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IMPACT OF USING INDUSTRY BENCHMARK FINANCIAL RATIOS ON PERFORMANCE OF BANKRUPTCY PREDICTION LOGISTIC REGRESSION MODEL

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Impact of using industry benchmark financial ratios on performance of bankruptcy prediction logistic regression model

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Abstract: The phenomenon of companies bankruptcy is crucial for business partners and financial institutions due to the fact that business failure might be the cause of huge losses. Researchers has continually been aimed for improving models performance in the prediction of companies bankruptcy. Some authors of scientific papers claim that the process of evaluation of the companies situation requires comparison of its characteristics defined as financial ratio with situation of whole sector in order to obtain reliable conclusions. In this paper, a hypothesis that usage of the industry benchmarks (transformation of raw financial ratios values into sectoral deciles groups numbers) improves results of bankruptcy prediction logistic regression model is verified. Based on empirical results for Polish market, it turns out that although models estimated on different types of data have similar discriminatory power, logistic regression using raw financial ratios obtained a bit better results than its industry equivalents defined as sectoral deciles groups numbers. It is worth emphasizing that empirical part of paper uses information about 109K companies what is the rarity in bankruptcy prediction papers – researchers usually use small datasets that include less than several hundred records.

Keywords: bankruptcy prediction, financial ratios, industry financial ratios, sectoral financial ratios, logistic regression, financial econometrics

JEL codes: C52, C53, C58

1. Introduction

Companies play a key role in the economy. Financial problems of firms might lead to their bankruptcy. This phenomenon has extremely negative impact on many people e.g. owners, investors or employers. What is more, this aspect of companies activity is crucial for other businesses – bankruptcy of a company might be the cause of losses for financial institutions. Sometimes the rate of bankruptcy firms in the country is treated as measure of economy health and its condition (Pociecha *et al*. 2014). That is why this phenomenon is in the field of interest to academics and practitioners.

Term of bankruptcy prediction has been developed for a few decades. Features of analyzed objects have an important role in model building process. In the context of the company condition evaluation, the core information forms data from financial statements and financial ratio analysis. Financial ratios are specially defined firm characteristics that describe its situation and are very helpful in prediction business failure. Some researchers claim that ranges of optimal (good) financial ratios vary across industries and years (Figura 2013; Kuciński, Byczkowska, 2017) and in company condition evaluation process it is better to analyze particular firm's financial ratios values in comparison to whole industry deciles or mean financial ratios values (Krysiak, Staniszewska, Wiatr, 2015; Mioduchowska-Jaroszewicz, 2019). It allows to obtain correct conclusions regarding the financial situation of a firm. The knowledge from fields of statistics and econometrics is used to build models that predict companies failure as soon as possible. Techniques, that are very often used by researchers in bankruptcy prediction process, are following: discriminant analysis, logistic models and neural network (Bellovary, Giacomino and Akers, 2007).

Financial ratios have a very important role in bankruptcy prediction process. Those measures are applied in different ways in companies' failure prediction models: as raw financial ratios or industry-relative financial ratios (Platt H. and Platt M, 1991). Literature suggests that industry-relative variables have potential to improve prediction results (Platt H. and Platt M, 1991). There are few papers that compare those two approaches and their results are not sufficient to unambiguously evaluate which one is better. The aim of the paper is to check if application of industry benchmarks as transformation of raw financial ratios values into sectoral deciles groups numbers improves results of bankruptcy prediction logistic model for Polish companies.

Paper is organized as follows: section 2 shows literature review, part 3 describes methodology, point 4 presents empirical results and section 5 includes conclusions.

2. Literature review

Bankruptcy prediction has many decades of history in the scientific field. The beginning point of researchers interest in this field is very difficult to set but very often publication of Baver (1966) is connected with this topic. He was probably one of the first authors that used in his study financial data in order to predict businesses failure. Unfortunately, his research had the important disadvantage as univariate approach. It seems impossible to predict company bankruptcy based on particular variable and the multivariate approaches are crucial in this process.

The first multivariate methodology (in the context of business failure) as linear discriminant analysis was used by Altman (1968). He studied 66 companies (33 bankrupted and 33 non-bankrupted) and analyzed its 22 financial ratios. In final model Altman used 5 financial ratios: working capital divided by total assets, retained earnings divided by total assets, earnings before interest and tax divided by total assets, market value of equity divided by total liabilities and sales divided by total assets.

The first discriminant analysis model based on Polish companies data was applied by Mączyńska (1994) that used finally 6 features in her discriminatory function: the relation of the sum of gross profit and depreciation to total liabilities, the relation of balance sheet total to total liabilities, the relation of gross profit to balance sheet total, the relation of gross profit to sales, the relation of stocks to sales and the relation the sales to balance sheet total.

Because of the fact that discriminant analysis models have very restricted assumptions, logistic regression has become more and more popular in the area of bankruptcy prediction since the 1980s. The first researcher that applied logistic regression to bankruptcy prediction was Ohlson (1980). He used 9 financial ratios including the logarithm of the relation of total assets to price index, total liabilities divided by total assets, working capital divided by total assets, current liabilities divided by current assets, binary variable signalizing if total liabilities are greater than total assets, net profit divided by total assets, revenues divided by total liabilities, binary variable informing if company makes loss during last two years, net profit change.

One of the first logistic regression models using data of Polish firms in order to their bankruptcy prediction was proposed in research by Hołda from 2000 (Pociecha *et al*. 2014). It used 5 predictors, e.g. liquidity ratio, rescaled debt ratio, total revenue ratio, rescaled rotation ratio and rescaled profitability ratio.

There are many papers that focus on companies' failure prediction models (e.g. Yu *et al.*, 2014; Amendola, Restaino and Sensini 2015; Tian and Yu, 2017; Veganzones and Séverin, 2018; Bărbuţă-Mişu and Madaleno, 2020). Ptak-Chmielewska (2014) claims that there are some difficulties in application of foreign models into Polish economic reality. That is why there are also many researches of companies failure in Poland (e.g. Wierzba 2000; Gruszczyński 2003; Hamrol, Czajka and Piechocki 2004, Prusak 2005).

What is more, the fact that particular financial ratio is an excellent predictor of firms bankruptcy might depend on its distribution in studied firms population rather than economic way of construction the ratio (Pociecha *et al.*, 2014). That is why it is difficult to build one universal bankruptcy model. Common approach is to construct many different financial ratios and then select the most important characteristics based on their predictive power or significance levels in models (Nehrebecka 2018; Veganzones and Séverin 2018). Similar approach is used in this paper.

Although researchers have started to use different methods in companies failure prediction like e.g. decision trees, support vector machines, Bellovary, Giacomino and Akers (2007) shows that the most popular and broadly applied techniques in the modelling of bankruptcy prediction are discriminant analysis, logistic regression model and neural network. Financial institutions especially use logistic regression models for prediction of businesses failure due to its computational simplicity, good interpretability and recommendation of using this method by banking regulatory standards.

3. Methodology

In this section, methodology in the context of data transformation, statistical technique (logistic regression) and measures of assessing the quality of prediction models are described.

3.1. Transformation of financial ratios values into decile group numbers

Some researchers point that optimal financial ratios values are different across sector (and time) and they should be compared with their industry equivalents to get proper interpretability with taking into account suitable sectoral perspective (Krysiak, Staniszewska, Wiatr, 2015; Mioduchowska-Jaroszewicz, 2019). According to that, in the paper two data preparation processes are considered – original values of financial ratios and sectorial and seasonally' adjusted values based on deciles groups calculation. The process of data transformation to obtain deciles groups for one financial ratio is as following:

a. All financial ratios are calculated,
b. Dataset is divided into subgroups of the companies from the same sector (branch) and year.

c. Deciles ranges for each financial ratio and each subgroup (sector and year) are calculated.
d. Financial ratio value for each company in dataset is mapped with corresponding decile group number based on ranges from point c.

Finally, a new set of independent variables is obtained – deciles groups numbers corresponding to raw financial ratios values. This kind of data transformation assumes that not a specific value of raw financial ratio is important but crucial is the relative value of the financial ratio in relation to the peer group (understood as deciles groups numbers that are assigned for the particular company and particular financial ratio). Transformation of raw financial ratios into deciles groups numbers was done for all considered years and branches what gives comparativeness of those deciles groups across different industries and different periods of time (thereby different states of the economy). It allows to compare financial situation of different companies without time and industry bias.

3.2. Logistic regression and WOE transformation

Logistic regression is used to model relation between explanatory variables and a probability of occurrence a binary output. Binary character of modelling phenomenon might be interpreted as the occurrence of the event or lack of occurrence of this event, e.g. like in the case of firms failure – bankrupted and non-bankrupted companies. Logistic regression allows to calculate the probability of occurrence such an event (marked as success) using following formula (Pociecha *at al*. 2014):

$$P(x) = \frac{1}{1+e^{-x}}\ . \tag{1}$$

In the building of predictive models based on logistic regression, there is a commonly used concept connected with transformation of variables – *Weight of Evidence* (*WoE*) transformation. It has been using in the credit scoring field for a few decades, but very often it is applied also in other domains. This is some grouping process that allows e.g. transform a continuous explanatory variables into a few bins (very often based on deciles distribution of variable) and changes original variables values into *WoE* values specific for each created bin. The *WoE* is calculated for each bin by the following formula (Siddiqi, 2017):

$$WoE = ln\left(\frac{\%\ of\ non\text{-}bankrupted\ firms}{\%\ of\ bankrupted\ firms}\right). \tag{2}$$

This concept offers an easy way to deal with missing values (using a separate category for those values) and outliers (grouping reduces impact of outliers). It allows also to model non-linear relationship using linear models (Siddiqi, 2017). Applying this approach, the logistic regression model is estimated on the WoE-transformed variables instead of the predictors in original form.

The WoE values are needed in order to compute the *Information Values* (*IV*) that measures the predictive power of variables and is helpful in the process of features selection. It is calculated using formula (i means particular bin, n – number of all considered bins; Siddiqi, 2017):

$$IV = \sum_{i=1}^{n} (\%\ of\ non\text{-}bankrupted\ firms_i - \%\ of\ bankrupted\ firms_i) \cdot WoE_i\ . \qquad (3)$$

The *IV* statistic value that is less than 0.02 means a generally unpredictive feature, value between 0.02 and 0.1 points a week predictor, value between 0.1 and 0.3 indicates a medium predictor, measure value greater than 0.3 states a strong predictor (Siddiqi, 2017).

Often an alternative measure of the predictive power of variables is used, namely the *Gini coefficient* (Nehrebecka and Dzik, 2012). At the beginning a model with only one explanatory variable is estimated and then the statistics is calculated in order to measure the discriminant power of that feature. Details about *Gini* are presented in next subsection.

3.3. Assessing the discriminatory power of models

3.3.1. ROC Curve

The *Receiver Operating Characteristic Curve* (*ROC Curve*) is a graphical method that helps evaluate performance of a classification model. It plots the unity minus the specificity on x-axis and sensitivity on the y-axis at different classification cut-off points. The more convex line above the diagonal, the better discriminatory power of the model (Szeliga, 2017).

3.3.3. AUC

Graphical form of assessing the discriminatory power of models is an insufficient method because of the fact that it is hard to compare properties of different models based only on the plot. It seems that numeric measures are more convenient in comparison models. Therefore very often the area under the *ROC Curve* is calculated – *Area Under ROC Curve* (*AUC*) is a numeric measure that determine performance of models (their discriminatory power). This measure might achieve values between 0 and 1. The higher value of this measure, the better performance of the model – 1 means ideal discriminatory power, 0.5 indicates random classifier (Szeliga, 2017).

3.3.4. Gini coefficient

Another measure of goodness of discriminatory power is *Gini coefficient*. Its calculation is connected with *AUC* measure (Hand and Till, 2001):

$$Gini = \frac{AUC - 0.5}{0.5} = 2 \cdot AUC - 1 \, .$$

The higher value of the *Gini coefficient*, the better the model.

3.3.5. Kolmogorov-Smirnov statistic

Kolmogorov-Smirnov statistic is defined as the maximum distance between cumulative distribution function of non-bankrupted companies and cumulative distribution function of bankrupted firms. Higher Kolmogorov-Smirnov statistic value means better model (Řezáč M. and Řezáč F., 2017).

4. Results

In this section results of empirical research are presented.

4.1. Data

Data used in the paper was downloaded from Orbis database (Bureau van Dijk). Dataset includes Polish companies' financial data from years 2010-2019 and their basic characteristics like e.g. sector of activity, size and status.

Small companies were excluded from the analysis due to the fact of extremely big problem of missing financial data. Dataset includes companies with status *Active* for all analyzed period of time (observations marked as non-bankrupted) and firms with one following status *Active (insolvency proceedings)*, *Bankruptcy*, *Dissolved (bankruptcy)* even if it occurs for a while during years 2010-2019 (records marked as bankrupted). Companies from bankrupted group were checked in National Court Register (Polish Krajowy Rejestr Sądowy) and EMIS Bankruptcy Bulletin databases in order to assign the date of beginning the bankruptcy proceeding. Bankrupted cases without this date were deleted from the analysis. Dataset has information about 109K companies that were randomly divided into training and validation subsets – proportion was equal 70:30 with keeping similar rate of bad cases in whole subsample.

Firstly, wide scope of different financial ratios was calculated based on literature review. Secondly, the financial ratios' deciles ranges were computed for each year and sector activity (based on training subsample). It allows to convert the raw financial ratio values (for whole dataset) into deciles groups numbers for each observation.

Final dataset includes one observation for each company – in the bankrupted group financial data for the one year before beginning of the bankruptcy proceeding was selected; in the non-bankruptcy class financial data for the one year before last available financial statement was chosen. That selection for non-bankrupted firms was done in order to be sure that during last available financial year company did not have any financial problems and avoid the situation that last available year might be the beginning of the bad company situation. Thus, database includes 109 143 records – 1 064 (0,97%) bankrupted companies and 108 079 (99,03%) healthy firms. Two types of inputs – raw financial ratios values and corresponding them deciles groups numbers are included.

In order to limit initial range of financial ratios and keep only most predictive ones, the binning procedure named *fine classing* was applied (Siddiqi, 2017). For each created bin the WoE (*Weight of Evidence*) measure was calculated and the Gini coefficient was computed. Original variables values (raw financial ratios values and deciles groups number) were transformed into WoE values and were final form of inputs used in a modelling process. Correlation analysis was conducted and some characteristics were excluded due to the fact of too high correlation between explanatory variables. The final list of financial ratios that were used to estimate models were selected based on Gini coefficients values – variables with this measure above 25% were considered as the most predictive characteristics. The financial ratios that were finally used in bankruptcy predictive modelling process are presented in table 1.

Table 1. List of final explanatory variables used in models estimation process

Variable	Formula	Gini coefficient
WR1	$\frac{\text{Profit (loss) before taxation}}{\text{Current liabilities}}$	51.11
WR2	$\frac{\text{Equity}}{\text{Current liabilities}}$	46.68
WR3	$\frac{\text{Current assets}}{\text{Current liabilities}}$	42.90
WR4	$\frac{\text{Cash}}{\text{Current liabilities}}$	42.09
WR5	$\frac{\text{Current liabilities}}{\text{Sales}}$	37.79
WR6	$\frac{\text{Sales} - \text{Sales (previous period)}}{\text{Sales (previous period)}}$	36.40
WR7	$\frac{\text{Total liabilities}}{\text{Profit (loss)} + \text{Depreciaction}}$	36.33
WR8	$\frac{\text{Creditors}}{\text{Operating revenue}} \times 360$	35.60
WR9	$\frac{\text{Current assets} - \text{Stocks}}{\text{Total liabilities}}$	33.74
WR10	$\frac{\text{Financial expenses}}{\text{Current assets}}$	31.15
WR11	$\frac{\text{Equity}}{\text{Non-current liabilities}}$	28.99

Source: Own elaboration and calculations.

4.2. Models results

In the modeling process variables after WOE transformation were applied. Logistic regression models were estimated based on raw financial ratios and deciles number groups – results of models are presented in tables 2 and 3.

Table 2. Results of logistic models estimated on raw financial ratios values

Variable/model	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9
Intercept	-4.6246*** (0.0369)	-4.5542*** (0.044)	-4.5532*** (0.044)	-4.5523*** (0.0439)	-4.5588*** (0.0444)	-4.5565*** (0.0444)	-4.5587*** (0.0443)	-4.5563*** (0.0444)	-4.618*** (0.0444)
WR1_woe		-0.5949*** (0.043)	-0.5977*** (0.043)	-0.6068*** (0.0427)	-0.5707*** (0.0444)	-0.5246*** (0.0533)	-0.5731*** (0.044)	-0.5274*** (0.053)	-0.7794*** (0.0423)
WR2_woe					-0.3397*** (0.0522)	-0.3344*** (0.0525)	-0.3554*** (0.0403)	-0.3484*** (0.0407)	-0.4099*** (0.0418)
WR3_woe		-0.1639** (0.059)	-0.1945** (0.0609)		-0.0424 (0.065)	-0.0462 (0.0653)			-0.0094 (0.0559)
WR4_woe		-0.5296*** (0.0475)	-0.5441*** (0.0482)	-0.5678*** (0.045)	-0.5196*** (0.0487)	-0.5193*** (0.0488)	-0.5286*** (0.0463)	-0.5292*** (0.0465)	-0.5816*** (0.0474)
WR5_woe			0.1585* (0.065)		0.1492* (0.0649)	0.1495* (0.065)	0.138* (0.0626)	0.138* (0.0627)	-0.2091*** (0.0548)
WR6_woe		-0.5772*** (0.0421)	-0.5936*** (0.0428)	-0.5706*** (0.042)	-0.5818*** (0.0429)	-0.5797*** (0.043)	-0.5788*** (0.0426)	-0.5766*** (0.0427)	
WR7_woe						-0.0864 (0.0542)		-0.0851 (0.0541)	
WR8_woe		-0.3802*** (0.0461)	-0.4372*** (0.0525)	-0.3907*** (0.0461)	-0.3895*** (0.0528)	-0.3849*** (0.053)	-0.387*** (0.0527)	-0.3824*** (0.0528)	
WR9_woe		0.0375 (0.0705)	0.0203 (0.0718)	-0.0416 (0.0639)	-0.0012 (0.0742)	0.0013 (0.0745)			
WR10_woe		-0.288*** (0.0649)	-0.3024*** (0.0655)	-0.33*** (0.0633)	-0.3912*** (0.067)	-0.3985*** (0.0673)	-0.4073*** (0.0601)	-0.4132*** (0.0603)	
WR11_woe		-0.244*** (0.0498)	-0.2492*** (0.0501)	-0.2432*** (0.05)	-0.0107 (0.0607)	-0.0056 (0.0608)			
AIC	8356.15	6657.39	6653.43	6663.37	6611.94	6611.37	6606.43	6605.93	6889.47
BIC	8365.39	6740.58	6745.87	6737.32	6713.62	6722.29	6680.38	6689.12	6944.93

Notes:
*** – p-vale < 0.001; ** – p-value < 0.01; * – p-value < 0.05;
( ) – standard error;
stepwise – model 7; *forward* – model 8; *backward* – model 8

Source: Own calculation.

Table 3. Results of logistic models estimated on deciles groups numbers

Variable/model	model 10	model 11	model 12	model 13	model 14	model 15	model 16	model 17	model 18	model 19
Intercept	-4.6246*** (0.0369)	-4.5677*** (0.0433)	-4.5751*** (0.0434)	-4.5681*** (0.0427)	-4.5558*** (0.0433)	-4.5596*** (0.0436)	-4.5623*** (0.0437)	-4.5617*** (0.0436)	-4.5601*** (0.0436)	-4.6227*** (0.0439)
WR1_D_woe		-0.5602*** (0.0456)	-0.4834*** (0.0551)	-0.5502*** (0.0438)	-0.4042*** (0.0553)	-0.3819*** (0.0565)	-0.3807*** (0.0569)	-0.382*** (0.0568)	-0.3811*** (0.0566)	-0.7143*** (0.0459)
WR2_D_woe						-0.2707*** (0.0521)	-0.3042*** (0.0442)	-0.3072*** (0.0443)	-0.268*** (0.0521)	-0.3728*** (0.0438)
WR3_D_woe		-0.2982*** (0.057)	-0.2929*** (0.06)	-0.4486*** (0.0535)	-0.324*** (0.06)	-0.226*** (0.0629)	-0.1587** (0.055)	-0.1844** (0.0577)	-0.206*** (0.061)	-0.1815*** (0.053)
WR4_D_woe		-0.4816*** (0.0492)	-0.5005*** (0.05)		-0.4938*** (0.0507)	-0.4745*** (0.0508)	-0.4529*** (0.05)	-0.4649*** (0.0507)	-0.4646*** (0.0501)	-0.5044*** (0.0497)
WR5_D_woe			-0.0139 (0.0604)		0.0696 (0.0613)	0.082 (0.0609)		0.0907 (0.0606)		-0.1605** (0.0524)
WR6_D_woe		-0.5418*** (0.0497)		-0.5595*** (0.0492)	-0.5385*** (0.0508)	-0.541*** (0.0507)	-0.5331*** (0.05)	-0.5437*** (0.0506)	-0.5313*** (0.0501)	
WR7_D_woe			-0.3069*** (0.0541)		-0.2766*** (0.0543)	-0.2595*** (0.0549)	-0.2642*** (0.055)	-0.2658*** (0.055)	-0.2579*** (0.0549)	
WR8_D_woe		-0.3507*** (0.0487)	-0.3713*** (0.0544)	-0.4397*** (0.0474)	-0.3634*** (0.0552)	-0.3294*** (0.0553)	-0.2987*** (0.0494)	-0.3337*** (0.0552)	-0.2979*** (0.0496)	
WR9_D_woe		0.1234 (0.0689)	0.1449* (0.0696)	0.0125 (0.0662)	0.1137 (0.0705)	0.1047 (0.0722)			0.1143 (0.0714)	
WR10_D_woe		-0.2425*** (0.0642)	-0.2927*** (0.0637)	-0.2413*** (0.0627)	-0.2657*** (0.0647)	-0.3297*** (0.0659)	-0.3331*** (0.0612)	-0.3384*** (0.0613)	-0.3269*** (0.0658)	
WR11_D_woe		-0.2944*** (0.0494)	-0.258*** (0.0495)	-0.2784*** (0.0491)	-0.2613*** (0.0501)	-0.0918 (0.0585)			-0.093 (0.0584)	
AIC	8356.15	6878.99	6961.19	6976.61	6854.6	6828.69	6828.64	6828.40	6828.50	7033.26
BIC	8365.39	6962.19	7053.63	7050.56	6956.29	6939.61	6911.84	6920.83	6930.18	7088.72

Notes:
*** – p-vale < 0.001; ** – p-value < 0.01; * – p-value < 0.05;
( ) – standard error;
stepwise – model 16; *forward* – model 17; *backward* – model 18

Source: Own calculation.

The choice of the final model was done based on the Akaike information criteria (AIC) and Schwartz information criteria (BIC) – model having the lowest metrics is the best one. For the models that were estimated on raw financial ratios values, AIC suggests that the best model is model no. 8, while BIC points that the winner is model no. 7. In case of models based on deciles groups numbers, model no. 17 is chosen according to AIC metrics and model no. 16 is the best one based on BIC. However, the literature suggests that the AIC might reward the model that has a lot of parameters. This dependency is noticeable in the analysis. That is why final models were chosen by using BIC information criteria – the best ones are model no. 7 and model no. 16 (depending on type of outputs).

It is necessary to take into consideration the fact that models no. 7 and 16 do not include exactly the same range of predictors – only initial set of variables was equivalent. That is why in the comparison step models no. 9 and 19 were also considered. Those models include precisely the same set of characteristics – top 5 variables with highest predictive power according to Gini coefficient (table 1). It allows to compare models that only differ in type of data and evaluate impact of variables transformation using sectoral deciles grouping.

The results of diagnostic tests for chosen models are presented in the table 4.

Table 4. Results of diagnostic tests for selected models

Test	**Statistic value (*p-value* in brackets)**			
	model 7	**model 16**	**model 9**	**model 19**
Hosmer-Lemeshow (10 bins)	16.483 (0.036)	10.002 (0.265)	9.595 (0.295)	15.82 (0.045)
Hosmer-Lemeshow (15 bins)	18.093 (0.154)	12.347 (0.499)	17.023 (0.198)	17.492 (0.178)
Hosmer-Lemeshow (20 bins)	22.419 (0.214)	19.823 (0.343)	22.824 (0.197)	18.227 (0.440)
Osius-Rojek	1.833 (0.067)	2.184 (0.029)	0.852 (0.394)	0.002 (0.998)
LR (likelihood ratio)	– (0.000)	– (0.000)	– (0.000)	– (0.000)

Source: Own calculations.

The goodness of fit of the models to the data was checked using e.g. the Hosmer-Lemeshow test. Some researchers have negative opinion about this test (Allison 2013) due to its dependency on bins number. That is why the Osius-Rojek test was also conducted. Both tests assume in their null hypothesis that a model is well-fitted to the data. Because of the fact that Hosmer-Lemeshow has some critique comments, this test was considered as helper one and the Osius-Rojekt test was used as the main (primary) test evaluating goodness of fit of model to the data. Thus, models no. 7, 9 and 19 were well-fitted to the data at the 5%

significance level. The quality of the model no. 16 was negatively evaluated based on Osius-Rojek test (the null hypothesis was rejected at the 5% significance level). However, this model had positive results of the Hosmer-Lemenshow test – independently on number of used bins there was no reason to reject the null hypothesis at the 5% significance level. That is why model no. 16 was also considered as good one. Additionally, the total significance of all variables in particular models was verified by likelihood ratio (LR) test. According to the results of this test, the null hypothesis about the lack of significance of all variables in the model was rejected at the 5% significance level for all considered models – variables used in particular models are significant (together). Based on carried out tests all selected models were considered as good models.

In the next step, the predictions for all 4 models on training and validation sets were made. Finally, the evaluation of models prediction was done – results are shown in the table 5.

Table 5. Evaluation of selected models prediction

Measure	**model 7**	**model 16**	**model 9**	**model 19**
AUC (training data)	0.8036	0.7975	0.7905	0.7805
Gini (training data)	0.6072	0.5949	0.5809	0.5611
KS (trainig data)	0.4338	0.4195	0.4198	0.4055
AUC (validation data)	0.8117	0.8029	0.7925	0.5631
Gini (validation data)	0.6233	0.6059	0.5851	0.7816
KS (validation data)	0.4276	0.4220	0.4107	0.4019

Source: Own calculations.

Evaluation of models prediction shows very similar results between models in the context of training data as well as validation data in both analyzed scenarios. Despite of the fact that there are no significant differences in terms of prediction the probability of companies bankruptcy, it is noticeable that models estimated on the deciles groups numbers achieved a bit worse prediction results than models built on raw financial ratios values.

5. Conclusions

The phenomenon of business failure is crucial for people, different institutions (financial institutions, business partners) and the whole economy due to the fact that companies activity has an important impact on different spheres of social-economic life.

Researchers has continually been aimed for improving models performance in the prediction of companies bankruptcy. Some researchers claim that the process of the companies situation evaluation requires comparison of its characteristics defined as financial ratio with situation of whole sector in order to obtain reliable conclusions (Krysiak, Staniszewska, Wiatr, 2015; Mioduchowska-Jaroszewicz, 2019). In this paper there was an hypothesis that usage of the industry benchmarks (transformation of raw financial ratios values into sectoral deciles groups numbers) improves results of bankruptcy prediction logistic model. Based on empirical results for Polish market it turned out that this hypothesis was not confirmed – although models estimated on different types of data had similar discriminatory power, logistic regression using raw financial ratios values obtained a bit better results. It is worth noting that hypothesis was empirically verified by models estimated on real dataset that included information about 109K companies what is a rarity in bankruptcy prediction papers – researchers usually use small datasets that include less than several hundred records.

This paper shows that time-consuming process of transformation the financial ratios values into deciles groups numbers in order to obtain industry comparativeness is not necessary in the process of building the models of business failure prediction, because this transformation does not improve discriminatory power of the model. It also suggests that financial ratios might be considered as universal and standardized predictors (in modelling process) that characterize firm condition independently on sector of its activity.

On the other hand, it is important to take into consideration some limitations of this paper. Research includes one widely applied technique – logistic regression. What is more, it uses Polish companies data that might be specific – e.g. some researchers claim that there are difficulties in applying foreign models to Polish reality.

Furthermore, it is necessary to underline that although application the industry benchmarks in the shape of model inputs does not improve performance of bankruptcy prediction model, it does not mean that industry comparativeness is meaningless. Relating values of financial ratios to its sectoral equivalents is important to obtain correct and complete assessment of the company situation and it is crucial point to achieve reliable results of firm situation analysis (Skoczylas *et al*., 2009). Industry benchmarks of financial ratios is crucial in business environment.

Due to the fact that usage of other techniques to build a model might change final results, plans for further research includes comparison the performance of decision trees, neural network or support vector machine with taking into consideration the usage of analogical types of data – raw financial measures and deciles groups numbers (industry benchmarks data). Moreover, other countries are going to be considered.

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