumed that the usefulness of this approach depends, among others, on the length of the interval from which the information on the companies comes (De Leonardis and Rocci, 2014).

The purpose of this paper is to compare the efficiency of classification accuracy measures in selected methods for predicting the bankruptcy of companies, built only on the basis of financial ratios, with the classification accuracy of these methods after including selected macroeconomic indicators in the set of explanatory variables. The preliminary results of this research were discussed at the conference of the International Federation of Classification Societies (IFCS) in 2015 (Baryła et al., 2015).

Research on forecasting bankruptcy is usually based on one type (or one-type group) of models. The classical approach adopts a linear discriminant function or logit model. Machine-learning methods are frequently used, for example neural networks and classification trees, in addition using more specific methods such as survival analysis (e.g. De Leonardis and Rocci, 2008), hazard models (e.g. Hwang and Chu, 2014; Shumway, 2001; Trabelsi et al., 2015) and, naturally the literature on this subject is much more extensive. Among these proposals there are fairly rare comparative studies on the effectiveness of the proposed approaches.

The added value of our research is the presentation of the results of a complex comparative study to answer the following questions:

- how does the addition of macroeconomic indicators influences the classification accuracy of the selected methods?
- how does the way of balanced datasets creation (pairing or random sampling) influence the classification accuracy of the selected methods without and with macroeconomic indicators?
- how does the proportion of division datasets into the balanced training and test set (6:4) or (7:3) influence the classification accuracy of the selected methods with and without macroeconomic indicators?
- which specific macroeconomic indicators are useful for predicting corporate bankruptcy?

The answers to the above questions, as given in this paper, are based on empirical investigations concerning the economic situation of Poland as an example of a transformed economy in the European Union. To the best of the authors' knowledge, there are no studies in the literature taking into account the macroeconomic indicators used in bankruptcy prediction models in the context of pairing or random sampling balanced datasets and their division into the training and test set. In view of the above, the results of the empirical investigation carried out on the basis of the data relating to companies operating in Poland are of added value to the literature on bankruptcy prediction.

2. DATA AND RESEARCH PROCEDURE

A database downloaded from the website of the Emerging Markets Information Service (EMIS, https://www.emis.com/) was the basis for the empirical research conducted. Two balanced datasets were considered (Baryła et al., 2016):

- S_1 was created as a result of the application of a non-random technique of matching financially sound and bankrupt companies in pairs,
- S_2 was created as a result of the application of an independent random sampling of financially sound and bankrupt companies from relevant populations.

Each set consisted of 246 companies operating in the industrial processing sector in Poland.

The companies were described by:

- a dummy variable, which took the value '1' if the company went bankrupt in the period 2007-2010 or the value '0' if the company did not go bankrupt in 2005-2010,
- 32 financial ratios divided into four groups (see Table 1): liquidity ratios (4 variables: R_{01}–R_{04}), liability ratios (10 variables: R_{05}–R_{14}), profitability ratios (7 variables: R_{15}–R_{21}) and productivity ratios (11 variables: R_{22}–R_{32}). The financial data used were for 2005-2008. In the case of bankrupts, the ratio values reflected the financial situation of the company two years before its bankruptcy.

In the database, selected macroeconomic indicators were included, such as (e.g. Hwang and Chu, 2014):

- unemployment rate,
- Consumer Price Index,
- nominal GDP per capita,
- real GDP per capita,
- growth rate in real GDP,
- rate of change in industrial production,
- general business climate indicator.

Macroeconomic data were downloaded from the website of Statistics Poland (https://stat.gov.pl/en/). Apart from the macroeconomic indicators for individual years, delays in time of values of the selected indicators and values of residuals of a trend function, estimated for the selected indicators along with their delays in time, were also included in the database. In order to increase the set of values taken by the considered macroeconomic indicators in particular years, measurements at a regional level were considered where possible (NUTS 2 level). The examined objects were assigned to the regions where the main office of the company was located. The year to which the value of a macroeconomic indicator related was in conformity with the year from which the financial statements were prepared.

Table 1

Financial ratios in the database and their definitions

Liquidity ratios	Profitability ratios
R_{01} = Current assets / Short term liabilities R_{02} = (Current assets – Inventories) / Short term liabilities R_{03} = (Current assets − Inventories − Short term receivables) / Short term liabilities R_{04} = (Current assets − Short term liabilities) / Total Assets	R_{15} = EBITDA / Total Assets R_{16} = 100 ∗ Gross profit (loss) / Sales revenues R_{17} = 100 ∗ Net profit (loss) / Sales revenues R_{18} = 100 ∗ Net profit (loss) / Shareholders' equity R_{19} = 100 ∗ Net profit (loss) / Total Assets R_{20} = Operating profit (loss) / Total Assets R_{21} = Operating profit (loss) / Sales revenues
Liability ratios	**Productivity ratios**
R_{05} = (Long term liabilities + Short term liabilities) / Total Assets R_{06} = (Long term liabilities + Short term liabilities) / Shareholders' equity R_{07} = Long term liabilities / Shareholders' equity R_{08} = Shareholders' equity / Total Assets R_{09} = Short term liabilities / Total Assets R_{10} = Fixed assets / Total Assets R_{11} = (Net profit (loss) + Depreciation) / (Long term liabilities + Short term liabilities) R_{12} = Shareholders' equity / (Long term liabilities + Short term liabilities) R_{13} = Gross profit (loss) / Short term liabilities R_{14} = (Shareholders' equity + Long term liabilities) / Fixed assets	R_{22} = Sales revenues / (Short term receivables(t) + Short term receivables(t−1))/2 R_{23} = Sales revenues / (Fixed assets(t) + Fixed assets(t−1))/2 R_{24} = Sales revenues / (Total Assets(t) + Total Assets(t−1))/2 R_{25} = Sales revenues / Total Assets R_{26} = Short term liabilities / Operating costs R_{27} = Inventories / Sales revenues R_{28} = Inventories / Operating costs R_{29} = Short term receivables / Sales revenues R_{30} = Operating costs / Short term liabilities R_{31} = Sales revenues / Short term receivables R_{32} = 100 ∗ Operating costs / Sales revenues

Source: EMIS, https://www.emis.com/

Sets S_1 and S_2 were randomly divided into training and test sets by a ratio of 6:4 and 7:3, where in each subset half of the subjects were bankrupt companies, and the other half financially sound companies.

The research covered the following methods for predicting the bankruptcy of companies:

- linear discriminant analysis,
- logistic regression,
- classification tree based on the CART algorithm,
- neural network in the form of three-layer perceptron.
- A reduction in the set of explanatory variables was performed:
- in the case of the linear discriminant function and the logit model – using a backward or forward stepwise procedure (within a given model type),
- in the case of the classification tree – using the CART algorithm that ensures the selection of a subset of variables allowing one to specify decision-making rules,
- in the case of the neural network – on the basis of results obtained based on the above-mentioned techniques.

The research procedure consisted of two stages. The first involved using only financial ratios to predict the bankruptcy of companies; in the second, macroeconomic indicators were added to the financial ratios selected in the first stage, and then the explanatory variables were reduced once again. During evaluation of the statistical significance of the model parameters, the significance level of 0.05 was assumed.

An assessment of the classification accuracy of the considered methods for forecasting corporate bankruptcy was based on the following measures:

- sensitivity (percentage of bankrupts correctly classified by the model to the set of bankrupts),
- specificity (percentage of financially sound companies correctly classified by the model to the set of financially sound companies),
- overall accuracy (percentage of companies, both bankrupt and non-bankrupt, correctly classified by the model).

3. RESULTS OF EMPIRICAL RESEARCH

Tables 2 to 5 present the results obtained for the linear discriminant function, logit model, classification tree and neural network, respectively. For each of the sets S_1 and S_2 and for each division (6:4 and 7:3) there are presented:

- the financial ratios which remained in the model after the first stage of the research procedure (D_i – linear discriminant function, L_i – logit model, CT_i – classification tree, NN_i – neural network, $i = 1,...,4$),
- the financial ratios and macroeconomic indicators which remained in the model after the second stage of the research procedure (D_i^M – linear

discriminant function, L_i^M – logit model, CT_i^M – classification tree, NN_i^M – neural network, i = 1,...,4),

- the values of the classification accuracy measures based on the test set (results indicating a greater classification accuracy of a given method of the considered pair are marked in italics).

An analysis of the results in terms of the usefulness of taking into account the macroeconomic indicators in the methods for predicting the bankruptcy of companies was based on the comparison of the values of the classification accuracy measures calculated for the models obtained in the first and second stage of the research procedure. The compared models were of the same type and were estimated on the same set divided according to a specific ratio.

Table 2

Comparison of classification accuracy for discriminant functions

Type of sample	Division	Model	Test set		
			Sensitivity	Specificity	Overall accuracy
S_1	6:4	$D_1(R_{05}, R_{11})$	*67.35*	*73.47*	*70.41*
		$D_1^M(R_{05}, R_{11}, CPI, UR\_1, RGDPpc\_1)$	51.02	65.31	58.16
	7:3	$D_2(R_{02}, R_{32})$	*64.86*	64.86	64.86
		$D_2^M(R_{02}, R_{32}, UR\_1, RCIPR)$	62.16	*70.27*	*66.22*
S_2	6:4	$D_3(R_{11})$	*89.80*	59.18	*74.49*
		$D_3^M(R_{11}, GBCI)$	73.47	*63.27*	68.37
	7:3	$D_4(R_{06}, R_{20})$	59.46	*81.08*	70.27
		$D_4^M(R_{06}, R_{20}, CPI\_1, CPI\_2, UR, \mathrm{UR}\_1, GRRGDP, GBCI)$	*83.78*	75.68	*79.73*

D_i − linear discriminant function without macroeconomic indicators (i=1,...,4), D_i^M − linear discriminant function with macroeconomic indicators (i=1,...,4), *CPI* − Consumer Price Index (t), *CPI*_1 − Consumer Price Index (t−1), *CPI*_2 − Consumer Price Index (t−2), *GBCI* − general business climate indicator (t), *GRRGDP* − growth rate in real GDP (t), *RCIPR* − rate of change in industrial production residuals (t), *RGDPpc*_1 − real GDP per capita (t−1), *UR* − unemployment rate (t), *UR*_1 − unemployment rate (t−1).

Source: authors' own.

Table 3

Comparison of classification accuracy for logit models

Type of sample	Division	Model	Test set: Sensitivity	Test set: Specificity	Test set: Overall accuracy
S_1	6:4	$L_1(R_{11}, R_{12})$	*77.55*	*69.39*	*73.47*
		$L_1^M(R_{11}, R_{12}, UR\_1, RGDPpc\_2)$	69.39	65.31	67.35
	7:3	$L_2(R_{02}, R_{11})$	72.97	*72.97*	72.97
		$L_2^M(R_{02}, R_{11}, CPI, CPI\_1, NGDPpc, NGDPpc\_1, RGDPpc, RGDPpc\_1, RCIP)$	*75.68*	70.27	72.97
S_2	6:4	$L_3(R_{02}, R_{11}, R_{13})$	*87.76*	61.22	*74.49*
		$L_3^M(R_{11}, GBCI)$	77.55	*63.27*	70.41
	7:3	$L_4(R_{11}, R_{13})$	75.68	72.97	74.32
		$L_4^M(R_{11}, R_{13}, CPI\_2, RGDPpcR\_1, GBCI)$	*83.78*	*75.68*	*79.73*

L_i − logit model without macroeconomic indicators (i=1,...,4), L_i^M − logit model with macroeconomic indicators (i=1,...,4), *CPI* − Consumer Price Index (t), *CPI*_1 − Consumer Price Index (t−1), *CPI*_2 − Consumer Price Index (t−2), *GBCI* − general business climate indicator (t), *NGDPpc* − nominal GDP per capita (t), *NGDPpc*_1 − nominal GDP per capita (t−1), *RCIP* − rate of change in industrial production (t), *RGDPpc* − real GDP per capita (t), *RGDPpc*_1 − real GDP per capita (t−1), *RGDPpc*_2 − real GDP per capita (t−2), *RGDPpcR*_1 − real GDP per capita residuals (t−1), UR_1 − unemployment rate (t−1).

Source: authors' own.

On the basis of the results presented in Tables 2 to 5, it can be concluded that:

- the introduction of macroeconomic indicators contributed to the increasing sensitivity of the model, in particular in the case of set S_2 (in 4 cases out of 6),
- the introduction of macroeconomic indicators contributed to the increasing specificity of the model, in particular in the case of set S_2 (in 6 cases out of 9),
- the introduction of macroeconomic indicators contributed to the increasing sensitivity of the model, in particular in the case of the division of the considered sets into training and testing parts by a ratio of 7:3 (in 6 cases out of 6),
- the introduction of macroeconomic indicators contributed to the increasing specificity of the model, in particular in the case of the division of the considered sets into training and testing parts by a ratio of 6:4 (in 5 cases out of 9),

- the introduction of macroeconomic indicators contributed to the increasing sensitivity or specificity of the model, in particular in the case of set S_2 (in 10 cases out of 15),
- the introduction of macroeconomic indicators contributed to the increasing sensitivity or specificity of the model, in particular in the case of division of the considered sets into training and testing parts by a ratio of 7:3 (in 10 cases out of 15),
- the introduction of macroeconomic indicators contributed to the increasing sensitivity of the model, in particular in the case of the neural network and logit model (in 2 cases out of 4), whereas in the case of the linear discriminant function and classification tree, only 1 improvement was noted in the 4 considered pairs,
- the introduction of macroeconomic indicators contributed to the increasing specificity of the model, in particular in the case of the classification tree (in 3 cases out of 4), whereas in the case of other methods, 2 improvements were noted in the 4 considered pairs.

Table 4

Comparison of classification accuracy for classification trees

Type of sample	Division	Model	Test set		
			Sensitivity	Specificity	Overall accuracy
S_1	6:4	$CT_1(R_{13})$	*71.43*	59.18	65.31
		$CT_1^M(R_{13}, RGDPpc\_1, NGDPpc\_2)$	67.35	*63.27*	65.31
	7:3	$CT_2(R_{11})$	*81.08*	75.68	*78.38*
		$CT_2^M(R_{11}, UR\_1, CPI\_2)$	67.57	*78.38*	72.97
S_2	6:4	$CT_3(R_{11})$	*89.80*	61.22	*75.51*
		$CT_3^M(R_{11}, GRRGDP)$	57.14	*77.55*	67.35
	7:3	$CT_4(R_{11}, R_{20})$	81.08	72.97	77.03
		$CT_4^M(R_{11}, R_{20}, RGDPpcR)$	*83.78*	72.97	*78.38*

CT_i − classification tree without macroeconomic indicators (i=1,...,4), CT_i^M − classification tree with macroeconomic indicators (i=1,...,4), *CPI*_2 − Consumer Price Index (t−2), *GRRGDP* − growth rate in real GDP (t), *NGDPpc*_2 − nominal GDP per capita (t−2), *RGDPpc*_1 − real GDP per capita (t−1), *RGDPpcR* − real GDP per capita residuals (t), *UR*_1 − unemployment rate (t−1).

Source: authors' own.

Table 5

Comparison of classification accuracy for neural networks

Type of sample	Division	Model	Test set		
			Sensitivity	Specificity	Overall accuracy
S_1	6:4	$NN_1(R_{11}, R_{12})$	87.76	*65.31*	*76.53*
		$NN_1^M(R_{11}, R_{12}, UR\_1, RGDPpc\_2)$	87.76	57.14	72.45
	7:3	$NN_2(R_{11})$	86.49	*75.68*	*81.08*
		$NN_2^M(R_{11}, UR\_1, CPI\_2)$	*91.89*	59.46	75.68
S_2	6:4	$NN_3(R_{11})$	*89.80*	61.22	75.51
		$NN_3^M(R_{11}, GRRGDP)$	87.76	*65.31*	*76.53*
	7:3	$NN_4(R_{11}, R_{20})$	86.49	62.16	74.32
		$NN_4^M(R_{11}, R_{20}, RGDPpcR)$	*89.19*	*72.97*	*81.08*

NN_i − neural network without macroeconomic indicators (i=1,...,4), NN_i^M − neural network with macroeconomic indicators (i=1,...,4), CPI_2 − Consumer Price Index (t−2), $GRRGDP$ − growth rate in real GDP (t), $RGDPpc\_2$ − real GDP per capita (t−2), $RGDPpcR$ − real GDP per capita residuals (t), UR_1 − unemployment rate (t−1).

Source: authors' own.

In summing up this study, one can conclude that among the considered 32 financial ratios, the liability ratio appears most frequently, defined as a proportion of the net profit to liabilities (R_{11} in Table 1), which appears 26 times in the 32 considered models (Tables 2–5). The profitability ratio takes second place, defined as the proportion of the operating profit (loss) to total assets (R_{20} – 6 times). Both the liquidity ratio, defined as the proportion of the current assets to short term liabilities (R_{02} – 5 times) and liability ratio, defined as a proportion of the gross profit (loss) to short term liabilities (R_{13} – 5 times), take third place. This leads to the general conclusion that the most important factors of bankruptcy risk are the incorrect proportions in liability ratios. Productivity ratios do not play an important role in bankruptcy prediction; this statement is consistent with the economic theory of corporate bankruptcy.

The inclusion of macroeconomic indicators to the set of explanatory variables generally increased the classification effectiveness, mainly in the case of a random selection to the sample (S_2) and division into training and testing parts in the proportion 7:3.

When analysing the considered methods in the version with macroeconomic indicators (D_i^M, L_i^M, CT_i^M, NN_i^M, i = 1,...,4) in terms of frequency of the analysed variables, it can be noted that the most commonly used indicators were: real nominal or growth of GDP per capita, which appears 15 times in the 16 considered models, Consumer Price Index – 8 times, unemployment rate – 8 times and general business climate indicator – 4 times. It can be observed that the frequency of the appearing macroeconomic indicators is more uniform than the financial ratios. As such, these indicators of economic situation and growth, the labour market and business climate significantly help describe bankruptcy risk.

It is difficult to recommend to the practitioner the best (on average) method for bankruptcy prediction. When taking the overall accuracy of the classification as a quality measure of the model with macroeconomic explanatory variables, it can be noted that the differences between the linear discriminant model (average overall accuracy 68.12%), logistic regression (72.62%), classification tree (71.00%) and neural network (76.44%) are not significant. Thus the problem of the choice of the best model for bankruptcy selection still remains open.

GENERAL CONCLUSIONS

The results of the conducted empirical studies confirm the hypothesis that changes in the economic environment of companies affect their financial situation and the risk of bankruptcy. A weak economic situation may contribute to a deterioration in both the condition of entire sectors of business activity and the financial situation of individual companies. The inclusion of macroeconomic indicators to the studies resulted, in many cases, in the improvement of the classification accuracy of the considered methods for predicting corporate bankruptcy.

The presented research results were obtained adopting certain assumptions and limitations. In further studies there should be considered:

- other methods for predicting the bankruptcy of companies,
- additional macroeconomic indicators,
- financial market indicators.

In spite of the problems occurring in the process of collecting data (e.g. changes in the principles of preparation and publication of financial statements in Poland) which are the basis for modelling and forecasting the risk of corporate bankruptcy in Poland, the outlined direction of the further research is very interesting and merits special attention.

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