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Corporate Bankruptcy Prediction

International Trends and Local Experience

Edited by
Błażej Prusak

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Special Issue Editor

Błażej Prusak

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Special Issue Editor
Błażej Prusak
Gdańsk University of Technology
Faculty of Management and Economics
Poland

Editorial Office
MDPI
St. Alban-Anlage 66
4052 Basel, Switzerland

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Contents

About the Special Issue Editor

Błażej Prusak works as an Associate Professor of Economics in the Management and Economics Faculty of Gdańsk University of Technology, Poland. He is Head of the Finance Department. His main research interests are corporate bankruptcy prediction, institutional aspects of corporate bankruptcy, business valuation, investment projects, financial analysis, risk management, and stock recommendations. Currently, he is a representative of the Editorial Board of the *Intellectual Economics Journal*, as well as a member of the Reviewer Board of the *Journal of Risk and Financial Management*. He is the author or co-author of several monographs about corporate bankruptcy, financial analysis, stock recommendations and market ratios. He has also published in several international journals.

Preface to ”Corporate Bankruptcy Prediction—International Trends and Local Experience”

In 2018, the 50-year anniversary of the publication of the landmark article by prof. Edward Altman was marked. Its main goal was to apply a multidimensional discriminant analysis to forecast corporate bankruptcy. Many years have passed since its publication and forecasting corporate bankruptcy is still an important issue in the area of corporate finances. With the development of new statistical methods and IT tools, bankruptcy prediction has become more effective. However, scientists continue looking for more sophisticated solutions.

In the 1970s, logit and probit methods became popular. Then, in the 1990s, artificial neural networks and genetic algorithms began to be used. In the 21st century, along with the development of information technology, a variety of techniques used for forecasting bankruptcy were developed. The main emphasis is focused on support vector machines, fuzzy logic, random forests and multiple-model approaches. The publications contained in the following book illustrate research in which the authors developed bankruptcy prediction models for different countries using traditional as well as advanced methods.

Another important area of bankruptcy forecasting is the selection of explanatory variables and the development of more dynamic models. These concepts were raised in the study of Oliver Lukasson, Art Andersson, and Tomasz Korol. Sebastian Tomczak and Piotr Staszkeiwicz raised issues concerning the lack of universality of models designed for a given country. The difficulties regarding the effectiveness of models in various phases concerned the business cycle. The models developed for economic prosperity are not always effective in periods of recession, and vice versa. An important article regarding the reliability of financial statements and audits was also included in the research. Bankruptcy prediction models are most often developed using financial data and indicators. When such data are distorted, incorrect results of the company’s financial condition forecast are automatically obtained.

I hope that this book will inspire you to conduct new research in the field of forecasting the risk of bankruptcy.

Błażej Prusak
Special Issue Editor

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Article

Support Vector Machine Methods and Artificial Neural Networks Used for the Development of Bankruptcy Prediction Models and Their Comparison

Jakub Horak *, Jaromir Vrbka and Petr Suler

School of Expertness and Valuation, Institute of Technology and Business in Ceske Budejovice, Okruzni 517/10, 37001 Ceske Budejovice, Czech Republic; vrbka@mail.vstecb.cz (J.V.); petr.suler@cez.cz (P.S.)
* Correspondence: horak@mail.vstecb.cz

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Abstract: Bankruptcy prediction is always a topical issue. The activities of all business entities are directly or indirectly affected by various external and internal factors that may influence a company in insolvency and lead to bankruptcy. It is important to find a suitable tool to assess the future development of any company in the market. The objective of this paper is to create a model for predicting potential bankruptcy of companies using suitable classification methods, namely Support Vector Machine and artificial neural networks, and to evaluate the results of the methods used. The data (balance sheets and profit and loss accounts) of industrial companies operating in the Czech Republic for the last 5 marketing years were used. For the application of classification methods, TIBCO's Statistica software, version 13, is used. In total, 6 models were created and subsequently compared with each other, while the most successful one applicable in practice is the model determined by the neural structure 2.MLP 22-9-2. The model of Support Vector Machine shows a relatively high accuracy, but it is not applicable in the structure of correct classifications.

Keywords: neural networks; support vector machine; bankruptcy model; prediction; bankruptcy

1. Introduction

In financial bankruptcy analysis, the diagnosis of companies at risk for bankruptcy is crucial in preparing to hedge against any financial damage the at-risk firms stand to inflict (Kim et al. 2018). According to Rybárová et al. (2016), bankruptcy models are early warning systems based on the analysis of selected indicators able to identify a thread for financial health of a company. Kiaupaite-Grushniene (2016) states that creation of reliable models of bankruptcy prediction is essential for various decision-making processes. According to Mousavi et al. (2015), frequently used models are mainly Altman Z-Score, Taffler Z-Score, and Index IN95.

A wide number of academic researchers from all over the world have been developing corporate bankruptcy prediction models, based on various modelling techniques. Numerous statistical methods have been developed (Balcaen and Ooghe 2004). Despite the popularity of the classic statistical methods, significant problems relating to the application of these methods to corporate bankruptcy prediction remain. Problems related to statistical methods according to Balcaen and Ooghe (2004, p. 1):

1. The dichotomous dependent variable,
2. The sampling method,
3. Nonstationarity and data instability,
4. The use of annual account information,
5. The selection of the independent variables,
6. The time dimension.

For the purpose of this article, Support Vector Machines (SVM) and artificial neural networks are used. These two methods have been used by many authors to predict corporate bankruptcy, and their results suggest that these two methods are more appropriate than traditional statistical methods (Shin et al. 2005; Xu et al. 2006; Kim et al. 2018; Vochozka and Machová 2018; Machová and Vochozka 2019; Krulický 2019). SVM is sensitive to model form, parameter setting and features selection. SVM, firstly developed by Vapnik in 1995 (Vapnik 1995), is a supervised learning model with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis (Burges 1998). According to Lu et al. (2015), compared with other algorithms, SVM has many unique advantages when applied in solving small sample, nonlinear, and high-dimensional pattern recognition problem. The concept of a neural network has been developed in biology and psychology, but its use goes to other areas, such as business and economics (Vochozka 2017). They are especially valuable where inputs are highly correlated, missing, or there are nonlinear systems and they can capture relatively complex phenomena (Enke and Thawornwong 2005). Like any method, SVM or artificial neural networks have disadvantages. Although SVM or artificial neural networks have a good performance on classification accuracy, one main disadvantage of these methods is the difficulty in interpreting the results (Härdle et al. 2009).

The aim of the paper is to develop bankruptcy prediction models and compare results of different methods using classification methods, namely Support Vector Machines and artificial neural networks (multilayer perceptron artificial neural networks—MLP and radial basis function artificial neural networks—RBF). Further to the defined goal, we will ask a research question: "Are artificial neural networks (also NN) more accurate in predicting bankruptcy than SVM?"

The article meets the formal criteria of a scientific text. In the part of literature review there are described methods for evaluation of corporate bankruptcy, attention is paid to artificial neural networks and SVM methods. The methodological part describes used data for the calculation, specifies the particular variables used and presents two above mentioned methods. In the results part there are presented the results achieved by SVM method, then the results obtained by artificial neural networks and the results of both methods are compared. The results are also compared with the results of other authors and the added value of the article is defined. The final part summarizes the results, presents the variables that have the greatest predictive power and suggests further research in this area.

2. Literature Review

Company activities are directly or indirectly influenced by various external and internal factors (Boguslauskas and Adlyte 2010). Purvinis et al. (2005) argue that unfavourable business environment, risky decisions of business managers, and unexpected and disadvantageous events may influence a company in insolvency and lead to bankruptcy. Hafiz et al. (2015) state that bankruptcy models are mainly needed by financial entities, e.g., banks. Their advantage consists especially in their ability to provide clear information about potential risks and eliminate such problems in a timely manner. They are important for current and future decision-making (López Iturriaga and Sanz 2015). Predictive models of financial bankruptcy enable to take timely strategic measures in order to avoid financial distress (Baran 2007). For other stakeholders, such as banks, effective and automated rating tools will enable to identify possible financial distress of potential clients (Gestel et al. 2006). The ability to accurately predict business failure is a very important topic in financial decision-making (Mulačová 2012).

A very useful tool to predict the development of companies going to bankrupt is by using artificial neural networks (ANNs) or Support Vector Machine (SVM). Currently, neural networks are applicable in various areas. ANNS are used for solving possible future difficulties, e.g., for predicting company bankruptcy (Pao 2008; Klieštik 2013). Sayadi et al. (2014) state that their main advantages are the ability to generalize and to learn. According to Machová and Vochozka (2019), the disadvantages of ANNs include possible illogical behaviour of networks and required high quality data. Vochozka and Machová (2018) state that ANNs are currently one of the most popular prediction methods.

The SVM method has become a powerful tool for solving problems in machine learning. Many SVM algorithms include solving of convex problems, such as linear programming, quadratic programming, as well as nonconvex and more general problems with optimization, such as integer programming, bilevel programming, etc. However, there are also certain disadvantages of SVM. An important issue that has not been solved fully is choosing the parameters of the core functions. In practical terms, the crucial problem of SVM is its high algorithmic complexity and extensive requirements for the memory of required quadratic programming in complex tasks (Tian et al. 2012).

The aim of Erdogan (2013) was to apply the SVM method in analysing bank bankruptcy. In this work, the SVM method was applied for the analysis of financial indicators. The author states that SVB is able to extract useful information from financial data and can thus be used as a part of early warning system. Chen and Chen (2011) state that the prediction of financial crisis of a company is an important and widely discussed topic. They used particle swarm optimization (PSO) to obtain optimized parameter settings for the SVM method. Moreover, they used the PSO's integrated commitment with the SVM approach to create a model of predicting financial crisis. Experimental results have shown that the approach is efficient in finding better parameter settings and significantly improves the success rate in predicting company financial crisis. Since financial indicators are independent variables, Park and Hancer (2012) applied ANNs on bankruptcy of a company operating in catering and compared the results with the results of logit model. On the basis of empirical results of these two methodologies, ANNs showed higher accuracy than logit model in sample testing. Dorneanu et al. (2011) use ANNs for predicting company bankruptcy. According to the authors, the use of ANNs for the prediction is extremely effective, since the percentage of prediction accuracy is higher than in the case of using conventional methods. The objective of Kim (2011) is to provide an optimal approach to company bankruptcy predicting and to explore functional characteristics of multivariate discriminant analysis, ANNs and the SVM method in predicting the bankruptcy of a specific company. The results have shown that ANNs and SVM are models applicable for predicting company bankruptcy and show promising results. On the basis of the information obtained, the objective of this paper can be considered relevant.

3. Materials and Methods

The Albertina database will be the source of data concerning industrial companies operating in the Czech Republic. In terms of sufficient amount of data and in particular the number of companies in liquidation and thus the relevance of the results, more fields within section C—Manufacturing of the CZ-NACE (comes from French – Czech Nomenclature statistique des Activités économiques dans la Communauté Européenne) = Classification of Economic Activities, will be used, namely in the groups 10–33:

- 10: Manufacture of food products.
- 11: Manufacture of beverages.
- 12: Manufacture of tobacco products.
- 13: Manufacture of textiles.
- 14: Manufacture of wearing apparel.
- 15: Manufacture of leather and related products.
- 16: Manufacture of wood and products of wood and cork, except furniture.
- 17: Manufacture of paper and paper products.
- 18: Printing and reproduction of recorded media.
- 19: Manufacture of coke and refined petroleum products.
- 20: Manufacture of chemicals and chemical products.
- 21: Manufacture of basic pharmaceutical products and pharmaceutical preparations.
- 22: Manufacture of rubber and plastic products.
- 23: Manufacture of other non-metallic mineral products.
- 24: Manufacture of basic metals; foundry.

- 25: Manufacture of fabricated metal products, except machinery and equipment.
- 26: Manufacture of computer, electronic and optical products.
- 27: Manufacture of electrical equipment.
- 28: Manufacture of machinery and equipment.
- 29: Manufacture of motor vehicles (except motorcycles), trailers and semi-trailers.
- 30: Manufacture of other transport equipment.
- 31: Manufacture of furniture.
- 32: Other manufacturing.
- 33: Repairs and installation of machinery and equipment.

For the same reasons, the selection of data will not be limited by the size of companies and the number of employees. The output will thus be applicable not only in specific companies, but basically in the whole economic sector.

The data series will consist of five consecutive fiscal years—for each year all the companies in liquidation will be selected and similarly, randomly selected three times the number of active enterprises. The numbers of companies for individual years are then as follows:

- Year 2013: 488 in liquidation, 1464 active,
- Year 2014: 416 in liquidation, 1248 active,
- Year 2015: 354 in liquidation, 1062 active,
- Year 2016: 287 in liquidation, 862 active,
- Year 2017: 163 in liquidation, 489 active.

The same companies will be selected for each year. Different numbers are due to the fact that some companies went bankrupt during the monitored period, ceased to be active and went into liquidation, etc. The sample starts in 2013, that is, in the period of constant economic growth following the period of economic crisis. The authors tried to avoid the results of the models to be affected by economic crisis.

Financial statements, specifically balance sheets and profit and loss statements of all the above mentioned companies will be analysed. Table 1 shows selected financial data and their averages per individual years.

Table 1. Selected financial data of data sample.

Active Companies						
Financial Data	**2013**	**2014**	**2015**	**2016**	**2017**	**Total**
Total assets	113,590.43	112,398.89	72,359.06	92,463.05	102,843.14	91,228.91
Fixed assets	51,794.64	48,418.16	32,899.65	41,244.60	49,662.11	40,808.34
Current assets	61,093.99	63,352.86	38,750.26	50,275.42	52,550.73	49,762.88
Liabilities in total	113,590.43	112,398.89	72,359.06	92,358.40	102,843.14	91,228.91
Equity	51,663.05	53,660.95	39,599.74	42,971.99	59,471.72	44,077.03
Borrowed capital	61,076.00	58,079.58	32,437.83	46,616.22	42,632.01	46,275.94
Operating result	1574.10	14,159.14	4604.23	7104.33	10,576.95	6263.25
Economic result for accounting period	1282.11	11,387.14	3168.16	5231.82	9325.24	4916.57
Companies in Liquidation						
Financial Data	**2013**	**2014**	**2015**	**2016**	**2017**	**Total**
Total assets	22,033.59	21,401.33	20,401.53	14,201.20	10,273.09	77,297.73
Fixed assets	6307.66	6768.54	5231.99	5439.59	1481.12	33,904.17
Current assets	15,615.94	14,447.03	15,116.56	8639.67	8670.90	42,801.79
Liabilities in total	22,033.23	21,390.77	20,400.42	14,201.20	10,273.09	77,254.27
Equity	5454.03	5998.58	7499.03	1768.26	2140.76	37,917.64
Borrowed capital	16,453.56	15,338.02	12,813.47	12,382.05	8064.87	38,566.51
Operating result	−1791.99	−166.49	−1219.85	214.53	284.29	7107.70
Economic result for accounting period	−1910.42	−151.22	−1492.21	116.79	141.06	5516.93

Note: all data in the Table are given in thousands of CZK. Source: own construction.

The data will be checked. Only the data that, at first sight, is not defective or intentionally distorted will be kept on the file for further analysis. This will eliminate record lines (a line represents financial statements per company and year) including:

1. Different assets and liabilities balance,
2. Negative assets,
3. Negative fixed assets,
4. Negative tangible fixed assets,
5. Negative current assets,
6. Negative financial assets,
7. Negative inventories.

The input continuous variables will be:

- AKTIVACELK—Total assets resulting from past economic operations. Thus it means the future economic benefit of the company.
- STALAA—Fixed assets are long-term, fixed and noncurrent. This item includes asset components used for the company business in a long term (more than 1 year) and consumed over time.
- HIM—Intangible fixed assets will depreciate, expressed by the level of depreciation. Intangible fixed assets have a significant impact on the value of the enterprise, they maintain their value for a longer time and are not exposed to the fast operating cycle.
- OBEZNAA—Current assets characterize the operating cycle. They continuously circulate and change their form. They include cash, material, semi-finished products, work in progress, products, or receivables from customers.
- Z—Inventories are current (short-term) assets of the company. They are consumed during operation. In general, inventories include material, inventories for production of its own products and goods
- KP—Short-term receivables are payable in less than 1 year from the date when their arise and represent the creditor's right to seek fulfilment of a certain obligation from the other party, the receivable is extinguished when the obligation is paid.
- FM—Financial assets including long-term and short-term financial assets. Long-term financial assets hold their value for a longer period of time, they do not change into cash quickly. They include securities, bonds, certificates of deposit, obligations, term deposits or loans granted to companies. Short-term financial assets are used for operation, especially for payment of liabilities. Short-term assets represent high liquidity; the expected holding is less than one year. They mainly include money in bank accounts, treasury, checks, clearing notes, valuables or short-term securities and shares.
- PASIVACELK—Total liabilities—information concerning the source to cover the company's assets.
- VLASTNIJM—Equity is the internal source of finance for business assets and capital formation. It includes, in particular, contributions of the founders (owners or partners) to the capital stock and components arising from the business management.
- FTZZ—Reserve funds, undistributable reserves and other funds from profit represent the company's internal sources of finance increasing the company's equity without changing its capital stock. Reserve funds are used as internal resources to cover future losses of the company. Undistributable reserves are created by cooperatives also to cover the loss.
- HVML—Profit/loss brought forward is part of liabilities, an item of equity. These are resources created after tax in previous years. These are funds which are not transferred to funds or distributed and paid. It consists of three parts - retained earnings, loss carried forward and other profit/loss brought forward.

- HVUO—Profit and loss of the current financial period is the sum of profit and loss from operations and financial activities in the financial period and the profit before tax. For calculation, the income tax for ordinary activities is deducted.
- CIZIZDROJE—External resources are the company's debts which must be paid within a certain period of time. These are the company's payables to other entities.
- KZ—Current liabilities are payable within 1 year and used for financing (together with equity) of the normal operation of the company. In particular, they include short-term bank loans, payables to employees and institutions, debts to suppliers or delinquent tax.
- V—Production is goods and services that are used to meet the needs. They result from business activities of the company and characterize the main business activities—production.
- VS—Production consumption mainly includes the costs of consumed material, energy, travel expenses, maintenance and repairs, or low-value assets. It is a sum item which correlates with consumption of materials, services and energy.
- SPMAAEN—Material and energy consumption is an item accounting for inventories - current assets. Energy consumption rises proportionally and positively correlates with the production volume. However, material costs may decrease as the production volume increases. Material consumption is directly dependent on consumption standards and purchase prices.
- SLUZBY—Services are systematic external activities that satisfy human needs, or the business needs in their own course.
- PRIDHODN—Value added represents the sales margin, sales, stock level changes of internally produced inventories, or capitalization less production consumption. It includes the sales margin as well as production.
- MZDN—Payroll costs generally comprise of the employee's gross wages and premiums paid by the employer for each employee's social security and health insurance.
- NNSOCZAB—Employee's social security and health insurance costs.
- OHANIM—Depreciation of intangible and tangible fixed assets provides a tool for gradually assigning the value of fixed assets to expenses. Therefore, it means a gradual assignment of the fixed asset cost value to expenses. It represents depreciation of fixed assets.

The categorical output variable will be considered as:

- STAV—Identifies the situation of the company whether active or in liquidation. There will only be two possible outcomes.

The variables were chosen so that it was possible to express the main features of the company´s capital structure, sources of assets financing, corporate payment history, customers´ payment history, cost structure, and the ability to generate outcomes (sales) and realized added value. The selection of indicators is based on the analysis of the existing Altman Z-Score (Altman 1968, 2000, 2003; Altman and Hotchkiss 2006), IN (Neumaierová and Neumaier 2005, 2008), Taffler index (Taffler and Tisshaw 1977; Taffler 1983), Kralicek Quick Test (Kralicek 1993), Harry Pollak´s method (Pollak 2003), and Vochozka´s method (Vochozka 2010; Vochozka and Sheng 2016; Vochozka et al. 2017). The conditions of external environment are not considered, as all companies in the dataset operate in one market, and therefore they are all influenced equally. The output is thus analogy to certain extent. If patterns are identified (although given by a large number of input variables combinations), it is possible to observe a similar development of two companies showing just about the same combination of input variables on the basis of similarity.

The Statistica software, version 13 of TIBCO will be used to apply the classification methods.

3.1. Support Vector Machines

Machine Learning option in the Data Mining module will be used to apply SVM. The file will be divided into a train (75%) and a test (25%) data subset. Then SVM type 2 will be specified where the error function is identified as:

$$\frac{1}{2}w^T w - C\left[v\varepsilon + \frac{1}{N}\sum\nolimits_{i=1}^{N}(\zeta_i + \zeta_{i}\cdot)\right], \tag{1}$$

which minimizes the entity to:

$$\begin{array}{c} \left[w^T \varnothing(x_1) + b\right] - y_i \leq \varepsilon + \zeta_i \\ y_i - \left[w^T \varnothing(x_1) + b_i\right] \leq \varepsilon + \zeta_{\cdot i} \\ \zeta_i,\ \zeta_{\cdot i} \geq 0,\ i = 1,\ \ldots,\ N,\ \varepsilon \geq 0. \end{array} \tag{2}$$

Then the SVM (kernel function) will be selected. In this case, it will be Sigmoid that should be able to identify the extreme values:

$$K\left(X_i, X_j\right) = \tan\mathrm{h}\left(\gamma X_i \cdot X_j + C\right), \tag{3}$$

where $K\left(X_i, X_j\right) = \varphi(X_i)\cdot\varphi\left(X_j\right)$, which means that SVM function represents an output value of input variables projected in multidimensional space using transformation φ.

The results (value 10, seed 1000) will then be cross-validated. A maximum of 10,000 iterations will be performed with a possible ending in case of the error 0.000001.

3.2. Artificial Neural Networks

Classification analysis based on multilayer perceptron neural networks and radial basis function neural networks. ANS (automatic neural network) mode will be used. In case of unsatisfactory results, the result may be corrected using the custom network designer.

The set will be divided by random into three groups of enterprises—i.e., a train file (where neural networks are trained to achieve the best results)—70% of the data, a test file (identify if the classification of trained neural structures is successful)—15% data and a validation file (used for additional verification of the result)—15% of data. Only MLP and RBF will be used in the calculation. For MLP networks, the minimum number of hidden neurons will be set to 8 and the maximum number to 25 while for RBF, the minimum will be 21 and the maximum will be 30 hidden neurons. The number of networks for training will be 10,000 whereas 5 networks with the best results will be retained. The error function will be the sum of squares:

$$E_{SOS} = \frac{1}{2N}\sum_{i=1}^{N}(y_i - t_i)^2\ , \tag{4}$$

where N is number of training cases, y_i is predicted target variable t_i, t_i is target variable of a i-th case.

The BFGS algorithm (Broyden–Fletcher–Goldfrarb–Shanno) will be used for calculation, for more details see Bishop (1995).

Another error function will be entropy (or, cross entropy error function):

$$E_{CE} = \sum_{i=1}^{N} t_i \ln\left(\frac{y_i}{t_i}\right), \tag{5}$$

The activation functions shown in Table 2 will be considered for NN.

Table 2. Activation functions of MLP and RBF hidden and output layer.

Function	Definition	Range
Identity	a	$(-\infty; +\infty)$
Logistic sigmoid	$\frac{1}{1+e^{-a}}$	(0;1)
Hyperbolic tangent	$\frac{e^a-e^{-a}}{e^a+e^{-a}}$	(−1;+1)
Exponential	e^{-a}	$(0; +\infty)$
Sine	$\sin(a)$	$[0; 1]$
Softmax	$\frac{\exp(a_i)}{\sum\exp(a_i)}$	$[0; 1]$
Gaussian	$\frac{1}{\sqrt{2\pi\sigma}}\exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$	

Source: own construction.

Neural networks work as follows: the data of a specific company are entered and subsequently, as an independent variable, the data are converted using the activation function and weights into the values of hidden neurons, which are the input variables for the second round of calculation. Here, the activation function and trained weights as used as well. The result obtained is subsequently compared at a given interval, and it is determined whether or not the company is able to survive possible financial distress.

Other settings will remain default. The result will be a bankruptcy model (the development of the company will be evaluated using two variables—survival of the company or a bankruptcy tendency—thus, the dependent variable will only take two values 0 or 1). The model development will be an iterative and recurrent process with actions to improve. The data to be analysed does not have to follow the normal distribution, the dependent variable is binary. The resulting model will have generalized characteristics—it will be applicable for prediction and the efficiency of classification into groups should be better than by chance, i.e., the efficiency of classification should be higher than 50%.

4. Results

4.1. Support Vector Machines

The defined inputs were used for calculation of a SVM model in C ++ code. The basic parameters are: 22 input continuous variables, 1 output categorical variable, classification type 2, Sigmoid function. 1162 vectors were created for active companies and 1161 vectors for companies in liquidation. The relevance of the model is examined in more detail in Table 3.

Table 3. SVM model prediction status.

	Status—Active Company	Status—In liquidation	Status—All
Total	4606	1582	6188
Correct	4578	130	4708
Incorrect	28	1452	1480
Correct (%)	99.39	8.22	76.08
Incorrect (%)	0.61	91.78	23.92

Source: own construction.

The accuracy of classifications, or predictions is more than 76%. This is certainly positive in terms of the model success. However, remember that this percentage consists of more than 99% of correct predictions of active companies and only above 8% of predictions of the companies in liquidation. Therefore, the model is not fully applicable in practice.

4.2. *Artificial Neural Networks*

10,000 artificial neural structures were calculated of which 5 with the best characteristics were retained (see Table 4).

Table 4. Retained neural networks.

Statistics	1	2	3	4	5
Network name	MLP 22-6-2	MLP 22-9-2	MLP 22-12-2	MLP 22-8-2	MLP 22-12-2
Training performance	81.46353	83.01016	82.2253	82.40997	83.05633
Testing performance	80.38793	81.89655	81.03448	81.25	81.14224
Validation performance	81.35776	82.65086	83.40517	82.65086	83.40517
Training algorithm	BFGS 170	BFGS 332	BFGS 56	BFGS 110	BFGS 220
Error function	Entropy	Entropy	SOS	Entropy	Entropy
Hidden activation func.	Tanh	Tanh	Identity	Logistic	Tanh
Output activation func.	Softmax	Softmax	Logistic	Softmax	Softmax

Source: own construction.

The best characteristics of generated neural structures are exclusively shown by MLP networks. NNs have 22 neurons in the input layer (based on 22 input continuous variables), 6 to 12 neurons in the hidden layer and 2 neurons in the output layer (based on one output categorical variable that can take two values). Entropy was the error function in four cases, the sum of squares in one. The identity, logistic and hyperbolic tangent functions were used to activate the hidden layer of neurons. The logistic and Softmax functions were used to activate the output layer of neurons. The performance of individual networks is always above 81% in the train data set and above 80% in the test data set and above 81% in the validation set. Thus, the performance seems very high. Table 5 shows the performance decomposition.

Table 5. Predictions of artificial neural networks.

Network	Statistics	Status—Active Company	Status—In liquidation	Status—All
1.MLP 22-6-2	Total	4606	1582	6188
	Correct	4226	804	5030
	Incorrect	380	778	1158
	Correct (%)	91.75	50.82	81.29
	Incorrect (%)	8.25	49.18	18.71
2.MLP 22-9-2	Total	4606	1582	6188
	Correct	4234	889	5123
	Incorrect	372	693	1065
	Correct (%)	91.92	56.20	82.79
	Incorrect (%)	8.08	43.81	17.21
3.MLP 22-12-2	Total	4606	1582	6188
	Correct	4315	773	5088
	Incorrect	291	809	1100
	Correct (%)	93.68	48.86	82.22
	Incorrect (%)	6.32	51.14	17.78
4.MLP 22-8-2	Total	4606	1582	6188
	Correct	4320	771	5091
	Incorrect	286	811	1097
	Correct (%)	93.79	48.74	82.27
	Incorrect (%)	6.21	51.26	17.73
5.MLP 22-12-2	Total	4606	1582	6188
	Correct	4252	873	5125
	Incorrect	354	709	1063
	Correct (%)	92.31	55.18	82.82
	Incorrect (%)	7.69	44.82	17.18

Source: own construction.

Ideally, we are looking for a neural structure which shows the highest number of correctly classified cases. However, it is very important for NN to be able to predict (classify) both active companies (i.e., businesses capable of surviving a potential crunch) and companies in liquidation (i.e., businesses in bankruptcy). In this respect, 2.MLP 22-9-2 and 5.MLP 22-12-2 networks appear to be the most successful. There is a minimum difference between them. But a higher number of correct predictions of bankruptcy for 2.MLP 22-9-2 network is more advantageous. The dominance of both networks is illustrated by the chart in Figure 1.

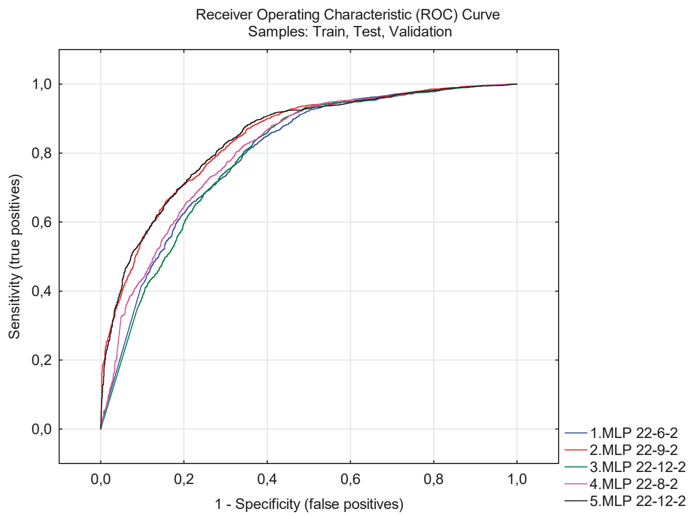

Figure 1. Threshold operating characteristics of neural network classification. Source: own construction.

Ideally, the characteristics are close to (0,1). The 2.MLP 22-9-2 and 5.MLP 22-12-2 networks are closest to this point.

4.3. SVM/NN Comparison

It is obvious from the results that the SVM model has a quite high level of reliability. However, the structure of correct classifications, i.e., 99% of correct predictions of active companies and only above 8% of predictions of companies in liquidation, makes this model inapplicable.

On the contrary, five NN models were retained by applying the methodology for creating NN. In all cases, those are MLPs that are applicable in practice. There are minimum differences between networks. Still we can identify the best neural network which is NN 2.MLP 22-9-2 without any doubt: very closely followed by NN 5.MLP 22-12-2. There is just a minimum difference between them.

This answers our research question. In this case, the answer is very simple. Artificial neural networks are much more accurate than SVM in predicting possible bankruptcy. Unlike SVM all retained NNs are well applicable in practice.

It is a bankruptcy model. We thus define a tool to identify the companies unlikely to survive a possible financial distress. In particular, we examine the ability of the tool to identify a company that can be expected to face financial distress in the future. The SVM model showed a great ability to predict the second opposite situation at first glance, that is, the ability of the company to survive a possible financial distress. In this case, the prediction of the model is correct in 99.39% of cases. However, the ability to predict bankruptcy is at the 8.22% level. In general, the SVM model predicts the future development of the company with 76.08% accuracy, which could be considered a good result. However, the problem is that the model would achieve the same or almost the same predictive power even if it did not predict any company that is going to bankrupt. In fact, the SVM method did not meet the requirements, although it shows a rather interesting result. The SVM model is thus nonapplicable.

As the confusion matrix in Table 5 indicates, artificial neural networks show higher prediction power—nearly up to 83%, but what is even more important, they have greater ability to predict companies that are going to bankrupt. Taking into account the most successful neural structure, 2.MLP 22-9-2, its accuracy is 82.79%. It is able to predict correctly 91.92% of companies that are able to survive a potential financial distress, and 56.2% of companies that are going to bankrupt. The prediction is thus applicable in practice.

Now the task is to find a generally acceptable model able to predict a potential financial distress. The Altman Z-Score (Altman 1968, 2000, 2003; Altman and Hotchkiss 2006) and many other models (Neumaierová and Neumaier 2005, 2008; Taffler and Tisshaw 1977; Taffler 1983; Kralicek 1993; Pollak 2003) were based on the data that are not relevant for the current corporate environment (small data volume, data more than 50 years old, etc.). Although the Altman Z-Score is still being used, corporate practice is well aware of their weaknesses. The paper aimed to find an alternative that respect the time lag and which would be easily applicable and showing an appropriate level of accuracy. Very often, it is about being able to detect a potential risk associated with a particular company. Subsequently, we would be able to analyse such a company in more detail, assessing whether the risk is real or not.

This requirement is definitely met by the generated neural networks, in particular 2.MLP 22-9-2. It is based on the current data in the environment where the resulting model of neural networks will be applied. As stated above, it is the first indication of possible problems used as an impulse for a more detailed analysis. The resulting model is interesting from another aspect. Despite its easy applicability, the artificial neural network assesses the future development on the basis of 22 variables characterizing the amount of company assets, structure of its financing, payment history of the company and the customers, cost structure, and the ability to generate sales (as a quantified output of core business). The individual indicators are described in Data and Methods.

Since 2000, many authors have tried to predict company bankruptcy using the models of neural networks. As an example, we can mention Becerra et al. (2002), who analysed the use of linear models and the models of neural networks for the classification of financial distress. Their calculation included 60 British companies from the period between 1997 and 2000. Zheng and Jiang (2007) used the data of Chinese listed companies between 2003 and 2005. All similarly created models are rather outdated, as they use the data that were up to date before the world financial crisis. This paper shows an up-to-date and simple model (most existing studies create relatively complex hybrid models—e.g., Xu et al. 2019), which can be gradually updated using new data, and thus even become more accurate (due to neural networks learning).

5. Discussion and Conclusions

Bankruptcy prediction is always a topical issue. This is due to very complicated business relationships between entrepreneurs and competition in the current business environment. It is characterized by instability, perhaps even turbulence. All the more important is to find a low-input tool that can evaluate future development of any company in the market.

The aim of this paper was to develop bankruptcy prediction models and evaluate the results obtained from classification methods, namely Support Vector Machines and artificial neural networks (multilayer perceptron artificial neural networks—MLP and radial basis function artificial neural networks—RBF).

In total, six models were created: 1 SVM, 5 NN. Consequently, a comparison was made between them. NN 2.MLP 22-9-2 appears to be the most successful model that is applicable in practice (NN code C++ forms). The financial variables with the highest bankruptcy predictive power are presented in Table 6.

Table 6. Sensitivity analysis.

Variables	1.MLP 22-6-2	2.MLP 22-9-2	3.MLP 22-12-2	4.MLP 22-8-2	5.MLP 22-12-2	Average
OHANIM	1.307736	8.298830	1.623772	1.197549	1.143286	2.714235
PRIDHODN	1.302244	4.395480	1.584667	2.339157	2.748509	2.474011
VS	1.319040	2.663396	1.602347	3.742576	2.887139	2.442900
HVML	1.269237	2.125292	1.520003	1.517179	3.173511	1.921044
MZDN	1.294799	2.563237	1.561902	1.494294	2.231695	1.829185
OBEZNAA	1.274424	2.737114	1.627830	1.209418	2.123338	1.794425
SPMAAEN	1.324918	2.146751	1.295759	1.266527	2.599045	1.726600
STALAA	1.173915	2.153740	1.231161	1.038480	2.572654	1.633990
Z	1.289484	2.095527	1.494067	1.115624	1.585507	1.516042
V	1.315965	2.092471	1.608308	1.113233	1.146686	1.455333
FTZZ	1.278720	1.379155	1.539660	1.668709	1.389535	1.451156
CIZIZDROJE	1.527338	1.269488	1.853573	1.073045	1.487208	1.442131
SLUZBY	1.422673	1.335220	2.002430	1.127664	1.204212	1.418440
FM	1.076257	1.418978	1.601751	1.185785	1.525021	1.361559
HVUO	1.298108	1.459786	1.454034	1.219113	1.350517	1.356312
KZ	1.258229	1.441923	1.204971	1.326370	1.334837	1.313266
HIM	1.095701	1.904764	1.004551	1.328013	1.228624	1.312330
VLASTNIJM	1.288897	1.338126	1.526678	1.225678	1.160983	1.308072
KP	1.280438	1.581155	1.337826	1.034392	1.196151	1.285992
NNSOCZAB	1.016164	1.991251	1.058640	1.060163	1.284383	1.282120
AKTIVACELK	1.274310	1.452314	1.154554	1.014583	1.388433	1.256839
PASIVACELK	1.274334	1.446461	1.154320	1.014663	1.368253	1.251606

Source: own construction.

The highest bankruptcy predictive power have "Depreciation of intangible and tangible fixed assets", "Value added" and "Production consumption". All three items are logical for the manufacturing industry.

The existing models (Altman index, Neumaier index and many others) are based on the standard statistical methods. Their deficiencies were identified by Balcaen and Ooghe (2004):

- Dependent variable dichotomy,
- Sampling method,
- Stationarity and data instability,
- Selection of variables,
- Using information from financial statements, and
- Time dimension.

Neural networks can resolve some of the defined problems. It is primarily the time dimension. For all the existing models, the previous development of the company, consequently evaluated as Active or in Liquidation, cannot be taken into account. Neural networks are able to handle large data volumes. Therefore, the values of variables of selection do not need to be restricted. It may appear that the dataset will be a limit when application for another period and different market (especially when used abroad). However, it is not the case, as we identified a structure with a relatively strong prediction power. Although it was trained and subsequently validated twice on a selected sample, the neural network can be quickly adapted to the specificities of a different market. Artificial neural network can adapt to a new environment by retraining it on a dataset sample of a given market. Due its ability to meet the requirement for changing the setting of its internal parameters, neural network can thus be considered flexible and widely applicable.

The future focus should to collect data other than information from financial statements. It will also be necessary to define the company status other than just Active or in Liquidation. However, the data problem may not be resolved.

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Assessment of Bankruptcy Risk of Large Companies: European Countries Evolution Analysis

Nicoleta Bărbuță-Mișu [1,*] and Mara Madaleno [2]

[1] Department of Business Administration, "Dunarea de Jos" University of Galati, 800008 Galati, Romania
[2] GOVCOPP—Research Unit in Governance, Competitiveness and Public Policy, Department of Economics, Management, Industrial Engineering and Tourism (DEGEIT), University of Aveiro, 3810-193 Aveiro, Portugal; maramadaleno@ua.pt
* Correspondence: Nicoleta.Barbuta@ugal.ro; Tel.: +40-724-362-007

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Abstract: Assessment and estimation of bankruptcy risk is important for managers in decision making for improving a firm's financial performance, but also important for investors that consider it prior to making investment decision in equity or bonds, creditors and company itself. The aim of this paper is to improve the knowledge of bankruptcy prediction of companies and to analyse the predictive capacity of factor analysis using as basis the discriminant analysis and the following five models for assessing bankruptcy risk: Altman, Conan and Holder, Tafler, Springate and Zmijewski. Stata software was used for studying the effect of performance over risk and bankruptcy scores were obtained by year of analysis and country. Data used for non-financial large companies from European Union were provided by Amadeus database for the period 2006–2015. In order to analyse the effects of risk score over firm performance, we have applied a dynamic panel-data estimation model, with Generalized Method of Moments (GMM) estimators to regress firm performance indicator over risk by year and we have used Tobit models to infer about the influence of company performance measures over general bankruptcy risk scores. The results show that the Principal Component Analysis (PCA) used to build a bankruptcy risk scored based on discriminant analysis indices is effective for determining the influence of corporate performance over risk.

Keywords: European large companies; bankruptcy risk; company performance; bankruptcy prediction; Principal Component Analysis

1. Introduction

Bankruptcy and bankruptcy prediction is a very real issue worldwide both in academic research and in practice considering the evolution at a global level: the upward trend in business insolvencies continued in 2018 (increase by 10% in 2018 compared to 2017), mainly due to the surge in China by 60% and, to a lesser extent, an increase in Western Europe by 2% (Euler Hermes Economic Research 2019).

In Western Europe, although a downside trend in insolvencies was recorded from 2014 to 2017, the increase mentioned by 2% in 2018 compared to 2017 was determined by different evolution by other countries: a noticeable upturn of 12% in the UK due to the Brexit-related uncertainties that added headwinds on businesses; a stabilization of insolvencies can be seen in France, Spain and Belgium, although in France in 2018, 54,751 companies went bankrupt, corresponding to a fairly high 1.3% of the active business universe (Dun & Bradstreet 2019); an increase in the Nordic countries of 10% in Sweden, 3% in Norway, 19% in Finland and 25% in Denmark. This trend comes from economic and fiscal reasons or exceptional factors, especially for Denmark and Finland. At the same time, other countries of the region registered slower declines in 2018 compared to 2017, notably the Netherlands (from −23% to −6%), Portugal (−12%), Ireland (−10%) and Germany (−4%). In Italy, 11,207 companies filed for bankruptcy in 2018, down by a significant 5.8%, but the newly-elected populist government is likely to embark on a series of populist policies that are at odds with improving the country's operating environment (Dun & Bradstreet 2019).

According to Euler Hermes Economic Research (2019), in Central and Eastern Europe, we can see economies that forecast to moderate in line with the slowdown in the Eurozone, but remain robust enough to see another decrease in insolvencies, albeit at more limited time, i.e., Hungary from −18% in 2018 to −11% in 2019 and the Czech Republic, respectively −17% and −10%. Romania registered a rebound in insolvencies, −3% in 2018 and +3% in 2019. Other countries continued to rise in insolvencies: 3% for Bulgaria in 2019 where the changes in the Insolvency law done in 2017 kept on boosting the bankruptcies of sole proprietorships, Slovakia of 16%, Poland of 5% where businesses have a structural problem of profitability and will face a noticeable deceleration of the economy.

Over time, researchers have tried to find diverse methods to estimate business failure: patrimonial method based on net working capital and treasury; financial ratios method especially based on individual analysis of profitability, liquidity, solvency and financial autonomy; and score method highlighted in numerous models for which Altman (1968), Ohlson (1980), and Zmijewski (1984) models are the most cited ones and that are based on accounting variables (Avenhuis 2013). These bankruptcy prediction models use different explanatory variables and statistical techniques and may provide valuable information about the financial performance of the companies and their risks. More than that, we must mention that the predictive power of these bankruptcy prediction models differ between countries, sectors of activity, time periods, firms' ages, or firms' sizes.

There is a constant effort to use the models developed for firms in different economies, even if decision makers know or at least should know that assumptions used for fitting the original models are probably not valid anymore. There is a continuous concern and preoccupation for designing models for prediction risk of bankruptcy. Assessing of the level of advancement of bankruptcy prediction research in countries of the former Eastern Bloc, in comparison to the latest global research trends in this area, Prusak (2018) found that the most advanced research in this area is conducted in the Czech Republic, Poland, Slovakia, Estonia, Russia, and Hungary. In addition, the best world practices are reflected in the research provided in Poland, the Czech Republic, and Slovakia.

The main problem of the bankruptcy prediction models developed in the literature is that these models cannot be generalized because these were developed using a specific sample from a specific sector, specific time period and from a specific region or country. As the above-mentioned statistics show, there are many other specific factors that increase the bankruptcies in a country: changes in economic environments, law frameworks, incomparability of populations of interest, etc. (Král' et al. 2016). That is why it is necessary to adapt these models to the specificity of the sector, country or time period analyzed and to use combined techniques of estimation in designing these specific models.

In this paper, considering the context presented, the large companies from the European Union are analysed. The aim of this research is twofold: to improve the knowledge of bankruptcy prediction for European large companies and to analyse the predictive capacity of factor analysis, such as Principal Component Analysis (PCA) using as a basis the discriminant analysis (models for assessing bankruptcy risk, commonly used in the literature). Our paper is distinguishing from other studies by using a sample of large companies active in the EU-28 countries in the period 2006–2015 and by own original selection of bankruptcy prediction models (Altman, Conan and Holder, Tafler, Springate and Zmijewski) used in the PCA analysis.

The rest of the paper is organised as follows: in Section 2, the literature review on risk, bankruptcy prediction, models and techniques used to assess and forecast the risk of bankruptcy is presented. The data and methodology are presented in the Section 3. The paper then follows with analysis of results and discussions in Section 4. Concluding remarks pointing out some policy implications, future research suggestions and limitations of the study are discussed in the Section 5.

2. Literature Review

Financial risks show the possibility of losses arising from the failure to achieve financial objectives. The financial risks related to the financial operation of a business may take many different forms: market risks determined by the changes in commodities, stocks and other financial instruments prices, foreign exchange risks, interest rate risks, credit risks, financing risks, liquidity risks, cash flow risk, and bankruptcy risk. These financial risks are not necessarily independent of each other, the interdependence being recognized when managers are designing risk management systems (Woods and Dowd 2008). The importance of these risks will vary from one firm to another, in function of the sector of activity of the firms, the firm size, development of international transactions, etc.

Bankruptcy refers to the situation in which the debtor company becomes unable to repay its debts and can be considered to be the consequence of a company's inability to survive market competition, reflected in terms of job losses, the destruction of assets, and in a low productivity (Aleksanyan and Huiban 2016). The risk of bankruptcy or insolvency risk shows the possibility that a company will be unable to meet its debt obligations, respectively the probability of a company to go bankrupt in the next few years. Assessing of bankruptcy risk is important especially for investors in making equity or bond investment decisions, but also for managers in financial decision making of funding, investments and distribution policy. Failure prediction models are important tools also for bankers, rating agencies, and even distressed firms themselves (Altman et al. 2017).

The essential information for executive financial decisions, but also for investors decisions are provided by financial statements. Thus, companies' financial managers should develop the financial performance analysis and problem-solving skills (Burns and Balvinsdottir 2005; Scapens 2006), without limiting their duties in verifying accounting data (Diakomihalis 2012) in order to maintain the firm attractive for investors. The image of financial performance of companies is affected by the estimation of its position in front of investors, creditors, and stakeholders (Ryu and Jang 2004). For this estimation there are used many indicators that reflect the company's position such as: net working capital, net treasury, liquidity, solvency, profitability, funding capacity, cash-flow, etc., or a mix between them, such as Z-scores.

The design of reliable models to predict bankruptcy is crucial for many decision-making processes (Ouenniche and Tone 2017). The approach used for bankruptcy prediction has evolved over time starting to Beaver (1966, 1968) model based on univariate analysis for selected ratios and which had very good predictive power. Then, Altman (1968) made strides by developing a multiple discriminant analysis model called the Z-Score model. Bankruptcy prediction models could be divided into two general categories depending on the type of variable used: static models (Altman 1968, 2000, 2002; Taffler 1982, 1983, 1984; Ohlson 1980; Zmijewski 1984; Theodossiou 1991) or dynamic models (Shumway 2001; Hillegeist et al. 2004).

In the literature of bankruptcy prediction, the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are the most cited ones that are based on accounting variables. These bankruptcy prediction models use different explanatory variables and statistical techniques. Therefore, the predictive power of these bankruptcy prediction models differs. However, when the original statistical techniques are used, the accuracy rates for the models of Altman (1968), Ohlson (1980), and Zmijewski (1984) are respectively 80.6%, 93.8%, and 95.3% (Avenhuis 2013). Studying the efficacy of Altman's z-score model in predicting bankruptcy of specialty retail firms doing business in contemporary times, Chaitanya (2005) found that all but two of the bankruptcies (94%) would have been accurately predicted.

Ashraf et al. (2019) found that both models by Altman (1968) and Zmijewski (1984) are still valuable for predicting the financial distress of emerging markets and can be used by businessmen, financial specialists, administrators, and other concerned parties who are thinking about investing in an organization and/or want to enhance their organization performance. Elviani et al. (2020) studied the accuracy of the Altman (1968), Ohlson (1980), Springate (1978) and Zmijewski (1984) models in bankruptcy predicting trade sector companies in Indonesia using binary logistic regression.

Their results proved that the most appropriate and accurate models in predicting bankruptcy of trade sector companies in Indonesia are the Springate and Altman models.

Related to methodologies used in creating bankruptcy risk models we can mention bankruptcy prediction models based on: statistical methodologies (Models of Altman 1968, 2000, 2002; Altman et al. 2017; Model of Springate 1978; Model of Conan and Holder 1979; Models of Taffler 1982, 1983, 1984; Model of Fulmer et al. 1984), stochastic methodologies (Model of Ohlson 1980; Model of Zmijewski 1984; Model of Zavgren 1985; Theodossiou 1991), and artificial intelligence methodologies (Zhang et al. 1999; Kim and Han 2003; Shin et al. 2005; Li and Sun 2011) and data envelopment analysis (DEA) methodologies (Koh and Tan 1999; Cielen et al. 2004; Paradi et al. 2004; Shetty et al. 2012; Ouenniche and Tone 2017). Aziz and Dar (2006) reviewed 89 studies on the prediction of bankruptcy risk in the period 1968–2003 in order to carry out a critical analysis of the methodologies and empirical findings of the application of these models across 10 different countries (Finland, Norway, Sweden, Belgium, UK, Italy, Greece, USA, Korea and Australia). They found that the multi-variable models (Z-Score) and logit were most popular in the 89 papers studied.

The multitude of models created demonstrate an intense concern for bankruptcy prediction, considering also the evolution of number of bankruptcies in the world. However, the first bankruptcy models are still applied and provide important information. For example, Altman's model was applied to Jordanian companies, non-financial service and industrial companies, for the years 1990–2006. The study shows that Altman's model has an advantage in company bankruptcy prediction, with a 93.8% average predictive ability of the five years prior to the liquidation incident (Alkhatib and Bzour 2011). Chung et al. (2008) also examined the insolvency predictive ability of different financial ratios for ten failed financial companies during 2006–2007 in New Zealand and found that, one year prior to failure, four of the five Altman (1968) ratios were superior to other financial ratios for predicting corporate bankruptcy. In other countries, such as Romania aggregate indexes of financial performance assessment for the building sector companies were created (Bărbuţă-Mişu 2009; Bărbuță-Mișu and Codreanu 2014) or well-known modes, such as the Conan and Holder model were adjusted to the specificity of Romanian companies (Bărbuţă-Mişu and Stroe 2010). In studies about bankruptcy prediction, in Romania was preferred Conan and Holder (1979) model to evaluate the financial performance of the companies.

The majority of authors proposed models adapted to the specificity of the economies. Brédart (2014) developed an econometric forecasting model on United States companies using three simple and a few correlated and easily available financial ratios as explanatory variables and their results show a prediction accuracy of more than 80%. Dakovic et al. (2010) developed statistical models for bankruptcy prediction of Norwegian firms acting in the industry sector. They modelled the unobserved heterogeneity among different sectors through an industry-specific random factor in the generalized linear mixed model. The models developed are shown to outperform the model with Altman's variables.

To solve the problem of bankruptcy prediction some statistical techniques such as regression analysis and logistic regression are used (De 2014). These techniques usually are used for the company's financial data to predict the financial state of company as healthy, distressed, high probability of bankruptcy. As we know, Altman (1968) used financial ratios and multiple discriminant analysis (MDA) to predict financially distressed companies. However, further, it was found that the usage of statistical techniques or MDA depends on the constraint as linear separability, multivariate normality and independence of predictive variables (Ohlson 1980; Karels and Prakash 1987). Thus, bankruptcy prediction problem can be solved using various other types of classifiers, such as neural network that compared to MDA, logistic regression and k-nearest neighbour method proved a higher performance. For instance, Tam (1991) found that the neural network performs better than other prediction techniques.

Otherwise, Xu and Zhang (2009) have investigated whether the bankruptcy of certain companies can be predicted using traditional measures, such as Altman's Z-score, Ohlson's (1980) O-score, and the option pricing theory-based distance-to-default, previously developed for the U.S. market, in order to find if these models are useful for the Japanese market. They have found that the predictive power is substantially enhanced when these measures are combined.

In addition, Jouzbarkand et al. (2013) compiled two models for the prediction of bankruptcy, related to the Iranian economic situation. Using the logistic regression method, they studied the Ohlson (1980) and Shirata (1995) models, examining and comparing the performance of these models. Their results show that models created are able to predict the bankruptcy. For classifying and ranking the companies, they used their business law to determine the bankrupt companies and a simple Q-Tobin to specify the solvent companies.

Discriminant analysis was the prevailing method, and the most important financial ratios came from the solvency category, with profitability ratios also being important (Altman et al. 2017). The performance of five bankruptcy prediction models, such as Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001) and Hillegeist et al. (2004) was studied by Wu et al. (2010) building their own integrated model using a dataset for U.S.A. listed firms. Wu et al. (2010) found that Shumway's (2001) model performed best, Hillegeist et al.'s (2004) model performed adequately, Ohlson's (1980) and Zmijewski's (1984) models performed adequately, but their performance deteriorated over time, while Altman's Zscore performed poorly compared with all other four models analysed. However, the integrated model outperformed the other models by combining both accounting and market data, and firms' characteristics.

The factor analysis is often used together with other methodologies, in order to improve bankruptcy prediction models (Cultrera et al. 2017). Principal Component Analysis (PCA), the statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components started to be used in analysis and prediction of bankruptcy risk. Adalessossi (2015) used discriminant function named Z-scores model of Altman, financial ratio analysis, and the principal component analysis on a sample of 34 listed companies from different sectors and sizes in order to find out if the three methods used in this study converge toward similarity results. The comparison of the three methods indicates unanimously that, out of the 34 companies, only eight companies have had the best financial performances and are not likely to go on to bankruptcy.

Onofrei and Lupu (2014) have built a quick warning model for the Romanian companies in difficulty, using the following methodologies: the Principal Components Analysis, the multivariate discriminant analysis and the logit analysis in order to determine which are the best predictors of bankruptcy for the Romanian companies. They found that the best predictor for the Romanian market is the multiple discriminant analysis method with a predictive power between 68–95%, while the logit method registering slightly weaker results with a predictive power between 53–82%.

De (2014) developed the principal component analysis (PCA) and general regression auto associative neural network (GRAANN) based hybrid as a one-class classifier in order to test the effectiveness of PCA-GRAANN on bankruptcy prediction datasets of banks from Spain, Turkey, US and UK. They concluded that PCA-GRAANN can be used as a viable alternative for any one-class classifier. Checking related literature, we found that PCA is more used with artificial neural network methods for prediction bankruptcy risk where the effectiveness was proved. However, in this paper we proposed to use PCA based on the five discriminant analysis measures, i.e., Z-score determined by the following models: revised Z-score Altman, Conan and Holder, Tafler, Springate and Zmijewski in order to test the efficiency in predicting the risk of bankruptcy. Afterwards, we made use of econometric techniques and the PCA score created by country and year to test its influence over performance. The principal component analysis to build the bankruptcy risk score of the five models selected is used, since there is no consensus in the literature so as to which is the best bankruptcy prediction model. In this way we may capture the components that will exert more impact in bankruptcy prediction.

3. Data and Methodology

In this section we describe the data and all methodologies used to assess bankruptcy risk, as well as to create the bankruptcy risk indexes by year and country that are presented in the results section. It starts by describing the models used to assess bankruptcy risk measures, which are commonly used in the literature and afterwards describes the Principal Component Analysis (PCA) used to create the bankruptcy risk index measures by year and country (by country, Greece had to be taken out from the sample due to missing data able to allow us to create the index for this country).

3.1. Data Description

The source of the data is Amadeus database, provided by Bureau van Dijk Electronics. In the sample we have included only large non-financial companies from the former EU-28 countries, for the period 2006–2015, that act in all sectors of activity (with the conclusion of the Brexit, the EU is now with 27 countries, instead of 28. However, UK was used because at the beginning of the analysis it belonged to the EU-28 and we will keep this representation through the article). The selection criteria for large companies included in the sample are in accordance with the classification of the small and medium enterprises (SMEs) published in Commission Recommendation of 6 May 2003 (European Commission 2003) concerning the definition of micro, small and medium-sized enterprises. Thus, in order to select the large companies for EU-28 countries, as selection criteria of these companies we used: number of employees greater than 250, total assets greater than €43 million and turnover greater than €50 million. These criteria were applied simultaneously for the data available for the last year included in the sample, i.e., year 2015. We found 22,581 active large companies. We did not consider small and medium enterprises (SMEs) due to the high fluctuations over time in foundation and closing of these firms compared to large companies. Our intention was to study the risk of bankruptcy to large companies that had a more stable activity over time. Our data period was from 2006 until 2015.

Where it was applicable, because of some data missing, we deleted data for years and companies with no available information for calculation of variables of risk of bankruptcy models. In addition, we eliminated from database the inconclusive values and outliers. Thus, remained in the study 154,459 valid year-observations. However, we still worked with an unbalanced panel, due to missing years of data in the sample. Additionally, we have taken out from our sample all countries which did not present a number of companies higher than 1000. From the 28 available countries we ended up working with 20 of these countries.

3.2. Models for Assessing Bankruptcy Risk

As we mentioned in the literature review, there are numerous models for bankruptcy risk prediction based on Z score method, but in this paper we selected the following five models: Altman's Models (1968, 2000), Conan and Holder Model (1979), Springate's Model (1978), Taffler's Model (1982, 1983), Zmijewski's Model (1984). We used these five models since these are the most referenced one's to predict bankruptcy and have a high level of accuracy as we presented in the Section 2. There are a number of key models that have been developed by various authors and presented in the bankruptcy prediction literature over the last three decades, but these five appear in most of the recent studies where bankruptcy models are tested. For these models we determined all variables necessary and the Z scores for all companies included in the sample for the period 2006–2015.

3.2.1. Altman's Models

Altman (1968) is the dean of insolvency prediction models and the first researcher that successfully used the step-wise multiple discriminate analysis to develop a prediction model with a high degree of accuracy of 95%. The original study included a sample comprising 66 industrial companies, 33 bankrupts and other 33 non-bankrupts for a period of analysis of 20 years (1946–1965).

The author found a total of 22 potential variables, based on data provided by annual reports of the companies, and by them, he retains five variables with the highest significance, as a result of using statistical techniques and discrimination analysis. Generally, these variables include profitability ratios, coverage ratios, liquidity ratios, capitalization ratios, and earnings variability (Altman 2000).

The final discriminant function of first Altman model (1968) takes the following form:

$$Z1\ \text{Altman} = 0.012\ X1 + 0.014\ X2 + 0.033\ X3 + 0.006\ X4 + 0.999\ X5 \quad (1)$$

where:
Z1 Altman = Overall Index Altman
X1 = Working Capital/Total Assets
X2 = Retained Earnings/Total Assets
X3 = Earnings Before Interest and Taxes/Total Assets
X4 = Market Value Equity/Book Value of Total Debt
X5 = Sales/Total Assets

Because this original model cannot be applied to unlisted companies in the Stock Exchange, the model was completely re-estimated, substituting the Market Value of Equity with Book Values of Equity in X4 (Altman 2000), resulting the Revised Z-Score Model that is used for our sample.

A Revised Z-Score Model (rza)

This change of the Market Value of Equity determined not only the change of new variable's parameter, but determined the change of all coefficients, as well as the classification criterion and related cut-off scores.

The results of the revised Z-Score model with a new X4 variable is:

$$Z2\ \text{Altman} = 0.717\ X1 + 0.847\ X2 + 3.107\ X3 + 0.420\ X4 + 0.998\ X5 \quad (2)$$

The description of the variable used is the following:

X1—Working Capital/Total Assets

This ratio is the measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered in this ratio. Ordinarily, a company experiencing consistent operating losses will have shrinking current assets in relation to total assets.

X2—Retained Earnings/Total Assets

Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. Retained earnings may be affected by a substantial reorganization or stock dividend and for this reason, in research studies, some appropriate readjustments should be made to the accounts. In this ratio, the age of the company is considered implicitly. For example, a relatively young company will probably show a low ratio because it had not enough time to build up its cumulative profits. Therefore, it may be argued that a young company is somehow discriminated against in this analysis, and its chance of being classified as bankrupt is relatively higher than another older company. That's why we have included in our sample only large companies that have a higher chance of remaining on the market. This is precisely the situation manifested in the real world because the incidence of failure is much higher in a company's earlier years. Those companies with high retained earnings, relative to total assets, have financed their assets through retention of profits and have not utilized as much debt.

X3—Earnings before Interest and Taxes/Total Assets

This ratio is a measure of the true productivity of the company's assets, independent of any tax or leverage factors. Since a company's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure.

Furthermore, insolvency in a bankruptcy sense occurs when the total liabilities exceed a fair valuation of the company's assets with value determined by the earning power of the assets.

X4—Book Value of Equity/Book Value of Total Debt

Equity is measured by the Book Value of Equity divided by Total Debt, debt including both current and long-term. The measure shows how much the firm's assets can decline in value (measured by book value of equity plus debt) before the liabilities exceed the assets and the company becomes insolvent.

X5—Sales/Total Assets

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. This ratio is quite important because it is the least significant ratio on an individual basis. Because of its unique relationship to other variables in the model, the Sales/Total Assets ratio ranks second in its contribution to the overall discriminating ability of the model.

The interpretation of the Z2 Altman is:

Z2 Altman > 2.9 − Safe zone
1.23 < Z2 Altman < 2.9 − Grey zone
Z2 Altman < 1.23 − Distress zone

In order to eliminate industry effects, the next change of the Z-Score model analysed the characteristics and accuracy of the model without variable X5—Sales/Total Assets (Altman 2002). He does this in order to minimize the potential industry effect which is more likely to take place when such an industry-sensitive variable as asset turnover is included. This particular model is also useful within an industry where the type of financing of assets differs greatly among firms and important adjustments, like lease capitalization, are not made (Bărbuţă-Mişu 2017).

In particular, Altman et al. (1998) have applied this enhanced Z Score model to emerging markets corporates, specifically Mexican firms that had issued Eurobonds denominated in US dollars. In the emerging market model, they added a constant term of +3.25 so as to standardize the scores with a score of zero equated to a default rated bond.

3.2.2. Conan and Holder's Model (zcc)

The Conan and Holder (1979) model was developed to analyse the degradation of the financial situation of small and medium enterprises (SMEs). The appraisals for the proposed score function were based on an initial set of 50 indicators studied by the category: the asset structure, the financial dependence, the treasury, the working fund, the exploitation, the profitability, etc. Then, the formulation and model results are based on the analysis of 31 rates (financial variables), applied on 190 small and medium enterprises acting in various fields: industry, trade, services and transport during 1970–1975. Of the 190 selected companies, 95 companies were bankrupt, and another 95 were healthy businesses whose activities were appropriate waist and bankrupt companies.

The model developed by Conan and Holder is included in the statistical tested methods, and has the advantage of simplifying the calculation, so that it continues to be used today.

The Conan and Holder model is:

$$Z\ \text{Conan and Holder} = 0.24\ X1 + 0.22\ X2 + 0.16\ X3 - 0.87\ X4 - 0.10\ X5 \quad (3)$$

where:

Z Conan and Holder = Overall Index Conan and Holder

X1 = Gross Operating Surplus/Total Debts, expresses the profitability by creditors, the profit achieved by using borrowed capital.

X2 = Permanent Capital/Total Liabilities, expresses the solvency of the company on long term, a measure of debt guarantees through permanent capital.

X3 = (Current assets − Stocks)/Total Liabilities, expresses the liquidity of the company, the capacity of paying debts by transforming into cash of receivables, financial short-term investments, cash, and cash equivalents.

X4 = Financial Expenditures/Net Sales, expresses the rate of financial expenses, the share of financial expenses in net sales.

X5 = Personnel Expenditures/Added Value, expresses the rate of personnel costs, i.e., the share of remuneration of the personnel by the added value of the company.

The interpretation of the Z Conan and Holder score function is as follows:

Z Conan and Holder < 0.04 − a probability of a bankruptcy risk of >65%;
0.04 < Z Conan and Holder < 0.16 − a probability of bankruptcy between 30–65%;
Z Conan and Holder > 0.16 − a probability of bankruptcy of <30%.

3.2.3. Springate's Model (zs)

This Canadian business insolvency prediction model was developed in 1978 at Simon Fraser University by Gordon L.V. Springate, following procedures developed by Altman in the US data. Springate (1978) used step-wise multiple discriminate analysis to select four out of 19 popular financial ratios that best distinguished between sound business and those that actually failed. This insolvency prediction model achieved an accuracy rate of 92.5% using the 40 companies tested by Springate.

The Springate model takes the following form:

$$Z\ \text{Springate} = 1.03\ X1 + 3.07\ X2 + 0.66\ X3 + 0.4\ X4 \tag{4}$$

Z Springate = Overall Index Springate

X1 = Working Capital/Total Assets measure of the net liquid assets of the firm relative to the total capitalization.

X2 = Earnings Before Interest and Taxes/Total Assets is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors.

X3 = Earnings before Taxes/Current Liabilities is a measure of the true productivity of the firm's assets, independent of any leverage factors.

X4 = Sales/Total Assets illustrate the sales generating ability of the firm's assets. It is one measure of management's capability in dealing with competitive condition.

The interpretation of Z Springate model is:

Z Springate > 0.826, the company is performant;
Z Springate <= 0.826, the company is bankrupted.

3.2.4. Taffler's Model (ztta)

Taffler (1983) proposed a model based on an extensive survey of the vast array of data. The original model was developed to analyse industrial (manufacturing and construction) companies only with separate models developed for retail and service companies. Using computer technology, 80 carefully selected financial ratios were calculated using accounts of all listed industrial companies failing between 1968 and 1976 and 46 randomly selected solvent industrial firms (Agarwal and Taffler 2007).

This information was processed through a series of statistical methods, and the model was built using multivariate discriminant method. The Z-score model was derived by determining the best set of ratios which, when taken together and appropriately weighted, distinguished optimally between the two samples. Leverage, profitability, liquidity, capital adequacy and other parameters were evaluated for model creation. The model is applicable to companies in the form of joint stock companies, whose shares were subject to public offering and traded on various stock exchanges (Belyaeva 2014).

The Z Taffler model is:

$$Z\ \text{Taffler} = 3.2 + 12.18\ X1 + 2.5\ X2 - 10.68\ X3 + 0.029\ X4 \tag{5}$$

where:

Z Taffler = Overall Index Taffler

X1 = Profit before Tax/Current Liabilities is a measure of the true productivity of the firm's assets, independent of any leverage factors.

X2 = Current Assets/Total Liabilities expresses the payment capacity on short-term of the company, i.e., the ability of current assets to be converted into cash to meet the payment obligations. This ratio estimates the liquidity of the company by showing the company can pay its creditors with its current assets if the company's assets ever had to be liquidated.

X3 = Current Liabilities/Total Assets shows the share of a company's assets which are financed through short-term debt. If the ratio is low, most of the company's assets are financed through equity and long-term debts. If the ratio is high, most of the company's assets are financed through short-term debt.

X4 = (Quick Assets − Current Liabilities)/Daily Operating Expenses with the denominator proxied by: (Sales − Profit Before Tax − Depreciation)/365

The interpretations of Z Taffler model is as follows:

Z Taffler $>$ 0.3 shows that the company has good chances for performance

0.2 $<$ Z Taffler $<$ 0.3 shows the grey zone (undefined area)

Z Taffler $<$ 0.2 shows that the company is almost bankrupt.

Thus, in the case of this model, if the computed Z Taffler score is positive, the firm is solvent and is very unlikely indeed to fail within the next year. However, if its Z Taffler score is negative, it lies in the "at risk" region and the firm has a financial profile similar to previously failed businesses. The high probability of financial distress is depending on how much negative is the Z Taffler score (Agarwal and Taffler 2007).

3.2.5. Zmijewski's Score (zzzmij)

The Zmijewski Score (Zmijewski 1984) is a bankruptcy model used to predict a firm's bankruptcy in two years. Zmijewski (1984) criticised previous models, considering that other bankruptcy scoring models oversampled distressed firms and favoured situations with more complete data.

Thus, in Zmijewski (1984) study, two methodological issues are examined that are related to the estimation of bankruptcy prediction models. The two biases are choice-based sample biases and sample selection biases. The choice based bias is the result of over-sampling distressed firms. When a matched-pair (one-to-one match) design is for a study to predict bankruptcy, the potential of bankruptcy is overstated. This lead to biased probabilities in the models. The sample selection biases occur when the probability of distress given complete data are significantly different from the probability of distress given incomplete data (Avenhuis 2013).

The ratio used in the Zmijewski (1984) score was determined by probit analysis (probit should be regarded as probability unit) in order to construct the bankruptcy prediction model. Like the logit function, the probit function maps the value between 0 and 1, and, in this case, scores greater than 0.5 represent a higher probability of default. The accuracy rate of the Zmijewski (1984) model for the estimation sample was 99%.

The constructed probit function with the variables and estimated coefficients from the study of Zmijewski (1984) is as follows:

$$Z\ \text{Zmijewski} = -4.336 - 4.513\ X1 + 5.679\ X2 + 0.004\ X3 \tag{6}$$

where:

Z Zmijewski = Overall Zmijewski Index

X1 = Net Income/Total Assets is a profitability ratio that measures the net income produced by total assets during a period by comparing net income to the average total assets.

X2 = Total Liabilities/Total Assets shows the share of a company's assets which are financed through debt. If the ratio is less than 0.5, most of the company's assets are financed through equity. If the ratio is greater than 0.5, most of the company's assets are financed through debt.

X3 = Current Assets/Current Liabilities expresses the payment capacity on short-term of the company.

While Altman used the ratio Earnings before Interest and Taxes (EBIT)/Total Assets for profitability, where EBIT eliminates the effect of different capital structures and of taxation and make easier the comparing of the firm profitability, Zmijewski (1984) used the ratio: Net Income/Total Assets, thus considering the effects of funding sources used and of the firm taxation.

Zmijewski (1984) classified the companies thus:

(i) Firms with probabilities greater than or equal to 0.5 were classified as bankrupt or having complete data.
(ii) Firms with probabilities less than 0.5 were classified as non-bankrupt or having incomplete data.

3.3. Principal Component Analysis

There exist many indicators in financial analysis which allow to assess the risk of bankruptcy of a company (Armeanu et al. 2012; Armeanu and Cioaca 2015; Cultrera et al. 2017; Arroyave 2018; Prusak 2018).

In order to make an appropriate assessment, we need to reduce the number of indicators. A solution is indicated by Armeanu et al. (2012): using Principal Component Analysis (PCA), cluster and discriminant analysis techniques. The authors used these three methods to build a scoring function and afterwards to identify bankrupt companies. Their sample consisted on listed companies on Bucharest Stock Exchange. Heffernan (2005) points that bankruptcy risk predicting models, developed based on discriminant analysis (like Altman and Conan-Holder) can easily mislead. This is due to the fact that they rely on historical data, but also on the fact that the result is binary (either the debtor is solvent or not). However, in the present article we consider the following possible scenarios (Armeanu et al. 2012; Armeanu and Cioaca 2015): delays in monthly repayments, failure to pay them, failure to pay fees or penalty interest, and so on, and that is why we rely on large companies' data. Discriminant analysis models may not include the state of solvency, insolvency and restructuring at once, and we would like to infer about it using principal component analysis jointly with discriminant analysis. PCA methods are less recognized in the literature to predict bankruptcy risk (Cultrera et al. 2017).

We use PCA based on the five discriminant analysis measures identified previously in Section 3.2. Software Stata is used for studying the effect of performance over risk and bankruptcy scores were obtained by year of analysis and country. Descriptive statistics of this data and Pearson correlation values considering country scores and year scores are presented in tables presented in Section 4.

3.4. Econometric Methodologies

In order to analyse the effects of risk scores over firm performance, we applied a dynamic panel-data estimation model, with GMM estimators to regress earnings before interest and taxes to total assets over risk by year. By doing so in a Generalized Method of Moments (GMM) context, we may construct more efficient estimates of the dynamic panel data model (these models contain one or more lagged dependent variables, allowing for the modelling of a partial adjustment mechanism). In the context of panel data, we usually must deal with unobserved heterogeneity. Static models are (almost) always misspecified, because the within-group error terms are serially correlated, thereby invalidating both point estimates and statistical inference. Conversely, dynamic models tend to be correctly specified, because the dynamics are in the estimated part of the model rather than displaced into the error terms, which invalidates static FE/RE estimation. Dynamic models are much richer in economic content by virtue of being able to distinguish short-run and long-run effects of independent variables on dependent variables.

Additionally, we used Tobit models to infer about the influence of company performance measures over general bankruptcy risk scores. The Tobit model, also called a censored regression model, is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable. Our dependent variable is censored from both below and above provided we have limited the risk variable to be between −3 and 3, inclusively. Tobit models to predict bankruptcy have also been used by Sigrist and Hirnschall (2019) recently. The assumption of the Tobit model is that there exists a latent variable Y* which follows, conditional on some covariates X a Gaussian distribution: $Y^{*}|X \sim N\left(F(X), \sigma^{2}\right)$. The mean F(X) is assumed to depend linearly on the covariates X through $F(X) = X^{T}\beta$ where β is a set of coefficients. This latent variable Y* is observed only if it lies in an interval. Mousavi et al. (2019) used instead of PCA, a DEA model to measure the operational efficiency scores of Japanese companies, in the first step. In the second step, the efficiency score is used as the dependent variable in a Tobit regression to investigate whether corporate governance variables influence the operational efficiency of firms.

4. Results and Discussion

As we presented in the Section 3.1, in this study we used data from European large companies where insolvencies are more present. Figure 1 plots the frequency of corporate insolvencies in Europe by country for 2018 (Euler Hermes Economic Research 2019). We can see that the first place in the frequency of bankruptcies was occupied by France (with 26.02%) corresponding to 54,965 companies bankrupted, followed by United Kingdom with 10.26% frequency corresponding to 21,669 companies bankrupted and 9.16% to Germany with 19,350 companies bankrupted. In our sample we used a great part of these countries. As we are able to observe, among countries with a high number of corporate insolvencies were also Italy, Belgium, Romania, Denmark, Sweden, Hungary, Norway, and Austria. From the countries used in our sample, France, United Kingdom, Germany, Turkey, Italy, Belgium, Romania, Denmark and Sweden were in the top ten of the Frequency of corporate insolvencies in Europe in 2018 (Figure 1).

Table 1 presents the number of companies from EU-28 countries included in the sample. We can observe that a high number of firm-year observations from large companies came from United Kingdom i.e., 28.60% of all observations analysed (also the country with the second number of bankruptcies), followed by Germany with 16.17%, Italy with 11.49%, France with 9.97% and Spain with 7.28%. Related to the number of firm-year observations of large companies by years, we can observe that the highest number of observations was in 2014 (18,513 companies) and 2013 (18,395 companies), respectively 12.02% and 11.94% of the sample analysed.

Table 2 presents the data descriptive statistics for the variables used for calculation of Z score for all five models used. In average, the companies from the sample show a need of exploitation capital of 14% by the total assets, an operational profitability of 6%, a rotation speed of assets 1.48 times per year, a current liquidity by 2.31 showing the capacity to pay debts by converting of assets in cash, the share of financial expenditure of 0.11% by sales, the share of personnel expenses of 69% in value added and a degree of debts of 64% by total assets. In addition, from Table 2 it is visible the disparity of values of mean and standard deviation of the bankruptcy measures. Moreover, the different number of observations considered for both the creation of financial ratios as well as bankruptcy indicators of interest are clearly visible.

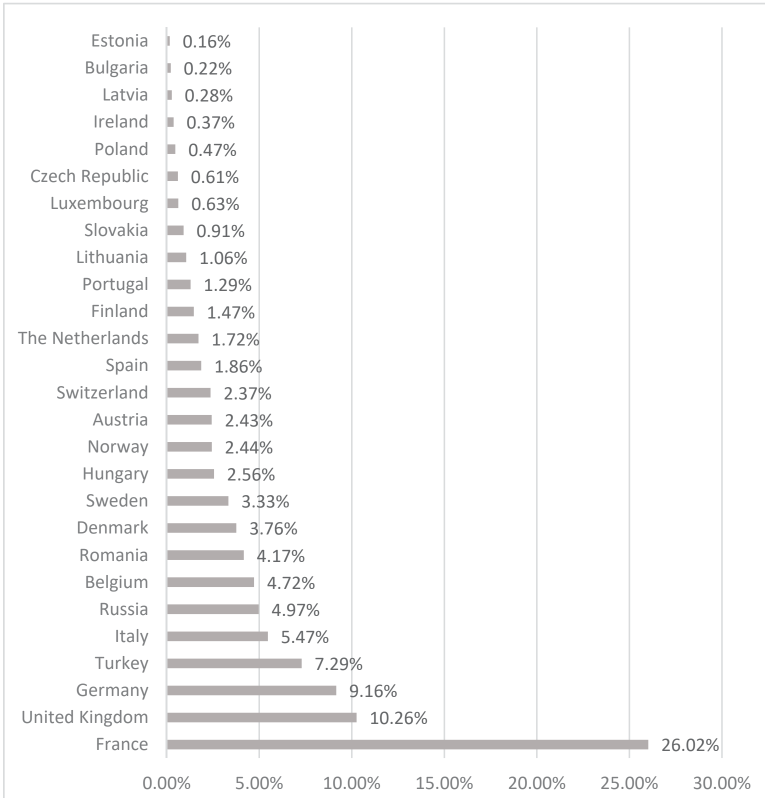

Figure 1. Frequency of corporate insolvencies in Europe, by country in 2018. Source: Euler Hermes Economic Research. 2019. Insolvency Outlook. Euler Hermes, Allianz, Economic Research, 1–14 January 2019. Own elaboration.

Table 1. Total number of companies within the sample by country and year.

Acronym	Country	Number Companies	Frequency	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
AT	Austria	2175	1.41%	1	56	5	96	340	372	380	401	428	96
BE	Belgium	5956	3.87%	579	535	604	610	618	626	633	636	639	476
BG	Bulgaria	1119	0.73%	101	92	110	110	106	119	120	120	121	120
CZ	Czech Republic	4270	2.77%	407	370	393	448	460	482	490	493	461	266
DE	Germany	24,917	16.17%	2105	2276	2603	2758	2908	3039	3106	3172	2667	283
ES	Spain	11,213	7.28%	1096	993	1179	1194	1228	1261	1285	1304	1298	375
FI	Finland	2304	1.50%	193	208	213	231	229	244	250	254	264	218
FR	France	15,356	9.97%	1775	1595	1560	1413	1593	1395	1114	1654	2099	1158
GB	Great Britain (UK)	44,060	28.60%	3558	3811	4078	4324	4612	4913	5155	5392	5550	2667
GR	Greece	1741	1.13%	167	131	177	188	191	192	194	194	193	114
HR	Croatia	1190	0.77%	101	96	116	117	125	126	127	128	128	126
HU	Hungary	1849	1.20%	42	137	212	223	236	230	235	237	173	124
IE	Ireland	1482	0.96%	97	136	140	145	171	175	189	198	194	37
IT	Italy	17,697	11.49%	1750	1519	1802	1828	1855	1930	1947	1979	1974	1113
NL	The Netherlands	5868	3.81%	345	471	258	597	500	705	785	817	879	511
PL	Poland	1668	1.08%	163	165	182	198	187	154	157	171	196	95
PT	Portugal	2555	1.66%	222	215	248	255	267	281	288	287	271	221
RO	Romania	2144	1.39%	234	64	0	0	297	303	310	311	322	303
SE	Sweden	5115	3.32%	475	476	548	570	517	506	512	524	537	450
SK	Slovakia	1382	0.90%	136	130	154	162	159	141	141	123	119	117
Total		154,061		13,547	13,476	14,582	15,467	16,599	17,194	17,418	18,395	18,513	8870

Source. Performed by the authors based on data provided by Amadeus database.

Table 2. Variables, formulas, and descriptive statistics.

Formula	Variable	Obs	Mean	Std. Dev.	Min	Max
Working capital/Total assets	wcta	153,459	0.14	0.76	−198.44	113.86
Retained Earnings/Total Assets	reta	148,986	0.24	1.29	−364.35	274.07
EBIT/Total assets	ebitta	153,459	0.06	0.24	−42.14	61.11
Book Value of Equity/Book Value of Total Debt	bvebvtd	153,278	2.44	176.82	−657.29	50,409.00
Sales/Total assets	sta	153,459	1.48	3.99	0.00	1322.52
Revised Z Altman	rza	148,821	3.02	75.50	−306.70	21,172.06
EBIT/Current liabilities	ebitcliabil	151,123	240.93	101,682.60	−4,900,820.00	38,700,000.00
Permanent capital/Total debts	ppi	153,278	2.77	176.83	−656.29	50,410.00
(Current assets − Stocks)/Total Liabilities	curnt	153,278	2.31	172.72	−38.15	45,178.00
Financial expenditures/Sales	fs	145,515	0.11	8.93	−1.11	2169.55
Personnel Expenditures/Added Value	pexpenditura	140,104	0.69	3.81	−609.22	440.32
Z Connan	zcc	135,073	64.97	25,813.04	−1,176,196.00	9,298,852.00
Working capital/Total assets	wcta_1	153,459	0.14	0.76	−198.44	113.86
Earnings Before Interest and Taxes/Total Assets	ebitta_1	153,459	0.06	0.24	−42.14	61.11
Earnings Before Taxes/Current Liabilities	ebtcl	151,096	229.24	103,167.50	−5,151,934.00	39,400,000.00
Sales/Total Assets	sta_1	153,459	1.48	3.99	0.00	1322.52
Z Springate Model	zs	151,096	152.23	68,090.55	−3,400,276.00	26,000,000.00
Profit Before Tax/Current Liabilities	pbtcl	151,096	229.24	103,167.50	−5,151,934.00	39,400,000.00
Current Assets/Total Liabilities	cat	153,278	2.89	219.41	−39.30	55,223.00
Current Liabilities/Total Assets	clt	153,459	0.43	0.75	−113.76	199.44
(Quick Assets − Current Liabilities)/(Sales − Profit Before Tax − Depreciation)/365	qaclspbtd	144,735	−792,000,000,000	301,000,000,000,000	−115,000,000,000,000,000	10,200,000
Z Taffler	ztta	144,730	−23,000,000,000	8740,000,000,000	−3,320,000,000,000,000	47,900,0000
Net Income/Total Assets	nincomt	153,459	0.04	0.26	−62.33	26.68
Total Liabilities/Total Assets	tliat	153,432	0.64	1.12	−71.28	390.32
Current Assets/Current Liabilities	cac	151,123	−653.97	403,912.70	−90,700,000.00	84,800,000.00
Z Zmijewski	zzzmij	151,118	−3.44	1615.68	−362,744.00	339,315.60

Source. Performed by the authors based on data provided by Amadeus database.

Tables A1 and A2 (at the Appendix A) presents the correlation matrix among the variables used both to produce the bankruptcy risk indicators and the five bankruptcy risk scores. In addition, Tables A1 and A2 presents the Pearson correlation values and statistical significance. From here it is seen that there are ratios used to produce the bankruptcy indicators which are highly correlated among them, significantly, with negative or positive correlation (i.e., strong positive significant correlation (0.821) between Book Value of Equity/Book Value of Total Debt and Current Assets/Total Liabilities; strong positive significant correlation (0.778) between Book Value of Equity/Book Value of Total Debt and (Current assets − Stocks)/Total Liabilities, almost perfect positive correlation (0.998) between EBIT/Current liabilities and Profit Before Tax/Current Liabilities etc.), but mostly have low to moderate correlation. However, between bankruptcy indicators constructed through discriminant analysis, correlation values are very low, and very close to zero with statistical significance.

Table 3 indicates that after applying PCA, the number of observations decreased as compared to Table 2. In fact, by restricting the sample to all those values obtained for the general risk score greater than 3 or smaller than 3, our sample was reduced to 133,751 firm-year observations. Risk is the score computed through PCA considering all companies, years and countries.

Table 3. Descriptive Statistics of scores computed based over Principal Component Analysis (PCA).

Variable	Obs	Mean	Std. Dev.	Variable	Obs	Mean	Std. Dev.
risk	133,751	−0.00331	0.004657	riskAT	133,751	−0.23914	3.094626
risk2015	133,751	0.004167	0.006804	riskBE	133,751	0.433947	50.73316
risk2014	133,751	−0.01011	0.001642	riskBG	133,751	0.485776	14.48578
risk2013	133,751	0.264434	26.89755	riskCZ	133,751	0.555987	60.98777
risk2012	133,751	0.006104	1.469264	riskDE	133,751	−0.01741	0.468755
risk2011	133,751	0.085679	9.797604	riskES	133,751	0.188694	3.364935
risk2010	133,751	0.001579	1.400829	riskFI	133,751	1.197073	115.5954
risk2009	133,751	0.012124	2.556249	riskFR	133,751	−0.00996	0.00155
risk2008	133,751	0.029394	3.814389	riskGB	133,751	0.731819	71.07321
risk2007	133,751	−0.00539	0.608735	riskHR	133,751	0.226101	3.129303
risk2006	133,751	−0.01938	0.606729	riskHU	133,751	0.158191	19.79164
				riskIE	133,751	0.061467	10.7725
				riskIT	133,751	0.297428	2.719817
				riskNL	133,751	−0.29214	3.178018
				riskPL	133,751	−0.07491	3.281825
				riskPT	133,751	3.345667	299.3375
				riskRO	133,751	1.151802	109.7751
				riskSE	133,751	−0.30931	3.435378
				riskSK	133,751	0.317604	36.03616

Source. Performed by the authors based on data provided by Amadeus database.

Overall, countries presented higher mean scores as well as negative mean for some countries, and also standard deviation is higher for countries scores. A plot of year bankruptcy risk scores will allow us to see their behaviour along years. Figure 2 presents these data evolution for countries. After the final data treatment, the total number of companies available to analyse by country and year are presented in Table 4.

Correlation values (Table 5) seem to be very strong among Austria and Spain, Croatia, Italy, the Netherlands, Poland and Sweden; strong (higher than 90% and positive; some near perfect linear positive correlation) between Belgium, Czech Republic, Germany, Finland, France, Great Britain, Hungary, Portugal, Romania, and Slovakia; Bulgaria and Ireland; Germany, Finland, France, Great Britain, Hungary, Portugal, Romania, and Slovakia; Spain, Croatia, Italy, the Netherlands, Poland, and Sweden; Finland, France, Great Britain, Hungary, Portugal, Romania, and Slovakia; between France, Great Britain, Hungary, Portugal, Romania and Slovakia; among Great Britain and Hungary, Portugal, Romania, and Slovakia; Croatia, Italy, the Netherlands, Poland, and Sweden; between Hungary, Portugal, Romania, and Slovakia; Italy, Poland, and Sweden; the Netherlands, Poland and Sweden; Between Poland and Sweden; Portugal, Romania, and Slovakia; and finally between Romania and Slovakia. As such, no clear pattern is identified regarding for instant the geographic distance among the countries, but high correlation values maybe due to commercial transactions performed among these countries.

Regarding year, whose correlation values are presented in Table 6, the score Pearson correlation values were very high, near to one and positive. In the next we will be analysing the evolution plots of scores of bankruptcy risk by country and by year. Figures 2 and 3 present these evolutions respectively.

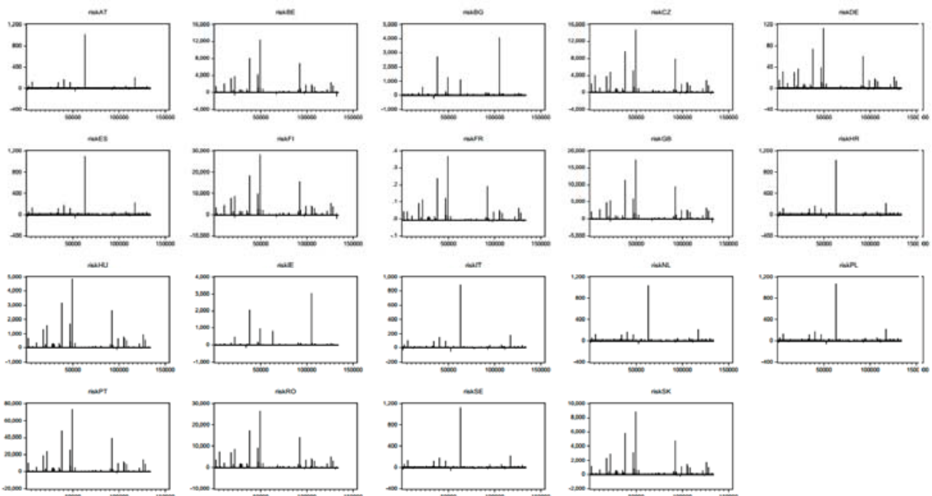

Figure 2. Plot of scoring bankruptcy risk by country. Source. Performed by the authors based on data provided by Amadeus database.

Table 4. Number of firms after limiting the risk values by country and year.

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
AT	1	0	4	90	315	347	352	363	396	80	1948
BE	576	463	600	606	613	620	628	634	635	471	5846
BG	95	65	107	104	102	119	120	120	121	120	1073
CZ	403	273	388	445	455	480	488	490	459	265	4146
DE	2018	1693	2501	2664	2840	2973	3042	3113	2613	273	23,730
ES	1086	760	1167	1172	1213	1241	1269	1286	1280	367	10,841
FI	155	138	174	186	194	204	207	211	223	170	1862
FR	1738	1265	1542	1389	1572	1381	1095	1633	2064	1132	14,811
GB	3217	2772	3702	3884	4078	4363	4553	4773	4890	2347	38,579
HR	100	64	116	117	124	124	126	127	128	126	1152
HU	36	99	202	212	220	217	222	224	162	115	1709
IE	89	93	125	127	149	153	170	166	160	30	1262
IT	1746	1221	1798	1825	1855	1930	1946	1976	1973	1113	17,383
NL	239	199	55	16	13	17	25	29	26	0	619
PL	72	52	76	85	75	51	59	61	83	17	631
PT	221	141	245	253	259	270	274	264	257	205	2389
RO	152	0	0	0	297	303	310	311	322	303	1998
SE	218	205	269	282	244	245	249	261	273	240	2486
SK	130	94	149	153	128	139	139	121	117	116	1286
Total	12,292	9597	13,220	13,610	14,746	15,177	15,274	16,163	16,182	7490	133,751

Source. Performed by the authors based on data provided by Amadeus database.

Table 5. Pearson correlation values among scoring PCA bankruptcy risk variables obtained by country.

Score	riskAT	riskBE	riskBG	riskCZ	riskDE	riskES	riskFI	riskFR	riskGB	riskHR	riskHU	riskIE	riskIT	riskNL	riskPL	riskPT	riskRO	riskSE	riskSK
riskAT	1																		
riskBE	0.093 ***	1																	
riskBG	0.037 ***	0.337 ***	1																
riskCZ	0.093 ***	0.998 ***	0.363 ***	1															
riskDE	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1														
riskES	0.997 ***	0.016 ***	0.008 ***	0.016 ***	0.016 ***	1													
riskFI	0.093 ***	1.000 ***	0.337 ***	0.998 ***	0.998 ***	0.016 ***	1												
riskFR	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1.000 ***	0.016 ***	0.998 ***	1											
riskGB	0.093 ***	1.000 ***	0.337 ***	0.998 ***	0.998 ***	0.016 ***	1.000 ***	0.998 ***	1										
riskHR	1.000 ***	0.098 ***	0.039 ***	0.098 ***	0.098 ***	0.997 ***	0.098 ***	0.098 ***	0.098 ***	1									
riskHU	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1.000 ***	0.016 ***	0.998 ***	1.000 ***	0.998 ***	0.098 ***	1								
riskIE	0.037 ***	0.337 ***	1.000 ***	0.363 ***	0.363 ***	0.008 ***	0.337 ***	0.363 ***	0.337 ***	0.039 ***	0.363 ***	1							
riskIT	0.982 ***	−0.098 ***	−0.032 ***	−0.098 ***	−0.098 ***	0.994 ***	−0.098 ***	−0.098 ***	−0.098 ***	0.981 ***	−0.098 ***	−0.032 ***	1						
riskNL	0.997 ***	0.174 ***	0.065 ***	0.174 ***	0.174 ***	0.987 ***	0.174 ***	0.174 ***	0.174 ***	0.997 ***	0.174 ***	0.065 ***	0.963 ***	1					
riskPL	1.000 ***	0.085 ***	0.033 ***	0.085 ***	0.085 ***	0.998 ***	0.085 ***	0.085 ***	0.085 ***	0.999 ***	0.085 ***	0.033 ***	0.983 ***	0.996 ***	1				
riskPT	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1.000 ***	0.016 ***	0.998 ***	1.000 ***	0.998 ***	0.098 ***	1.000 ***	0.363 ***	−0.098 ***	0.174 ***	0.085 ***	1			
riskRO	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1.000 ***	0.016 ***	0.998 ***	1.000 ***	0.998 ***	0.098 ***	1.000 ***	0.363 ***	−0.098 ***	0.174 ***	0.085 ***	1.000 ***	1		
riskSE	0.999 ***	0.071 ***	0.029 ***	0.071 ***	0.071 ***	0.999 ***	0.071 ***	0.071 ***	0.071 ***	0.999 ***	0.071 ***	0.029 ***	0.986 ***	0.995 ***	0.999 ***	0.071 ***	0.071 ***	1	
riskSK	0.093 ***	0.998 ***	0.363 ***	1.000 ***	1.000 ***	0.016 ***	0.998 ***	1.000 ***	0.998 ***	0.098 ***	1.000 ***	0.363 ***	−0.098 ***	0.174 ***	0.085 ***	1.000 ***	1.000 ***	0.071 ***	1

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, ***, represent statistically significant at 10%, 5% and 1%, respectively.

Table 6. Pearson correlation variables among scoring PCA bankruptcy risk variables obtained by year.

Scores	risk	risk2015	risk2014	risk2013	risk2012	risk2011	risk2010	risk2009	risk2008	risk2007	risk2006
risk	1										
risk2015	1.000 ***	1									
risk2014	1.000 ***	1.000 ***	1								
risk2013	1.000 ***	1.000 ***	1.000 ***	1							
risk2012	1.000 ***	1.000 ***	1.000 ***	1.000 ***	1						
risk2011	0.998 ***	0.998 ***	0.998 ***	0.998 ***	0.998 ***	1					
risk2010	1.000 ***	1.000 ***	1.000 ***	1.000 ***	1.000 ***	0.998 ***	1				
risk2009	1.000 ***	1.000 ***	1.000 ***	1.000 ***	1.000 ***	0.998 ***	1.000 ***	1			
risk2008	0.998 ***	0.998 ***	0.998 ***	0.998 ***	0.998 ***	1.000 ***	0.998 ***	0.998 ***	1		
risk2007	1.000 ***	1.000 ***	1.000 ***	1.000 ***	1.000 ***	0.998 ***	1.000 ***	1.000 ***	0.998 ***	1	
risk2006	1.000 ***	1.000 ***	1.000 ***	1.000 ***	1.000 ***	0.998 ***	1.000 ***	1.000 ***	0.998 ***	1.000 ***	1

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, ***, represent statistically significant at 10%, 5% and 1%, respectively.

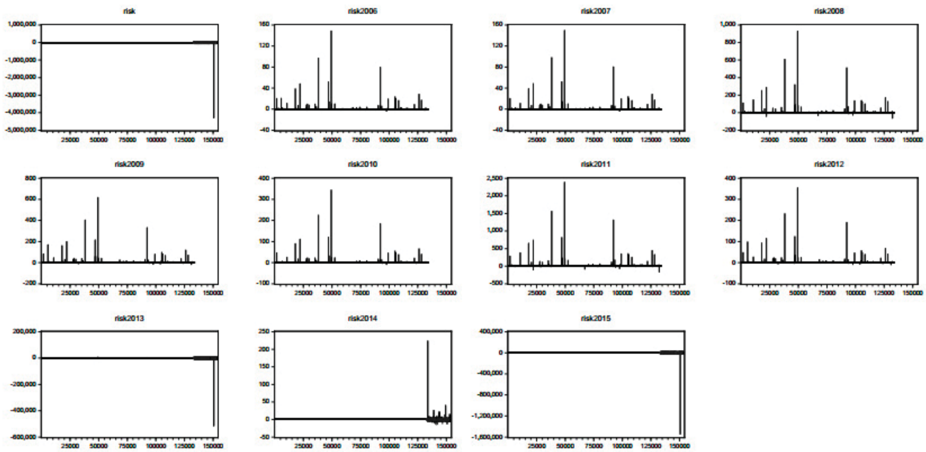

Figure 3. Plot of scoring bankruptcy risk by year. Source. Performed by the authors based on data provided by Amadeus database.

Figure 2 plots the evolution of the score values obtained through PCA from the discriminant indices calculous by country. There are some countries which evidence a very similar behaviour like Belgium, Czech Republic, Finland, France, Great Britain, Hungary, Portugal, Romania, Slovakia and Germany. Another group of similar behaviour in terms of scores is that of Austria, Spain, Italy, Croatia, the Netherlands, Poland and Sweden. The two other similar countries in terms of scores are Ireland and Bulgaria.

Regarding years, the years 2006 until 2012 were very similar years in terms of score behaviour. As such, unstable values are more observed in these years with peaks and downs, which included all countries. In the following we decided to apply first a dynamic panel-data model by regressing the ratio EBIT over Total Assets in the bankruptcy scoring variables by year and a probit estimation considering as dependent variable risk and as independent variables firm performance measures.

Table 7 presents the estimation results of the panel-data model.

Table 7. Dynamic panel data results.

Dynamic Panel-Data Estimation			
Wald chi2(4)		8.04	
Prob > chi2		0.0901	
ebitta	Coef.	z	P > |z|
risk2014	310280	2.04	0.041
risk2013	−9.35136	−2	0.045
risk2011	−0.03367	−0.33	0.743
risk2009	−101.797	−2.08	0.038
GMM-type:	L(2/.).wcta		

Source. Performed by the authors based on data provided by Amadeus database.

The dynamic panel data results indicate that the only score risk variables which have not been omitted due to collinearity issues were the risk measures for years 2014, 2013, 2011 and 2009. The years 2009 until 2011 are characterized by the financial crisis which has spread out through Europe, having a negative influence over firm performance as measured by the ratio of Earnings Before Interest and Taxes and Total Assets, but with significance only for the year 2009 at 5%.

Aleksanyan and Huiban (2016) study confirm also the dramatic increase in bankruptcy risk in the French food industry observed over the period 2010–2012, highlighting that among food industry sub-sectors, the meat industry was primarily responsible for the evolution of bankruptcy risk in the period mentioned.

The years of 2013 and 2014 were years of starting recovery, and we might infer from the results that despite the negative influence of 2013 risk score over performance, in 2014 we already have a positive contribution of bankruptcy risk score over performance, both years with statistical significance at 5%.

Table 8 reports the Tobit estimation results for general risk among countries, while Table 9 presents the same Tobit estimation results but this turn by country. This turn we are testing the influence of performance measures over risk scores since we are analysing the dependent censored variable risk.

Table 8. Tobit estimation results.

Tobit Regression: Dependent = Risk						
	Coef	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00012 **	2.05	0.041	0.00019 *	1.90	0.057
sta				0.000006	0.96	0.339
wcta				0.0001 ***	3.68	0.000
const	−0.00332	−250.91	0.000	−0.00334 ***	−213.66	0.000
	LR chi2	4.19		LR chi2	18.9	
	prob chi2	0.0406		prob chi2	0.0003	

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, *** statistically significant at 10%, 5% and 1%, respectively. Ebitta = earnings before interest and taxes (ebit)/total assets; sta = sales/total assets; wcta = working capital/total assets.

Model significance was confirmed at 5% and results seem to indicate that performance measures positively influence risk scores. Thus the higher the performance is the higher will be the risk score and as such bankruptcy risk decreases with performance, a result which was expected. Bankruptcy is one of the most discussed topics in the literature, owing to its importance to the economy of any country. Bankruptcy costs are high and authors have tried to develop bankruptcy prediction models through years. Our scoring methodology through PCA applied to discriminant analysis of bankruptcy risk therefore indicates that performance is the solution to decrease this risk.

Discriminant analysis of bankruptcy risk argues that positive high values of bankruptcy risk positions companies in the safe zone, meaning a low risk of bankruptcy or a probability of bankruptcy lower than 30% (zcc index). Lower values positions firms between the grey zones or in the distress zone (see Section 3.2). Therefore, we may argue that for our sample of firms, these large companies had good chances for performance provided their higher results, thus being non-bankrupt or with lower chances to become so. However, these results depended on the year of analysis provided that Table 7 demonstrates that 2009, 2011 and 2013 were years of negative influence of bankruptcy risk scores over companies' results.

Company performance variables were all statistically significant and with a positive impact over the bankruptcy risk score in Austria, Bulgaria, Spain, Finland, Great Britain, Croatia, Ireland, Italy, The Netherlands, Portugal, Romania, and Sweden. The ratio sales to total assets had a negative and non-significant impact over the risk score in Belgium, Czech Republic, Hungary and Slovakia. It is positive and non-significant in Poland and France. The only countries where performance (independently of its measure) did not seem to exert an influence over the bankruptcy risk score were Germany and Poland.

Since Germany is on the top ten of the number of corporate insolvencies, this might mean that other corporate variables despite the ones considered here to represent performance in our analysis, might be influencing bankruptcy risk scores under the years in analysis. The Principal Component Analysis here employed to build a bankruptcy risk scored based on discriminant analysis indices was found to be effective for determining the influence of corporate performance over risk. It was useful to understand that different countries evidence different results regarding this influence, as well as different risk scores with respect to years reveal to be different. It could be useful to understand this impact in the future by using other scoring techniques, like data envelopment analysis, or even by detailing years and countries analysis.

Table 9. Tobit estimation results by country.

Tobit Regression: Dependent = Risk									
	AT = Austria			**BE = Belgium**			**BG = Bulgaria**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00060 ***	39.82	0.0000	−0.00017	−0.53	0.598	0.00007 ***	19.19	0.0000
sta	0.000002 ***	8.01	0.0000	−0.00002	−0.89	0.375	0.000002 ***	4.30	0.0000
wcta	0.000032 ***	36.01	0.0000	0.00018 *	1.83	0.067	0.00004 ***	15.75	0.0000
const	−0.00337 ***	−6822.46	0.0000	−0.00332 ***	−74.97	0	−0.00337 ***	−3544.58	0.0000
LR chi2		2114.45			4.50			646.96	
prob chi2		0.0000			0.2126			0.0000	
	CZ = Czech Republic			**DE = Germany**			**ES = Spain**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00020 ***	26.54	0.0000	0.00056	0.90	0.3710	0.00007 ***	5.04	0.0000
sta	−0.00000	−0.77	0.4440	−0.00006	−1.09	0.2760	0.000003 *	1.93	0.0530
wcta	0.00004 ***	12.80	0.0000	0.00011	1.38	0.1660	0.00002 ***	3.12	0.0020
const	−0.00337 ***	−2204.68	0.0000	−0.00310 ***	−27.57	0.0000	−0.00337 ***	−1570.65	0.0000
LR chi2		3370.88			3.62			53.54	
prob chi2		0.0000			0.3060			0.0000	
	FI = Finland			**FR = France**			**GB = Great Britain (UK)**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00011 ***	19.32	0.0000	0.00102 **	2.37	0.0180	0.00005 ***	15.28	0.0000
sta	0.000004 ***	8.10	0.0000	0.00006	1.37	0.1720	0.000003 ***	6.45	0.0000
wcta	0.00003 ***	8.97	0.0000	0.00005	1.09	0.2770	0.00003 ***	15.21	0.0000
const	−0.00338 ***	−2800.20	0.0000	−0.00345 ***	−39.57	0.0000	−0.00337 ***	−4094.65	0.0000
LR chi2		527.87			9.77			787.56	
prob chi2		0.0000			0.0206			0.0000	
	HR = Croatia			**HU = Hungary**			**IE = Ireland**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00006 ***	10.42	0.0000	0.00014 **	2.21	0.0270	0.00008 ***	26.52	0.0000
sta	0.000004 ***	5.64	0.0000	−0.00000	−0.07	0.9450	0.000003 ***	7.28	0.0000
wcta	0.00003 ***	13.65	0.0000	0.00011 ***	4.97	0.0000	0.00003 ***	27.08	0.0000
const	−0.00337 ***	−3219.78	0.0000	−0.00337 ***	−293.47	0.0000	−0.00337 ***	−5373.66	0.0000
LR chi2		476.75			34.35			1265.69	
	IT = Italy			**NL = The Netherlands**			**PL = Poland**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00004 ***	5.25	0.0000	0.00006 ***	14.94	0.0000	0.00009	0.90	0.3710
sta	0.000004 ***	4.41	0.0000	0.000003 ***	9.42	0.0000	0.000012	1.28	0.2010
wcta	0.00004 ***	11.45	0.0000	0.00003 ***	12.46	0.0000	0.00005	1.26	0.2100
const	−0.00338 ***	−2531.81	0.0000	−0.00337 ***	−4554.27	0.0000	−0.00339 ***	−214.04	0.0000
LR chi2		247.05			428.15			6.47	
prob chi2		0.0000			0.0000			0.0909	
	PT = Portugal			**RO = Romania**			**SE = Sweden**		
Indep.	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**	**Coef**	**t**	**p > t**
ebitta	0.00006 ***	31.90	0.0000	0.00004 ***	13.50	0.0000	0.00007 ***	30.34	0.0000
sta	0.000005 ***	20.11	0.0000	0.000002 ***	5.15	0.0000	0.000002 ***	5.92	0.0000
wcta	0.00002 ***	36.12	0.0000	0.00002 ***	10.94	0.0000	0.00003 ***	19.77	0.0000
const	−0.00337 ***	−0.0001	0.0000	−0.00337 ***	−4030.59	0.0000	−0.00337 ***	−4809.04	0.0000
LR chi2		2477.79			815.74			1272.57	
prob chi2		0.0000			0.0000			0.0000	

SK = Slovakia			
Indep.	**Coef**	**t**	**p > t**
ebitta	0.00010 ***	3.40	0.0010
sta	−0.000002	−0.53	0.5970
wcta	0.00006 ***	4.65	0.0000
const	−0.00336 ***	−539.59	0.0000
LR chi2		52.95	
prob chi2		0.0000	

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, *** statistically significant at 10%, 5% and 1%, respectively. Ebitta = earnings before interest and taxes (ebit)/total assets; sta = sales/total assets; wcta = working capital/total assets.

5. Conclusions

The purpose of this paper was to improve the knowledge of bankruptcy prediction of companies and to analyse the predictive capacity of factor analysis based over discriminant analysis using five models for assessing bankruptcy risk well-known in the literature: Altman, Conan and Holder, Tafler, Springate and Zmijewski. We used data for non-financial large companies from Europe for the period 2006–2015. In order to analyse the effects of risk scores over firm performance, we applied a dynamic panel-data estimation model, with GMM estimators to regress firm performance indicator over risk by year and we used Tobit models to infer about the influence of company performance measures over general bankruptcy risk scores by country. In summary, results evidence that PCA used to build a bankruptcy risk scored based on discriminant analysis indices is effective for determining the influence of corporate performance over risk.

Results reveal a negative influence of risk scores over firm performance in the financial crisis years of 2009–2011. However, bankruptcy risk scores increase performance (as measured through the ratio Earnings before Interest and Taxes over Total Assets) in the upcoming years of recovery, especially from 2014 onwards. These results were obtained by applying dynamic panel data estimations. Afterwards, using Tobit estimations we analyze the influence of performance measures over risk score (the variable risk was censored between three, negative and positive, inclusively). The higher the performance the higher the risk score, meaning the lower the bankruptcy risk probability. The scoring methodology through PCA applied to discriminant analysis of bankruptcy risk indicators used to obtain the bankruptcy risk scores by year and country highlight that higher performance is the solution to decrease bankruptcy risk.

Therefore, and provided that bankruptcy can be caused by poor management, improper sales forecasting, inexperienced management, rapid technological advances, preference changes, and inability of the firm to follow as a leader in these changes, our sample of large companies in Europe and results obtained lead us to conclude that firms' strategy is vital in terms of market survival. The literature already points that better corporate governance simultaneously improve firm performance and reduce firm risk, especially during crisis (Wang et al. 2019). Our results seem to highlight the importance of good corporate governance as a key indicator for firm performance and lower bankruptcy risk, with clear differences among European countries. In future works we intend to use other scoring techniques to predict bankruptcy risk like data envelopment analysis in order to be able to understand differences among countries and years, and to test the performance of bankruptcy models using different risk build scores.

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Appendix A

Table A1. Pearson Correlation values.

Variable	wcta	reta	ebitta	bvebvtd	sta	rza	ebitcliabil	ppi	curnt	fs	pexpenditura	zcc	wcta_1
wcta	1												
reta	−0.256 ***	1											
ebitta	−0.3086 ***	0.4387 ***	1										
bvebvtd	0.006 **	0.002	−0.002	1									
sta	−0.658 ***	0.394 ***	0.404 ***	−0.004	1								
rza	−0.029 ***	0.040 ***	0.034 ***	0.998 ***	0.055 ***	1							
ebitcliabil	−0.000	0.001	0.000	0.002	−0.001	0.001	1						
ppi	0.008 ***	0.002	−0.002	1.000 ***	−0.004	0.998 ***	0.002	1					
curnt	0.008 ***	0.001	−0.002	0.778 ***	−0.003	0.777 ***	−0.001	0.778 ***	1				
fs	−0.002	−0.003	−0.005 *	0.019 ***	−0.004	0.007 ***	0.000	0.019 ***	0.013 ***	1			
pexpenditura	0.002	−0.004	−0.011 ***	−0.004	0.003	−0.001	−0.000	−0.004	−0.002	−0.002	1		
zcc	−0.000	0.001	0.000	0.005 *	−0.001	0.001	1.000 ***	0.005 *	−0.001	−0.000	−0.000	1	
wcta_1	1.000 ***	−0.256 ***	−0.309 ***	0.006 **	−0.658 ***	−0.029 ***	−0.000	0.008 ***	0.008 ***	−0.002	0.002	−0.000	1
ebitta_1	−0.309 ***	0.439 ***	1.000 ***	−0.002	0.404 ***	0.034 ***	0.000	−0.002	−0.002	−0.005 *	−0.011 ***	0.000	−0.309 ***
ebtcl	−0.000	0.001	0.000	0.002	−0.001	0.001	0.998 ***	0.002	−0.001	0.000	−0.000	0.998 ***	−0.000
sta_1	−0.658 ***	0.394 ***	0.404 ***	−0.004	1.000 ***	0.055 ***	−0.001	−0.004	−0.003	−0.004	0.003	−0.001	−0.658 ***
zs	−0.000	0.001	0.000	0.002	−0.001	0.001	0.998 ***	0.002	−0.001	0.000	−0.000	0.998 ***	−0.000
pbtcl	−0.000	0.001	0.000	0.002	−0.001	0.001	0.998 ***	0.002	−0.001	0.000	−0.000	0.998 ***	−0.000
cat	0.008 ***	0.001	−0.002	0.821 ***	−0.003	0.819 ***	−0.000	0.821 ***	0.996 ***	0.008 ***	−0.002	−0.000	0.008 ***
clt	−0.928 ***	0.246 ***	0.350 ***	−0.006 **	0.715 ***	0.033 ***	−0.001	−0.009 ***	−0.005 **	−0.003	0.002	−0.001	−0.928 ***
qaclspbtd	0.000	−0.002	−0.012 ***	−0.008 ***	0.000	−0.005 *	0.000	−0.009 ***	0.000	0.000	0.000	0.000 ***	0.000
ztta	0.000	−0.002	−0.012 ***	−0.008 ***	0.000	−0.005 *	0.000	−0.009 ***	0.000	0.000	0.000	0.998 ***	0.000
nincomt	0.012 ***	0.354 ***	0.658 ***	−0.000	−0.030 ***	0.010 ***	0.001	−0.000	−0.001	−0.011 ***	−0.009 ***	0.002	0.012 ***
tliat	−0.741 ***	0.341 ***	0.495 ***	−0.006 **	0.824 ***	0.042 ***	−0.001	−0.006 **	−0.005 **	0.000	0.002	−0.001	−0.741 ***
cac	−0.002	0.001	0.001	0.001	−0.000	0.000	0.337 ***	0.001	0.000	0.000	−0.000	0.337 ***	−0.002
zzzmij	−0.005 *	0.002	0.002	0.001	0.003	0.003	0.337 ***	0.001	0.000	0.000	−0.000	0.337 ***	−0.005 *

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, *** represent statistically significant at 10%, 5% and 1% respectively.

Table A2. Pearson Correlation values.

Variable	ebitta_1	ebtcl	sta_1	zs	pbtcl	cat	clt	qaclspbtd	ztta	nincomt	tliat	cac	zzzmij
wcta													
reta													
ebitta													
bvebvtd													
sta													
rza													
ebitcliabil													
ppi													
curnt													
fs													
pexpenditura													
zcc													
wcta_1													
ebitta_1	1												
ebtcl	0.000	1											
sta_1	0.404 ***	−0.001	1										
zs	0.000	1.000 ***	−0.001	1									
pbtcl	0.000	1.000 ***	−0.001	1.000 ***	1								
cat	−0.002	−0.000	−0.003	−0.000	−0.000	1							
clt	0.350 ***	−0.001	0.715 ***	−0.001	−0.001	−0.005 *	1						
qaclspbtd	−0.012 ***	0.000	0.000	0.000	0.000	0.001	0.002	1					
ztta	−0.012 ***	0.000	0.000	0.000	0.000	0.001	0.002	1.000 ***	1				
nincomt	0.658 ***	0.001	−0.030 ***	0.001	0.001	−0.001	0.012 ***	−0.016 ***	−0.016 ***	1			
tliat	0.495 ***	−0.001	0.824 ***	−0.001	−0.001	−0.005 **	0.727 ***	0.001	0.001	0.019 ***	1		
cac	0.001	0.363 ***	−0.000	0.363 ***	0.363 ***	0.000	0.001	0.000 ***	0.000 ***	0.001	−0.001	1	
zzzmij	0.002	0.363 ***	0.003	0.363 ***	0.363 ***	0.000	0.004	0.000	0.000	0.001	0.003	1.000 ***	1

Source. Performed by the authors based on data provided by Amadeus database. Note: *, **, *** represent statistically significant at 10%, 5% and 1% respectively.

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Comparison of Prediction Models Applied in Economic Recession and Expansion

Dagmar Camska * and **Jiri Klecka**

Department of Economics and Management, University of Chemistry and Technology Prague, Technická 5, 166 28 Prague 6, Czech Republic; jiri.klecka@vscht.cz
* Correspondence: dagmar.camska@email.cz

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Abstract: As a rule, the economy regularly undergoes various phases, from a recession up to expansion. This paper is focused on models predicting corporate financial distress. Its aim is to analyze impact of individual phases of the economic cycle on final scores of the prediction models. The prediction models may be used for quick, inexpensive evaluation of a corporate financial situation leading to business risk mitigation. The research conducted is drawn from accounting data extracted from the prepaid corporate database, Albertina. The carried-out analysis also highlights and examines industry specifics; therefore, three industry branches are under examination. Enterprises falling under Manufacture of metal products, Machinery, and Construction are categorized into insolvent and healthy entities. In this study, 18 models are selected and then applied to the business data describing recession and expansion. The final scores achieved are summarized by the main descriptive statistics, such as mean, median, and trimmed mean, followed by the absolute difference comparing expansion and recession. The results confirm the expectations, assuming that final scores with higher values describe better corporate financial standing during the expansion phase. Similar results are achieved for both healthy and insolvent enterprises. The paper highlights exceptions and offers possible interpretations. As a conclusion, it is recommended that users need to respect the current phase of the economic cycle when interpreting particular results of the prediction models.

Keywords: models predicting financial distress; phases of economic cycle; Czech Republic

1. Introduction

Forecasting corporate bankruptcy is a crucial task for modern risk management. The current economic environment shaped by globalization, turbulent economic changes, and fierce competition impose challenging conditions for businesses and their prosperity. Contrariwise, many enterprises do not survive in the long run, and they have to withdraw from the market. The findings of the European Commission (2012) show that almost half of new companies went bankrupt within the first five years of their existence. Although corporate defaults seem natural in a market economy, corporate failures have enormous consequences for whole economic systems (Peng et al. 2010; Lee et al. 2011). The consequences can be recognized not only on the macroeconomic but also on the microeconomic level. The parties affected could be suppliers, customers, managers, employees, investors, governmental bodies, and financial creditors. All of these entities want to mitigate business risks and protect themselves from entering or continuing business activities with potentially default entities.

Prediction of corporate bankruptcy or corporate default has been a significant research issue since the 1960s. Pioneering works were associated with names such as Altman (1968) or Beaver (1966). These efforts have led to the construction of prediction models (also called bankruptcy models or models predicting financial distress). These models provide a controlled description of a particular economic reality. It should not be neglected that these models are never 100% accurate as they work on probability roots based on empirical observations (De Laurentis et al. 2010). The most popular statistical techniques applied are multivariate discriminant analysis and logistic regression (Balcaen and Ooghe 2006; Ohlson 1980). Since 2000, statistical methods have been replaced by artificial intelligence and machine learning methods. These current approaches include neural networks, genetic algorithms, fuzzy logic, vector support machines, or ensemble classifier methods (Alaka et al. 2018; Kumar and Ravi 2007; Lessmann et al. 2015; Acosta-González and Fernández-Rodríguez 2014; Ahn et al. 2000; Du Jardin 2018; Lensberg et al. 2006; Min and Lee 2005; Ravisankar and Ravi 2010; Wu et al. 2010).

De Laurentis et al. (2010) point out that prediction models are part of a broader framework: their limits have to be perfectly understood, and their general application should be avoided. The current modelling approaches make it difficult to fulfill the conditions mentioned above. They do not follow the recommendation by Zellner (1992) known as the KISS principle: Keep It Sophisticatedly Simple, which is often paraphrased as Keep It Simple Stupid. Large financial providers of different types can use the most up-to-date techniques, but credit risk management of small- and medium-sized enterprises (SMEs) differs (Belás et al. 2018).

This different approach used by SMEs causes the popularity of basic statistical techniques to remain unchanged in daily practice and a number of scientific papers can be found as well. Prusak (2018) or Klieštik et al. (2018) provide an overview of the research conducted in selected central and eastern European countries. Research carried out in the area of the Czech Republic involves the works by Karas and Režňáková (2013), Klečka and Scholleová (2010), Čámská (2015, 2016), Machek (2014), and Pitrová (2011). Despite the simplicity, the models predicting financial distress should not be used as dogmas. Two issues discussed in detail within the literature review need to be taken into account. The first is the influence attributed to the economic cycle phases. The second aspect that needs to be considered is the sensitivity of belonging to particular industry sectors. The paper's main aim is to analyze the impact of the economic cycle phases upon final values of the models predicting financial distress, as designed by statistical techniques. The principal conclusions lead to a recommendation that while applying models predicting financial distress, the present current phase of the economic cycle should be respected without regard to a particular industry branch and general corporate financial standing.

This paper has a standard structure and consists of five parts. Section 1 sets the research into a broader context. It describes the terms of the business environment, consequences of corporate defaults, reviews of the current research in this respective field, and explains the paper's main goal. Financial distress and the financially healthy position of a company is defined in Section 2; specific issues, such as the influence of the economic cycle and the role of particular industry sectors are also to be found in this section. Section 3 focuses on the materials and methods, explaining the extraction of the data sample and models predicting financial distress applied. Finally, Sections 4 and 5 present the results of the analysis along with their interpretation, summary, conclusions, and recommendations.

2. Literature Review

The review on the sensitivity of the economic cycles can be considered to be helpful for readers to gain an insight into this research. The theoretical background also refers to some other issues related to models predicting financial distress. The first defines financial standing, considering healthy and distressed. It is necessary to classify companies correctly before prediction models are applied. Secondly, the companies under investigation must be assigned into relevant industry sectors. The type of industry influences the risk of bankruptcy, sensitivity to the economic cycles, and, particularly, the values of financial ratios entering into prediction models. The models applied will be discussed separately in Section 3.

Deterioration of the overall economic situation results in an increased number of bankruptcies (Svobodová 2013; Achim et al. 2012; Smrčka et al. 2013). Bruneau et al. (2012) examined whether corporate bankruptcies are influenced by macroeconomic variables and whether defaults determine the business cycle in France. Altman (2004) emphasized the impact of a turbulent economic environment on an increasing unexpected number of bankruptcies in the United States in 2001 and 2002. Liou and Smith (2007) considered including macroeconomic variables into prediction models as a logical step but also admitted that it happens only very rarely. Several other studies confirm that the use of macroeconomic variables improves the predictive accuracy of models (Korol and Korodi 2010; Hol 2007; Zhou et al. 2010). The main drawback of these approaches applied is that only one economic period is scrutinized and comparison over time is missing. Surprisingly, Topaloglu (2012) is an exception because the paper covers American bankruptcies in the manufacturing industry during the period 1980–2007, which allows the conclusion that accounting variables lose predicting ability when market-driven variables are included.

Macroeconomic deterioration triggers the increase of corporate defaults and it probably also influences values of financial ratios, which would result in the changed final values of models predicting financial distress. During the recession phase, the values of economic indicators could be expected to deteriorate contrary to the phase of expansion when these values would get improved. The question arises whether the impact described is significant and observable in most economic indicators, entering into the models predicting financial distress. Li and Faff (2019) concluded that market-based information assumes importance during periods of financial crisis, in contrast to accounting-based information, the importance of which in the same phase is reduced. It seems that bankruptcy models based on macroeconomic variables are not stable over time since they are not used recurrently, and neither are they scrutinized in the longer time horizons. It seems that the life cycle of prediction models containing macroeconomic variables is not long enough and cannot be used for more economic cycles.

To achieve the required accuracy in model testing, it is essential to categorize the enterprises correctly; basically, into one of two main groups, either as healthy or distressed entities. Financial distress can be defined in many different ways, and similarly, the terminology referring to such companies also differs (bankrupt, insolvent, in default). Merton (1974) defines the default as a situation when the enterprise value is lower than the value of debts. Moyer (2005) compares corporate financial distress to the situation when the box of assets becomes smaller than the box of debts. Using this approach, the enterprises are distinguished through their over indebtedness, such as in Schönfeld et al. (2018). Insolvency is mostly connected with the inability to pay debts, which can be short or long-termed (Crone and Finlay 2012; Deakin 1972; Du Jardin 2017; Foster 1986). Another possibility to define a default is a definition provided by credit rating agencies. The approach used by Moody's can be found in Hamilton et al. (2001). For research purposes, data availability has to be respected. Some research works are based on non-public information provided by financial creditors. In this research, however, only publicly available information is used exclusively. As a result, financial default is defined as corporate insolvency under the Czech Insolvency Act (Act No. 182/2006 Coll.). Insolvency can be declared because of an inability to pay claims or because of over indebtedness. The second group of companies examined is presented as healthy companies. Less attention is given to the definition of healthy enterprises in literature. In this paper, healthy companies are considered to be those having positive economic value added (Jordan et al. 2011). This approach was applied in Čámská (2015, 2016).

The last issue covered in this literature review is the sensitivity of belonging to a particular industry branch. Ganguin and Bilardello (2004) point out that some industries are riskier than others. They conclude that the type of industry influences the risk of deterioration. One reason for industry sensitivity is its exposure to the risk of default. Another reason is that different industries achieve different performance. The literature provides numerous pieces of evidence for this statement. Structure of capital sources (proportion of equity and liabilities) is determined by belonging to industry sectors (Frank and Goyal 2009; Öztekin 2015). Structure of working capital and connected corporate liquidity are also influenced by industries (Vlachý 2018). The same can be said about corporate profitability (Jackson et al. 2018). Belonging to a particular industry sector has an impact on the quality of financial performance predicted (Fairfield et al. 2009; Lee and Alnahedh 2016). Chava and Jarrow (2004) even highlighted that the coefficients of the models predicting financial distress should be calibrated according to the particular industry branches. This leads to a conclusion that financial ratios influenced by industry specifics entering into bankruptcy models could influence the results achieved. Due to these reasons, this paper strictly separates individual industry branches.

3. Materials and Methods

This part describes the materials and methods employed herein. The materials include the observations extracted from the prepaid corporate database, Albertina. The selected observations all have to meet some predefined requirements. Each observation describes one company and is based on the annual financial statements. The methods specify the steps conducted during the analysis leading to the results achieved. The description provided below contains a sufficient number of details, therefore allowing any professionals to replicate this research work.

3.1. Materials

This paper's idea is verified by the data specified in this subchapter. Information about corporate financial performance is mainly included in financial statements, such as a balance sheet and income statement. This quantitative research includes hundreds of companies, which means that the data analysis is based on publicly available financial statements. The selected financial statements were extracted from the prepaid corporate database, Albertina. What proved to be the main obstacle was rather complicated access to data since many companies do not report on time or they tend not to report at all despite reporting being an obligatory legal requirement in the Czech Republic. Some further details concerning the Czech disclosure discipline can be found in Strouhal et al. (2014) focusing on TOP100 companies according their sales and in Bokšová and Randáková (2013) focusing on insolvent entities.

The data selected and obtained can be divided into several subcategories. The first category includes data strictly polarized; on one hand, there are enterprises which declared insolvency. On the other hand, there are companies considered financially healthy due to their positive economic value added creation (Jordan et al. 2011). Their return on equity exceeds the required level of return published by the Ministry of Industry and Trade (2013, 2018). Both groups can be divided into two subparts describing different time periods. There are the companies which announced insolvency as a consequence of the latest global economic crisis in 2012 and 2013, and businesses which announced their insolvency after the year 2014 until the first quarter of 2019 during economic expansion. The analyzed financial statements always describe the accounting year one or two periods before the companies had become insolvent. The same process was applied to the healthy entities. The preceding sample focuses on the accounting year 2012 and the current one describes the year 2017. The year 2017 was selected for this research for the following reasons. The financial data for the year 2019 have not been reported yet and neither those for the year 2018 have been published in full. Secondly, the data sample contains three industry branches, specifically, Manufacture of fabricated metal products, except machinery and equipment (CZ-NACE 25), Manufacture of machinery and equipment (CZ-NACE 28), and Construction (CZ-NACE F). Previous works mentioned in the literature review confirmed that industry specifics are relevant. The companies in this research, therefore, needed to be classified according to their industry sectors. These sectors provide one of the largest homogenous data samples, i.e., for the purposes of this research they were not selected randomly.

Table 1 shows the structure of the data sample following the aforementioned description. Healthy and insolvent enterprises are strictly polarized. The years 2012 and 2017 reflect different periods for comparison. According to the economic cycle, the year 2012 represents a recession phase and the year 2017 an economic expansion phase. Special emphasis should be placed on the analyzed industry sectors—CZ-NACE 25, CZ-NACE 28, and CZ-NACE F. It seems that a particular phase of the economic cycle influenced the number of the businesses extracted from the Albertina database, confirming the logical premises of economic cycles in general. Significantly, healthy companies can be observed more frequently in the expansion phase, however, insolvent enterprises can be found more frequently in the recession phase. This also explains why the second time period for extracting insolvent enterprises cannot be shorter. The sample size for the insolvent companies would be negligible if the period was shortened. The only exception observed is the number of insolvent entities within the construction industry during the expansion period. This number is three times larger than during the recession period. This can be explained by the ongoing construction sector crisis or better disclosure discipline.

Table 1. Size of the analyzed sample.

Industry Branch	Healthy 2012	Insolvent 2012	Healthy 2017	Insolvent 2017
CZ-NACE 25	383	36	786	25
CZ-NACE 28	33	10	321	11
CZ-NACE F	229	33	1997	105

Source: authors' own work.

3.2. Methods

The analysis carried out was based on models predicting financial distress, whose accuracy was confirmed and verified on Czech businesses in previous works (Čámská 2015, 2016). Methods such as linear discriminant analysis and logistic regression belong to classical statistical methods applied in prediction of corporate default risk. The models applied were designed using these statistical techniques. Their frequent reuse depends on their ease of use and clear interpretability. Users do not need to have deep insight into advanced statistical, as well as non-statistical, techniques.

The conducted analysis was based on the 18 following models predicting financial distress. The bankruptcy models in this paper are marked by the following numbers: 1—Altman, 2—IN01, 3—IN05, 4—Doucha, 5—Kralicek, 6—Bonita, 7—Prusak 1, 8—Prusak 2, 9—PAN-E, 10—PAN-F, 11—PAN_G, 12—D2, 13—D3, 14—Hajdu and Virág, 15—Šorins and Voronova, 16—Merkevicius, 17—R model, and 18—Taffler. The exact models' specifications are accessible in the relevant literature cited below. The models introduced were designed in different countries and in different periods. Some models were constructed in the most developed economies and at the beginning of 1990s, were assumed to be best practice in the Czech Republic. In the late 1990s, these foreign designs were replaced by domestically designed models. These efforts were visible not only in the Czech Republic, but also in other countries in the Central and Eastern European region. Countries like Poland, Hungary, Lithuania, and Latvia, due to historical circumstances, underwent similar political and economic development as the Czech Republic.

The approaches imported from the most developed economies are represented by the American Altman Z-Score formula (Altman 1993), German Bonita Index (from the German original Bonitätsanalyse) (Wöber and Siebenlist 2009), Austrian Kralicek Quick Test (Kralicek 2007), and British Taffler (Agarwal and Taffler 2007). National efforts from previously transitioned economies described in this research include Czech IN01 (Neumaierová and Neumaier 2002), IN05 (Neumaierová and Neumaier 2005), Balance Analysis System by Rudolf Doucha (Doucha 1996), Polish Prusak 1, Prusak 2, PAN-E, PAN-F, PAN-G, D2, D3 (all described in Kisielińska and Waszkowski 2010), Hungarian Hajdu and Virág (Hajdu and Virág 2001), and Baltic approaches, such as Šorins and Voronova (Jansone et al. 2010), Merkevicius (Merkevicius et al. 2006), and R model (Davidova 1999).

The conducted analysis was then divided into the following phases. At the beginning, final values of the aforementioned models predicting financial distress were calculated for individual companies included in the data sample. Then, the final values calculated were summarized. Their summary was performed by general descriptive statistics, such as mean, median, or trimmed mean. Finally, the comparison between the time period of expansion and recession was conducted. The time of expansion was represented by the data sample describing the year 2017 defined previously. In contrast, the time of recession was presented by the data sample of the year 2012. The comparison was based on absolute differences expressed by Equations (1) and (2).

$$\text{Absolute difference} = \text{Indicator value}_{2017} - \text{Indicator value}_{2012}, \tag{1}$$

$$\text{Absolute difference} = (\text{Indicator value2017} - \text{Indicator value2012}) \times (-1). \tag{2}$$

The first equation was applied to 17 tested models whose higher values mean better financial standing. The second equation was applied to one model only. This exception is the Kralicek Quick Test (marked by the number 5) which has an opposite metric. Better financial standing is connected with a lower, not higher, final value. This explains why other forms to express the absolute difference were used. As for the two differences displayed above, their positive value reflects a more favorable classification of companies in 2017 and a negative value indicates a more favorable classification of companies in 2012.

4. Results

This part is dedicated to the results achieved. The main aim of this study was to examine the difference in corporate financial standing during a recession and expansion phase of the economic cycle. It also emphasizes the sensitivity of industry sectors and general differences in financial standing (healthy contrary to insolvent companies). The results are most frequently demonstrated by their visualization, as proposed by Čámská (2019). This process was chosen as a number of models were employed and it highlights the differences between the industry branches.

Statistical characteristics, such as the mean, median, and trimmed mean, were calculated for each subsample. Table 2 shows an example of the results when applying the Altman model for the insolvent and healthy enterprises in 2017. It seems that from a statistical point of view, some enterprises could serve as outliers. Since these entities represent realistic financial standing, the question whether to exclude them from the sample can be considered rather controversial. The healthy group contains mainly positive outliers whose financial standing is significantly better. In contrast, the insolvent group mostly consists of negative outliers whose financial standing is considerably worse. This affects the mean value. The trimmed mean cannot rely on the same assumption due to the different sample sizes. For healthy enterprises, the mean limitation of 1/20 (5%), except CZ-NACE 28 in 2012 (which uses 1/10 (10%)), was applied. The situation is much more difficult in the case of insolvent companies. The mean limitation of 1/10 (10%), except CZ-NACE 28 in 2012 and also in 2017 (in these cases applied limitation of 1/5 (20%)), was used. This suggests that the median is an optimal indicator for visualization.

Table 2. Descriptive statistics for Altman's Z-score in 2017.

Statistics	Healthy	Healthy	Healthy	Insolvent	Insolvent	Insolvent
	Mean	Median	Trimmed Mean	Mean	Median	Trimmed Mean
CZ-NACE 25	4.17	3.71	3.98	−1.23	0.74	−0.04
CZ-NACE 28	4.27	3.70	4.09	1.55	1.68	1.52
CZ-NACE F	4.22	3.73	4.04	0.72	0.83	0.76

Source: authors' own work.

Visualization can also express several criteria. The first takes into account a type of time period. In our case, the periods monitored (2012 and 2017) are different. The second criterion takes into consideration the type of industry branches. Again, the companies selected for the purpose of this study belong to three different industry branches. The third criterion applied here distinguishes companies according to their financial standing. The companies surveyed herein differ in their financial standing, presenting a strict polarization. Figures 1 and 2 display the results for the industry sector CZ-NACE F Construction. Figure 1 demonstrates healthy entities contrary to the insolvent companies presented in Figure 2. The different phases of the economic cycle are displayed by the separated curves in each figure. Models 5 and 18 (Kralicek and Taffler) are not included in the final visualization. It has been already highlighted that the Kralicek model is based on a different metric system, which leads to different results from the other applied models. The Taffler model has also been excluded due to its values range exceeding other prediction tools by 2–3 times. Higher total values are caused by the used individual indicators and especially assigned weights, which were chosen during the model's design.

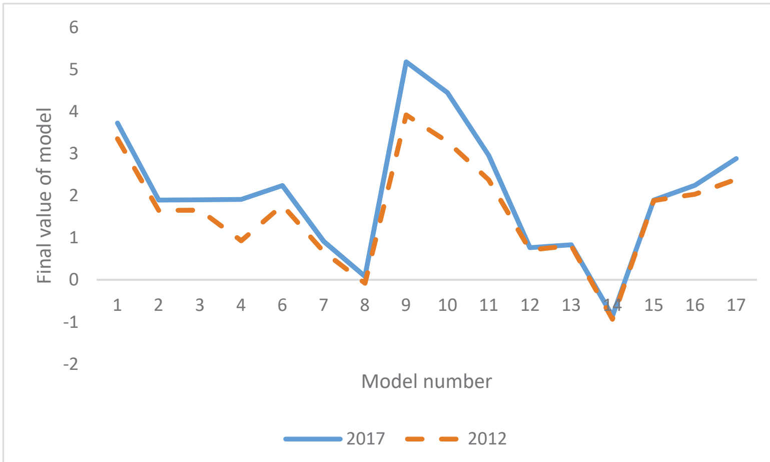

Figure 1. Indicator values of the studied models for healthy companies in Construction (CZ-NACE F). Source: authors' own work.

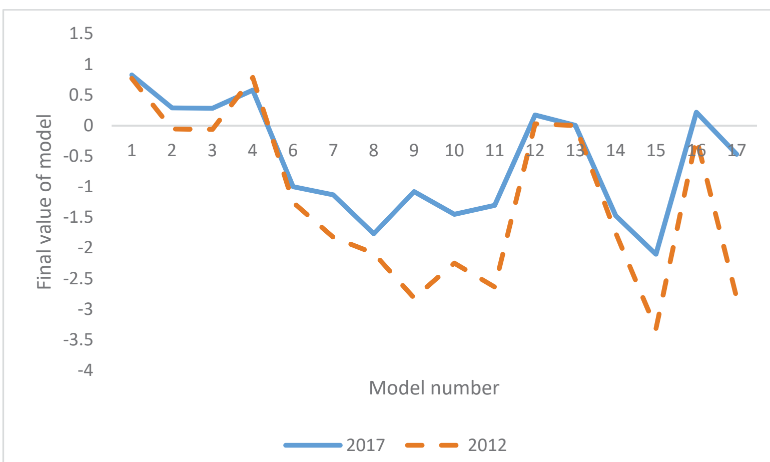

Figure 2. Indicator values of the studied models for insolvent companies in Construction (CZ-NACE F). Source: authors' own work.

Figure 1 confirms the research hypothesis that the recession phase leads to lower final values of models predicting financial distress. Figure 1 works with the companies defined as financially healthy. Figure 2 provides additional support for this claim and the differences for insolvent companies are even more significant. In the case of the models marked as 12 and 13, it should be noted that they were constructed by logistic regression and therefore their range of final values is from 0 to 1. Their visualized differences are insignificant in comparison with other models designed by linear discriminant analysis. The changed scale of graph would reveal that the differences are observable also for the models based on logistic regression.

Both Figures 1 and 2 concentrate on just one particular industry branch. They demonstrate the differences of the economic phases for the economic activity of CZ-NACE F Construction. The need to differentiate between sectors has already been emphasized in the theoretical part. The literature review highlighted the sensitivity of models predicting financial distress to particular industry branches. Figures 3 and 4 display results achieved in all branches included in the sample. The sample includes not only Construction (CZ-NACE F), but also Manufacture of fabricated metal products, except machinery and equipment (CZ-NACE 25), and Manufacture of machinery and equipment (CZ-NACE 28).

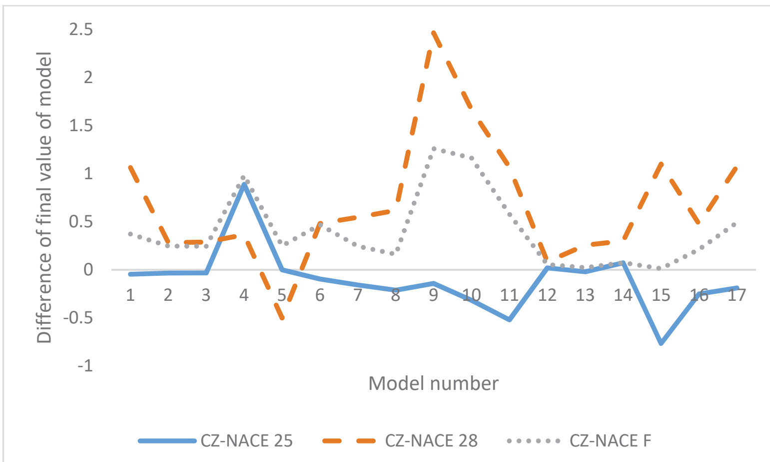

Figure 3. Absolute differences of the model indicators for healthy companies regarding 2012 and 2017 by branches. Source: authors' own work.

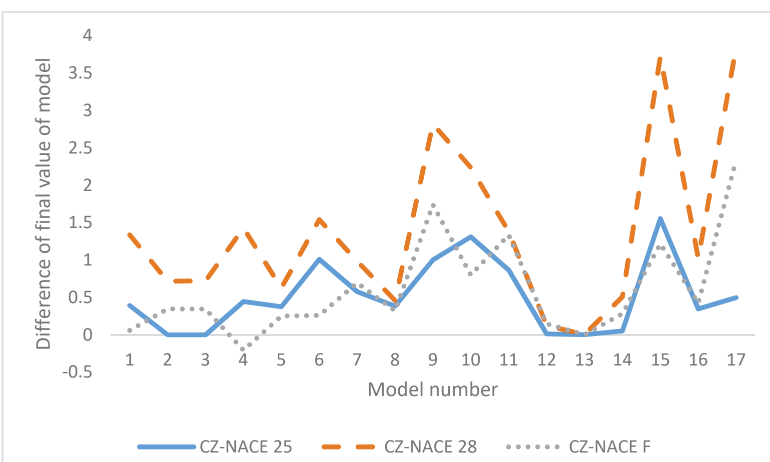

Figure 4. Absolute differences of the model indicators for insolvent companies regarding 2012 and 2017 by branches. Source: authors' own work.

Table 3 displays the results of the Wilcoxon test applied to all three industry branches studied. The null hypothesis is that there is no difference between the year 2012 and the year 2017. Small p-values lead to the rejection of the null hypothesis and to the acceptance of alternatives. The alternative can be presented as there are differences in the indicator values of the tested models between the recession phase (2012) and the expansion one (2017). The analysis was conducted for the healthy and also insolvent enterprises. *p*-values smaller than 10% are highlighted in the table. In these cases, the null hypothesis was rejected and the alternative was accepted. CZ-NACE 28 (Machinery) and CZ-NACE F (Construction) have reached convincing results for most models in the healthy, and also insolvent, sample. CZ-NACE 25 (Manufacture of metal products) does not support the alternative in many cases.

Table 3. *p*-values of the Wilcoxon test.

Company Type	Healthy	Healthy	Healthy	Insolvent	Insolvent	Insolvent
Model	**CZ-NACE 25**	**CZ-NACE 28**	**CZ-NACE F**	**CZ-NACE 25**	**CZ-NACE 28**	**CZ-NACE F**
Model 1	0.1246	0.0094	0.0177	0.3556	0.0167	0.4495
Model 2	0.9158	0.0219	0.0003	0.2126	0.1213	0.2582
Model 3	0.9118	0.0220	0.0003	0.2072	0.1213	0.2541
Model 4	0.0000	0.0039	0.0000	0.2467	0.2908	0.4406
Model 5	0.0219	0.2928	0.0001	0.0455	0.1329	0.0390
Model 6	0.8835	0.1783	0.0002	0.1236	0.0573	0.0666
Model 7	0.3279	0.0582	0.0921	0.1347	0.0573	0.0768
Model 8	0.1380	0.0418	0.2294	0.0889	0.1213	0.1336
Model 9	0.4733	0.0083	0.0037	0.1309	0.0039	0.0811
Model 10	0.4938	0.0361	0.0007	0.1549	0.0290	0.0864
Model 11	0.2264	0.1174	0.0231	0.1347	0.0573	0.0156
Model 12	0.1269	0.0070	0.0002	0.2180	0.2599	0.3074
Model 13	0.9997	0.0262	0.3491	0.5379	0.1392	0.6407
Model 14	0.9026	0.0926	0.5013	0.9415	0.9439	0.4031
Model 15	0.0000	0.0465	0.5648	0.2910	0.0112	0.0245
Model 16	0.0084	0.0440	0.2563	0.2292	0.0060	0.0673
Model 17	0.4545	0.0397	0.0635	0.2292	0.0137	0.0029
Model 18	0.5437	0.1081	0.1799	0.2778	0.0167	0.0158

Source: authors' own work.

Figures 3 and 4 do not reflect any distinction between the economic phases as their curves show the absolute differences defined by Equations (1) and (2). This enables the inclusion also of the Kralicek Quick Test into the graphs. Taffler, however, remains excluded and will be presented in a separate table. The curves above the horizontal axis mean that the models predicting financial distress reached higher values for the economic phase of expansion. On the contrary, curves below the horizontal axis mean that the bankruptcy models had higher values during the economic phase of recession.

Figure 3 represents healthy enterprises. The results obtained in the sectors of Construction and Machinery confirm the expectations. Final values of models predicting financial distress were all higher in the expansion phase except for the Kralicek Quick Test in the case of CZ-NACE 28. Surprisingly, CZ-NACE 25 (Manufacture of fabricated metal products) did not meet the expectations of the conducted research. The blue curve is situated below the horizontal axis for most models. It means that most models predicting financial distress provided better results for the recession than for the expansion phase in the case of CZ-NACE 25. The reasons will be explained below in the discussion.

The results of healthy companies are followed by the results for insolvent enterprises displayed in Figure 4. There are no significant differences between the individual industry branches subjected to analysis. The curves are situated above the horizontal axis, except for the Doucha approach, which was applied to the Construction sector. The results achieved can interpret the financial situation of the insolvent companies as significantly worse in the recession phase or significantly better in the expansion phase of the economic cycle, which met the preliminary expectations.

Friedman's test for comparing model performances for the different branches was applied. The results of the test provide the following interpretation. In the case of healthy companies, the industry branches CZ-NACE 28 (Machinery) and CZ-NACE F (Construction) do not differ significantly. In contrast, the industry sectors CZ-NACE 25 (Manufacture of metal products) and CZ-NACE F (Construction), as well as the pair CZ-NACE 25 (Manufacture of metal products) and CZ-NACE 28 (Machinery), differ significantly. The interpretation in the case of insolvent companies is following. The pairs CZ-NACE 28 (Machinery) + CZ-NACE F (Construction) and CZ-NACE 25 (Manufacture of metal products) + CZ-NACE 28 (Machinery) differ significantly. On the other hand, the industry sectors CZ-NACE 25 (Manufacture of metal products) and CZ-NACE F (Construction) do not differ significantly.

Again, the Taffler model has been excluded from the visualization. Its results are presented separately and can be seen in Table 4. Taffler′s absolute difference in the median confirms previous outcomes. The prediction models for the healthy enterprises belonging to the sector of Manufacture of metal products showed better scores in the recession phase (leading to the negative value of absolute differences). Other industry sectors, with no respect for basic financial standing, show positive values, which can be interpreted as better financial conditions in the expansion phase in contrast to the recession phase.

Table 4. Absolute differences of the Taffler model regarding 2012 and 2017 by branches.

Company Type	Healthy	Insolvent
CZ-NACE 25	−1.03	2.47
CZ-NACE 28	3.78	9.57
CZ-NACE F	2.08	5.94

Source: authors' own work.

The visualization submitted in the figures represents results without using in-depth statistical methods. The apparent advantage of this approach is the opportunity for quick interpretation by the user, without requiring in-depth statistical knowledge. Figures 5 and 6 show the summarized results achieved on statistical bases. As demonstrated in a visualization, the expectations failed to be met in all models predicting financial distress applied. Figures 5 and 6 contain results for descriptive statistics, such as the mean, median, and trimmed mean. A number of models confirming expectations (absolute frequency) is followed by the share of models confirming expectations (relative frequency). Models confirming expectations had the curves above the horizontal axis in Figures 3 and 4. Their values were higher in the expansion rather than in the recession period.

Figures 5 and 6 confirm that the selected descriptive statistic for visualization (median versus mean and trimmed mean) does not influence results significantly. The Machinery (CZ-NACE 28) and Construction (CZ-NACE F) sectors provided comparable results for most models, regardless whether companies were healthy or insolvent. As already discussed, the Kralicek Quick Test failed in the field of Machinery in the case of healthy enterprises. The same can be applied to the Šorins–Voronova model in the field of Construction. On the contrary however, the majority of models failed in the case of healthy enterprises belonging to the Manufacture of metal products. Only median analysis based on Doucha, D2, and Hajdu and Virág models reached a satisfactory outcome.

The situation of insolvent entities is displayed in Figure 6. The level of error seems much lower as many models detected insolvency correctly. The lowest accuracy occurs again in the Manufacture of metal products. In the case of median models, such as IN01, IN05, and D3, were against the expectations in CZ-NACE 25. All models applied to CZ-NACE 28 reached expectations. Unconvincing results (mean) were provided by models such as Doucha, Bonita, and Prusak 1 in the field of Construction. The Doucha model collapsed for all three descriptive statistics in this case.

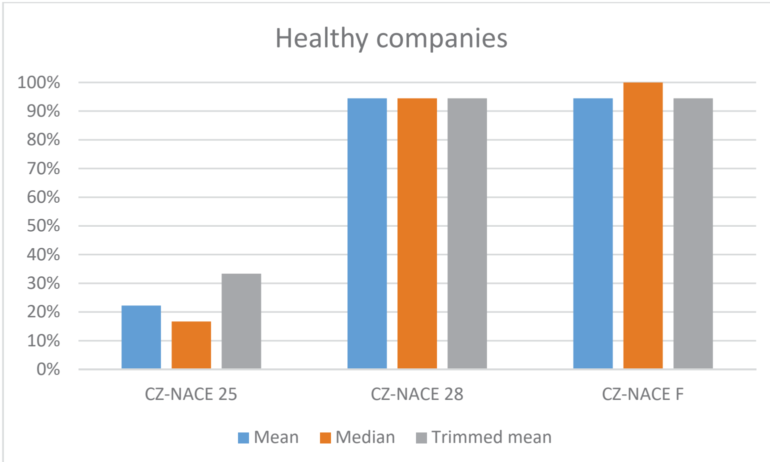

Figure 5. The number of models within each branch confirming better conditions for healthy companies. Source: authors' own work.

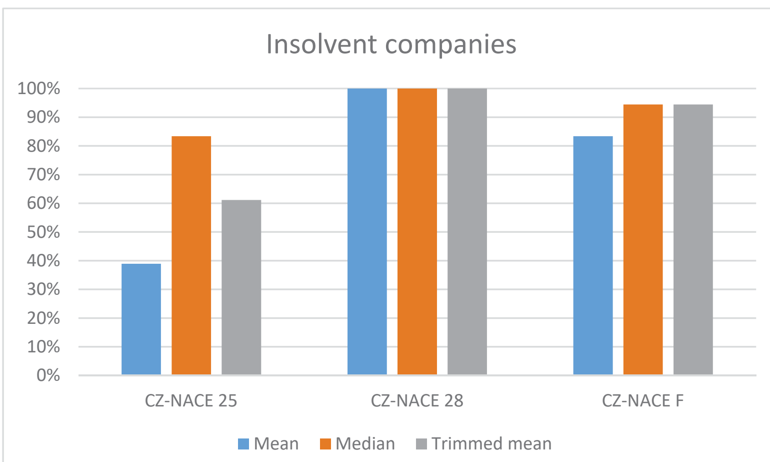

Figure 6. The number of models within each branch confirming better conditions for insolvent companies. Source: authors' own work.

5. Discussion and Conclusions

The results achieved, as described above, confirmed the working hypothesis that the phase of economic cycle influences corporate financial standing. Worse financial standing is expected in a recession phase and better financial conditions during an expansion phase. This finding has a significant consequence on models predicting financial distress related to forecasting corporate financial situation. If models predicting financial distress are applied, the users should respect overall economic conditions, including macroeconomic and industry development. The recession phase mostly leads to lower final scores of bankruptcy models; on the contrary, the expansion phase leads to higher final scores. The evaluation of a company, according to models predicting financial distress, should take into account the phases of the economic cycle. It seems it is not necessary to include macroeconomic variables into models, but the overall economic situation should be considered at least in an expert's decision when the final scores are interpreted.

The part describing the results emphasized the issue of healthy companies belonging to CZ-NACE 25. Figure 3 and Table 4 proved that most models predicting financial distress had better results in a recession period. This observation contradicts the expectations and results in other sectors (CZ-NACE 28 and CZ-NACE F). It should also be highlighted that the results of insolvent enterprises fulfilled the expectations. One explanation for this can be as follows. Firstly, the data sample of 2012 was previously extracted in the year 2014 for other research and the methodology applied was slightly different. Healthy companies should have created positive economic value added in three years in a row between the years 2010 and 2012, although only one year of positive economic value added was required for the data sample of 2017. This requirement excluded many companies as they were not deemed entirely financially healthy, but the same was applied to other analyzed sectors. Secondly, the industry situation and its development can influence the results. The development of the Manufacture of metal products (CZ-NACE 25) can be different from the development of Machinery (CZ-NACE 28) and Construction (CZ-NACE F).

Unconvincing results were obtained for different models predicting financial distress in three industry branches under examination. The unconvincing results are not a consequence of the models' design alone. If the users decide to predict financial distress promptly, they should use more than one prediction model. Multiple verifications can eliminate the randomness discussed previously. It is essential to realize that models predicting financial distress are designed for a quick evaluation of the corporate financial situation, they work on empirical bases, and they never function as natural law (De Laurentis et al. 2010). It should also be respected that economics belongs to the social sciences, although many processes can be quantified, and the behavior of economic entities can be described systematically.

Future research directions would benefit from the application of advanced statistical techniques. The methods enabling self-adaptation and learning are likely to have a unique position. Some approaches taking advantage of macroeconomic or industry variables are not published since they are part of the company's know-how. Although large financial providers of different kinds use these techniques, small- and medium-sized enterprises cannot apply them for mitigating their business risk. Unfortunately, as current research directions tend to move away from widespread application in practice, the primary intentions presented by Altman (1968) or Beaver (1966) are not met.

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Article

Corporate Bankruptcy Prediction Model, a Special Focus on Listed Companies in Kenya

Daniel Ogachi [1,*], Richard Ndege [2], Peter Gaturu [3] and Zeman Zoltan [1]

1 Department of Finance, Szent Istvan University, 2100 Gödöllő, Hungary; zeman.zoltan@gtk.szie.hu
2 Twenty Four Secure Security Services, Nairobi 50353-00100, Kenya; marisandege@gmail.com
3 BSS Department, Jomo Kenyatta University of Agriculture and Technology, Karen 62000-00200, Nairobi, Kenya; pmgaturu@gmail.com
* Correspondence: ogachdniel@gmail.com; Tel.: +36-3088-23119

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Abstract: Predicting bankruptcy of companies has been a hot subject of focus for many economists. The rationale for developing and predicting the financial distress of a company is to develop a predictive model used to forecast the financial condition of a company by combining several econometric variables of interest to the researcher. The study sought to introduce deep learning models for corporate bankruptcy forecasting using textual disclosures. The study constructed a comprehensive study model for predicting bankruptcy based on listed companies in Kenya. The study population included all 64 listed companies in the Nairobi Securities Exchange for ten years. Logistic analysis was used in building a model for predicting the financial distress of a company. The findings revealed that asset turnover, total asset, and working capital ratio had positive coefficients. On the other hand, inventory turnover, debt-equity ratio, debtors turnover, debt ratio, and current ratio had negative coefficients. The study concluded that inventory turnover, asset turnover, debt-equity ratio, debtors turnover, total asset, debt ratio, current ratio, and working capital ratio were the most significant ratios for predicting bankruptcy.

Keywords: bankruptcy; insolvency; financial distress; default; failure; forecasting methods

1. Introduction

Bankruptcy prediction is a technique of forecasting and projecting on company financial distress of both public and firms. The purpose of predicting bankruptcy is fundamental in assessing the financial condition of a company and prospects in its operations. Corporate bankruptcy prediction is a very crucial phenomenon in economics. The financial soundness of a company is of great importance to the various actors and participants of the business cycle. The participants and interested parties include the policymakers, investors, banks, internal management, and the general public referred to as consumers. Accurate prediction of the financial performance of companies is of great importance to various stakeholders in making important and significant decisions concerning their relationship and engagement with companies. Financial distress is a global phenomenon that affects companies across all sectors of the economy (Zhang et al. 2013).

Additionally, bankruptcy prediction is essential for investors as well as suppliers or retailers to the business. Credit lenders and investors need to evaluate the financial bankruptcy risk of a company before making an investment or credit-granting decisions to avoid a significant loss by banks and other credit lenders. A company's suppliers or retailers always conduct credit transactions with the company, and they also need to fully understand the company's financial status and make decisions on the credit transaction. To correctly predict a company's financial distress is of great concern to the various stakeholders of a company. Problems concerning bankruptcy have necessitated the need for studies to establish different stressors to companies to aid investors in making prudential investment decisions.

Corporate failures in significant economic companies have spurred research for better understanding to develop prediction capabilities that guide decision making in investments. Financial distress projections in companies are a product of available data from listed companies, public firms that have sunk. Available accounting ratios may be a vital indicator or signal to indicate danger. Typically, firms are quantified by many indicators that describe their business performance based on mathematical models constructed from past observations based on evidence from data.

Decisions of a corporate borrower on credit risk traditionally were exclusively based upon subjective judgments made by human experts, based on past experiences and some guiding principles. However, two significant problems associated with this approach include the difficulty to make consistent estimates and the fact that it tends to be reactive rather than predictive (Cleofas-Sánchez et al. 2016).

Bankruptcy prediction is of great importance to all participants in the insurance market, including insurance regulators, policyholders, agents, and insurance companies. As insurance products become more and more familiar to the public, they strengthen the consumers' willingness to buy products. However, as the service period of insurance products happens after the purchase of products, the consumer is very concerned when purchasing products of the insurance company about whether they will be able to pay in the future. Assessing the solvency of an insurance company in the future during the product service period is very important to the policyholder's purchase decision, and equivalently crucial to the operation of the insurance company.

In many instances, policyholders have a habit of thinking that large companies are financially stable and that they are solvency guaranteed, which is not always the case. In assessing the creditworthiness of companies, the various actors use solvency adequacy ratio indicators. In most companies, the companies have a given solvency adequacy ratio used as a yardstick for measuring performance, which is required to be made public. One of the questions that stakeholders ask themselves is whether the indicator is reliable for policyholders to forecast the solvency of a company using the current information.

This article, therefore, attempts to evaluate different bankruptcy prediction models that have been used in different countries over time. Several studies have been conducted in Kenya concerning bankruptcy prediction, with most studies trying to validate the Altman's Z-score developed in 1968 in projecting for corporate bankruptcy. None of the studies came up with a model that applies to listed companies in Kenya to determine the financial viability to make investment decisions. This study sought to bring new knowledge in the field of financial economics by developing a current and operative model that can be able to be used by investors in making investment decisions in both private and public companies based on earnings management. Recent cases have seen several listed companies going under with investors' finances even after declaring huge annual dividends to shareholders. This research study sought to answer a number of research questions. What is the contribution of debt coverage ratios on bankruptcy prediction? How do liquidity management ratios affect the financial performance of listed companies? Lastly, how activity ratios contribute to corporate earnings management concerning financial performance? The study conducted a trend analysis using canonical correlation and logistical regression model to determine relationships among various variables.

The remainder of this paper is organized into five chapters. Section 2 of this paper discusses the empirical orientation of the study based on available literature from other scholars. Section 3 presents data and methods of analysis used in the study, while Section 4 gives a highlight of empirical results and discussions inline with past literature. The last section, Section 5, provides conclusions deduced from the primary research findings.

2. Literature Review

2.1. Earnings Management and Bankruptcy Prediction

Studies have examined the causes of business failure indicated by values of bankruptcy scores established during the decline stage of the business. In a survey of the 70 Estonian manufacturing firms, the researcher obtained the causes of bankruptcy from court judgments. The firms classified the reasons and the types of failure, that is, internal factors, that are different from management deficiencies and external factors to the firm. Ohlson's model and a local (Grünberg's) bankruptcy prediction model were used to calculate bankruptcy scores for the first and second pre-bankruptcy years. Applying median tests form independent samples to examine whether the different failure types are associated with different failure risk. The findings revealed that multiple causes have a significantly higher bankruptcy risk than single reasons for the year before the declaration of bankruptcy. The results indicate that numerous reasons lead to a considerably higher insolvency risk as compared with a single cause for the year before bankruptcy disclosure (Lukason and Hoffman 2014).

Altman's first bankruptcy prediction model has gained prominence and is at the epicentre of all economists and scientists all over the world. Early detection of a possible threat to the financial performance of a company is a critical phenomenon in the world of economic analysis.

Financial misery and business failure is usually an extremely costly and disruptive event. Statistics have been used to predict financial distress in an attempt to forecast the future of businesses. Popular approaches to discriminant analysis and logistic regression are used to predict bankruptcy. Using a variety of cost ratios, the results by (Gepp and Kumar 2015) in their study showed that decision trees and survival analysis models have good prediction accuracy, which justifies their use and supports further investigation.

In another study, the researcher analyzed the influence of financial distress on the investment behaviour of companies. The study included companies from Germany, Canada, Spain, France, Italy, the United Kingdom, and the USA. The researcher sought to use several institutions from different study environments. Using the generalized method of moments (GMM) system, from panel data, the results showed that the influence of financial distress on investment is distinct according to the investment opportunities available to companies. So, companies in difficulties with fewer opportunities have the highest propensity to underinvest, while firms in problems with better opportunities do not present different investment behaviour than healthy companies (López-Gutiérrez et al. 2015).

The dwindling in the profitability of listed companies not only intimidates the interests of the enterprise and internal workforce but also leads to significant financial losses to investors. Therefore companies must establish early predictive signs of financial difficulties in companies that will help in issues relating to corporate governance. A study on 107 listed companies in the Shanghai Stock Exchange and the Shenzhen Stock Exchange to develop the phenomenon of financial distress interviewed companies that received the label of special treatment between the years 2001 and 2008. Data mining techniques were used to build a model for establishing financial trouble in companies. One of the critical contributions of the paper was the discovery that return on total assets, earnings per share, the net profit margin of total assets, and cash flow per share play an essential role in the prediction of deterioration in profitability. Therefore, the study provided a suitable method for forecasting the financial distress of companies (Geng et al. 2015).

In Lithuania, where private limited companies dominate the country, a bankruptcy prediction model was built to assess the probability of bankruptcy in companies. The study used 73 already bankrupt and 72 still operating companies to deduce a bankruptcy prediction model to be used for predicting bankruptcy of business ventures. The study used the following analysis techniques: Mann-Whitney U test techniques, correlations, and multivariate discriminant analysis. The findings revealed that the model was 89% accurate in predicting for bankruptcy of private companies in Lithuania (Šlefendorfas 2016).

In a study by (Laitinen and Suvas 2016), to establish the influence of Hofstede's original cultural dimensions on the prediction of financial distress, 1,255,768 non-failed and 22,594 failed yearly firm observations were obtained from 26 European countries. A model known as the logistic regression model was used to predict the future financial position of a company in an international context. The empirical findings revealed that Hofstede's dimensions significantly moderate the effects of economic predictors in failure prediction. However, the equity ratio, used as a solvency measure, and return on assets ratio (ROA), used to measure company success, play a vital role in bankruptcy prediction models, irrespective of the position of the moderating effects that they play at times. Solvency and profitability, therefore, are imperative forecasters of bankruptcy in international financial modelling. The contributions of regulating effects and further variables on the overall performance of prediction models are not resilient owing to the dominant role of the equity ratio across cultures.

For centuries, research in predicting bankruptcy has been very challenging. Models have been built from financial figures, stock market data, and specific firm variables—both low dimensional data and high on company managers and directors in the models of prediction. Relational models are found to have an improved prediction over financial models that are simple when detecting those firms that are riskier than others. Combining relational and economic data gives the most substantial performance increase (Tobback et al. 2017). Managers are expected to carefully build bankruptcy prediction models and adjust them to the size, type, and risk of the activities of the company (Boratyńska and Grzegorzewska 2018).

Most bankruptcy research seems to have relied on parametric models like multiple discriminant analysis and logit. The parametric models can only handle a finite number of predictors, which is the most significant limitation of the model. The gradient boosting model has been advocated thanks to its nature of accommodating for a vast amount of predictors that can be ranked in an orderly manner ranging from best to worst based on their predictive power. A study on 1115 U.S. bankruptcy filings and 91 predictor variables established that ownership structure/concentration and CEO compensation were treated as non-traditional reliable predictors, while unscaled market and accounting variables were treated as good predictors when studying firm size effects. Macro-economic variables, analyst forecasts, and industry variables were found to be the weakest predictors (Jones 2017).

Improving corporate financial risk management requires a dynamic financial distress prediction. Early researchers in constructing financial distress models ignored the time weight of samples. A study on dynamic financial distress prediction (DFDP) proposed two approaches based on time weighting and Adaboost support vector machine (SVM) ensemble, which are more suitable for DFDP in the case of financial distress concept drift (Sun et al. 2017).

Klepac and Hampel (2017) conducted a study on predicting financial distress of agriculture companies in the European Union. The survey interviewed 250 agriculture business companies, with 62 of them having defaulted in 2014. The findings revealed that increasing the distance to bankruptcy leads to a decrease in the average accuracy of the financial distress prediction. Therefore, there was a significant difference flanked by the active and distressed companies in terms of liquidity, rentability, and debt ratios.

A study was conducted in India, which is an emerging economy, to establish corporate distress prediction where bankruptcy details were not available. The study used firm-specific parameters to capture any signs of distress for the firms. The study used standard logistic and Bayesian modelling to predict distressed firms in the corporate sector of India. The study found out that the Bayesian methodology provides for a consistent predictive capability of identifying the early signal of failure in Indian companies (Shrivastava et al. 2018).

All over the world, several models have been designed to measure the insolvency of companies. Each model has several shortcomings during its application. One of the deficiencies facing models is the inability to transfer and apply one model from one country to the other because of the difference in the economic conditions among countries. A well-developed model in Hungary may not work well in another country; therefore, there is a recommendation to develop a predictive model that takes into account the specific conditions of a particular state using the real data on the financial situation (Svabova et al. 2018).

The literature suggests that firms with a higher prior history of affirmative corporate social responsibility (CSR) commitment are less likely to file for insolvency when they are financially distressed. However, they are expected to experience accelerated recovery from distress. Moral capital shrinks bankruptcy likelihood when the firm grows more massively. Additionally, capital mitigates bankruptcy likelihood when the firm relies on intangible assets to operate and when firms operate in a more litigious business environment (Lin and Dong 2018).

Financial ratios are essential in predicting the bankruptcy of business ventures. Various variables measure the financial soundness of an enterprise. In a study conducted in Indonesia on bank financial ratios, the researcher used the capital adequacy ratio (CAR), loan to deposit rate (LDR), non-performing loan (NPL), operating income operating costs (BOPO), return on assets (ROA), return on equity (ROE), and Net Interest Margin (NIM). Using logit regression with 40 banks, LDR had a significant effect on the profitability of banks in Indonesia. CAR, NPL, BOPO, ROE, and NIM had no considerable impact on bankruptcy.

Predicting bankruptcy has gained attention for almost a century now and remains one of the hottest topics of concern in economics. The financial distress prediction aims to design a model that blends the various economic variables to foresee the condition of the firm. Several methods proposed statistical modelling and artificial intelligence (Zięba et al. 2016). Textual disclosures introduce deep learning models for bankruptcy prediction. Mai et al. (2019) established that deep learning models yield superior forecasting on bankruptcy prediction. Blending textual data with ratio analysis can improve the prediction accuracy.

Most institutions and researchers have focused on bankruptcy prediction owing to the growth in the complexity of global economies and an increasing number of corporate failures ignited by the 2008 crisis. Fisher's linear discriminant has gained dominance and popularity in terms of accuracy (García et al. 2019).

Other bankruptcy predictor models of companies have been the convolutional neural network, which is applied to identify the bankruptcy vice in a variety of fields. Convolutional neural networks in financial analysis have been used to predict stock price movements. However, it is not a very commonly applied technique. Only very few studies have used it. The convolutional neural networks approach uses two methods of the balance sheet and the profit and loss account to test for bankruptcy. Hosaka (2019) established that predicting bankruptcy through trained networks is shown to have higher performance as compared with decision trees, intelligent machines, and linear discriminant analysis, which was according to a study they conducted in the Japanese Stock Markets using 102 delisted companies and 2062 financial statements of listed companies.

In another study to establish whether a sensitivity variable, industry beta, has a significant impact on the firm's likelihood of default, the study used logistic regression and multiple discriminant analysis on listed companies in India. The sensitivity variable for industry factors, industry beta, is found to be statistically significant in predicting defaults. Higher sensitivity to industry factors leads to an increased probability of default (Agrawal and Maheshwari 2019).

In another study to predict the financial distress companies in the trading and services sector in Malaysia, the researcher used using financial distress companies as the dependent variable and macroeconomic variables and financial ratios as the independent variables. Based on the results from a Logit analysis, the study established that turnover ratio, debt ratio, total assets, working capital ratio, net income to total assets ratio, and base lending rate are the independent variables used to predict financially distressed companies in the trading and services sector in Malaysia (Alifiah 2014).

Whether to use accounting- or market-based information to predict corporate default has been a long-standing research debate. Integrating a regime-switching mechanism, we establish a hybrid bankruptcy prediction model with various loadings on accounting- and market-based approaches to re-examine bankruptcy prediction. Recommendations include creditors to increase the loading on market-based information when large and liquid corporations are considered.

In the present states of the economy, there is an increasing number of organizations facing financial difficulties, which may, at times, lead to bankruptcy. The deficiencies of customary determining models inspire this examination. Partial least squares logistic regression allows for incorporating a large number of ratios into the model and also solves the problem of correlations taking into account the missing data in the matrix. The results obtained confirm the superiority of this method compared with conventional methods of projecting for bankruptcy because the model allows considering all the indicators in predicting financial distress (Ben Jabeur 2017).

2.2. Emergent Bankruptcy Prediction Systems

Banks frequently adopt expert systems in supporting their decisions when advancing credit. Machine learning techniques represent one type that has been used for decades in issuing loans. Banks use prudential choices of protecting the performance of companies by accessing corporate loan applicants. One of the methods they use is data envelopment analysis (DEA) to evaluate several decisions making units (DMU) ranked based on the best practice in their sector. Linear programming is imperative as it is used in calculating corporate efficiency, used as a measure of differentiating between financially sound companies and those that are economically distressed. The results based on a study that sampled 742 listed Chinese companies over ten years suggest that Malmquist DEA offers discernments into the competitive position of a company in addition to accurate financial distress predictions based on the DEA efficiency measures (Li et al. 2017).

Ratio analysis financial indicators are the most popular variables used in bankruptcy prediction models. They often exhibit heavily skewed results owing to the presence of outliers. It is not very clear how different approaches affect the predictive power of models that predict bankruptcy. One of the challenges faced in models is the lack of a clear cut way of how to handle outliers and extremes that affect the power of models—two ways of reducing outlier bias by omission and winsorization. The categorization of financial ratios is an effective way of handling outliers concerning the predictive performance of bankruptcy prediction models.

Predicting financial distress in empirical finance has received a lot of attention from researchers throughout the globe. Sampling small and medium enterprises in France using the Logit model, artificial neural networks, support vector machine techniques, partial least squares, and a hybrid model integrating support vector machine with partial least squares, it has been established that, within a year of financial distress, support vector machine should be preferred because it is the best and most accurate method for predicting for bankruptcy. In the case of two years, then the hybrid model outperforms the support vector machine, Logit model, partial least squares, and artificial neural networks with 94.28% overall accuracy of prediction. Financially distressed firms are found to be smaller, more leveraged, and with lower repayment capacity. In addition, they have lower profitability, liquidity, and solvency ratios. Creditors should, therefore, correctly evaluate the financial position of firms and be keen on any signs that may lead to negative growth to avoid capital loss and costs-related risks (Mselmi et al. 2017).

In the design of a monetary financial disaster prediction model, financial ratio selection and classifier design play the most critical roles. A methodology based totally on expert opinion, statistical concept, and computational intelligence method has been widely applied. In this study, a hybrid shape integrating a mathematical idea and computational talent technique were once developed using a genetic algorithm (GA) with statistical measurements and fuzzy useful judgment-based fitness features for essential ratio selection. In the experiments, two monetary ratio sets were used, one extracted from the recommendations of different research and the other from employing the use of the GA toolbox in the Statistical Analysis Software (SAS) program package. They have been utilized to take a look at the proposed ratio choice schemes. A distinction between the improved hybrid shape and different well-applied structures was also given. The experimental results of financial data based on less than a four-year period before bankruptcy occurrence were used to gauge the performance of the proposed prediction model (Chou et al. 2017).

Introduction to predictive bankruptcy is an objective and realistic problem facing companies and firms, and because of its frequency, it has discovered a specific niche in monetary and investment literature following the motto "prevention is better than cure". In this respect, more than a few fashions have been presented based totally on motives and motives for bankruptcy. Numerous research has been committed to discovering high-quality experimental techniques in predicting the economic crisis.

As a result, exceptional patterns have been generated uniquely to predict the financial crisis. Prediction of financial disaster is significant for all corporations owing to the fact it has a profound effect on the economic system and raises expenses, inflicting many social problems. There are many strategies and methods through which companies and monetary analysts can predict bankruptcy. A combination of various ratios used for bankruptcy prediction and classification fashions can help to choose financial ratios and amplify prediction accuracy.

Neural networks are one of the numerous methods of predicting financial distress of industrial groups, which is used right here considering elements such as accuracy and health of model for predicting financial distress in the industry. Concerning management, time-series prediction is one of the applications of neural networks. Corporate financial trouble is typically superb in capital market liquidity and economic development. When financial distress occurs, banks generally limit bankrupt companies and credits, and in exchange for loans, they demand more exceptional pastime to compensate for their increased risk. Given the reverse impacts of financial distress on capital markets and the economy, researchers and beneficiaries have tried to create and advance various predicting models using distinct procedures to minimize its effects and incurred losses (Salehi and Pour 2016).

Academicians and practitioners have conducted intensive research regarding models for bankruptcy prediction and default events to manage credit risk. Traditional statistics techniques (e.g., logistic regression and discriminant analysis), as well as early artificial intelligence models (e.g., artificial neural networks), have evaluated bankruptcy. In the study, machine learning models (support vector machines, bagging, boosting, and random forest) were tested to forecast for bankruptcy one year before the event and compare their performance with results from the neural networks, logistic regression, and discriminant analysis data for the years 1985 to 2013 on North American firms, analyzing more than 10,000 firm-year observations. Insightful findings revealed a substantial improvement in the accuracy of the prediction using machine learning techniques.

Comparing the best models, with all predictive variables, the machine learning technique related to random forecast led to 87% accuracy, whereas logistic regression and linear discriminant analysis led to 69% and 50% accuracy, respectively, in testing the sample. We find that bagging, boosting, and random forest models outperform the other techniques and that all prediction accuracy in the testing sample improves when additional variables are included (Barboza et al. 2017).

2.3. Kenya's Situational Context

In Kenya, many studies have been conducted to predict bankruptcy using ratios. One of the current studies undertaken investigated the financial soundness of small and medium-sized commercial banks in Kenya over four years, 2014 to 2017, using a model known as a bankometer. The aim was to compare the financial soundness of two bank categories using data from 12 medium-sized and 16 small banks. The equity to assets ratio, capital to assets ratio, non-performing loans ratio, ratio of loans to assets, operating cost to operating income ratio, and capital adequacy ratio was used to measure the financial health of banks. One of the key findings revealed that both small and medium-sized commercial banks were financially sound during the four years of study. The study established an insignificant difference in the relationship between the two bank categories. The findings also revealed that the studied bank experienced poor performance in loans and operations, while the capital adequacy of the two banks was below the benchmark. The results of the study are essential because they can be applied in formulating policies and strategies that will help in stimulating progress in the financial performance of the banking sector, as well as other industries of the Kenyan economy (Ouma and Kirori 2019).

Range et al. (2018) conducted a study to establish the use of sales to total assets as one of the Z-score ratios models in bankruptcy prediction of both private and public-owned sugar companies in Kenya. The public-owned companies under investigation included Nzoia Sugar, Nyanza Sugar Company, Mumias sugar, Miwani sugar, South, Muhoroni Sugar Company, and Chemelil Sugar Company. The private companies, on the other hand, include Butali Sugar, Sukari Industries Limited, Kibos Sugar, and Allied Industries Company West Kenya Sugar. The motivation of the study emanated continued financial difficulty being observed by sugar companies in Kenya. A study sample of 12 sugar companies, both private and public-owned, were included in this study. Five-year secondary data of financial statements of the companies were used in this study. The findings revealed that the sales/total assets ratio does not significantly influence the likelihood of bankruptcy of sugar companies in Kenya.

In another study, (Kihooto et al. 2016) sought to predict for bankruptcy among companies in the commercial and services sector, listed at the Nairobi Securities Exchange (NSE). The main objective of the study was to establish if companies in that sector are prone to bankruptcy. Secondary data over five years (2009 to the year 2013) were used in this study; the Altman's Z-score model findings indicate that, on average, the companies' Z-scores lay between −1.88 and 3.5, which is an indication that the companies are relatively not in danger of bankruptcy.

Numerous firms in developing and transitional economies are in a financial distress situation, owing to a low level of debt service coverage. (Shisia et al. 2014), in their study on financial distress, argued that company distress had become a significant global issue after the 2008 global financial crisis, which resulted in increased business failure. Business failure was associated with bankruptcy as well as insolvency. The study used Altman's failure prediction model in predicting corporate financial distress in Uchumi Supermarkets in Kenya. A five-year period from 2001 to 2006 was used. The data were obtained from the Uchumi supermarket secretariat. Important predictor ratios included total assets, retained earnings, current assets and liabilities, the book value of the equity and sales, and earnings before interest and taxes. The study used a multivariate discriminant analysis (MDA) statistical technique based on the Altman failure prediction model. The model was fundamental and relevant to Uchumi supermarket as it recorded declining Z-score values, indicating the company's real experience in financial distress, backing up the reasons Uchumi supermarket was de-listed from the NSE in 2006. The study suggests to the potential investors in companies to use the Altman failure prediction model as an assessment tool for predicting for bankruptcy. Declining Z-score values depict a failing company.

3. Data and Methodology

Ratio analysis is essential in a 10-year trend analysis. In this study, the ratios of interest to the researcher included total asset debt ratio, current ratio, quick ratio, turnover ratio, working capital ratio, and net income to total assets ratio. ROE, ROA, and net profit margin were selected as the dependent variables denoting the financial performance of companies. The study population for this research included all the listed companies in the Nairobi securities and exchange market (NSE). Currently, there are 64 listed companies in Kenya. Included in the listed companies are also companies that were delisted at some point owing to financial distress. The study used ten years of financial statements of listed companies. The financial statements were obtained from the Capital Markets Authority as well as the Nairobi Securities. Canonical correlations were used to establish relationships among variables, while Logit analysis was used in building a model for predicting the financial distress of a company. Logistic regression was significant in this study because the outcome variables in this study were a dichotomy. The variables have a non-linear relationship, which violates one of the assumptions of linear regression. Logistic regression was also vital because it helps in predicting the probabilities of predictor variables influencing the dependent variable. Logit analysis was necessary for the study because it provided for probabilities of occurrence of the outcome.

The study was guided by the model below:

$$\mathrm{Yi} = \alpha + \beta 1\mathrm{X}1 + \beta 2\mathrm{X}\,2 + \mu\mathrm{I} \tag{1}$$

where,

Xi, X2 . . . Xn = the independent (explanatory) variables (asset turnover, debt to equity ratio, debtors turnover, total asset, debt ratio, current ratio, quick ratio, inventory turnover ratio, working capital ratio);
Yi = dependents variables (return on assets, return on equity, and net profit margin);
Yi = 1 if a company is financially distressed;
Yi = 0 if a company is not financially distressed.

The first equation based on logistic regression can be denoted as

$$\ln\frac{P}{1-P} = \alpha\ + \beta 1X\,1 + \beta 2X\,2 + \mu\ (1) \tag{2}$$

Therefore, the probability of a company becoming financially distressed will be given by

$$p = \frac{1}{1+e^{-(\alpha + \mathrm{B1\ X1} + \mathrm{B2\ X\ 2} + \ldots\ \mathrm{BnXn})}} \tag{3}$$

Values with a figure of 0.5 and above denote that the company is financially distressed, while numbers below 0.5 show that a company is not economically distressed. A value of 0 indicates an indifferent state of the company. On the other hand, negative coefficients reduce the probability of financial distress, while positive factors increase the chance of occurrence of bankruptcy prediction. The study used Statistical Package for Sosial Sciences (SPSS) software to aid in data analysis.

Table 1 below shows the contextual ratios and formula used in the study.

Table 1. Contextual ratios and formula.

Variable	Grouping	Formula
Inventory turnover	Activity	Cost of goods sold/Inventory
Asset turnover	Activity	Sales/Total assets
Debt equity ratio	Debt Coverage	Debt/Equity
Debtors turnover	Activity	Net Credit Sales/Average Accounts Receivable
Debt ratio	Debt coverage	Total liabilities/Equity
Current ratio	Liquidity	Current assets/Current liabilities
Quick ratio	Liquidity	(Current assets − inventory)/Current liabilities
Working capital ratio	Liquidity	Current assets ÷ Current liabilities

4. Results and Discussions

4.1. Canonical Correlation Matrix

According to Table 2 below, Inventory Turnover, Asset Turnover, Debt-Equity Turnover, Debtors Turnover, Total Assets, Debt Ratio, Current Ratio, Quick Ratio, and Working Capital Ratios were independent variables, while return on assets and return on equity were the dependent variables. The table above shows the correlation matrix of both the independent and dependent variables. The findings revealed a positive correlation effect of Inventory Turnover (ITO), Debt-Equity Ratio (DER), Current Ratio (CR), and Working Capital Ratio (WCR) on the dependent variables. Asset Turnover (AT) and Debt Ratio (DR) have negative correlations with the dependent variable. Debtors Turnover (DT) has a positive association with Return on Equity (ROE) and a negative relationship with Return on Assets (ROA).

On the other hand, DR had a positive correlation with ROA and a negative relationship with ROE. ROA and ROE have been used as effective measures of financial performance. Higher levels of ROA and ROE denote excellent performance, while low rates denote possibilities of financial distress. The findings are similar to those in a study conducted by (Choi et al. 2018), who recommended ROA as a good predictor of bankruptcy prediction. Tota assets ratio had a negative influence on financial performance based on the findings of this study. The conclusions were contrary to the results from

(Range et al. 2018), who established that sales to total asset ratio had no significant contribution to bankruptcy prediction.

Table 2. Canonical correlation matrix. ROE, return on equity; ROA, return on assets; ITO, Inventory Turnover; AT, Asset Turnover; DER, Debt Equity Ratio; DT, Debtors Turnover; TA, Total Assets; DR, debt ratio; CR, Current Ratio; QR, Quick Ratio; WCR, Working Capital Ratio.

	ROA	ROE	ITO	AT	DER	DT	TA	DR	CR	QR	WCR
ROA	1.000										
ROE	0.064	1.000									
ITO	0.462	0.424	1.000								
AT	−0.054	−0.082	−0.110	1.000							
DER	0.342	0.514	0.256	0.078	1.000						
DT	−0.511	0.474	−0.078	0.142	−0.037	1.000					
TA	−0.636	−0.520	−0.410	0.017	−0.395	−0.004	1.000				
DR	−0.259	−0.265	−0.346	0.200	−0.393	0.063	0.490	1.000			
CR	0.299	0.312	0.009	0.511	0.268	0.109	−0.118	−0.011	1.000		
QR	0.385	−0.327	−0.030	0.369	−0.001	0.105	−0.028	0.024	0.262	1.000	
WCR	0.456	0.422	−0.017	−0.050	0.216	−0.074	−0.013	0.015	0.125	−0.035	1.000

4.2. Collinearity Statistics of the Variables

Based on the multicollinearity analysis shown in Table 3 below, the quick ratio was excluded from the subsequent investigation, the stepwise Logit analysis, because of its high multicollinearity. The independent variables chosen under this model included inventory turnover, asset turnover, debt-equity ratio, debtors turnover, total assets, debt ratio, current ratio, and working capital. ROE and ROA were the dependent variables of the study. Stepwise Logit analysis was conducted to evaluate the impact of a number of independent variables on the likelihood that companies will be financially distressed. Eight independent variable models were drawn to denote their relationship with the dependent variable.

Table 3. Collinearity statistics of the variables.

Variable	Tolerance	VIF
Inventory turnover	0.959	1.043
Asset turnover	0.925	1.081
Debt equity ratio	0.978	1.022
Debtors turnover	0.958	1.044
Total asset	0.947	1.056
Debt ratio	0.917	1.091
Current ratio	0.932	1.073
Quick ratio	0.372	2.685
Working capital ratio	0.969	1.032

4.3. Test Statistics

The final model was statistically significant, with a chi-square value of 119.969 and 3 degrees of freedom and sig value ($p < 0.005$) = 0.000. This indicates that the model was able to distinguish between financially distressed and non-financially distressed companies. Similar results were established by (Klepac and Hampel 2017), who said that being able to differentiate between economically distressed and non-financially distressed companies increases the average accurateness of the financial distress prediction. The findings are as tabulated below in Table 4.

Table 4. Test statistics.

N	550
Chi-Square	119.969
df	3
Asymp. Sig.	0.000

4.4. Logit Analysis

The findings in Table 5 show eight predictor variables that contribute to the logistic analysis model. The predictors include inventory turnover, asset turnover, debt-equity ratio, debtors turnover, total asset, debt ratio, current ratio, and working capital ratio. The dependent variables for the study included ROA and ROE. Wald statistic was conducted to show the contribution of each variable to the model. The p-value is significant to the model in establishing the level of significance and contribution of each variable. Variables with sig-value $p < 0.005$ contribute significantly to the model. Asset turnover, total assets, and working capital ratio have positive coefficients. This shows that they increase the chances of bankruptcy. They have a more significant contribution to predicting bankruptcy in companies. Higher values in the mentioned ratios can lead to financial distress in companies.

Table 5. Logit analysis results.

Iv	B	S.e	Wald	Sig-Value
Inventory turnover	−0.068	0.178	5.245	0.000 ***
Asset turnover	2.269	0.935	7.865	0.006 ***
Debt equity ratio	−4.987	1.452	6.458	0.003 ***
Debtors turnover	−0.075	0.009	8.456	0.001 ***
Total asset	2.853	0.759	9.985	0.003 ***
Debt ratio	−3.296	2.498	8.321	0.002 ***
Current ratio	−0.059	0.085	6.429	0.033 **
Working capital ratio	0.086	0.026	6.382	0.010 **

*** statistically significant at 1% level. ** Statistically significant at 5% level.

On the other hand, inventory turnover, debt-equity ratio, debtors turnover, debt ratio, and current ratio have negative coefficients. Negative coefficients reduce the risk of financial distress in listed companies in the Nairobi Securities and Exchange Market. Ratios are essential predictors of financial distress, as seen in a study conducted by (Geng et al. 2015), who found that return on total assets, earnings per share, the net profit margin of total assets, and cash flow per share play an essential role in the prediction of deterioration in profitability. On the other hand, (Ouma and Kirori 2019) established that the equity to assets ratio, capital to assets ratio, non-performing loans ratio, ratio of loans to assets, operating cost to operating income ratio, and capital adequacy ratio were significant predictors of the financial health of banks. Similarly, (Charalambakis and Garrett 2019) used leverage, size, profitability, retained earnings to total assets, and liquidity ratio as an export dummy variable, which proved to be essential predictors of bankruptcy prediction.

The logistic regression model can be as shown below:

$$P = \frac{1}{1 + e^{-(-0.068X1+2.269X2-4.987X3-0.075X4+2.853X5-3.296X6-0.059X7+0.086X8)}}$$

where,

X1 = Inventory turnover
X2 = Asset turnover
X3 = Debt equity ratio

X4 = Debtors turnover
X5 = Total asset
X6 = Debt ratio
X7 = Current ratio
X8 = Working capital ratio

Given the value of X1–X8, the cost of B can be established. A value greater than 0.5 shows the possibility of a company going into financial distress. This study, therefore, identified inventory turnover, asset turnover, debt equity ratio, debtors turnover, total asset, debt ratio, current ratio, and working capital ratio as the most significant ratios for projecting for bankruptcy. The findings show that financial ratios can be used to predict financially distressed companies in the Nairobi Securities and Exchange Market.

4.5. Classification Table

Table 6 below tabulates the percentage of correct classifications for the logistic model. The logistical model correctly classified 83% of overall cases, also known as the percentage accuracy in the classification, which is higher than 50%. The results, therefore, showed that the Bayesian logistic model is a strict mode of correctly classifying firms as either being distressed or not.

Table 6. Classification table.

				Predict
Logit Classification Output		**Distressed**		**Percentage Correct**
Observed		0	1	
Distressed	0	51	9	82.0
	1	8	52	84.0
Overall Percentage				83.0

5. Conclusions

Knowledge of an upcoming bankruptcy is a crucial aspect of the decision-making process of the imperilled company itself, as well as of other institutions interacting with the company. In this paper, we propose ratio analysis as an investigative tool for establishing bankruptcy, as the financial statements of a company are readily available. This study found out that the predictor variables that can be used to predict for bankruptcy in companies in the NSE included inventory turnover, asset turnover, debt equity ratio, debtors turnover, total asset, debt ratio, current ratio, and working capital ratio as the most significant ratios. A p-value greater than 0.5 shows a possibility of a company going into financial distress, while smaller amounts show the absence of financial trouble in companies listed in the NSE. Using listed and delisted companies in the NSE allowed the researchers to achieve significant results. Combining several ratios was also crucial in proposing a bankruptcy forecasting model relevant to making investment decisions by performing a comparative diagnosis using several variables for predicting financial distress. This study, therefore, made the following observations based on the findings from the research.

Several studies focused on validating the Altmans model for predicting for bankruptcy rather than developing a current model that can be used in corporate as well as public companies. The study recommends that investors must apply tested bankruptcy prediction models that can help in safeguarding their interests by making prudential decisions.

There is a need to conduct a comparative study in companies that are not listed but publish their financial statements. This will help in developing a robust model that can be used in the country when making investment decisions. For the researcher to improve on model construction, there is a need to construct an industry-based model. This will help in selecting effective models applicable in a sector.

The conflict of earnings management poses a significant threat in the construction of useful, accurate, and reliable models in Kenya. Therefore, there is a need for research on audited financial data to reduce the risk associated with earnings management in making investment decisions.

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An Ensemble Classifier-Based Scoring Model for Predicting Bankruptcy of Polish Companies in the Podkarpackie Voivodeship

Tomasz Pisula

Department of Quantitative Methods, Faculty of Management, Rzeszow University of Technology, al. Powstancow W-wy 10, 35-959 Rzeszow, Poland; tpisula@prz.edu.pl

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Abstract: This publication presents the methodological aspects of designing of a scoring model for an early prediction of bankruptcy by using ensemble classifiers. The main goal of the research was to develop a scoring model (with good classification properties) that can be applied in practice to assess the risk of bankruptcy of enterprises in various sectors. For the data sample, which included 1739 Polish businesses (of which 865 were bankrupt and 875 had no risk of bankruptcy), a genetic algorithm was applied to select the optimum set of 19 bankruptcy indicators, on the basis of which the classification accuracy of a number of ensemble classifier model variants (boosting, bagging and stacking) was estimated and verified. The classification effectiveness of ensemble models was compared with eight classical individual models which made use of single classifiers. A GBM-based ensemble classifier model offering superior classification capabilities was used in practice to design a scoring model, which was applied in comparative evaluation and bankruptcy risk analysis for businesses from various sectors and of different sizes from the Podkarpackie Voivodeship in 2018 (over a time horizon of up to two years). The approach applied can also be used to assess credit risk for corporate borrowers.

Keywords: bankruptcy prediction; ensemble classifiers; boosting; bagging; stacking; scoring models

1. Introduction

According to statistical data from 2018–2019, 30–60 businesses in Poland announce bankruptcy each month. Business bankruptcy is invariably an adverse phenomenon for the business itself and its employees, but it is also a problem for its creditors, banks and partners. The high number of bankruptcies reported may also lead to negative consequences locally—for the economic development and economic circumstances of the region—and on the national scale—for the economy of the whole country. For this reason, the issue of early prediction of business bankruptcy, and therefore the possibility of forecasting the risk of business bankruptcy over a long time horizon (even up to several years), is a very important financial and economic problem. In its financial and economic dimension, bankruptcy (i.e., business default) is defined as a situation in which a business is unable (for various reasons) to meet its liabilities towards creditors. For businesses operating in market economics conditions, a potential risk of bankruptcy always exists. The risk is the most commonly defined as the probability of defaulting on liabilities incurred (probability of default, PD). The subject of modeling risk of bankruptcy is also of enormous importance for institutions granting corporate loans, to whom the bankruptcy of a corporate debtor means a potential loss of the loan granted.

The main objective of this study was to design a scoring model based on ensemble classifiers which could be used to forecast the risk of bankruptcy for Polish businesses conducting activity in the Podkarpackie Voivodeship over a time horizon of up to two years. One of the reasons for using a developed scoring model based on ensemble classifiers to forecast bankruptcy risk for companies from the Podkarpackie region in this study is the fact that the Podkarpackie Voivodeship (along with several other Polish regions) just after a period of political transformation of Poland from socialism to market economy, was notably lagging behind in development. It belonged to the group of several eastern regions (voivodeships) from the so-called the eastern wall, which was overlooked and underestimated in the policies pursued by relevant governments. The selection of companies from the region was also influenced by the fact that the Podkarpackie Voivodeship is currently one of the "development tigers" in Poland and is catching up quickly. This is mainly due to the more effective policies of the current government aimed at equalizing the development opportunities of Polish regions. The Podkarpackie Voivodship is not a very large voivodeship in relation to other regions of Poland as it occupies 11th place in a ranking of all 16 voivodeships, with an area of 17,846 km^2 (source: Główny Urząd Statystyczny (2019) (Statistics Poland)—Local Data Bank, https://bdl.stat.gov.pl). The attractiveness of the voivodeship, however, is influenced by its geographical location, which is conducive to the development of ecological agriculture and tourism (also international—the Bieszczady Mountains). A big advantage of the region is also its border location (the region borders Ukraine and Slovakia—which also belongs to the EU). Due to its population size, the Podkarpackie region belongs to the group of medium-populated regions of Poland and takes 8th place in this ranking, with a population of approximately 2.1 million (source: Główny Urząd Statystyczny (2019) (Statistics Poland)—Local Data Bank, https://bdl.stat.gov.pl). The voivodeship also has no very developed industries, in comparison to other more industrialized regions of Poland. Nevertheless, the Podkarpackie Voivodeship belongs to the group of the fastest developing regions of Poland. In terms of income per capita, the Podkarpackie Voivodeship took 2nd place in 2018 in the ranking of 16 Polish regions-voivodships (revenues at the level of PLN 562.4 per inhabitant (source: Statistics Poland—Local Data Bank, https://bdl.stat.gov.pl). Also in 2018, the Podkarpackie region was the most dynamically developing region of Poland in terms of the growth of generated GDP (GDP). The Podkarpackie recorded an increase of 7.8% of GDP in 2018 compared to the previous year. In 2018, the GDP generated in the Podkarpackie already constituted 3.9% of Poland's GDP and was 9th place in the regions (ranking source: Statistics Poland—Local Data Bank, https://bdl.stat.gov.pl/BDL/start). This proves that the region's economy is already very dynamic but at present is still progressing. The economy of the Podkarpackie region stands out positively and has a very large impact on its potential cluster of aviation industry enterprises belonging to the so-called aviation valley and the dynamic development of road and transport infrastructure (e.g., the route of the international European North-South communication line Via Carpatia), as well as the development of innovation (innovative technologies) in the region. The companies that drive development in the region belong to Stowarzyszenie Dolina Lotnicza (2019) (Aviation Valley Association), that include many aviation industry companies that provide services to major aviation manufacturers around the world (e.g., Boeing, Airbus, source: http://www.dolinalotnicza.pl/en/business-card). These include companies such as 3M Poland, 3D Robot, Boeing Distribution Services, Pratt & Whitney Poland, Collins Aerospace, Goodrich Aerospace Poland, General Electric Company Poland, Hamilton Sundstrand Poland, Heli-One, Safran Transmission Systems Poland and MTU Aero Engines Poland. The very dynamic development of economic potential in the Podkarpackie region also affects the quality of life of its inhabitants. The Podkarpackie Voivodeship has been high in the quality of life rankings for several years. All these factors make it sensible to conduct a comprehensive analysis and an assessment of the risk of bankruptcy of enterprises operating in the Podkarpackie region using the most effective models of forecasting and assessing the risk of their bankruptcy. Therefore, first the work focused on developing an adequate scoring model for bankruptcy forecast using ensemble classifiers, and analyzing and verifying its prognostic capacity (classification efficiency), while only later on using it in practice to comprehensively assess the bankruptcy risk of enterprises from the Podkarpackie region belonging to various sectors of the economy (depending on the declared classification of their activities) that can also be distinguished by their size.

The article details the stages in which the scoring model was designed and implemented in practice. The scoring model design stage involved the comparison of the predictive capability of ensemble models used in this study with that of conventional single classifiers. The results of previous works of many authors (see e.g., Anwar et al. 2014; Barboza et al. 2017; Tsai et al. 2014) indicate that the models based on ensemble classifiers help achieve more accurate results and improve the discriminant capability of the model. On the basis of the scoring model designed, a bankruptcy risk assessment for businesses from the Podkarpackie Voivodeship was carried out based on the sector in which they operated and the size of the business.

The main innovation of the research presented in the article is that previous studies of other authors did not discuss the practical use of the scoring model for comprehensive analysis of the bankruptcy risk of companies (also from different sectors) operating in the Podkarpackie region, using the ensemble classifiers approach.

2. Literature Review

The various problems of bankruptcy of businesses are widely described in the literature. The significance and salience of the bankruptcy problem has motivated many authors to concentrate on this issue in their research. The first mentions of the subject of modeling business bankruptcy and forecasting its likelihood appeared in economic and financial literature in 1968. The first study on risk bankruptcy modeling was published by Altman (1968). The early bankruptcy prediction studies applied statistical methods and mainly concerned the use of different variants of discriminant analysis or logistic regression (Ohlson 1980; Begley et al. 1996). Since those models had significant limitations, artificial intelligence and machine learning methods that were successfully applied in image recognition tasks were gradually also implemented in bankruptcy forecasting. It was found that machine learning techniques such as neural networks (NNet), Support Vector Machines (SVM) and ensemble classifier methods have better forecasting capabilities and higher classification effectiveness than conventional approaches. An overview of the previous research on the application of statistical methods and machine learning techniques in business bankruptcy prediction can be found in studies such as the ones by Kumar and Ravi (2007) and Lessmann et al. (2015). Alaka et al. (2018) presented a comprehensive overview of literature and systematics of predictive models used in business bankruptcy forecasting, including: purpose of research, method of selecting variables for the model, sample size for analyzed businesses (also including bankrupt ones) and a comparison of the effectiveness of models' classification measures.

Some works deal with the issues of forecasting and assessing the risk of bankruptcy of enterprises, taking into account the specificities of the sector of their activity. Rajin et al. (2016) conducted a bankruptcy risk assessment for Serbian agricultural enterprises, which is one of the most significant sectors of the Serbian economy. The classification efficiency of several models was compared using the methods of linear discriminant analysis. Their research shows that models taking into account the specifics of economies and market characteristics (e.g., the European market—DF-Kralicek's model) give better results for the Serbian economy than models created for American markets (e.g., the classic Altman Z-Score model). Karas et al. (2017) dealt with similar problems, who showed that classic scoring models developed for the US economy (Z-Score Altman, Altman-Sabato's models) and IN05—designed and developed for the Czech enterprises—are less effective compared to the original validation results. This forces researchers to develop more adequate models, in particular taking into account the specificity and financial indicators of the agricultural sector and the economy of the country affecting the bankruptcy of enterprises. Receiver-Operating Characteristic (ROC) curves were used to measure the effectiveness of the models. Chen et al. (2013) dealt with the problems of forecasting the bankruptcy risk of industrial enterprises in the manufacturing sector in China. They used a modified variant of Multi-Criteria Linear Programming algorithm (so-called MC2LP algorithm) to forecast the risk of bankruptcy of 1499 Chinese enterprises from the studied sector and selected 36 financial indicators to assess their financial condition. The classification efficiency of the studied model was compared with the efficiency of the classic MCLP model and the SVM approach. Matrix correctness (compliance) matrices were used as measures of classification accuracy. The use of the model proposed by the authors enables setting up a variable value for the cut-off point (determining the expected belonging of objects to classes) and thus systematically correcting incorrect classification errors. Topaloglu (2012) dealt with the forecast of bankruptcy of American enterprises from the manufacturing sector using a multi-period logistic regression model, the so-called hazard models. The research period covered bankruptcies from 1980–2007 and the results show that macroeconomic diagnostic variables in a model such as GDP have the very large impact on the assessment of their bankruptcy. The study shows that accounting indicators for assessing the financial condition of enterprises used in the model lose their predictive power (become irrelevant) when global market and macroeconomic indicators are taken into account. Achim et al. (2012) studied the financial risk of bankruptcy for Romanian enterprises from the manufacturing sector using the Principal Component Analysis method in the period of 2000–2011, and thus taking into account the impact of the global crisis on financial markets. The research sample included 53 enterprises registered in Romania and operating in the production sector, including 16 selected and most frequently used financial indicators used in the study. The study shows good predictive quality of the model tested and presents its potential application possibilities. In the literature, you can also find works on the modeling of bankruptcy risk for enterprises operating in other sectors of the economy, e.g., Marcinkevicius and Kanapickiene (2014) for companies from the construction sector, as well as Kim and Gu (2010), Youn and Gu (2010) and Diakomihalis (2012) for companies in the hotel and restaurant sector.

It is also necessary to emphasize an important aspect in the research on the risk of bankruptcy of enterprises, which is taking into account the impact of economic cycles and selected macroeconomic variables of the market while considering the effect of cyclical economic conditions of countries. In Vlamis (2007) statistical logistic and probit regression models were used to forecast the risk of bankruptcy of American real estate companies in the period 1980–2001. It has been shown that financial indicators such as profitability, debt service and company liquidity are important determinants of the risk of bankruptcy of the surveyed enterprises. A number of key macroeconomic financial variables have also been used because the risk of borrowers' bankruptcy depends on the state of the economy and the current business cycle. Similar issues were dealt with in the publication by Hol (2007), which concerned the study of the impact of business cycles on the probability of bankruptcy of Norwegian companies. It has been shown that models that take into account the impact of economic cycles have better prognostic properties than models that only take into account the financial indicators of companies. In a similar study, Bruneau et al. (2012) analyzed the relationship between macroeconomic shocks and exposure to the risk of bankruptcy of companies in France belonging to different sectors of classification of activities. The study of the dependence of the risk of bankruptcy on economic cycles was carried out using the two-equation VAR model based on data from 1990–2010.

At this point one should also mention Polish authors' significant contribution to the development of bankruptcy forecast models which take into account the specific nature of the Polish economy. Their research is mostly based on classical techniques, using statistical methods or machine learning tools and the methods for predicting and evaluating the risk of business bankruptcy. The results obtained by Polish authors studying bankruptcy risk modeling can be found in publications by Korol (2010), Hadasik (1998), Hamrol and Chodakowski (2008), Mączyńska (1994), Prusak (2005) and Ptak-Chmielewska (2016). In the context of the research done by Polish authors, a very interesting and detailed comparative analysis of the subject of enterprise bankruptcy forecasting in East-Central Europe and an overview of models applied from the perspective of developing economies of the countries of the region in the transformation period was presented by Kliestik et al. (2018).

In recent years, ensemble classifiers have been successfully used for predicting bankruptcy of businesses. Some studies of this type include Barboza et al. (2017), Brown and Mues (2012) and Zięba et al. (2016). They are dedicated to the application of ensemble classifiers in forecasting bankruptcy of businesses and demonstrate that the ensemble classifiers offer better forecasting properties and accuracy than conventional statistical methods. Moreover, a study by Kim et al. (2015)

proved that ensemble models are more resistant to the sample imbalance problem (for bankrupt businesses and those at no risk of bankruptcy) during the statistical data preparation phase.

Many studies on the application of ensemble classifiers in business bankruptcy forecasting refer to boosting and bagging methods (sequential correction and classification error minimization, as well as component classifier result sampling and combining) in order to increase classification performance of the entire forecasting system. In studies by Cortes et al. (2007) and Heo and Yang (2014), Adaboost (an adaptive boosting algorithm) was applied to decision trees as basic classification models. The use of ensemble classifiers with a classifier boosting technique based on neural network classifiers was discussed in studies by Alfaro et al. (2008), Fedorova et al. (2013), Kim and Kang (2010) and West et al. (2005). A different approach was adopted by Kim et al. (2015) and Sun et al. (2017) who used support vector machines (SVM) as base classifiers, which were boosted as a group of ensemble classifiers. Bagging is also a method frequently used in practical applications of ensemble classifiers. This subject dealt with studies which analyze the classification effectiveness of such ensemble classifiers by relying on several models of base classifiers developed by Hua et al. (2007), Zhang et al. (2010) and Twala (2010). The use of ensemble classifiers with combining (stacking) the results of several classifiers in a single meta-classifier was discussed in studies such as those by Iturriaga and Sanz (2015), Tsai and Wu (2008) and Tsai and Hsu (2013). Furthermore, many studies are dedicated to the use of various techniques of combining the results of base model classification: such as neural networks in the form of self-organizing maps (SOMs), rough sets techniques, case-based reasoning and classifier consensus methods. Examples of the use of this type of ensemble classifiers were examined by Ala'raj and Abbod (2016), Du Jardin (2018), Chuang (2013) and Li and Sun (2012).

3. Environmental Background of the Research Conducted

3.1. Statistical Description of Bankruptcies in Poland

According to data from Ogólnopolski Monitor Upadłościow (2019) (Coface Nationwide Bankruptcy Monitor—source: http://www.emis.com, http://www.coface.pl/en) a total of 798 businesses declared bankruptcy in 2018. Most bankruptcies were reported in October and September (76 and 74, respectively) and in the following months: March, April, May (67, 66 and 65, respectively), with 61 bankruptcies reported in January. The months with the relatively lowest number of bankruptcies were declared in August (42) and February and December (45 bankruptcies). Comparing the structure of business bankruptcies by voivodeships in 2018 (Figure 1), we may notice that the highest number of bankrupt businesses were reported in the Mazowieckie Voivodeship—156 (which constitutes 22% of all bankrupt enterprises). Further positions in the ranking, with a significantly lower number of bankruptcies, are held by: Śląskie Voivodeship—84 (12%), Wielkopolskie Voivodeship—68 (10%), Dolnośląskie Voivodeship—61 (9%), Podkarpackie Voivodeship—47 (7%) and Małopolskie Voivodeship—44 (6%). The lowest number of bankruptcies is reported in: Lubuskie Voivodeship—13 (2%), Opolskie Voivodeship—15 (2%), Podlaskie Voivodeship—19 (3%) and Świętokrzyskie Voivodeship—20 (3%). During the first three months of the year 2019, most bankruptcies were also reported in the Mazowieckie Voivodeship—27, Dolnośląskie Voivodeship—15, Śląskie Voivodeship—14 and Wielkopolskie Voivodeship—11. Based on the latest available data from Q1 2019, the largest number of bankruptcies were recorded in the following voivodeships: Mazowieckie—27, Dolnośląskie—15, Śląskie—14, Wielkopolskie—11 and Łódzkie 10. The least in Świętokrzyskie—1, Opolskie—2, Podlaskie and Lubuskie—3, Warmińsko—Mazurskie—4. For the comparison in the Podkarpackie voivodeship, there were 6 bankruptcies.

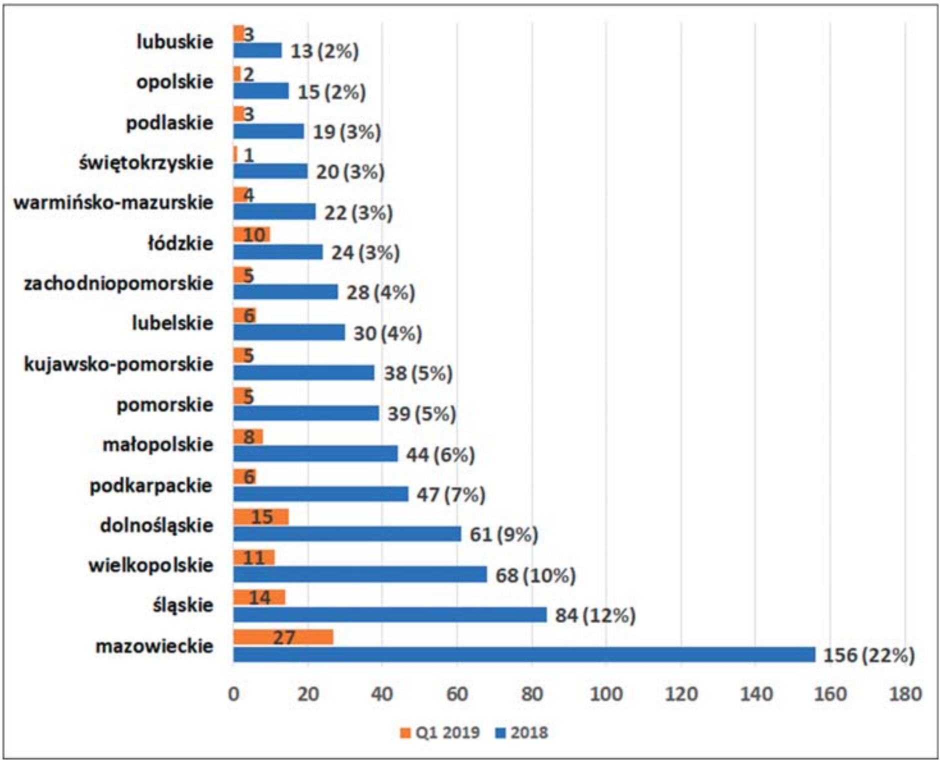


Figure 1. Number of bankruptcies in Polish voivodeships in Q1 2019 and in 2018. Source: own elaboration based on the data analyzed from Coface Nationwide Bankruptcy Monitor (http://www.emis.com).

When analyzing the number of bankrupt businesses in Poland in the year 2019 depending on their business activity, we may notice that the highest number of bankruptcies concerned businesses carrying out varied individual activities (one-person businesses, self-employment)—108 (27% bankrupt), followed by commercial law companies from the commerce (trade) sector—91 (22%), and from the industrial and service sector—70 (17%) and 63 (16%), respectively. In 2019, 51 (13%) businesses from the construction sector, 11 (3%) transport and logistics businesses and 9 (2%) businesses involved in other activities declared their bankruptcy. Figure 2 shows the distribution of the number of bankrupt businesses by their type and the sector of their activity.

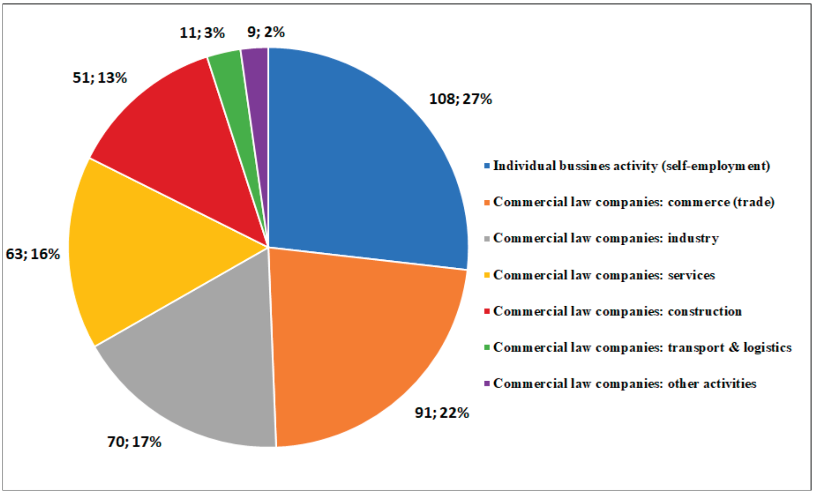


Figure 2. Number of business bankruptcies in Poland in 2019 by sector of activity. Source: own elaboration based on the data analyzed from Coface Nationwide Bankruptcy Monitor (http://www.emis.com).

3.2. Characteristics of Companies Operating in the Podkarpackie Voivodeship

According to Emerging Markets Information Service (2019)—EMIS (http://www.emis.com), in 2018 about 3679 companies and partnerships were registered and operating in the Podkarpackie Voivodeship (the number of available financial statements for 2018 in the database). Their reported sector of activity belonged to one of the following 18 areas: A—farming, forestry and fishing, B—mining and extraction, C—industrial processing, D—production of energy, supply of water, gas and other energy sources, E—waste, waste water and sewage management, F—construction, G—wholesale and retail, and servicing vehicles and motorcycles, H—transport and storage management, I—accommodation and food services, J—information and communications, K—finance and insurance, L—services for the property market, M—scientific, specialist and technological activity, N—administration and support, P—education, Q—health and social care, R—culture, entertainment and leisure, S—other services. Figure 3 presents the structure of the number of businesses operating in the Podkarpackie Voivodeship by sector.

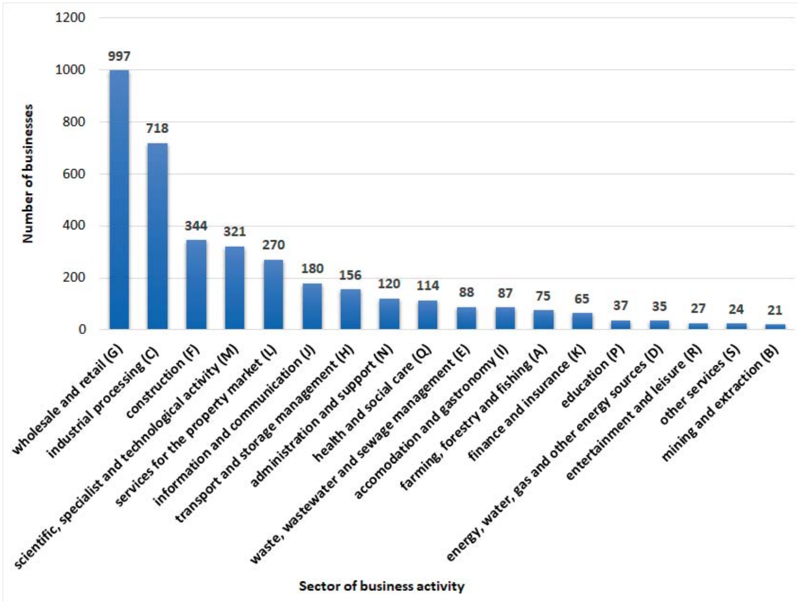


Figure 3. Businesses in the Podkarpackie Voivodeship by sector of activity. Source: own elaboration based on the data analyzed from 2018 (http://www.emis.com).

In 2018, 997 businesses in the Podkarpackie Voivodeship, a vast majority of this area's businesses, operated in the wholesale and retail sector. Economic activity in the field of industrial processing was declared by 718 enterprises, followed by sectors such as the construction, scientific, specialist and technological activity, and services for the property market sectors (344, 321, 270 businesses, respectively). The lowest number of businesses operated in sectors such as education—37, production of energy and supply of energy sources—35, culture—27, other services—24, as well as mining and extraction—21.

Figure 4 presents the structure of the number of businesses in the Podkarpackie Voivodeship by the duration for which they have functioned (in years). Most businesses, i.e., 1792 (which corresponds to 49% of all analyzed entities) have operated in the market for a very long time—10 years. Nearly as many businesses, i.e., 1720 (47% of the total number), have been active for a medium number of years, whereas 'young' enterprises (167), established in the period from 2017 to 2019 and active for up to two years, constituted only 4% of all businesses analyzed.

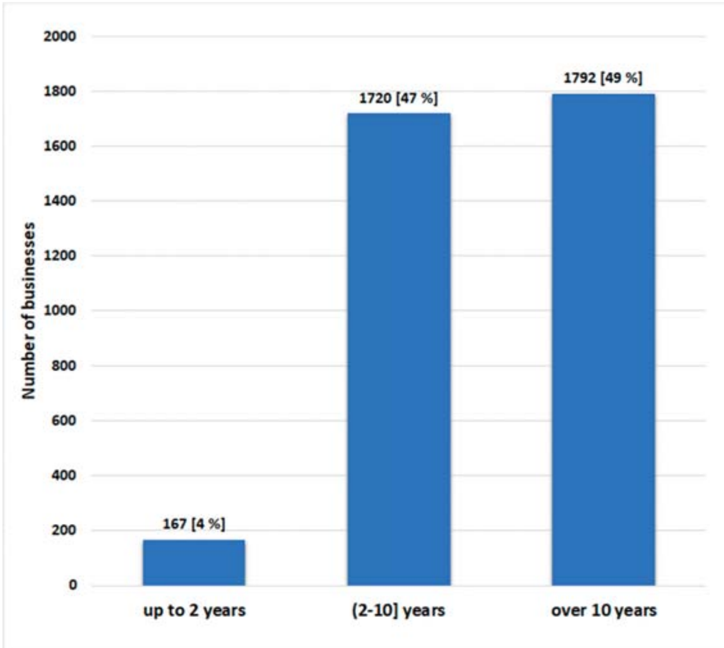


Figure 4. The structure of the number of businesses in the Podkarpackie Voivodeship by the duration of business activity (in years). Source: own elaboration based on the data analyzed from 2018 (http://www.emis.com).

An analysis of businesses operating in the Podkarpackie Voivodeship according to their size (Figure 5) shows that 40% (1461) of all enterprises are very small, they are the so-called micro-enterprises. Small businesses constituted a further 15%. Overall, over a half of businesses (55%) were either micro-enterprises or small enterprises. The number of medium and small enterprises was more or less equal, which corresponds respectively to 22% and 23% of all entities analyzed. The size of the enterprise was identified in accordance with the legal provisions of the classification of Polish enterprises adapted to EU law and directives. Micro enterprises were identified according to the rule: number of employees <10 and annual Turnover <= 2 m €. Small enterprises were identified as not being micro enterprises and fulfilling the conditions: number of employees <50 and annual Turnover <= 10 m €. Medium enterprises were identified as not being small and fulfilling the conditions: number of employees <250 and annual Turnover <= 50 m €. Therefore, large enterprises were identified according to the rule: number of employees >= 250 and annual Turnover >50 m € (source: https://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_pl).

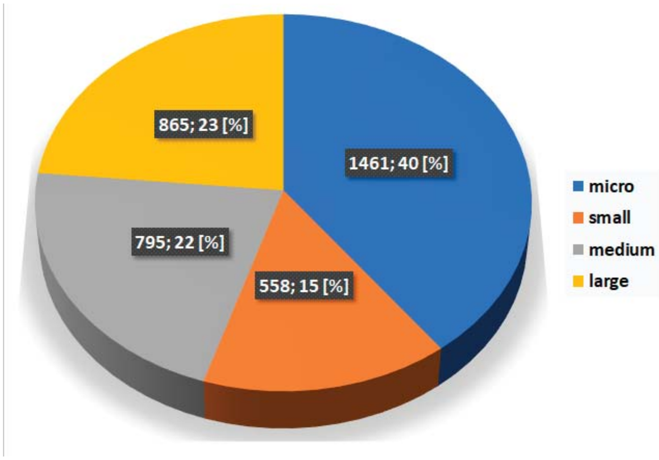


Figure 5. Structure of the number of businesses operating in the Podkarpackie Voivodeship by enterprise size. Source: own elaboration based on the data analyzed from 2018 (http://www.emis.com).

Among all businesses operating in the Podkarpackie Voivodeship, only 7 were listed in the stock market, while 3672 were non-listed companies. An analysis of legal forms of businesses in the Podkarpackie Voivodeship (Figure 6) shows that the vast majority (73.6%) are limited liability companies (private limited companies). There are 2.9% enterprises operating as public limited companies, and only 0.5% are limited partnerships. The remaining businesses, having other legal forms, constitute 23% of all enterprises analyzed in this study.

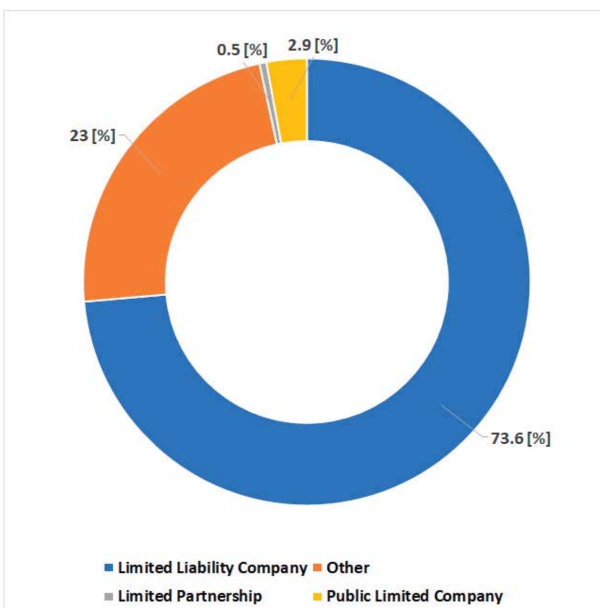


Figure 6. Distribution of the structure of businesses operating in the Podkarpackie Voivodeship by legal form of activity. Source: own elaboration based on the data analyzed from 2018 (http://www.emis.com).

4. Materials and Methods

As can be seen in the above analysis of literature, in practice business bankruptcy risk assessment makes use of various classifier models. Both classical statistical methods and more advanced non-statistical methods are used, with the latter based on various machine learning techniques. The use of so-called ensemble classifiers, i.e., classifiers designed to increase classification efficiency in relation to the conventional approach (which is based on single classifiers), are becoming increasingly popular—for obvious reasons. Table 1 contains an overview of business bankruptcy risk forecasting models that are most often used in practice.

Classical business bankruptcy forecasting models using single classifier models are very-well known and presented in many publications. Meanwhile, the presents study focuses mainly on a detailed presentation of the ensemble classifier methodology. A detailed discussion of classical models and models used in business bankruptcy forecasts can be found e.g., in monographs by Kuhn and Johnson (2013) and Hastie et al. (2013).

Table 1. List of methods applied in forecasting business bankruptcy risk.

<table>
<tr><th colspan="3">Methods Used in Forecasting Business Bankruptcy Risk</th></tr>
<tr><th colspan="2">Conventional Approach Based on Single Classifiers</th><th rowspan="2">Ensemble Classifiers</th></tr>
<tr><th>Statistical Methods</th><th>Non-Statistical Methods and Machine Learning</th></tr>
<tr><td>Logistic regression (LOGIT)</td><td>Mathematical programming</td><td>Stacking:
- a level 2 meta-classifier aggregating classification results from base classifiers</td></tr>
<tr><td>Linear discriminant analysis (LDA)</td><td>Expert systems</td><td>Boosting (e.g.):
- boosted trees,
- GBM (Stochastic Gradient Boosting Machine),
- boosted C5.0 trees,
- boosted Logit,
- other.</td></tr>
<tr><td>Classification and Regression Trees (C&RT)</td><td>Neural networks (NNet)</td><td>Bagging (e.g.):
- Random Forest (RF),
- bagged (LDA),
- averaged Neural Networks (avNNet),
- other.</td></tr>
<tr><td>Nearest Neighbor algorithm (k-NN) k-Nearest Neighbors</td><td>Support Vector Machine (SVM)</td><td></td></tr>
<tr><td>Naive Bayes classifier (NB)</td><td>Generalized Additive Models (GAM)</td><td></td></tr>
<tr><td></td><td>Multivariate Adaptive Regression Splines (MARS)</td><td></td></tr>
</table>

Source: own elaboration based on the literature analyzed.

4.1. *Ensemble Classifier Methodology*

The ensemble classifier methodology involves combining several single classifiers into an ensemble of classifiers performing the same task in order to improve the effectiveness of classification (the discriminant capability of the entire model) defined as correct assignment of objects into expected classes. This is done by suitably aggregating (often by weighing) results of classification obtained from component classifiers to arrive at a resultant classifier with the best possible forecasting capabilities (surpassing those of all base classifiers in use). Figure 7 shows a functional diagram of ensemble classifiers.

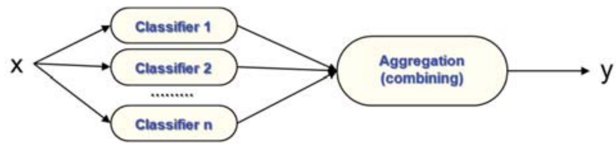


Figure 7. A diagram presenting the idea of using ensemble classifiers. Source: own elaboration.

A detailed description of ensemble classifier methodology, their types, characteristics and numerous practical applications can be found in monographs by Zhang and Ma (2012) as well as Zhou (2012). In practice, three well-known approaches: boosting, bagging and combining are applied in ensemble classifier methods. The terminology of boosting ensemble classifiers refers to a broad class of algorithms which enable boosting "weak classifiers", turning them into "strong qualifiers" (of excellent classification performance approaching that of perfect models). An example of such approach is AdaBoost—an adaptive boosting algorithm (Freund and Schapire 1997). In AdaBoost, classifiers of the same type, e.g., boosted classification trees, serve as base classifiers. Voting strategies are most commonly used in order to determine object classes, aggregating their output classifications, such as majority voting, plurality voting, weighted voting or soft voting. The AdaBoost.M1 adaptive boosting algorithm in the case of object classification for two classes contains the following steps (see: Algorithm 1, Zhang and Ma 2012, p. 14).

Algorithm 1 AdaBoost.M1 algorithm

1. *Inputs:* a set of input data for the training sample $\{x_i, y_i\}$, $i = 1, \ldots, N$, $y_i \in \{\omega_1, \omega_2\}$—learning with a pattern
2. Ensemble classifier: an ensemble classifier with the number of boosting cycles T—iterations
3. Initialization: initial distribution of weights for observation from training set $D_1(i) = 1/N$
4. Perform in loop FOR $t = 1, 2, \ldots, T$
   - Pick a random training subset S_t with distribution D_t
   - Train the base classifier on subset S_t, assume hypothesis $h_t : X \to Y$ concerning classification accuracy relative to the pattern
   - Calculate classification error for hypothesis $h_t : \varepsilon_t = \sum_i I[\![h_t(x_i \neq y_i)]\!]D_t(x_i)$
   - Interrupt if $\varepsilon_t > 1/2$.
   - Assume $\beta_t = \varepsilon_t/(1-\varepsilon_t)$
   - Adjust weight distribution: $D_{t+1}(i) = \frac{D_t(i)}{Z_t} \cdot \begin{cases} \beta_t, \ if\ h_t(x_i) = y_i \\ 1, \ otherwise \end{cases}$, where $Z_t = \sum_i D_t(i)$—is the normalization constant enabling D_{t+1} to become the correct probability distribution
5. End FOR loop
6. Weighted majority voting. For a given unnamed instance of z obtain a voting result concerning case membership in each of the classes $V_c = \sum_{t:h_t(z)=\omega_c} log\left(\frac{1}{\beta_t}\right), c = 1, 2.$
7. *Output:* Membership in the class of the greatest value of V_c.

The name of the second group of ensemble classifier making use of the bagging method is derived from the English abbreviation: Bootstrap AGGregatING (Breiman 1996). This group of ensemble classifiers involves bootstrap sampling to obtain training subsets for base classifiers. Each the classifier is therefore trained on a different training sample, and the results are aggregated. Here, classifiers of the same type are used most often as base classifiers. An example of such a type of ensemble classifiers is Random Forest. The bootstrap aggregation algorithm for object classification into two classes has the following steps (see: Algorithm 2, Zhang and Ma 2012, p. 12).

Algorithm 2 Bagging algorithm

1. *Inputs:* a set of input data for the training sample S; training algorithm with a pattern, base classifier T—ensemble size; R—percentage of the sample for determining training subsets for sampling
2. Perform in loop FOR $t = 1, 2, \ldots, T$
   - Randomly select a replication subset—training sample S_t by selecting R % of S at random
   - Train the base classifier on subset S_t, obtain hypothesis for classifier h_t concerning classification accuracy relative to the pattern
   - Add h_t to ensemble, $\varepsilon \leftarrow \varepsilon \cup \{h_t\}$
3. End FOR loop
4. Combine classification results in an ensemble combination—simple majority voting: for a given unnamed instance of x, obtain a voting result concerning case membership in each of the classes
5. Evaluate class membership results on the basis of ensemble classifier $\varepsilon = \{h_1, \ldots, h_T\}$ for the analysed case x
6. Let $v_{t,c} = 1$, if h_t selects class ω_c, otherwise 0
7. Obtain overall final vote result for each class $V_c = \sum_{t=1}^{T} v_{t,c},\ c = 1, 2$
8. *Output:* Membership in the class of the greatest value of $\mathrm{V_c}$.

A group of methods called ensemble combining represents a wholly different approach. The group includes the so-called combined methods utilizing results of classification functions for single (base) classifiers and aggregating them into the result classification function using the averaging approach (simple or weighted averaging of base classifier results), voting approach (using various types of voting strategies, e.g., majority voting) or stacked generalization approach. The stacking ensemble methodology, pioneered by Wolpert (1992), is based on a combined approach whereby base classifiers (level 1 classifiers) are trained on the same random samples, and then relevant classification results (their classification functions) are used as training samples for the new meta-classifier (level 2 classifier) and aggregated in result classifications.

4.2. Feature Selection Process in Bankruptcy Prediction

A deeply significant classification-related issue is the problem of choosing the appropriate (optimum) set of diagnostic variables (i.e., the feature selection problem). Detailed characteristics of methods used for the selection of relevant variables for forecast models can be found in studies by John et al. (1994) and Jovic et al. (2015). Wrapper methods are frequently used techniques which analyze possible predictor subsets and determine the effectiveness of their impact on the model's dependent variable on the basis of a search algorithm, the best subset of variables and the classification method applied. In order to search all variable subsets, the search algorithm is 'wrapped' around the classification model, hence the name of this group of methods. Wrapper feature selection methods are based on various approaches of searching for the optimum subset of predictors. Such approaches can be divided into two basic groups: deterministic and randomized. This group of deterministic methods applies various types of sequential algorithms, e.g., progressive stepwise selection or backward stepwise elimination. Wrapper feature selection methods most frequently use random algorithms such as simulated annealing, genetic algorithms or ant colony optimization. A method employing a genetic algorithm in order to search for the optimum subset of predictors is often used to select variables for bankruptcy models. The genetic algorithm of Feature Selection (see: Algorithm 3) is executed according to the procedure designed by Kuhn and Johnson (2013).

Algorithm 3 Genetic Algorithm Feature Selection (GAFS)

1. *Define:* stopping criteria, number of children for each generation (*gensize*), and probability of mutation (*pm*)
2. *Generate:* an initial random set of m binary chromosomes, each of length *p*
3. REPEAT
4. FOR each chromosome DO

   Tune and train a model and compute each chromosome's fitness

5. END
6. FOR reproduction k = 1, . . . , *gensize*/2 DO

   Select two chromosomes based on the fitness criterion
   Crossover: Randomly select a locus and exchange each chromosome's genes beyond the loci
   Mutation: Randomly change binary values of each gene in each new child chromosome with probability *pm*

7. END
8. UNTIL stopping criteria are met

4.3. Data Samples Description

The original research sample used in the study included data for 1739 Polish enterprises (bankrupt and not threatened with bankruptcy). This sample included calculated values for 19 financial indicators determining the financial condition of selected enterprises (characterized in detail in Section 5.1 and selected for the study using the wrapper search technique and genetic algorithm discussed in detail in Section 4.2). For bankrupt enterprises, the values of diagnostic variables were set at 1 or 2 years before the actual period of their bankruptcy. Statistical data came from the financial statements of enterprises from 2010–2018 available in the EMIS database (http://www.emis.com). Bankruptcy episodes were identified on the basis of statistics from the EMIS database source: Ogólnopolski Monitor Upadłościow (2019) (Coface Polish National Bankruptcy Monitor, source: http://www.emis.com, http://coface.pl/en). The balanced sample used included a total of 1739 research cases from all major sectors of the economy (865—cases for bankrupt enterprises and 874—randomly selected cases for enterprises not at risk of bankruptcy with strong financial conditions). The condition for the non-defaulted enterprises was evaluated on the basis of careful analysis and evaluation of values of many financial indicators, such as profitability ratios, debt ratios, management performance indicators etc., which determined their financial condition and low exposure to the bankruptcy risk. A 70% teaching sample was drawn from the research sample (1217 enterprises: 592—bankrupt and 625—not threatened with bankruptcy), which was used to train and calibrate the parameters of the bankruptcy models used. The remaining cases constituted a random 30% set for the test-validation sample (522—enterprises: 273—bankrupt and 249—not threatened with bankruptcy), which was used at the stage of validation of models to check their predictive properties for new, unknown cases. A separate research sample was designated for enterprises from the Podkarpackie Voivodeship, which included 2133 enterprises of various sizes from the Podkarpackie region registered in various sectors of economic activity. This sample included all enterprises operating in the Podkarpackie for which financial statements (in EMIS database) for 2018 were available. This sample was used as a research set to assess the risk of bankruptcy (in the 2-year horizon up to 2020) of enterprises in the Podkarpackie region under analysis based on an estimated scoring model using the approach of ensemble classifiers.

4.4. Procedure of Mapping PD into Scores

In this study, the score scaling approach discussed in detail in the literature was used (see e.g., Siddiqi 2017, pp. 240–41). The relationship between the score and logarithms for the so-called odds ratio: $Odds = \frac{1-PD}{PD}$—expressing the ratio of odds: (1-PD)—that the business in question will be classified as healthy versus the odds that the business will be bankrupt (PD) is:

$$Score = a_0 + a_1 \cdot \ln(Odds). \tag{1}$$

By introducing the concept of *pdo*—the number of points in the scoring system which doubles the value of the odds ratio, for a given value of the score we obtain the following relationship:

$$Score + pdo = a_0 + a_1 \cdot \ln(2 \cdot Odds). \tag{2}$$

By solving the system of Equations (1) and (2) we obtain formulas of the linear relationship ratios of score scaling depending on ln(*Odds*), and therefore on the probability of default (PD):

$$\begin{aligned} a_1 &= \frac{pdo}{\ln(2)}, \\ a_0 &= Score_0 - a_1 \cdot \ln(Odds). \end{aligned} \tag{3}$$

4.5. Validation Measures of Bankruptcy Prediction Models

Commonly used measures of classification accuracy were applied in the validation of estimated bankruptcy models. They are described by Siddiqi (2017) and Thomas (2009) clearly and in detail. The confusion matrix is probably the most frequent approach in the assessment of classification accuracy of models. Table 2 presents a general form of the confusion matrix.

Table 2. Confusion matrix for the validation of classification consistency of the bankruptcy model.

ReportedBankruptcy	**Forecast Bankruptcy**	
	B	**NB**
B (negative class: bankrupt)	TN (True Negative)	FN (False Negative)
NB (positive class: non-bankrupt)	FP (False Positive)	TP (True Positive)

Source: own elaboration.

Quantities shown in the table have the following meaning: TN—number of actually bankrupt businesses correctly classified by the model, TP—number of healthy businesses correctly classified by the model as healthy businesses, FN—number of actually bankrupt businesses incorrectly classified by the model as healthy businesses, FP—number of actually healthy businesses incorrectly classified by the model as bankrupt. $AC = \frac{TN+TP}{TN+FN+FP+TP} \cdot 100\%$ is the measure of the overall effectiveness of correct classification. The effectiveness of correct classifications for the 'bankrupt' class alone can be specified as: $AC_B = \frac{TN}{TN+FN} \cdot 100\% = 1 - Err_B$, where: Err_B—is the so-called type I error of incorrect classifications for the class of bankrupt businesses. Likewise, the effectiveness of correct classification for the businesses at no risk of bankruptcy alone can be determined as follows: $AC_{NB} = \frac{TP}{FP+TP} \cdot 100\% = 1 - Err_{NB}$, where: Err_{NB}—is the so-called type II error of incorrect classification for the class of healthy businesses. Obviously, the higher the values of classification accuracy measures, the better the effectiveness of the models assessed.

The GINI coefficient and the related area under curve ROC (Receiver Operating Characteristic) AUC_{ROC} are also often used as measures of bankruptcy model classification effectiveness (see e.g., Agarwal and Taffler 2008, Barboza et al. 2017). The ROC curve is a graphic representation in a coordinate system (Y = Sensitivity, X = (1 − Specificity)) of a relationship of the cumulative percentage (structural ratio) for bankrupt businesses from the contingency table for the predicted *i*th category of a point score ($score_i$): $\omega\_sk_{B,i} = \frac{\sum_{j=1}^{i} n_{B,j}}{n_B}$ and the corresponding cumulative structural ratio for businesses at no risk of default: $\omega\_sk_{NB,i} = \frac{\sum_{j=1}^{i} n_{NB,j}}{n_{NB}}$. In the case of classification results ordered relative to the score in the contingency table with k different scoring categories, the GINI coefficient, and thus AUC_{ROC}, is determined by the following formula (see e.g., Thomas 2009, pp. 117–18):

$$GINI = 1 - \sum_{i=1}^{k-1} (\omega_{skB,i+1} - \omega_{skB,i}) \cdot (\omega_{skNB,i+1} + \omega_{skNB,i}) = 2 \cdot AUC\ (ROC) - 1. \quad (4)$$

The GINI coefficient takes values from interval [0,1]. High values of the coefficient, approaching 1, mean that the model being assessed is highly effective (nearly perfect). Meanwhile, the measure of the area under curve AUC_{ROC} ranges from 0.5 to 1. Value 0.5 means that the model classifies businesses in the analyzed classes in a completely random way (i.e., its use is pointless), while 1 is a value attained by the best model which perfectly identifies membership in a class.

Information Value (IV), Kolmogorov-Smirnov (KS) statistics and less frequently, the divergence coefficient (Div) are also used to evaluate the effectiveness of bankruptcy forecasting models at the validation stage. IV is calculated by the following formula (see e.g., Thomas 2009, p. 106):

$$IV = \sum_{i=1}^{k} \left(\frac{n_{NB,i}}{n_{NB}} - \frac{n_{B,i}}{n_B} \right) \cdot \ln \left(\frac{n_{NB,i}/n_{NB}}{n_{B,i}/n_B} \right) \quad (5)$$

where: n_B is the number of bankrupt businesses, n_{NB} is the number of businesses with no risk of bankruptcy, $n_{B,i}$ is the number of businesses for the ith scoring category and $n_{NB,i}$ is the corresponding number of businesses with no risk of bankruptcy. The higher IV values, the better discriminant properties of the model subjected to assessment.

The Kolmogorov-Smirnov (KS) statistic compares the empirical distributions of populations containing bankrupt businesses and healthy businesses (a goodness of fit measure). The greater the differences in cumulative distribution functions for the score (higher KS values), the better discriminant capabilities of the model (i.e., the better the scoring model is in separating bankrupt businesses from healthy ones). KS statistic values are calculated by the following formula (see e.g., Thomas 2009, p. 111):

$$KS = \max_{i=1,\ldots,k} \left| \omega\_sk_{B,i} - \omega\_sk_{NB,i} \right|. \quad (6)$$

The last validation measure applied to the bankruptcy forecasting models assessed is distribution divergence (Div) given by the formula (see e.g., Siddiqi 2017, p. 261):

$$Div = \frac{(\mu_{NB} - \mu_B)^2}{0.5 \cdot (var_{NB} + var_B)} \quad (7)$$

where: μ_{NB}—mean score distribution value for the healthy businesses population, μ_B—mean score distribution value for bankrupt businesses population and var_{NB}, var_B—respective variances of these distributions.

4.6. Optimal Cut-Off Point for Scoring Determination

There are several methods of determination the optimal cut-off point for the scoring models. These methods are described in depth in the literature (see e.g., Zweig and Campbell 1993). One of the methods of determining the optimum cut-off point for the score (used in the research) was to find a score value that maximizes the value of the following expression:

$$\max_{score_i} \left\{ M_1(score_i) = \omega\_sk_{B,i}(score_i) - \frac{k_{NB}}{k_B} \cdot \frac{1 - p_B}{p_B} \cdot \omega\_sk_{NB,i}(score_i) \right\} \quad (8)$$

where: k_B is the cost of type I error: the model incorrectly classifies a bankrupt business as a healthy one, k_{NB} corresponds to the cost of type II error where the model incorrectly classifies a healthy business as bankrupt, and p_B is the probability of membership in the bankrupt class estimated on the basis of the training sample (the percentage of bankrupt businesses in the sample).

5. Research Results

The ensemble classifier methodology will be applied to design a scoring model in order to predict bankruptcy events of Polish businesses operating in the Podkarpackie Voivodeship. Each stage of design will be presented in detail together with its potential for a practical application.

The process of designing a scoring model using ensemble classifiers for businesses operating in the Podkarpackie Voivodeship was divided into several stages:

1. The choice of a suitable subset of financial ratios (bankruptcy predictors) determining the financial circumstances of the businesses analyzed (feature selection stage).
2. Training and calibration of base models applied and ensemble models selected on the basis of the training sample. Determining the function of the probability of default and membership in forecast classes for both samples: training sample, and test and validation sample (which is not taken into account at the stage of calibration of the evaluated models).
3. Determining the score value for the training sample and the test sample with a suitable scaling of the value of the resulting probability of default function for the estimated models and their transformation into corresponding resulting point score values.
4. Validation of estimated models. Determining the values of validation statistics for the models applied and analysis of their discriminant capabilities for the training sample and the test sample. Selection of the best forecasting model.
5. For the best model, determining the optimum cut-off point for the score value, i.e., the point below which a business should be categorized as bankrupt.
6. Bankruptcy forecasts for analyzed businesses from the Podkarpackie Voivodeship in individual sectors of economic activity and business size. Final comparative analysis of results and final conclusions.

5.1. Feature Selection Stage—Selection of Ratios/Bankruptcy Risk Determinants

Twenty-two financial ratios commonly applied in financial analysis of businesses were initially proposed for the assessment of the financial standing of analyzed business entities:

- Financial liquidity ratios: X1—Current ratio = Current assets to Short-term liabilities total (all liabilities with maturity shorter than one year): CA/STL, X2—Quick ratio = (Current assets − Inventories) to Short-term liabilities total: (CA-I)/STL, X3—Cash ratio = Cash and Cash equivalents to Short-term liabilities total: Cash/STL
- Profitability ratios: X4—Operating profit margin = Operating earnings to Net sales: OE/NS [%], X5—Return on assets (ROA) = Net profit (Total Revenue − Cost of Goods Sold − Operating Expenses − Other Expenses − Interest and Taxes) to Assets total (Balance sheet total): NP/BST [%], X6—Return on equity (ROE) = Net profit to Equity: NP/E [%], X7—Return on invested capital = Net profit to (Assets total − Short-term liabilities total): NP/(BST-STL) [%], X8—Net profitability = Net profit to Revenues from sales: NP/RS [%], X9—gross profit margin on sales = (Revenues from sales − Cost of goods sold) to Revenues from sales: (RS-CoGS)/RS [%], X10—operating return on assets = EBIT (Earnings Before Interest and Taxes) to Assets total: EBIT/BST [%]
- Debt ratios: X11—Overall debt = Liabilities total to Assets total (Balance sheet total): TL/BST [%], X12—Debt to equity = Liabilities total to Equity: (TL/E) [%], X13—Debt to EBITDA = Liabilities total to EBITDA: TL/EBITDA, X14—Financial leverage = Assets total (Balance sheet total) to Equity: BST/E [%]
- Management effectiveness ratios: X15—Receivable turnover = Revenues from sales to Short-term receivables: RS/STR, X16—Asset turnover = Revenues from sales to Assets total (Balance sheet total): RS/BST, X17—Inventory turnover = Revenues from sales to Inventories: RS/I, X18—Liability

turnover = (Revenues from sales + Inventories) to Short-term liabilities total: (RS+I)/STL, X19—Working capital turnover = Revenues from sales to (Current assets − Short-term liabilities total): RS/(CA-STL)

- Capital structure ratios: X20—Structure of Equity to Assets total (Balance sheet total): E/BST [%], X21—Structure of Fixed assets to total assets (Balance sheet total): FA/BST [%], X22—Structure of Fixed assets to Current assets: FA/CA [%]

With the help of *wrapper* techniques (discussed in Section 4.2 above), an optimum subset of predictors was selected by means of the genetic algorithm and a potentially best set of financial ratios for bankruptcy forecasting models being trained was determined. Linear discriminant analysis (LDA) was used as a forecasting model in the search algorithm, while the general classification accuracy (AC) measure was applied as the measure of the effectiveness of predictor subsets. The calculations were performed by means of the *R* statistical analyses package and function *gafs()* from the *caret* library. Parameters for the genetic algorithm were as follows: *poSize = 50*—the number of subsets assessed in each iteration, *pcrossover = 0.8* (crossover probability) —a high probability that the new generation will not be an exact copy of the chromosomes of parents from the previous generation, *pmutation = 0.1* (mutation probability)—a low probability of chromosome alterations in the subsequent mutation, *elite = 0*—the number of best subsets capable of survival in each generation. By means of a suitable genetic algorithm randomly searching for the best subset of diagnostic variables, a set of 19 optimum financial ratios (accuracy for the set was AC = 0.89) using 5-fold cross-validation (cv) procedure. Table 3 contains values of selected measures of discriminant capabilities and significance for individual diagnostic variables.

Table 3. Discriminant capability measures—ranking of predictors.

Ratio	Discriminant Measures		
	IV	GINI	V-Cramer
X9 (Z8)—Return On Sales (profit margin) (gross) [%]	5.81	0.86	0.84
X11 (Z10)—Overall Debt [%]	4.82	0.88	0.87
X12 (Z11)—Debt to Equity [%]	4.04	0.81	0.79
X13 (Z12)—Debt/EBITDA	2.76	0.72	0.66
X5 (Z4)—Return on Assets (ROA) [%]	1.66	0.68	0.60
X8 (Z7)—Net Profit Margin [%]	1.62	0.67	0.58
X10 (Z9)—Operating Return on Assets [%]	1.59	0.66	0.57
X4 (Z3)—Operating Profit Margin [%]	1.57	0.66	0.57
X7 (Z6)—Return On Invested Capital [%]	1.40	0.65	0.55
X20 (Z18)—Equity To Total Assets Structure [%]	1.39	0.65	0.55
X6 (Z5)—Return On Equity ROE [%]	1.18	0.63	0.51
X18 (Z16)—Liability Turnover	0.93	0.61	0.46
X21 (Z19)—Fixed Assets to Total Assets Structure [%]	0.89	0.57	0.38
X17 (Z15)—Inventory turnover	0.75	0.59	0.42
X15 (Z13)—Receivable Turnover	0.72	0.58	0.40
X19 (Z17)—Working Capital Turnover	0.66	0.58	0.39
X3 (Z2)—Cash Ratio	0.66	0.58	0.39
X1 (Z1)—Current Ratio	0.59	0.57	0.37
X16 (Z14)—Asset Turnover	0.28	0.52	0.22

Source: own elaboration using Statistica software.

5.2. Calibration of the Parameters of Bankruptcy Risk Forecast Models (Calibration Stage)

Eight single classifier models were used in forecasting the probability of default (PD) (Table 3). Classification functions for those models, the so-called level 1 classifiers, served as inputs for a level 2 ensemble meta-classifier, which aggregated them into final classification results. k-NN (k-Nearest Neighbors) was the stacking ensemble classifier. Alternatively, boosting and bagging ensemble classifier approaches were also applied. For comparison purposes, boosting ensemble classifiers were also used: GBM—Stochastic Gradient Boosting Machine (Friedman 2002) and boosted logistic regression classifier (Logit Boost). The Random Forest (RF) model and averaged Neural Networks (avNNet) were used as bagging classifiers (Breiman 2001). A bankruptcy prediction model calibration procedure was based on samples described in detail in Section 4.3. Calculations were performed with the help of procedures written with the use of the R package libraries (https://cran.r-project.org/). In particular, the following libraries were used: *caret*, *caretEnsemble*, *caTools*, *pROC*, *MASS*, *nnet*, *kernlab*, *rpart*, *earth*, *mgCV*, *klaR*, *gbm*, *plyr*, *randomForest* and other auxiliary ones. A cross validation approach was employed in the calibration procedure of the optimum model (k = 5-fold CV cross-validation). The approach assumed an area under ROC curve values (AUC_{ROC}) as a measure of models' discriminant quality (effectiveness). Figure 8 illustrates the process of increasing classification effectiveness for the boosting ensemble model depending on the number of iterations of the boosting algorithm for various complexity of classification trees trained. It very clearly shows why ensemble classifiers surpass single (individual) classifiers in terms of quality.

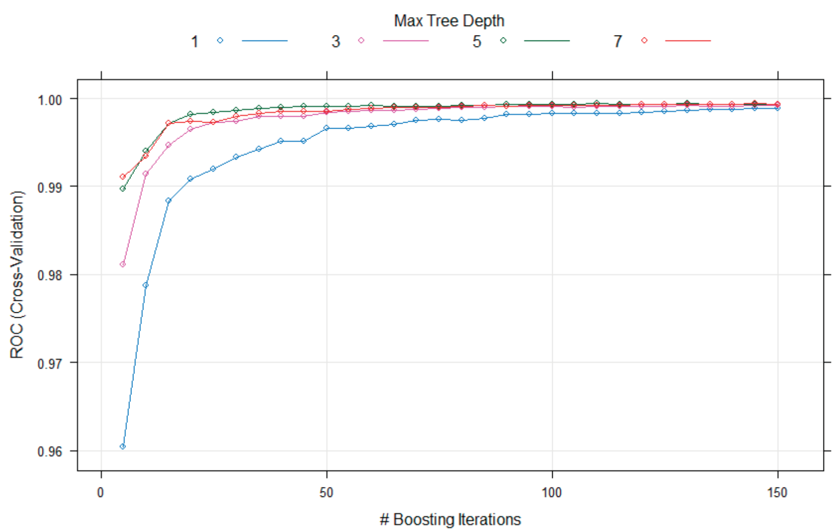


Figure 8. GBM model training process with the use of the stochastic gradient boosting algorithm. Source: own elaboration using R package.

A table in Appendix A (Table A1) presents the final best configurations of the considered bankruptcy prediction models and optimum values of their parameters.

5.3. Determining Score for the Optimum Model (Score Scaling Stage)

Forecast values of classification functions of the models analyzed (probability of default, PD) in the scoring model should be transformed into corresponding values of score through appropriate scaling. In the calculations, it was assumed that for $Score_0 = 600$ the number points which doubles the odds that the business is not at risk of default, evaluated as 50:1 (Odds = 50), is pdo = 20. With the above assumptions, scaling parameters were estimated and the score function was described by the following relationship: $Score = 487.12 + 28.85 \cdot \ln\left(\frac{1-PD}{PD}\right)$. Figure 9 illustrates the scaling obtained for the score when the GBM ensemble model is used for the training sample.

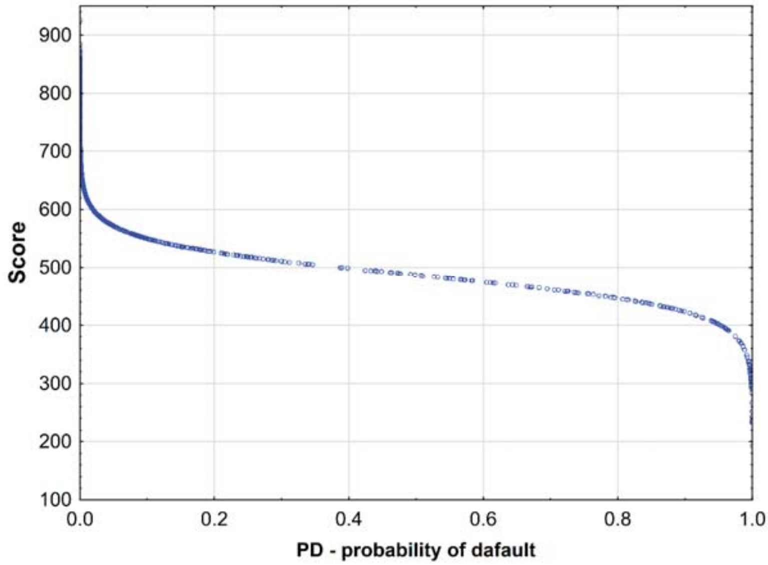


Figure 9. Score scaling in relation to the corresponding probability of default (PD) for the GBM model. Source: own Elaboration using Excel.

5.4. Model Validation (validation Stage)

Figure 10 presents ROC curves for five classification models assessed. It is clear that the GBM model perfectly (in 100% cases) predicted membership of businesses in either class (bankrupt and healthy) (AUC = 1). The worst of the models compared, NB—Naive Bayes, also had high prediction accuracy expressed by measure (AUC = 0.92), although it was still significantly inferior to other models.

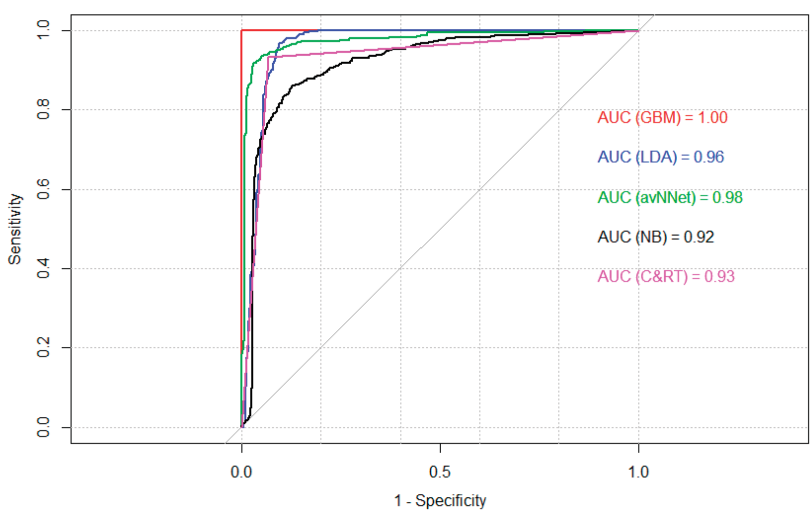
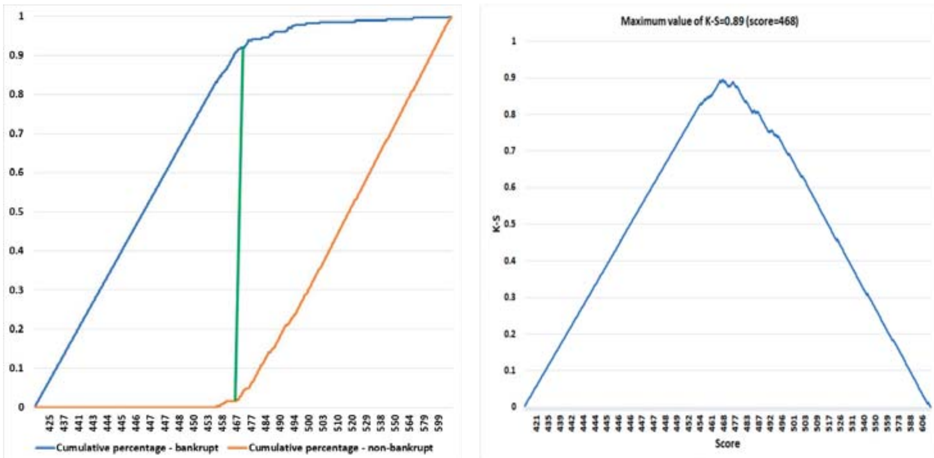


Figure 10. ROC curves for models LDA, NB, C&RT, avNNet and GBM for the training sample. Source: own elaboration using the R package.

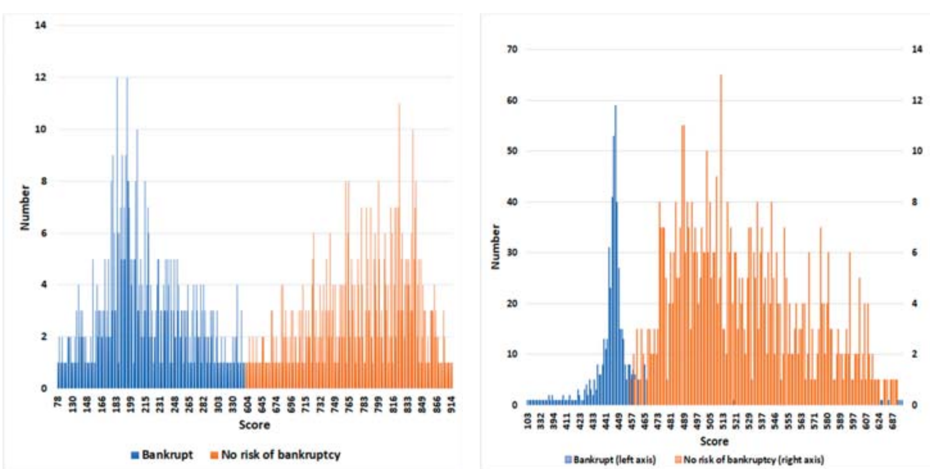
Figure 11 presents a graphic interpretation of KS = 0.89 (for score = 468) for the LDA model when testing its effectiveness with regard to the test and validation sample. High values for this KS statistics mean that the model is rather effective.



(**a**) (**b**)

Figure 11. Interpretation of the Kolmogorov-Smirnov validation statistic for the LDA model and the test and validation sample: (**a**) Difference in cumulative distribution function for both classes relative to score; (**b**) Relationship of KS as the maximum difference between cumulative distribution functions for both classes relative to score. Source: own elaboration using Excel.

Figure 12 presents a comparison and interpretation of a very high discriminant capability of the ensemble GBM model (divergence Div = 92.1) and the LDA model with a relatively weaker discriminant capability (divergence Div = 2.6) rated on the basis of the training sample.



(**a**) (**b**)

Figure 12. Score distribution for healthy and bankrupt businesses: (**a**) for the GBM model and very high divergence of distributions Div = 92.1; (**b**) for the LDA model and low divergence of distributions Div = 2.6. Source: own elaboration using Excel.

5.5. Optimal Cut_Off Point Determination Stage

The next step for the ensemble GBM classifier-based forecasting model with the best classification properties expressed by the value of validation measures involved determining values of the optimum cut_off point below which the businesses analyzed were regarded as being at risk of default (bankrupt). In the calculations, it was assumed that the ratio of the above costs is $\frac{k_{NB}}{k_B} = \frac{1}{2}$ (double cost for the incorrect classification of bankrupts, as the event appears to be more detrimental for the practical application of the model) and a probability of $p_B = 0.486$ in the training sample was determined. The optimum cut_off point was calculated for $score_{cut\_off} = 386$ by means of formula (8). Therefore, all businesses for which the point value of the score is score ≤ 386 must be forecast as members of the bankruptcy (B) class, while the remaining ones as members of the non-bankruptcy (NB) class. Still, for the estimated optimum ensemble GBM model in the score value interval [387–486], there is a very high potential risk of default (PD > 0.5), determined on the basis of the training sample (contained in the interval [0.96–0.51]). Consequently, if we rely on the classical procedure allowing us to consider a business (for which PD > 0.5) bankrupt (at risk of default), then the score interval (387 <= score <= 486) should be defined as a "gray zone", where it is difficult to clearly determine the membership of a given business in either the bankruptcy class or the non-bankruptcy class. Businesses of this type were assessed as uncertain, leaning towards potential bankruptcy (contingent on unfavorable circumstances affecting their financial health).

Figure 13 presents an interpretation of the optimum cut-off point for the score, determined in the above manner.

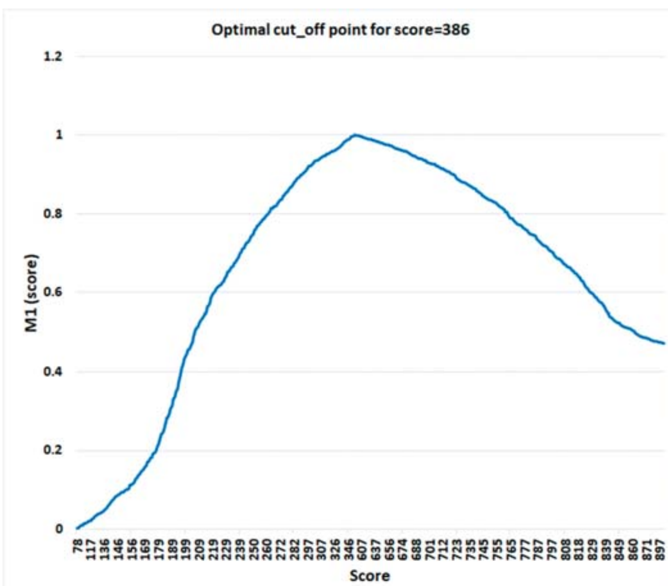


Figure 13. Optimal score cut-off point for the GBM model. Source: own elaboration using Excel.

5.6. Classification of Enterprises from the Podkarpacie Region (Prediction Stage) Depending on the Risk of Their Bankruptcy

Applying the classification rule:

$$\begin{gathered} \text{IF } (score \le 386) \text{ THEN bankrupt within h} \le 2 \text{ years;} \\ \text{IF } (score > 486) \text{ THEN healthy;} \\ \text{IF } (score > 386 \text{ AND } score \le 486) \text{ THEN uncertain (grey zone);} \end{gathered} \tag{9}$$

a forecast of bankruptcy (membership in either risk class) was determined over a time horizon of maximum 2 years (up to 2020) for businesses operating in the Podkarpackie Voivodeship in various sectors of economic activity and depending on the enterprise size. Table 4 is a contingency table presenting the forecast number of businesses classified as members of each of the 3 bankruptcy risk classes by different economic activity sectors.

Table 4. Predicted number of businesses at risk of bankruptcy in time horizon h = 2 (until 2020) and predicted number of businesses in an uncertain condition in the Podkarpackie Voivodeship for various sectors.

Sector	Number of Businesses Forecast by the Ensemble Scoring Model in a Given Bankruptcy Risk Class (h = 2 years, until 2020)		
	Bankrupt (B)	**Uncertain ("Grey Zone")**	**Healthy (No Risk of Bankruptcy) (NB)**
A—farming, forestry and fishing	2 (4%) (small = 1; medium = 1)	3 (6%) (micro = 1; small = 1; large = 1)	45 (90%) (micro = 10; small = 12; medium = 10; large = 13)
B—mining and extraction	0	0	12 (100%) (micro = 4; small = 1; medium = 4; large = 3)
C—industrial processing	11 (2%) (micro = 1; small = 4; medium = 5; large = 1)	27 (5%) (micro = 6; small = 9; medium = 3; large = 9)	543 (93%) (micro = 84; small = 83; medium = 175; large = 201)
D—energy, water, gas and other energy sources	0	0	25 (100%) (micro = 4; small = 3; medium = 6; large = 12)
E—waste, wastewater and sewage management	0	2 (3%) (small = 1; medium = 1)	65 (97%) (micro = 11; small = 5; medium = 18; large = 31)
F—construction	7 (3%) (micro = 2; small = 1; medium = 2; large = 2)	10 (5%) (micro = 9; large = 1)	203 (92%) (micro = 55; small = 44; medium = 52; large = 52)
G—wholesale and retail	17 (2%) (micro = 9; small = 3; large = 5)	19 (3%) (micro = 5; small = 4; medium = 5; large = 1)	698 (95%) (micro = 185; small = 121; medium = 226; large = 166)
H—transport and storage management	2 (3%) (micro = 1; small = 1)	3 (4%) (small = 1; large = 2)	70 (93%) (micro = 18; small = 10; medium = 20; large = 22)
I—accommodation and gastronomy	7 (13%) (micro = 4; medium = 2; large = 1)	4 (7%) (micro = 1; medium = 2; large = 1)	45 (80%) (micro = 17; small = 8; medium = 6; large = 14)
J—information and communication	0	3 (5%) (micro = 3)	52 (95%) (micro = 16; small = 7; medium = 11; large = 18)
K—finance and insurance	0	4 (33%) (micro = 1; small = 2; large = 1)	8 (67%) (small = 2; medium = 4; large = 2)
L—services for the property market	2 (3%) (micro = 1; small = 1)	10 (14%) (micro = 5; small = 2; medium = 2; large = 1)	61 (83%) (micro = 20; small = 8; medium = 12; large = 21)
M—scientific, specialist and technological activity	1 (2%) (micro = 1)	2 (3%) (micro = 1; large = 1)	58 (95%) (micro = 24; small = 8;medium = 14; large = 12)

Table 4. *Cont.*

Sector	Number of Businesses Forecast by the Ensemble Scoring Model in a Given Bankruptcy Risk Class (h = 2 years, until 2020)		
	Bankrupt (B)	**Uncertain ("Grey Zone")**	**Healthy (No Risk of Bankruptcy) (NB)**
N—administration and support	2 (5%) (micro = 2)	3 (7%) (micro = 1; large = 2)	38 (88%) (micro = 11; small = 3; medium = 8; large = 16)
P—education	0	0	9 (100%) (micro = 1; small = 2; medium = 2; large = 4)
Q—health and social care	1 (3%) (large = 1)	2 (5%) (small = 1; large = 1)	35 (92%) (micro = 10; small = 5; medium = 8; large = 12)
R—entertainment and leisure	0	2 (18%) (micro = 2)	9 (82%) (micro = 5; small = 2; medium = 2)
S—other services	0	1 (9%) (micro = 1)	10 (91%) (micro = 3; medium = 5; large = 2)
Total	52 (2%) micro = 4%; small = 3%; medium = 2%; large = 2%	95 (5%) micro = 7%; small = 6%; medium = 2%; large = 4%	1986 (93%) micro = 89%; small = 91%; medium = 96%; large = 94%

Source: own elaboration using Statistica software.

Figure 14 presents the forecast probability of potential bankruptcy risk (up to h = 2 years) for the enterprises surveyed from the Podkarpacie for various sectors of classification of their activities, which were estimated on the basis of the optimal ensemble model (GBM) for which the classification functions were used in the developed scoring model.

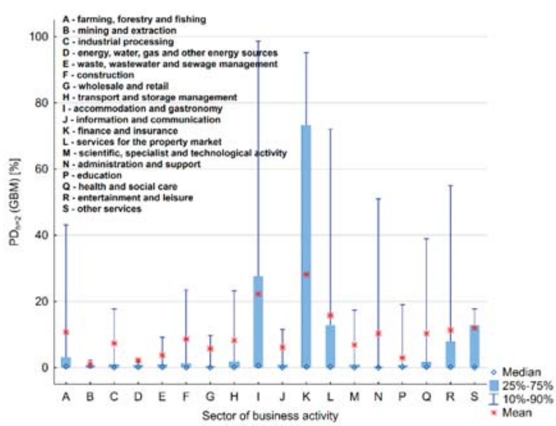


Figure 14. Descriptive statistics characterizing the probability distribution of bankruptcy (over a 2-year time horizon) for the surveyed enterprises from the Podkarpacie for various sectors of their business activities. Source: own elaboration using Statistica.

Figure 15, on the other hand, shows the predicted values of such probability of bankruptcy for the surveyed enterprises from the Podkarpackie, depending on their enterprise size.

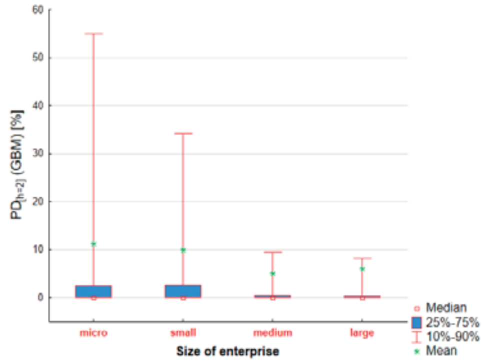


Figure 15. Descriptive statistics characterizing the probability distribution of bankruptcy (over a 2-year time horizon) for the surveyed enterprises from Podkarpackie depending on the size of the enterprise. Source: own elaboration using Statistica.

Table 5 presents a proper assessment of the classification effectiveness of the developed bankruptcy early warning model on observed and available at the time of conducting the confirmed court tests of 39 actual enterprises that declared bankruptcies in the Podkarpackie Voivodeship (in 2019). They were included in the test sample of 2133 enterprises. This confirms the fairly good quality of the model for which the effectiveness (ex-post) of correct recognition by the implemented scoring model for new (not taken into account at the calibration stage) of actually bankrupt enterprises is about 79% (which seems to be acceptable result), while for enterprises not threatened with bankruptcy, the efficiency of the model is much better and is equal to 95%.

Table 5. The actual effectiveness of the classification compatibility of the model verified on the basis of a sample of enterprises from the Podkarpackie Voivodeship.

Reported Bankruptcy	Forecast Bankruptcy (h = 2 years) to 2020		
	Bankrupt	Uncertain (Potentially Bankrupt)	Healthy (No Risk of Bankruptcy)
Bankrupt	31 (79%)	3 (8%)	5 (13%)
No risk of bankruptcy	21 (1%)	92 (4%)	1981 (95%)

Source: own elaboration.

6. Discussion

The comparative analysis of the classification effectiveness of ensemble models in juxtaposition with several classical bankruptcy forecasting methods indicates that ensemble classifiers are characterized by considerably better values of validation measures, both for the training sample and the test sample, surpassing all of the analyzed base classifiers in terms of accuracy. The best ensemble classifier, GBM (decision trees supported by a stochastic gradient boosting algorithm) offered full accuracy of correctly classified bankrupt and healthy businesses ($AC = 100\%$, $AC_B = 100\%$, $AC_{NB} = 100\%$) for the training sample and over 99% for the test sample (Tables A2 and A3). In addition, other values of validation statistics demonstrate nearly perfect predictive capability of the GBM ensemble model for the training sample: $AUC_{ROC} = 1$, statistic $KS = 1$, divergence $Div = 92.1$ and information value $IV = 5.3$ and the test sample: $AUC_{ROC} = 0.99$, statistic $KS = 0.99$, divergence $Div = 22.1$ and information value $IV = 7.1$. The Generalized Additive Model (GAM) seems to be the best classical model, yet it displays inferior values of validation statistics, both for the training sample: $AC = 97$, $AUC_{ROC} = 0.99$, $KS = 0.96$, $Div = 5.8$, $IV = 5.3$, and for the test sample: $AC = 97\%$, $AUC_{ROC} = 0.99$, $KS = 0.96$, divergence $Div = 43.0$, $IV = 7.1$. This confirms the earlier findings of other authors and allows us to say that in practical applications, bankruptcy models based on ensemble classifiers outperform other classical approaches and are an interesting alternative to the conventional method of using single classifiers.

Based on the analysis of the value of the probability of bankruptcy (Figure 14) of the enterprises surveyed in the Podkarpackie Voivodeship in individual sectors of their business activity (estimated on the basis of the best ensemble classifier model—GBM, which has the best forecasting and classification capabilities) and on the basis of an analysis of their predicted belonging to three Bankruptcy risk classes (Table 4), the following comparative analysis can be carried out assessing the exposure to bankruptcy risk of enterprises operating in the region in 2018 in view of their potential bankruptcy by 2020.

In sector A (farming, forestry and fishing) with a total of 50 enterprises surveyed, the developed scoring model predicted bankruptcy within a time horizon of up to two years (up to 2020) 4% of all enterprises in this sector, including uncertain enterprises from the second class of bankruptcy risk (from the so-called "gray zone"), i.e., with a significant probability of bankruptcy (PDt = 2 > 50%), the percentage of potentially bankrupt enterprises (over a 2-year horizon) increases to 10%. The average probability of bankruptcy for enterprises in this sector is 11% (min = 0%, max = 99.9%). Every 10 enterprise in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) in the range of 43%–99.9%. It is therefore quite heavily exposed to the risk of bankruptcy.

In sector B (mining and extraction) with a total of 12 enterprises, the scoring model qualified all enterprises as not being threatened with bankruptcy. The average probability of bankruptcy for enterprises in this sector is 1% (min = 0%, max = 6.8%). Every one of the 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) in the range of 2.3%–6.8%. Therefore, it was the first of the three least risky sectors of the region's economy.

In sector C (industrial processing) with a total of 581 enterprises, the scoring model predicted bankruptcy for 2% of all enterprises in this sector within a time horizon of up to two years (up to 2020), including uncertain enterprises from the second class of bankruptcy risk (from "grey zone"), while the number of potentially bankrupt enterprises increased to 7%. The average probability of bankruptcy for enterprises in this sector is 7.4% (min = 0%, max = 100%). Every enterprise in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) greater than 17.7%.

Sector D (energy, water, gas and other energy sources) with a total of 25 enterprises was the second of the three least risky sectors in the region's economy. The scoring model qualified all enterprises as not being threatened with bankruptcy. The average probability of bankruptcy for enterprises in this sector is 2.2% (min = 0%, max = 43.3%). Every 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) that was greater than 1.7%.

In sector E (waste, wastewater and sewage management) with a total of 67 enterprises, the scoring model qualified 97% of enterprises as not being threatened with bankruptcy, and 3% as uncertain. The average probability of bankruptcy for enterprises in this sector is 3.8% (min = 0%, max = 83.7%). Every 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) that was greater than 9.2%.

In F sector (construction) with a total of 220 enterprises, the scoring model predicted bankruptcy within a time horizon of up to two years (up to 2020) for 3% of all enterprises in this sector, though after including uncertain enterprises with the second class of bankruptcy risk (from the "grey zone"), the percentage of potentially bankrupt enterprises increases to 8%. The average probability of bankruptcy for enterprises in this sector is 8.6% (min = 0%, max = 100%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) that was greater than 23.5%.

In sector G (wholesale and retail) with a total of 734 enterprises, the scoring model predicted bankruptcy for 2% of all enterprises in this sector for up to two years (up to 2020). After including uncertain enterprises from the second class of bankruptcy risk (from the "gray zone"), the percentage of potentially bankrupt enterprises rose to 5%. The average probability of bankruptcy for enterprises in this sector is 5.7% (min = 0%, max = 100%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) that was greater than 9.8%.

In the H (transport and storage management) sector with a total of 75 enterprises, the scoring model predicted bankruptcy for 3% of all enterprises in this sector for up to two years (up to 2020), including uncertain enterprises from the second class of bankruptcy risk (from the "gray zone"), while the percentage of potentially bankrupt enterprises increased to 7%. The average probability of bankruptcy for enterprises in this sector is 8.2% (min = 0%, max = 100%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) that was greater than 23.2%.

The I sector (accommodation and gastronomy) with a total of 56 enterprises was the sector most exposed to the risk of bankruptcy. The scoring model predicts bankruptcy in the time horizon of up to two years (up to 2020) for as much as 13% of all enterprises in this sector, including uncertain enterprises in the second class of bankruptcy risk (from the "gray zone"), meaning the percentage of potentially bankrupt enterprises increased to 20%. The average probability of bankruptcy for enterprises in this sector is 22.2% (min = 0%, max = 100%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) that was greater than 98.6%.

In the J (information and communication) sector with a total of 55 enterprises, the scoring model qualified 95% of enterprises as not being threatened with bankruptcy, and 5% as uncertain. The average probability of bankruptcy for enterprises in this sector is 6.1% (min = 0%, max = 89.4%). Every 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) greater than 11.6%.

In the K (finance and insurance) sector with a total of 12 enterprises, the scoring model qualified 67% of enterprises as not being threatened with bankruptcy, and 33% as uncertain. The average probability of bankruptcy for enterprises in this sector is 28.2% (min = 0%, max = 96%). Every 10 enterprises in this sector had a probability of bankruptcy in a 2-year horizon (up to 2020) within 95.2–96%. This is a very specific sector (financial sector), hence the ambiguous interpretation of the results of the examined model belonging to risk classes.

In the L sector (services for the property market) with a total of 73 enterprises, the scoring model predicted bankruptcy for 3% of all enterprises in this sector within a 2-year horizon (up to 2020), including uncertain enterprises from the second class of bankruptcy risk (from the "gray zone"), where the percentage of potentially bankrupt enterprises increases to 17%. The average probability of bankruptcy for enterprises in this sector is 15.8% (min = 0%, max = 99.7%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) in the range of 72.1%–99.7%. It is therefore also one of the sectors with high exposure to the risk of bankruptcy.

In the sector M (scientific, specialist and technological activity) with a total of 61 enterprises, the scoring model predicted bankruptcy for 2% of all enterprises in this sector within a time horizon of up to 2 years (up to 2020). After including uncertain enterprises from the second class of bankruptcy risk (from the "gray zone"), the percentage of potentially bankrupt enterprises increased to 5%. The average probability of bankruptcy for enterprises in this sector is 6.9% (min = 0%, max = 98.1%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) greater than 17.4%.

The N sector (administration and support) with a total of 43 enterprises was also one of the sectors with a high exposure to the risk of bankruptcy. The scoring model predicted bankruptcy within a 2-year horizon (up to 2020) for 5% of all enterprises in this sector, including uncertain enterprises from the second class of bankruptcy risk (from the "gray zone"), when the percentage of potentially bankrupt enterprises increases to 12%. The average probability of bankruptcy for enterprises in this sector is 10.3% (min = 0%, max = 99.8%). Every 10 enterprises in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) greater than 51%.

Sector P (education) with a total of only nine enterprises was the third least risk affected sectors in the region's economy. The scoring model qualified all enterprises as not threatened with bankruptcy. The average probability of bankruptcy for enterprises in this sector is 3% (min = 0%, max = 19.1%). Every 10 enterprises in this sector had a probability of bankruptcy within a 2-year horizon (up to 2020) greater than 19%.

In the Q (health and social care) sector with a total of 38 enterprises, the scoring model predicted bankruptcy within a 2-year horizon (up to 2020) for 3% of all enterprises in this sector, including uncertain enterprises from the second class of bankruptcy risk (from "gray zone"), when the percentage of potentially bankrupt enterprises increases to 8%. The average probability of bankruptcy for enterprises in this sector is 10.3% (min = 0%, max = 98.8%). Every 10 enterprise in this sector had a probability of bankruptcy over a 2-year horizon (up to 2020) greater than 39%.

In the R (entertainment and leisure) sector with a total of 11 enterprises, the scoring model qualified 82% of enterprises as not being threatened with bankruptcy, and much because 18% as uncertain. The average probability of bankruptcy for enterprises in this sector is 11.3% (min = 0%, max = 61%). Every 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) in the range of 54.9%–61%. Therefore, it is a sector in which ambiguity in the interpretation of the results of the examined model to risk classes can also be observed.

In the last sector S (other services) with a total of 11 enterprises, the scoring model qualified 91% of enterprises as not threatened with bankruptcy, and 9% as uncertain. The average probability of bankruptcy for enterprises in this sector is 12% (min = 0%, max = 91.7%). Every 10 enterprises in this sector had a probability of bankruptcy in the 2-year horizon (up to 2020) greater than 17.7%. It is also a sector in which ambiguity can be observed in interpreting the belonging of the results of the examined model to risk classes.

Based on the results from Table 4 and based on the analysis of the value of the probable bankruptcy probability (Figure 15) for the surveyed enterprises depending on their size, the following relationships illustrating the degree of their exposure to the risk of bankruptcy can be seen. In the sector for very small (micro) enterprises (535 of which were included in the study), the developed scoring model qualified 89% of these enterprises as not threatened with bankruptcy, 4% as bankrupt and a further 7% as uncertain (from the "gray zone"), but potentially with a significant risk of their bankruptcy above 50%. In the sector of small sized enterprises, of which 356 was developed in the study, the scoring model qualified 91% of such enterprises as not threatened with bankruptcy, 3% as bankrupt and another 6% as uncertain (from the "gray zone"). In the sector of medium enterprises (606 included in the study), the scoring model qualified 96% of enterprises as not threatened with bankruptcy, 2% as bankrupt and another 2% as uncertain (from the "gray zone"). Similarly for the large enterprise sector (636 enterprises) the scoring model in the study classified 94% of enterprises as not at risk of bankruptcy, 2% as bankrupt and another 4% as uncertain (from the "gray zone").

One also should pay attention to limitations of the analyses presented. The limitation of the model developed may be the fact that the developed and implemented scoring model has been estimated on the basis of statistical data for enterprises from various sectors of activity. It is very difficult to develop a model with good accuracy (a sufficiently high classification efficiency) that would be good in such a situation, since various sectors often very specific and incomparable. However, on the other hand, the results obtained (Table 5) for 39 actual bankruptcies of enterprises in the Podkarpackie Voivodeship observed and confirmed in 2018, the efficiency of correct recognition by the scoring model of really bankrupt enterprises is about 79%, while for non-bankrupt enterprises the equivalent figure is 95%. The effectiveness of the scoring model for the separate class: bankrupt at 79% is sufficient and acceptable, but of course can be discussed further. It can show that designed model includes three classes of bankruptcy risk (bankrupt, non-bankrupt and "gray zone"—difficult to say, but potentially also bankrupt). In the classic approach with only two classes (bankrupt, non-bankrupt), one should add another 8% to the model effectiveness (including the class of uncertain enterprises—"gray zone" for which the probability of bankruptcy is high and greater than 0.5). Then the efficiency of the correct classifications of estimated model increases to 87%, which seems to be a good result. Overall accuracy for the model (without division into classes) is 94%.

Also, the selection of such a large set of as many as 19 indicators as determinants of the financial condition of enterprises in the models raises the question of whether it should not be limited to the set of only a few most important indicators. Such a large collection may raise suspicions that many of the variables may be strongly correlated with each other, which may affect the quality, especially of classic models, such as LDA. In the study, such a large set of factors was conditioned by the choice using the wrapper method and genetic algorithm, and the final application of the type of ensemble classifiers that are not so sensitive to the interdependence of variables. However, for the sake of accuracy, it is worth emphasizing that the correlation between variables has never been greater than 0.87. However, in future research, it is worth considering reducing the number of predictors of bankruptcy.

7. Conclusions

The results of the analyses presented in the paper lead to several general conclusions that can be a summary of the research:

- The scoring model designed for the early prediction of bankruptcy risk for Polish businesses from the Podkarpackie Voivodeship using ensemble classifiers was highly effective in forecasting and accurately evaluating the risk of default of the analyzed businesses.
- An analysis of the forecast is obtained suggests that small enterprises are more exposed to risk of default than medium or large enterprises.
- The sector of business activity and unique characteristics of the economic activity influences a potentially higher risk of business bankruptcy. A higher number of potential bankruptcies is reported in some sectors of economic activity than in others.
- A higher risk of business bankruptcy for some particular industry branches may be caused the situation where bankruptcy models are sensitive to enterprises belonging to industry sectors. This can be considered as one of the limitations of the study presented in the paper. A potentially higher risk of business bankruptcy for some particular industry branches can be influenced by the model design. It would have to be examined in further research whether the estimated separate models for each sector would indicate lower values of PD and therefore lower exposure to the risk of bankruptcy of companies.
- Another limitation of the study is that bankruptcy models are sensitive to the phase of economic cycle (presented model does not cover it), but the influence of economic cycles on bankruptcy risk can be considered in further extensions of research.
- The approach presented in the paper can be used not only to assess the risk of bankruptcy of enterprises by market analysts and regional analysts, but also in banking activities to assess credit risk for corporate loans, where similar models are of course successfully implemented.
- The study may be extended in the future with an analysis and an assessment of the risk of bankruptcy for enterprises from other regions of Poland with the development of individual separate ensemble models for enterprises from key sectors of the country's economy. It can also be extended to a comparative analysis of the risk of bankruptcy in given sectors of the economy for a group of countries, e.g., EU, Visegrad Group countries or the Three Seas Initiative countries.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. Optimum configuration and set of parameters for bankruptcy models applied.

Classification Model Applied	Optimum Model Configuration (Training Sample) Parameter Selection Criterion: AUC (ROC) Sampling: (k = 5 fold) Cross-Validation
	Model Parameters:
Individual (single) classifier	
LDA (M1) linear discriminant analysis model $LDA = \alpha_1 Z_1 + \ldots + \alpha_m Z_m$	$\alpha_1 = -8.3 * 10^{-3}$, $\alpha_2 = 6.6 * 10^{-3}$, $\alpha_3 = -8.1 * 10^{-5}$ $\alpha_4 = 5.0 * 10^{-3}$, $\alpha_5 = -2.1 * 10^{-5}$, $\alpha_6 = 1.1 * 10^{-6}$ $\alpha_7 = 8.3 * 10^{-5}$, $\alpha_8 = 2.7 * 10^{-4}$, $\alpha_9 = -4.1 * 10^{-3}$ $\alpha_{10} = -3.7 * 10^{-2}$, $\alpha_{11} = -1.8 * 10^{-5}$, $\alpha_{12} = 3.2 * 10^{-5}$ $\alpha_{13} = 2.3 * 10^{-5}$, $\alpha_{14} = -2.7 * 10^{-2}$, $\alpha_{15} = -1.3 * 10^{-8}$ $\alpha_{16} = 9.8 * 10^{-3}$, $\alpha_{17} = -1.5 * 10^{-6}$, $\alpha_{18} = -3.7 * 10^{-2}$, $\alpha_{19} = -6.6 * 10^{-8}$
LOGIT (M2) logistic regression model $L = LOGIT = ln\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 Z_1 + \ldots + \alpha_m Z_m$	$\alpha_0 = 1.0 * 10^{15}$, $\alpha_1 = -6.9 * 10^{12}$, $\alpha_2 = 2.1 * 10^{12}$ $\alpha_3 = -5.1 * 10^{11}$, $\alpha_4 = 6.9 * 10^{12}$, $\alpha_5 = -1.3 * 10^{10}$ $\alpha_6 = 4.0 * 10^{8}$, $\alpha_7 = 4.9 * 10^{11}$, $\alpha_8 = 9.2 * 10^{11}$ $\alpha_9 = -3.7 * 10^{12}$, $\alpha_{10} = -1.4 * 10^{13}$, $\alpha_{11} = -3.7 * 10^{9}$ $\alpha_{12} = 9.0 * 10^{10}$, $\alpha_{13} = -6.5 * 10^{9}$, $\alpha_{14} = 2.2 * 10^{13}$ $\alpha_{15} = 1.8 * 10^{6}$, $\alpha_{16} = 4.4 * 10^{12}$, $\alpha_{17} = -4.1 * 10^{10}$ $\alpha_{18} = -1.1 * 10^{13}$, $\alpha_{19} = -2.2 * 10^{8}$
NNet (M3) neural network (single hidden layer network)	Network configuration: 19-5-1 Neuron activation function: logistic Error function = entropy fitting Calibrated parameter for weights: decay = 0.1
SVM Radial (M4) Support Vector Machine	Cost parameter: C = 1 Hyper parameter: sigma = 11.969
C&RT (M5) classification tree model	Tree complexity parameter (cp = 0.037) Tree split: $X_{11} \geq 40.79$ (class: bankrupt) $X_{11} < 40.79$ (class: no risk of bankruptcy)
MARS splines (M6)	product degree = 1 (degree of interaction); nprune = 12 (number of base functions);
Generalized Additive Model (GAM—M7)	Select = TRUE (feature selection); Link Function = Logit; Method = GCV.Cp (GCV method for an unknown parameter of model complexity)
Naive Bayes (M8)	Laplace Correction fL = 0 Distribution type usekernel = FALSE (Binomial) Bandwidth adjustment adjust = 1
Ensemble meta-classifier (stacking)	
k-NN k-nearest neighbours, inputs: classification functions for base models (M1-M8)	Nearest neighbour parameter k = 9
Ensemble classifier (boosting)	
Stochastic Gradient Boosting Machine (GBM)	Shrinkage = 0.2; n.minobsinnode = 15 (min. node size); n.trees = 130–boosting iterations interaction.depth = 5 (max. tree depth)
Boosted Logistic Regression (Logit Boost)	nIter = 13 (boosting iterations)

Table A1. *Cont.*

Classification Model Applied	Optimum Model Configuration (Training Sample) Parameter Selection Criterion: AUC (ROC) Sampling: (k = 5 fold) Cross-Validation
	Model Parameters:
Ensemble classifier (bagging)	
Random Forest (RF)	mtry = 5 randomly selected predictors ntree = 500 (number of trees)
Averaged NNet (avNNet)	*bag = TRUE; n = 5*—bootstraps; *size = 5*—number of neurons in the hidden layer for component networks; *decay = 0.9*—decay parameter for weights;

Source: own elaboration and calculations using R and Statistica software.

Table A2. Validation statistics for selected classical models of single bankruptcy classifiers in comparison to ensemble classifiers applied for the training sample.

Classification Model	Training Sample						
	AC	AC_B	AC_{NB}	AUC_{ROC} (GINI)	KS Statistics	Divergence (Div)	Information Value (IV)
Base classifiers							
Linear discriminant analysis (LDA)—M1	88.4	94.6	82.5	0.96 (0.92)	0.87	2.6	5.2
Logistic regression (Logit)—M2	96.8	96.1	97.6	0.97 (0.94)	0.94	28.9	5.3
Neural network (NNet)—M3	93.0	94.1	92.0	0.95 (0.90)	0.86	7.5	5.2
Support Vector Machine (SVM Radial—M4)	96.4	95.4	97.4	0.99 (0.98)	0.93	17.2	5.2
Classification tree (C&RT)—M5	93.2	93.2	93.3	0.93 (0.86)	0.87	11.9	5.2
MARS splines—M6	96.0	95.8	96.3	0.99 (0.98)	0.94	8.0	5.2
Generalized Additive Model (GAM)—M7	97.7	98.0	97.4	0.99 (0.98)	0.96	5.8	5.3
Naive Bayes—M8	70.9	42.1	98.2	0.91 (0.82)	0.73	1.0	5.2
Ensemble classifier (stacking)							
Meta-classifier ensemble: kNN—model results M1-M8 as inputs	97.3	97.1	97.4	0.99 (0.98)	0.96	23.0	5.3
Ensemble classifiers (boosting)							
Stochastic Gradient Boosting Machine (GBM)	100	100	100	1.0 (1.0)	1.0	92.1	5.3
Logit Boost	97.9	97.3	98.5	0.99 (0.98)	0.96	20.5	5.3

Table A2. *Cont.*

Classification Model	Training Sample						
	AC	AC_B	AC_{NB}	AUC_{ROC} (GINI)	KS Statistics	Divergence (Div)	Information Value (IV)
Ensemble classifiers (bagging)							
Random Forest (RF)	100	100	100	1.0 (1.0)	1.0	6.4	5.3
Averaged NNet (avNNet)	94.0	94.6	93.4	0.98 (0.96)	0.89	11.6	5.3

Source: own elaboration and calculations using R and Statistica software.

Table A3. Validation statistics for selected classical models of single bankruptcy classifiers in comparison to ensemble classifiers applied for the test/validation sample.

Classification Model	Test Sample						
	AC	AC_B	AC_{NB}	AUC_{ROC} (GINI)	KS Statistics	Divergence (Div)	Information Value (IV)
Base classifiers							
Linear discriminant analysis (LDA)—M1	90.2	96.0	84.0	0.98 (0.96)	0.89	11.8	7.1
Logistic regression (Logit)—M2	96.5	94.5	98.8	0.97 (0.94)	0.93	46.2	7.1
Neural network (NNet)—M3	92.1	94.5	89.5	0.95 (0.90)	0.86	11.2	7.1
Support VectorMachine (SVM Radial)—M4	89.8	92.3	87.1	0.97 (0.94)	0.82	10.8	7.1
Classification tree (C&RT)—M5	94.2	95.2	93.1	0.94 (0.88)	0.88	14.8	7.1
MARS splines—M6	96.7	96.3	97.2	0.99 (0.98)	0.95	41.7	7.1
Generalized Additive Model (GAM)—M7	97.5	97.8	97.2	0.99 (0.98)	0.96	43.0	7.1
Naive Bayes—M8	68.4	41.7	97.6	0.93 (0.86)	0.78	7.8	7.1
Ensemble classifier (stacking)							
Meta-classifier ensemble: kNN model result M1-M8 as inputs	98.1	97.8	98.4	0.99 (0.98)	0.97	22.2	7.1
Ensemble classifiers (boosting)							
Stochastic Gradient Boosting Machine (GBM)	99.4	99.3	99.6	0.999 (0.998)	0.99	57.6	7.1
Logit Boost	98.5	98.2	99.6	0.99 (0.98)	0.98	20.6	7.1

Table A3. *Cont.*

Classification Model	Test Sample						
	AC	AC_B	AC_{NB}	AUC_{ROC} (GINI)	KS Statistics	Divergence (Div)	Information Value (IV)
Ensemble classifiers (bagging)							
Random Forest (RF)	98.6	98.2	99.2	1.0 (1.0)	0.98	4.5	7.1
Averaged NNet (avNNet)	93.8	96.0	91.5	0.97 (0.94)	0.89	10.2	7.1

Source: own elaboration and calculations using R and Statistica software.

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Review

A Comprehensive Review of Corporate Bankruptcy Prediction in Hungary

Tamás Kristóf * and Miklós Virág

Department of Enterprises Finances, Corvinus University of Budapest, Fővám tér 8, 1093 Budapest, Hungary; miklos.virag@uni-corvinus.hu

* Correspondence: tamas.kristof@uni-corvinus.hu

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Abstract: The article provides a comprehensive review regarding the theoretical approaches, methodologies and empirical researches of corporate bankruptcy prediction, laying emphasis on the 30-year development history of Hungarian empirical results. In ex-socialist countries corporate bankruptcy prediction became possible more than 20 years later compared to the western countries, however, based on the historical development of corporate bankruptcy prediction after the political system change it can be argued that it has already caught up to the level of international best practice. Throughout the development history of Hungarian bankruptcy prediction, it can be tracked how the initial, small, cross-sectional sample and classic methodology-based bankruptcy prediction has evolved to today's corporate rating systems meeting the requirements of the dynamic, through-the-cycle economic capital calculation models. Contemporary methodological development is characterized by the domination of artificial intelligence, data mining, machine learning, and hybrid modelling. On the basis of empirical results, the article draws several normative proposals how to assemble a bankruptcy prediction database and select the right classification method(s) to accomplish efficient corporate bankruptcy prediction.

Keywords: bankruptcy prediction; classification; credit risk modelling; corporate failure; rating systems

1. Introduction

In recent years, the increasing relevance of corporate bankruptcy prediction as a research field has been corroborated also by the fact that several comprehensive reviews emerged in literature with the aim to summarise the key findings of earlier published results. Central-Eastern Europe is not an exception of global tendencies, see inter alia (Kliestik et al. 2018; Pavol et al. 2018; Popescu and Dragota 2018; Prusak 2018; Marek et al. 2019). Corporate bankruptcy prediction in ex-socialist countries became possible more than 20 years later compared to western countries, since before the political system change no bankruptcy event in today's market economy sense existed in the centrally managed planned economies. However, based on the historical development of corporate bankruptcy prediction after the political system change, it can be argued that it has already caught up to the level of international best practice regarding the examined research problems, applied methods, and empirical results.

In Hungary the legislation system was needed to be adjusted to the new socio-economic processes in a relatively short time after the political system change. The establishment of bankruptcy regulations had almost no dogmatic precedents, since the legal field of insolvency had been completely missing from the Hungarian legislative system for forty years. The Act of Bankruptcy as of 1991 qualified a company as insolvent, if its debts exceeded its assets, it did not pay obligations 60 days after maturity, the foreclosure of liabilities was resultless, and/or it cancelled the payments. The Act of Bankruptcy has been modified several times since 1991, however, the fundamental concept of insolvency has not substantially changed. In the current Hungarian legislation system legal failure can have four forms:

- Bankruptcy procedure is a process, in which the debtor initiates a payment moratorium and attempts to make a bankruptcy-agreement.
- Liquidation procedure is a process, which aims to pay off the creditors by dissolving the insolvent debtor without successor in accordance with the law.
- Winding up is a process, when an economic organization, which is in principal still solvent, decides to dissolve itself without successor and pay off the creditors.
- Compulsory strike-off is a process, which results in the dissolution of the economic organization without successor if the court decides so, in particular because of failed winding-up.

Hungary can be proud of the fact that corporate bankruptcy prediction began as early as possible, and has already achieved a 30-year development history having extensive range of results. Many of them, however, were published only in Hungarian making it difficult to analyse by international scholars, and so far no comprehensive review has been written in an international journal to evaluate them. In our opinion time has come to resolve this gap.

The article attempts to synthesize the historical development tendencies of theoretical approaches, methodologies, and empirical researches of corporate bankruptcy prediction, laying emphasis on the 30-year development history of Hungarian empirical corporate bankruptcy prediction models. Throughout the development history of Hungarian bankruptcy prediction, it can be tracked, how the initial, small, cross-sectional sample and classic methodology-based bankruptcy prediction has evolved to today's corporate rating systems meeting the requirements of the dynamic, through-the-cycle economic capital calculation models. Contemporary methodological development is characterized by the domination of artificial intelligence, data mining, machine learning and hybrid modelling.

The article evaluates the development of bankruptcy prediction methodology starting from the linear statistical methods arriving at the contemporary artificial intelligence-based machine learning procedures, providing Hungarian empirical results to the application of all methods.

The research method of completing the literature review was to collect and evaluate all theoretical, methodological and empirical publications that appeared in the field of Hungarian corporate bankruptcy prediction. Considering the fact that Hungary is a relatively small country and the research field is comparatively narrow, it has been possible to provide a review encompassing the all-inclusive set of studies. The range of studies also included the works of Hungarian researchers published abroad together with the publications of Transylvanian-Hungarian bankruptcy modellers.

In our opinion this article might serve as an instructive story for other countries being in similar shoes and for scholars interested in development histories and case studies of the professional field. Since it turned out soon that well-known international corporate bankruptcy models did not perform well in Hungary, emphasis was laid on own empirical model development efforts leading to a diverse experimentation with several approaches and techniques.

2. Theoretical Considerations

Corporate failure has been a research focus for social scientists for a long time. One of the fundamental questions of management and organisation sciences is why certain organisations survive, whereas others disappear (Virág et al. 2013). In recent decades substantial number of publications have emerged in the literature in the fields of business failure, corporate survival, bankruptcy prediction, organisational mortality, financial distress, default prediction, and credit scoring, which might seem to be at first glance different things, however, it is a mutual effort of them that they attempt to predict the occurrence of a failure event with the help of corporate descriptive variables by applying similar methods (Kristóf and Virág 2019a).

It can be concluded that bankruptcy prediction primarily supports the empirical research of corporate survival and failure by exploring the reasons for failure, and by constantly developing the multivariate classification and forecast methodology (Kristóf and Virág 2019b). Bankruptcy prediction has gone through significant progress in the recent 50 years.

In the economic system, the continuous inflow and outflow of economic organizations is a natural phenomenon. According to Schumpeter (1934), corporate failure is a necessary element of effective market economy, which enables to transform the human, physical, and financial resources to other, more productive companies.

Organizational termination has been explained by many approaches of organisational theory (Mellahi and Wilkinson 2004). Classic industrial organisation and organisational ecology emphasise on the deterministic role of environment, and scholars in this field argue that external industrial and environmental conditions leave limited freedom for the managers to make decisions, that is why it is not the managers who are responsible for corporate failure. On the other side, representatives of behaviourist, political, decision theoretic, and organisational psychologist schools pursue a voluntarist approach and blame the activities, decisions, and perceptions of managers for failure. Truth is obviously somewhere between the deterministic and voluntarist approaches.

Two tendencies might be distinguished in the research field of organisational survival (Anheier and Moulton 1999). A greater part of studies examining organisational survival/failure has been carried out at the macro level. Besides modelling financial solvency, the relevant studies survey the dynamics of organisational population, together with entrance and exit from the population. The most extensive survival-researches have been conducted by the representatives of the population ecology approach. A smaller part of studies examining the organisational survival has been performed in forms of organisation-specific analyses. Emphasis has been laid on organisational efficiency and performance criteria. From management side inter alia different behavioural characteristics, inadequate organisational structure, information asymmetry, unfounded decisions, lack of foresight and self-conceit effect might also play a role in failure (Jáki 2013a, 2013b). In the management literature organisational survival is often published in the form of 'rise and fall' of different companies (Kristóf 2008b).

On the basis of case studies and quantitative analyses, several theories were born to explain organisational survival (Virág et al. 2013). However, generalisations derived from empirical researches did not converge into a unified theory of organisational survival; they rather remained competitive and complementary streams. Under such circumstances theories are regarded as 'good', which reveal organisational survival from the most possible aspects, namely which are simultaneously able to deal with the contingency, transaction cost, principal-agent, political, life cycle, cognitive, structural, resource-based, evolutionary and decision theoretic sides of survival, and do not intend to achieve a groundlessly high level of abstraction. A deep analysis of relevant organisational theoretic schools was accomplished by Kristóf (2005b). Considering the fact that the findings of organizational theoretic schools and empirical models partially arrived at controverting results, it is not recommended to define a generic, unified theoretical-methodological framework to research organisational survival.

It raises interesting theoretical problems on how the elaborated mathematical-statistical bankruptcy prediction models can contribute to the economic theories explaining organisational survival and failure. According to Blaug (1980) it can be observed in many fields of economic sciences that different econometric studies arrive at contradicting conclusions, and taking into account the available data no best method exists, on the basis of which it could be decided which conclusion harmonizes best with reality (Scott 1981). Consequently, one might examine contradicting hypotheses throughout several decades (Westgaard 2005).

Despite the fact that as a result of enormous model development efforts a great number of appreciated relationships were found, throughout the decades-long history of bankruptcy prediction no unified consent has been achieved which explanatory variables might best predict corporate failure. The exceptionally wide range of forecast methods, together with the different modelling databases from diverse countries, industries and periods make it remarkably challenging to hypothesise what causes corporate failure and how. The lack of theoretical background to explanatory variables is a true limitation to elaborate a general comprehensive theory of bankruptcy prediction. Without a generally accepted theory, nevertheless, it might be inspiring to conclude that any empirically developed model could well operate in a different period and in a different economic environment. Accordingly, it can be argued that no bankruptcy prediction model might function independently of time, space, and economic environment (Kristóf 2008b). In this aspect Hungary is a special case even among the Central-Eastern European countries, where world-famous and widely applied models showed substantially worse performance compared to their origin and experiences gained with them in other countries (Režňáková and Karas 2015; Altman et al. 2017). No wonder that country-specific bankruptcy prediction models might significantly differ from one another although being estimated using the same modelling techniques and variables (Laitinen and Suvas 2013).

Scientific predictability problem of bankruptcy forecasting is not a unique phenomenon in the field of social sciences. Predictability in social sciences has been serving as a basis of scientific discussions for a long time (Kristóf 2006). Until the end of 1950s scientific theories were judged based on their ability to make predictions. Only in the 1970s did the evaluation of heuristic power supersede the predictive power. The possibility of exact bankruptcy prediction is to be rejected from the theoretical side, since in society and economy there are no universalities like the laws of nature, on the basis of which long-run generalizations could be formed; it is only true in the case of some trivial regularities. If it were possible to exactly predict bankruptcy and similar socio-economic events, then it would be in principal also possible to list the future economic events. However, if this list became known, it would surely inspire several actors to conduct activities, which would obstruct the occurrence of the predicted event.

Hence it is impossible to give an obvious explanation to corporate survival/failure from the viewpoint of philosophy of science. The solution to this problem is the multi-sided theory-building, concurrent observance of more approaches, and simultaneous application of more forecast methods. Theory must drive empirical model development; in addition, the examination of statistical assumptions should be carried out in theoretical context (Virág et al. 2013). To support the development of the scientific field the results of hypothesis-examinations have to be fed back to theory-formulation.

In accordance with the goals of the article, from this point, the general term ‘organisation’ mentioned in organisational theoretical approaches will be restricted to economic organisations (companies). Overlapping the theoretical explanations, it is worthwhile to consider which methods might be applicable to accomplish efficient corporate bankruptcy prediction.

The use of financial ratios in corporate failure prediction is based on the assumption that the failure process is characterised by a systematic deterioration in the values of the ratios (Laitinen 1991). It can be argued that different financial predictors might be efficient in the different phases of the corporate failure process (Laitinen 1993). Accordingly, firm failure processes have become more and more important concepts, since they allow considering the behaviour of failing firms in the longer perspective, leading to the breakthrough role of dynamization approaches in bankruptcy prediction (Lukason and Laitinen 2019).

3. Methodological Development in the International Literature of Corporate Bankruptcy Prediction

Corporate bankruptcy prediction has attracted substantial attention in science for many decades. According to the research of Du Jardin (2010) throughout the historical development of bankruptcy prediction, models were published worldwide by applying more than 50 different methods and 500 variables. The article encompasses the most distributed methods having the greatest impact on scientific research and practical application.

From a methodological point of view, bankruptcy prediction is a binary classification problem with the aim to differentiate between solvent and insolvent groups of companies as good as possible (Virág 2004). Bankruptcy prediction is regarded as a boundary discipline between corporate finance and statistics (data mining), which attempts to predict the future solvency of companies using financial ratios as explanatory variables applying multivariate methods (Nyitrai 2015a).

Throughout the first half of the 20th century, there were no sophisticated statistical methods and computers available to predict bankruptcy. The financial ratios of failing and non-failing companies were compared, and it was concluded that in case of bankrupt companies the most frequently used ratios behaved worse (Fitzpatrick 1932). The first methodological breakthrough came to pass when Durand (1941) published a univariate discriminant analysis (DA)-based credit scoring model. This method became worldwide spread later with the univariate DA model of Beaver (1966).

Realising that the classification of observations using one variable does not provide a reliable result, Myers and Forgy (1963) applied multivariate regression analysis and DA to elaborate a credit rating system for banking clients. In case of riskier clients multivariate DA showed better results, in particular compared to the earlier applied expert rating system, so more and more attention was given to the method. The breakthrough success was achieved by the world-famous multivariate DA model of Altman (1968), which was able to classify the companies in the sample with 95 percentage of classification accuracy. Since its first publication, the model has gone through several revisions. Despite its great number of successful applications, however, the limitations of the model have come to pass, which can be first led back to the rigorous statistical assumption system of DA, second to the application of a hard default definition as a target variable, and third the usability of the model has been reduced by the fact that it had been developed in a relatively narrow range of companies (American stock exchange corporations), thereby limiting its applicability to populations different from the modelling database.

Since the 1970s the development of the field has been dominated by the modernisation of mathematical-statistical classification methods and the IT solutions supporting them (Nyitrai 2015a). Passing through the distribution and variance assumptions of DA, logistic regression (logit) has become a more and more popular bankruptcy prediction method, which was first applied by Chesser (1974) on a credit risk database. In the global distribution of logit, the publication of Ohlson (1980) represented a milestone, which developed a logit model on a sample of 105 insolvent and 2058 solvent companies, thereby expressing that insolvent companies represent a smaller share in the population compared to the solvent ones. The application of probit regression began in the 1980s for similar methodological reasons (Zmijewski 1984).

Nonparametric methods having no statistical assumption behind appeared in bankruptcy prediction also since the 1980s. Decision trees, which are even today widespread tools to solve classification problems and to accomplish efficient data mining, were first applied for bankruptcy prediction by Frydman et al. (1985).

The 1990s brought new challenges to bankruptcy forecasting scholars and practitioners (Prusak 2005). Several critiques concerned linear or linearizable, robust models and the earlier applied methods. As a result, neural networks (NN) belonging to the family of artificial intelligence methods have been given a boost to improve the reliability of bankruptcy forecast models (Kristóf 2005a). NNs were first applied for bankruptcy prediction by Odom and Sharda (1990). The authors proved that the performance of the three-layer backpropagation networks outperformed the results of earlier methods. Since then NNs have been widely distributed, have gone through substantial developments, and represent one of the most popular methods of today.

In parallel with the spreading of NNs, modern visual clustering procedures have been gaining a wide role in bankruptcy prediction. Self-organising maps (SOM) operating on the principle of unsupervised NNs enabled to cluster databases with unknown output into solvent and insolvent classes (Kiviluoto 1998). Multidimensional scaling (MDS) visualizes the hidden relationships between data, reducing them into multidimensional coordinates (Neophytou and Molinero 2004).

The bankruptcy prediction application of neuro-fuzzy systems has become an intensively researched object since the beginning of 2000s, providing better results compared to traditional NNs (Vlachos and Tolias 2003). In parallel, the support vector machine (SVM) procedure has also been proven to achieve higher classification accuracy than earlier applied methods, which was first published based on a sample of Australian companies using twenty-fold cross-validation (Fan and Palaniswami 2000). In addition, the methods of rough set theory (RST) (Dimitras et al. 1999), k nearest neighbour (KNN) (Ardakhani et al. 2016), Bayes-networks (Sun and Shenoy 2007), genetic algorithms

(GA) (Lensberg et al. 2006), learning vector quantization (LVQ) (Neves and Vieira 2016) and case-based reasoning (CBR) (Bryant 1997) also began to spread in the 2000s.

By the 2010s ensemble methods as a special case of method-combinations have gained significance instead of individually applying certain classification methods (Marqués et al. 2012). The essence of them is multiple bootstrapping and applying classification procedures on several subsamples. The classification power of the final model is the average of that of the individual models, usually outperforming the classification power without using ensemble methods. The most frequently applied ensemble methods are boosting, bagging, random subspace, random forest, Gauss-processes and autoencoder belonging to the family of machine learning procedures (Nyitrai 2015a; Wang 2017). Today's bankruptcy prediction researches are unambiguously dominated by machine learning, data mining, artificial intelligence and hybrid modelling through creatively combining different new methods (Barboza et al. 2017). Bankruptcy prediction as a multivariate classification problem is a very popular topic in data mining competitions aiming at finding more and more reliable and contemporary algorithms, accordingly a constantly widening range of innovative solutions are becoming public day by day.

4. Empirical Development of Hungarian Corporate Bankruptcy Prediction

Under Hungarian conditions, it became possible to scientifically examine bankruptcy prediction at the beginning of 1990s by the appearance of the Bankruptcy Act regulating the cases of legally going into bankruptcy. Throughout the recent thirty years the Hungarian literature and practice of bankruptcy prediction have gone through a substantial improvement. Considering the various research goals and databases, however, the empirically measured differences between the classification powers of the elaborated models have to be interpreted in light of the range and definition of explanatory and target variables. The importance of the scientific field can be well represented by the fact that so far fourteen PhD theses in Hungary have dealt with the theoretical backgrounds, methodological challenges and/or the practical application of corporate bankruptcy prediction (Virág 1993; Arutyunjan 2002; Kiss 2003; Imre 2008; Kristóf 2008b; Oravecz 2009; Kotormán 2009; Felföldi-Szűcs 2011; Hámori 2014; Madar 2014; Nyitrai 2015a; Bozsik 2016; Fejér-Király 2016; Koroseczné Pavlin 2016). The year of 2016 was particularly strong when three PhD theses were published.

4.1. The Era of Classic DA and Logit Models

The first Hungarian corporate bankruptcy prediction study was elaborated by Péter Futó in 1989 who worked in the Industrial Economic Institution. The research used annual report data of Hungarian industrial companies from 1986–1987 and the occurrence of insolvency event in 1988 by using variance analysis (VA) and simplified DA. The definition of insolvency event was the fact the companies could not pay their obligations in at least two months throughout the first six months of 1988. The study was not published; its results were interpreted later by Virág and Hajdu (1998). Empirical results revealed that under Hungarian circumstances it became possible to examine which financial ratios might be extensively applied to predict bankruptcy.

The first published Hungarian bankruptcy models were elaborated by Miklós Virág after a 10 months long study trip in the United States using annual report data from 1990 and 1991 applying DA and logit (Virág 1993). The author applied 15 financial ratios. Within the 154 manufacturing companies involved in the research, 77 were solvent and 77 became insolvent in 1992 (in line with the novel Bankruptcy Act insolvent companies had to declare bankruptcy against themselves). The four-variate DA model had 78, and the five-variate logit model had 82 percentage of classification accuracy (Virág 1996).

Virág and Hajdu (1996) created an early warning bankruptcy model family in 1996 indicating bankruptcy dangers for different sectors and branches of the economy using DA, based on the financial data of 10,000 economic units. Altogether 41 bankruptcy models were built: one for the total economy, ten for the national economic sectors, and thirty for the branches. The accuracy of the 1996 bankruptcy model family covering national economic sectors and branches was well over the earlier models because of the details of the range of activities, namely all of them had more than 90 percent of classification accuracy. The authors drew the conclusion first time in Hungary that throughout the financial classification it was reasonable to examine how the financial situation of a company equated to companies operating in the same industry, and whether or not they became bankrupt (Hajdu and Virág 2001).

Hámori (2001) transformed the financial ratios to his logit model in a way that they could be evaluated monotonously. The author defined certain limits for the value-range of ratios, and he modified the outlier data with predefined theoretical maximum values. To avoid multicollinearity, he created four factors from the ratios. The sample consisted of 685 solvent and 72 insolvent companies. The classification accuracy of the four-factor-model was 95 percent.

Arutyunjan (2002) tested the applicability of foreign DA models on Hungarian agricultural firms. All in all, the author did not regard foreign models as reliable on the database and developed instead an own logit model achieving 92 percentage of classification accuracy.

Virág and Dóbé (2005) examined the solvency of national economic sectors applying the earlier elaborated bankruptcy model family. Input variables were considered using the sector-level aggregated ratios taking into account 30 national economic sectors and 15 financial ratios. The authors defined the average ratio values as units of analysis (centroids). It was concluded that the average picture of the majority of sectors better resembled their own surviving companies, than the bankrupt ones.

4.2. The Era of NNs and Basel II

Kiss (2003) approached the problem from the viewpoint of credit score modelling, defining a mutual comprehensive development framework between bankruptcy prediction and credit scoring. The results of his PhD thesis was the hierarchical ordering of statistical methods, in addition to the elaboration of organisational, IT and decision support framework of scoring systems.

Using the database of the first Hungarian bankruptcy model Virág and Kristóf (2005a) developed NN-based models. Experimenting with different structures a four-layer backpropagation network showed the best result outperforming the DA model by 9 percentage points, and the logit model by 5 percentage points Virág and Kristóf (2005b). The authors later performed a more complex empirical research on the same database comparing the performance of four classification procedures using the industrial mean relative ratios, and again found that NNs outperformed the traditional methods (Virág and Kristóf 2006).

Because of the fact that the Hungarian introduction of Basel II had been approaching, the Supervisory Authority of Financial Institutions launched a tender in 2006 to elaborate databases to support the application of risk management methods in financial institutions. The winner study (Info-Datax 2006) first attempted to explore the problems of statistical methods applied to probability of default (PD) prediction from the methodological side, and then used principal component analysis (PCA) for data reduction. Within the framework of empirical research, the authors compared the performance of DA, logit and decision trees on a sample of 1500 companies. All the three models showed 87–88 percentage of classification accuracy.

Certain methodological reviews of bankruptcy prediction were provided by Halas (2004); Szabadosné Németh and Dávid (2005); Oravecz (2007); Szűcs (2014); Ratting (2015); Reizinger-Ducsai (2016), however, the authors did not carry out own empirical model development. The applicability of earlier published international models were examined on small samples by Kotormán (2009) on agricultural enterprises, Rózsa (2014) on dairy firms, Pető and Rózsa (2015) on meat processing companies, Dorgai et al. (2016) on commercial enterprises and Fenyves et al. (2016) on hotels with more or less success. A small-sample model development was performed by Sütő (2018) and Ékes and Koloszár (2014).

Organisational theoretic approaches explaining corporate survival, theoretical, methodological and practical problems of bankruptcy prediction, together with the best-practice application of corporate failure models were brought together by Kristóf (2008b). Considering the industrial mean corrected variables, comparing the results of models built with and without PCA, altogether the NN models showed the best result by 84 percentage of area under receiver operating characteristic (AUROC), pursued by the logit model developed on the principal components (83 percentage), and then came the performance of decision trees developed using the original variables (81 percentage). In addition, the MDS and SOM were first time applied in Hungary for bankruptcy modelling purposes in the same study, proving the clustering and variable selection capabilities of the two methods.

Meanwhile, the bankruptcy prediction in Transylvania also attempted to catch up to international best practice. The first Transylvanian-Hungarian bankruptcy prediction models were developed by Benyovszki and Kibédi (2008) on a sample of 129 companies from Baia Mare using logit and probit, achieving 81 percent of classification accuracy with both models. The most comprehensive theoretical, methodological and empirical researches were carried out in Szeklerland in the 2010s, when different logit and NN-based models were developed on a sample of companies from Hargitha County (Fejér-Király 2015, 2016, 2017). Based on the empirical findings it can be concluded that the behaviour of Hargitha County companies is different from Hungarian experiences, since no size variable became significant in Transylvania, whereas turnover ratios showed real added value, in contrast to earlier experiences in Hungary. In addition, it was proven that applying PCA and the inclusion of macroeconomic variables provided better models.

Felföldi-Szűcs (2015) researched the predictability of buyers' non-performance derived from granting commercial loans on the sample of 905 Hungarian small and middle enterprises. The target variable was the 90 days past due event happened on behalf of the buyers. Correspondingly to banking credit risk models the author proved by logit that behavioural, non-financial variables contributed to better discriminatory power, compared to models developed using the traditional financial ratios (Felföldi-Szűcs 2011). It was an important finding in Hungary, and corroborated the results gained in other European countries, especially for small and medium enterprises (SMEs) (see i.a. Lukason and Andresson 2019).

4.3. The Challenges of Data Transformations and Method Combinations

Besides the substantial number of publications regarding comparative analytical bankruptcy prediction studies, more and more emphasis was laid on publications emphasising the importance of data preparation and data transformation procedures (Kristóf 2008a). The study of Hámori (2014) drew attention to the detection and handling of different data preparation anomalies (missing values, outliers, division by zero, double negative divisions, null per null divisions etc.) together with demonstrating a handbook-like methodological guidance and case studies to resolve the perceived problems.

Representativity of modelling sample and the problem of sampling bias were in-depth researched by Oravecz (2009). The results of her PhD thesis were the definition of missing data handling techniques together with the elaborated reject inference methods applicable in credit score modelling to manage sampling bias. The author justified on a sample of 2279 observations using logit that stronger sampling bias led to weaker model performance.

Within the framework of a small-sample empirical research Virág and Kristóf (2009) projected the dissimilarities between solvent and insolvent observations into coordinates of a lower dimensional space applying MDS, and developed a logit model on the reduced dimensional coordinates achieving outstanding classification accuracy.

The impact of relating stock balance sheet items to flow profit-and-loss statement items on the performance of bankruptcy prediction models was in-depth researched by Nyitrai (2017). The effects of handling outliers on model performance in different manners were examined by Nyitrai and Virág (2019). It was concluded that categorisation by Chi-square automatic interaction detection (CHAID) decision trees more effectively handled outliers than coercing by external percentiles or by the mean ± different standard deviations.

Examining further the favourable impact of decision trees on model performance, it was demonstrated by Kristóf and Virág (2012) on a sample of 504 Hungarian companies that the performance of logit and NN models can be further improved by applying variables discretized by CHAID decision trees compared to the application of original variables. However, PCA did not provide added value to the classification power of the models.

The efficiency of combining decision trees and NNs was proven by Bozsik (2011). The author ordered single-layer perceptron networks to the peaks of C4.5 decision trees on a sample of 250 companies using 17 variables. Both the developed brute force and fine-tuned slim models achieved 84 percentage of classification accuracy.

The impacts of company size and industry on bankruptcy models were examined by Nyitrai (2018), using the sample of annual report data from 2007–2015 of 2614 Hungarian enterprises. On the basis of the developed logit models it was proven that both company size and industry influence the design and performance of bankruptcy models.

4.4. Dynamization and Through-the-Cycle Modeling

In line with the through-the-cycle modelling requirements of Basel Capital Accord Imre (2008) applied first in Hungary time-series input variables of 2000 companies from 2002–2006, supplementing the accustomed variables by company form, county and industry. The target variable of the decision tree, logit and NN models was the occurrence of 90 days past due event. In static approach (without dynamizing the variables) the AUROC on the testing sample was 90 percentage in case of logit and NN models in contrast to the 83 percent performance of decision trees. However, by applying the dynamized variables expressing the timely change, the model performance of NN improved to 92 percentage, that of logit to 91 percentage, and that of decision trees to 84 percentage, thereby it was proven first time in Hungary that the application of dynamized variables did have a positive impact on the classification power of bankruptcy prediction models.

Insolvency prediction of 10–250 million HUF revenue Trans-Danubian companies was researched by Bareith et al. (2014) applying NNs with 1-1 hidden layers. Because of the impact of financial crisis, the database was partitioned into two economic cycles: 2002–2008 and 2009–2012. In both periods the financial ratios of three historical years were considered, filtering out the non-relevant variables with the help of a relative importance (RI) based variable selection. More dynamic variables were included in both periods. The model developed on the 2002–2008 period achieved 85 percentage of classification accuracy, compared to the 79 percentage of classification accuracy measured on the model developed using data of the 2009–2012 period. The authors performed a similar empirical research two years later on companies from Csongrád County without partitioning the period of data collection, and achieved an even higher performing neural network model (Bareith et al. 2016). Financial ratios of liquidated small enterprises were in-depth examined by Koroseczné Pavlin (2016) throughout the years before going into liquidation, showing considerable empirical results in the field.

In line with the Basel requirements, Madar (2014) elaborated a corporate rating system applying logit, which was suitable to estimate long-term PD and economic capital, using the database of a credit institution portfolio from 2007–2012 containing 78,516 observations. The author converted the original variables with the help of weight-of-evidence (WOE) transformation. The target variable was the censored default rate. The study revealed the importance of model stability and PD calibration, and proposed techniques to resolve the problems, considering the fact that in crisis periods substantially higher PD can be measured compared to the periods of economic growth.

In the field of dynamic modelling Bauer and Endrész (2016) published an outstanding study that applied a very long historical database from 1996–2014. Combining micro and macro variables the authors developed a probit model for the population of Hungarian double-entry bookkeeping companies, specifying legal failure as the target variables, handling the heterogeneity by company size. The AUROC of the model was 86 percentage.

With the aim of a Central Bank and credit institution sector research Banai et al. (2016) developed PD models for the total population of credited Hungarian SMEs by linking the database of the Central Credit Information (CCI) and financial report data, supplemented with macroeconomic variables. Data collection considered the period of 2007–2014, the target variable was the non-performing event derived from delinquent loan payment. Dynamic logit models were segmented per company size. Certain variables were categorized, lagged or discretized. The micro enterprise model had 75, the small enterprise model 79 and the middle enterprise model 84 percentage of AUROC. The model performance was less favourable than the previously developed model using legal failure as the target variable, since the non-performing event of CCI (60 days past due) is a significantly softer criterion than legal failure.

Similar research was carried out by Nyitrai and Virág (2017b) on time series financial ratios of 1542 Hungarian companies from the period of 2001–2014. Logit was applied using ten-fold cross-validation. Variables were retrospectively dynamized for all historical periods with the help of the formula earlier published by Nyitrai (2014). AUROC showed tendentiously stronger model performance when considering more and more historical years through model development. It was concluded that in case of companies younger than 10 years it was worthwhile to apply as many years as available, however, in case of companies older than 10 years the application of the last 10 years resulted in best model performance. The same authors performed similar empirical research on a different sample containing 1354 companies, which corroborated the findings (Nyitrai and Virág 2017a), which was also in compliance with the findings of an earlier modelling research performed by three different decision trees on a sample of 1082 enterprises (Virág and Nyitrai 2015).

The positive impact of dynamization on predictive power was again proven by Nyitrai (2019b) with the help of a recent Hungarian empirical research. Trends of financial ratios were expressed by indicator variables, and the minimum and maximum values of previous periods were represented as benchmarks in the models. Applying ten-fold cross-validation the developed DA, logit and decision tree models showed that dynamized variables improved classification accuracy compared to models developed from the original static variables. In addition, it was demonstrated by Nyitrai (2019a) that creating categorical variables from the number of nodes of CHAID decision trees coming from subsequent years arrived at better predictive power compared to the approach by using the original data as input variables.

To meet the requirements of IFRS-9 international accounting standards for financial instruments it became necessary to extend the one-year range of failure event to long-term. Forward-looking to the term of financial instruments Kristóf and Virág (2017) and Kristóf (2018b) developed 20-year PD forecast models for Hungarian companies applying continuous, non-homogeneous Markov chains.

4.5. Machine Learning and Data Mining

SVM was applied on a Hungarian corporate database for the first time by Virág and Nyitrai (2013) on the sample of the first bankruptcy model. Using different kernel functions the SVM model was altogether able to classify the observations 5 percentage points better than the best benchmark NN model.

Within the framework of experimenting with machine learning procedures on Hungarian companies Virág and Nyitrai (2014a) applied the RST method on the first Hungarian bankruptcy model database. In addition, the authors attempted to find answer to the question whether it was worthwhile to disregard model interpretability to achieve higher classification accuracy. Results showed that applying RST through generating easily interpretable 'if-then' rules provided similar results compared to SVM; accordingly, the trade-off between the interpretability and performance of the models became out of question.

Virág and Nyitrai (2014b) compared the performance of the two most frequently applied ensemble methods (adaboost, bagging) in the case of C4.5 decision trees using the sample of 976 Hungarian companies having financial report data for the period of 2001–2012. Model performance of the original financial ratios was compared to the model developed using the ratios after industrial mean correction, and to the model developed using dynamized ratios. To avoid sampling problems, hundred-fold cross-validation was applied. The best result was achieved by using the bagging procedure, which was underperformed by the adaboost procedure by 1 percentage point, and by 6 percentage points using the standalone C4.5. Empirical results again proved the favourable model performance impact of dynamized variables; however, industrial mean ratios did not contribute to improvement.

The KNN was applied to Hungarian bankruptcy prediction first by Nyitrai (2015b). The study examined the classification accuracy of different models developed on a balanced sample of 1000 observations using different k values, distance definitions, and variables 1, 2 and 3 years before bankruptcy and derived from multi-period variables. The best result was achieved by the model developed using the multi-period variables (80 percentage), which was followed by the model using variables 1 year before the occurrence of bankruptcy (77 percentage). Results also revealed that certain financial ratios rather give early warning indication to potential bankruptcy in the short-run, whereas others in the long-run. The author performed empirical research in the same year using CHAID decision trees and arrived at similar conclusions (Nyitrai 2015a).

CBR as a relative method to KNN was applied for Hungarian bankruptcy prediction by Kristóf (2018a) on a sample of 1,828 micro-enterprises. To make input variables orthogonal to one another the study applied PCA. The nearest neighbours were determined by the reduced dimensionality tree (RDT) method. Although the classification accuracy of the CBR model outperformed the decision trees and was similar to logit, eventually it was smaller than that of the benchmark NN model.

After carrying out the proper data preparation steps on a balanced sample of 1534 Hungarian small enterprises Boda et al. (2016) applied the component-based object comparison for objectivity (COCO) proximity analysis with different step-functions, the WizWhy data mining procedure with different layers and rule-systems, in addition logit and NN as benchmark models. Eventually COCO, logit and NN also provided 80 percent of classification accuracy, however, the WizWhy model optimised with different logics and hybrid rule systems built on already realised partial results achieved 92 percentage of classification accuracy.

Realizing the opportunities of flexible and adaptive artificial intelligence modelling Bozsik (2016) developed several hybrid artificial intelligence-based bankruptcy models by combining the advantages of different methods. From the innovative study the fuzzy system combined by SVM (FSVM) using Gauss-kernel function showed exceptional classification accuracy (93 percent). Another remarkable hybrid model was the five-layer adaptive neuro-fuzzy (ANFIS) developed by Gauss membership functions having 84 percentage of classification accuracy.

Boros (2018) experimented with several machine learning algorithms examining their impact on credit risk models using a sample of 10,000 companies. After variable selection, PCA and WOE categorisation eventually the NN model with 82 percent of AUROC became better than the SVM model (81 percent of AUROC) followed by stochastic gradient boosting (76 percent of AUROC). Initial models developed using variables without categorisation showed significantly worse performance.

4.6. Summary of Hungarian Bankruptcy Models

Evaluating the most important features and results of Hungarian corporate bankruptcy prediction, it can be argued that the country can be really proud of the rich set of empirical models and methodological development throughout the analysed period. Table 1 provides a systematic summary of the studies in a chronological order showing a comprehensive picture how development took place in time.

Table 1. Summary of Hungarian empirical corporate bankruptcy models.

Author	Year	Explanatory Variables	Target Variable	Size of Sample	Classification Method	Model Performance [1]
Miklós Virág	1993	financial ratios	legal failure	154	DA, Logit	82%
Miklós Virág and Ottó Hajdu	1996	financial ratios	legal failure	10,000 (partitioned per industry)	DA	98%
Gábor Hámori	2001	financial ratios	legal failure	757	Factor/Logit	95%
Alex Arutyunjan	2002	financial ratios	legal failure	146	DA, Logit	92%
Miklós Virág and Tamás Kristóf	2005	financial ratios	legal failure	154	DA, Logit, NN	87%
Info-Datax	2006	financial ratios	Basel II default	1500	PCA/DA, Logit, CART	88%
Miklós Virág and Tamás Kristóf	2006	industrial mean corrected financial ratios	legal failure	154	DA, Logit, CART, NN	86%
Balázs Imre	2008	dynamized financial ratios, qualitative characteristics	90+ delinquency	2000	Logit, CART, NN	92%
Tamás Kristóf	2008	industrial mean corrected financial ratios, qualitative characteristics	legal failure	504	PCA/DA, Logit, CHAID, NN	84%
Annamária Benyovszki and Kamilla Kibédi	2008	financial ratios	legal failure	129	Logit, Probit	81%
Beatrix Oravecz	2009	loan application variables	defaulted loan	2279	Reject inference/Logit	79%
Miklós Virág and Tamás Kristóf	2009	financial ratios	legal failure	100	MDS/Logit	94%
József Bozsik	2011	financial ratios	legal failure	250	C4.5/NN/brute force, fine-tuned slim	84%
Nóra Felföldi-Szűcs	2011	receivable behavioural variables, financial ratios	non-performing buyer	1398	PCA/Logit	75%
Tamás Kristóf and Miklós Virág	2012	financial ratios	legal failure	504	CHAID split/PCA/Logit, RPA, NN	95%
Miklós Virág and Tamás Nyitrai	2013	financial ratios	legal failure	154	NN, SVM	95%
Tibor Bareith, Rita Koroseczné Pavlin and György Kövér	2014	financial ratios	legal failure	8004 (partitioned per period)	RI/NN	85%
László Madar	2014	financial ratios, qualitative characteristics	legal failure, withdrawn tax number, initiated execution	78,516	WOE/Logit	72%

Table 1. *Cont.*

Author	Year	Explanatory Variables	Target Variable	Size of Sample	Classification Method	Model Performance [1]
Miklós Virág and Tamás Nyitrai	2014	financial ratios	legal failure	154	NN, SVM, RST	89%
Tamás Nyitrai	2014	dynamized financial ratios	legal failure	1000	CHAID	78%
Miklós Virág and Tamás Nyitrai	2014	dynamized financial ratios	legal failure	976	Adaboost/Bagging/C4.5	83%
Nóra Felföldi-Szűcs	2015	receivable behavioural variables, financial ratios	90+ delinquency	905	Logit	70%
Tamás Nyitrai	2015	dynamized financial ratios	legal failure	1000	KNN	80%
Tamás Nyitrai	2015	dynamized financial ratios	legal failure	1000	CHAID	78%
Miklós Virág and Tamás Nyitrai	2015	dynamized financial ratios	legal failure	1082	CART, CHAID, C4.5	81%
Tibor Bareith, Rita Koroseczné Pavlin and György Kövér	2016	financial ratios	legal failure	2483	RI/NN	96%
Dániel Boda, Martin Luptak, László Pitlik, Gábor Szűcs and István Takács	2016	financial ratios	legal failure	1534	Logit, NN, COCO, Wizwhy	92%
Péter Bauer and Marianna Endrész	2016	financial ratios, qualitative characteristics, macro variables	legal failure	1,585,663 firm-year observations	Probit	86%
Gergely Fejér-Király	2016	financial ratios, macro variables	legal failure	1075	PCA/Logit, NN	97%
József Bozsik	2016	financial ratios	legal failure	200	Gauss/FSVM, ANFIS	93%
Ádám Banai, Gyöngyi Körmendi, Péter Lang and Nikolett Vágó	2016	dynamized financial ratios, macroeconomic data	60+ delinquent payment	2,166,541 firm-year observations (partitioned per size)	Logit	84%
Tamás Nyitrai and Miklós Virág	2017	dynamized financial ratios	legal failure	1354	Logit	81%
Tamás Nyitrai and Miklós Virág	2017	dynamized financial ratios	legal failure	1542	Logit	92%
Tamás Nyitrai	2018	dynamized financial ratios, size, industry	legal failure	2614	CHAID/Logit	91%
Bence Boros	2018	financial ratios	non-performing loan	10,000	PCA/WOE/Logit, NN, SVM, gradient boosting	82%

Table 1. *Cont.*

Author	Year	Explanatory Variables	Target Variable	Size of Sample	Classification Method	Model Performance [1]
Tamás Kristóf	2018	financial ratios	legal failure	1828	PCA/Logit, CHAID, NN, RDT-CBR	87%
Tamás Nyitrai	2019	dynamized financial ratios	legal failure	3370	DA, Logit, CHAID	83%
Tamás Nyitrai	2019	dynamized financial ratios	legal failure	2098	CHAID/DA	95%
Tamás Nyitrai and Miklós Virág	2019	dynamized financial ratios	legal failure	2996	CHAID/DA, Logit, CHAID, CART, NN	87%

[1] According to classification matrix or AUROC (see the applied model performance indicator in the body text of the article for each model). The best model performance is presented, if more than one model was developed.

5. Conclusions

After the comprehensive review of relevant literature and the completely analysed 30-year of Hungarian empirical results the following normative proposals can be drawn for researchers and practitioners working in the field of corporate bankruptcy prediction.

- Considering the validity of a key theoretical finding that no bankruptcy prediction model might function independently of time, space and economic environment, it is not recommended to apply bankruptcy models on Hungarian companies that were developed on foreign corporate samples, regardless of their popularity and high citation. If it is not possible to develop an own bankruptcy model, the study revealed that a great number of Hungarian bankruptcy models were already published, which had been developed on representative Hungarian samples using diverse methods, proven to be applicable to reliably estimate the PD for Hungarian companies.
- It was also proven throughout several empirical researches in Hungary that appropriate implementation of data preparation and data transformation steps truly contribute to the predictive power of models; thereby it can be concluded that it is even more essential to professionally carry out them than to make the decision which classification method to apply. Within data transformation steps the categorisation of input variables must be emphasised, which simultaneously improve the predictive power of models, handle outliers and make models more stable in time. For this purpose, categorisation with decision trees and WOE can also be regarded as efficient.
- Studying the characteristics of bankruptcy models developed on historical databases in Hungary it can be concluded that the dynamization of input variables improve the classification accuracy of bankruptcy models. The longer historical time-series we have when dynamizing the variables, the better results we might expect. This finding is intensely true to improve model stability. At the same time, it has to be emphasised that such models can only be applicable to companies having the desired number of closed financial years, accordingly for younger companies another model has to be developed, which might have a worse classification power.
- Hungarian empirical results have also shown that in case if—beyond to the financial ratios calculated from public sources—reliable information is available about the financial behaviour of the given corporate clients/partners, including such behavioural variables to model development, better model performance can be achieved compared to model development considering only traditional financial ratios, especially when modelling the financial risks of SMEs.
- Assembling bankruptcy prediction modelling database, the problem of sampling bias has to be handled with care, otherwise it might result in a worse model performance. However, sampling problems perceived on smaller databases might be well handled by cross-validation, which provides a suitable method to prevent overtraining. At the same time, however, the definition of target variable also has a substantial impact on model performance, since the non-performing

event derived from delinquent payment; represent a substantially lower criterion compared to legal failure. In addition, if large modelling sample is available, it is worthwhile to develop models separately for segments and/or industries.

- With regard to model development methodology, nowadays the two most spread techniques are the logit and NN-based bankruptcy modelling pursued by the decision trees. Considering the fact that the application of artificial intelligence and data mining-based methodologies are constantly emerging, it is recommended that at least as a benchmark model the classification power of the three most frequently applied methods must be compared to the performance of any new model. Development of innovative hybrid models are expressively supported, since they successfully combine the advantages of certain methods with others, thereby contributing to better model performance. In addition, it has to be recognised that the application of traditional bankruptcy prediction methods setting rigorous mathematical-statistical criteria (DA) might evidently raise model performance problems, which is a substantial argument against their interpretability accustomed in recent decades.

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Cross-Country Application of Manufacturing Failure Models

Sebastian Klaudiusz Tomczak [1,*] and Piotr Staszkiewicz [2,*]

1 Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, Wybrzeże Wyspiańskiego 27, 50-370 Wrocław, Poland
2 Collegium of Business Administration, SGH Warsaw School of Economics, al. Niepodległości 162, 02-554 Warsaw, Poland
* Correspondence: sebastian.tomczak@pwr.edu.pl (S.K.T.); piotr.staszkiewicz@mail.com (P.S.)

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Abstract: The post-Altman models suffer from moral amortization. This paper asks whether models developed in one country can be applied in other economies. One of the characteristics of the prediction model is that a date drives the estimation. Thus, the estimated model based on one economy is not necessarily applicable to other economies. To verify such a statement, we carried out a literature review to identify the manufacturing models constructed during the last 30 years that were reported in reputable scientific journals. Our literature comprised 75 papers, and with the application of the citation count and citation mining, we selected a sample and traced the selected papers to the cross-country application. Our results indicated an existing gap in the cross-economy validation of existing manufacturing models. Our study has implications for policy, as the application of the prediction models to cross-economies' consolidated financial statements is biased.

Keywords: failure; bankruptcy; chapter 11; regression count; meta-analysis; literature review; manufacturing insolvency; prediction; citation mining

1. Introduction

This study asks whether failure prediction models developed in one country can be consistent with the data from another region. The issue of the prediction of corporate insolvency is still a valid question in the research area. Since Altman's pioneering study (Altman 1968), there are a tremendous number of models reported in the literature. The practical use of the Altman model is not in question; however, this group of models suffers from long-term instability, methodological issues in respect of estimation and sampling, and cross-country validation. This research deals with the latter issue.

This research issue is significant as the global economy is becoming more integrated and cross-dependent than it was at the time Altman presented his local model. Thus, its contribution to understanding model construction and application brings both the research community and professionals towards a better application of the prediction models.

We focus on the manufacturing sector, as limiting the study to one subset allows for better control on variables like type of industry, capital requirements, and type of supervision, which are difficult to control between models.

To address the research question, we applied a combination of narrative literature review, citation regression count for sample determination, and citation mining. We identified the research population based on a key terms search on the Web of Science (the WoS) database. We allowed a time window of 30 years. We referred to a single data source for the abstracts to assure the consistency of the data. Our results are robust in terms of the different sample specifications and citation source selection. Our findings indicate a research gap in terms of cross-country model validation.

This paper contributes both to the failure prediction literature and to meta-analysis. Firstly, the paper provides robust data on the manufacturing model discussion. Secondly, it identifies the research gap for further studies in respect of the cross-country validation of the manufacturing model. Thirdly it extends a previous citation count regression with citation mining.

The paper is structured as follows. Section 2 presents the significant literature; Section 3 introduces the materials and methods; Sections 4 and 5 show the results and robustness of the results, respectively; Section 6 discusses the results and concludes the paper.

2. Literature Review

Shareholders, managers, creditors, and business partners are all interested in extending the lifetime operation of a company. Therefore, to understand and predict company failure, a highly sophisticated method has been created and used. This has been an area of extensive research for over 50 years. Until now, the most well-known model is the Altman model (Altman 1968). Altman was the first to apply a multidimensional discriminant analysis to predict corporate bankruptcy. To date, many of his models have been released (Altman and Hotchkiss 2011; Altman 2018), verified (Grice and Ingram 2001; Reisz and Perlich 2007; Tomczak and Radosiński 2017), and modified (Altman et al. 2017). In addition to the Altman model, other models have also been developed for the manufacturing sector and for other economies, for example, Poland (Pawełek et al. 2016), the Czech Republic (Karas and Režňáková 2017), and the Slovak Republic (Siekelová et al. 2015). There are numerous syntheses of the failure prediction literature.

(Altman 1984) has presented a review of the development of discriminatory models. The author showed a historical outline of the development of research on discriminatory models until the end of the 1970s. In the early 1980s, (Scott 1981) offered a classification of the methodological research into statistical models and those based on the theory of bankruptcy. (Dimitras et al. 1996) developed a literature review covering the period from 1932 to 1994, with the authors focusing on 47 scientific articles presenting predictive models for industrial enterprises. (O'Leary 1998) described the development of research on the application of artificial neural networks to bankruptcy prediction. In 2002, numerous syntheses of the bankruptcy research literature appeared, (Calderon and Cheh 2002) extended O'Leary's discussion on the use of neural networks in an assessment of the risk of failure and crime. (Tay and Shen 2002) presented a study on proxy collections. (Daubie and Meskens 2002, p. 79), synthesizing the discussion up to the end of the 20th century, believed that a better understanding of the causes of bankruptcy processes could lead to more favorable choices of variables used to identify problems and consequently give rise to better models.

(Bellovary et al. 2007) reviewed 165 models published after 1965, indicating that the average number of contained variables varies by around 10, with the accuracy of the model not related to them. They also drew attention to the trends prevailing in particular periods of research on bankruptcy prediction issues. While discriminatory analysis was the leading trend in 1960–1970, a decade later, between 1980 and 1990, researchers focused on logit models and neural networks. (Ravi Kumar and Ravi 2007) presented a review of statistical methods and artificial intelligence used in research on bankruptcy until 1968 to 2005. The authors pointed out that researchers used virtually all known statistical and artificial intelligence techniques to assess the risk of bankruptcy, and that current research on single models gives way to research on hybrid models using combinations of single models and artificial intelligence rules to identify optimal solutions. The 2007 financial crisis stimulated a renaissance of the credit risk and failure research.

Most recent reviews, like (Alaka et al. 2018) or (Shi and Li 2019), also do not address the issue of the cross-validation of the models. Thus, this indicates a technical research gap considered in this paper. As the presented review deals with the syntheses, the specific papers analysis will contribute actual evidence to the research knowledge base.

Following the initial literature review on bankruptcy prediction models, besides the Altman model, there are no common worldwide models developed and verified in one country and tested in another country. Therefore, this paper adopts the following working hypothesis:

Hypothesis 1 (H1). *Manufacturing insolvency models are reapplied on other economies.*

If this hypothesis is confirmed, the initial impression would not be justifiable. On the contrary, this would identify a research gap for further investigations.

3. Materials and Methods

We used the Web of Science Clarivate Analytics (the WoS) sociometric database as the primary population source. We searched the WoS according to the keyword "bankruptcy prediction model" and then "manufacture" and covered the period from 1990 to 2019. Population identification was carried out in December 2019. The identified population of 75 scientific articles met the selection criteria. The six unavailable papers were excluded from the population and an additional four papers were omitted as they do not refer to manufacturing. The final usable population consisted of 65 scientific papers. Detailed information can be found in (Supplementary Materials).

Selected methods used in the analyzed articles are given in Table 1. Mostly statistical techniques, such as multiple discriminant analysis (MDA), the logit model (LR), and probit model, were used in the analyzed papers and they are comparable with other methods. They are very easy to use but strict assumptions for the statistical approaches must be met to apply them, e.g., linearity, normality, and pre-existing functional forms relating criterion variables to predictor variables (Kim et al. 2018). In turn, artificial intelligence, e.g., neural network (NN) and support vector machine (SVM) methods are more complex, and in contrast to the statistical approach, they do not require advanced mathematical and statistical knowledge and do not need any assumptions (Horváthová and Mokrišová 2018).

Table 1. The list of methods used in the selected papers.

Period	Methods					
	MDA	LR	NN	SVM	DT	Other
2019–2010	23	17	8	7	6	20
2009–2000	8	3	2	3	0	11
1999–1990	0	1	0	0	0	1
Total	31	21	10	10	6	32

The metadata in the form of detailed variables were extracted from all papers which constitute the general population. The list of variables and their definitions are presented in Table 2.

In contrast to the original study presenting the methodology used (Staszkiewicz 2019b), we applied the later version of the citation count model similar to that reported for the Baltic region review (Staszkiewicz 2019a). A time-weighted number of citations was used as a dependent variable. The binary variables for Poland, Czech, Hungary, and Slovakia differentiate the Central Europe geographic area, while the Business and Economics variable filters the application area.

The following regression equation was applied:

$$\begin{gathered} TC/Year = \beta_0 + \beta_1 \times Publication_{\mathrm{Year}} + \beta_2 \times Method + \beta_3 \times TimeSpan + \\ \beta_4 \times Sample + \beta_5 \times R_{\mathrm{Czech\ Republic}} + \beta_6 \times R_{\mathrm{Hungary}} + \beta_7 \times R_{\mathrm{Poland}} + \beta_8 \times R_{\mathrm{Slovak}} + \\ \beta_9 \times R_{\mathrm{Slovenia}} + \beta_{10} \times Business\ \&\ Economics + \varepsilon, \end{gathered} \tag{1}$$

where

β_i is the coefficient of the variable i and ε is the error term.

Table 2. The list of variables and their definitions.

Variable	Definition	Range
TC/Year	The number of citations divided by the number of years (in the denominator the year of publication is one)	<0,+∞)
$\text{Publication}_{\text{Year}}$	2019 + 1 minus year of publication natural number	<1,+∞)
Method	Binary variable value 1 for a survey using statistical methods, 0 in other cases	0 or 1
Sample	Size of the sample, the number was taken from each paper in the population (data extracted manually)	<0,+∞)
Period	The time range was taken from each study and the mean average analyzed research period in each paper	<0,+∞)
$R_{\text{Czech Republic}}$	Binary variable value 1 for the Czech Republic survey, 0 in other cases	0 or 1
R_{Hungary}	Binary variable value 1 for the Hungary survey, 0 in other cases	0 or 1
R_{Poland}	Binary variable value 1 for the Poland survey, 0 in other cases	0 or 1
R_{Slovak}	Binary variable value 1 for the Slovak Republic survey, 0 in other cases	0 or 1
R_{Slovenia}	Binary variable value 1 for the Slovenia survey, 0 in other cases	0 or 1
Business and Economics	Binary variable value 1 for the Business and Economics survey, 0 in other cases	0 or 1

The model estimates the average paper citation count. The model allows for identification of the leverage papers, used later for the citation mining in order to check the cross-validation of the manufacturing failure models.

Estimations were carried out using the ordinary least squares (OLS) with the correction of heteroskedasticity.

Based on the regression model, the leverage observation was identified, which indicates the heterogenic papers in the population (sample). Each paper (home paper) within the sample was reconciled to the external citation (host papers). The host papers were examined if the authors reapplied a model from the home paper on a different economy to that of the home paper. If so, the null hypothesis was rejected for the home paper.

4. Results

Table 3 shows the distribution of the population in Central Europe.

Table 3. Number of papers by country.

Country	Number of Articles
Czech Republic	12
Hungary	1
Poland	6
Slovak Republic	2
Slovenia	1
Unallocated	47
Total	65

In the whole population, there is only one paper that concerns all Central European countries, namely, Altman et al. (2017). An important part of the population are items that cannot be clearly attributed to the area. Descriptive statistics of the population are presented in Table 4.

Table 4. Descriptive statistics of the population.

Variable	Mean	Med.	Min.	Max.	5% Perc.	95% Perc.	Std. Dev.	Skew.	Kurt.	Mean
TC/Year	1.7	0.5	0.0	18.0	0.0	8.1	3.2	3.1	11.4	1.7
$\text{Publication}_{\text{Years}}$	7.2	6.0	1.0	28.0	2.0	16.0	5.2	1.7	3.6	7.2
Method	0.7	1.0	0.0	1.0	0.0	1.0	0.5	−0.9	−1.2	0.7
Period	7.7	5.0	0.0	50.0	1.0	18.0	8.3	3.0	11.8	7.7
Sample	53,026.9	475.0	0.0	3,191,734.0	4.0	27,909.0	395,467.1	8.1	64.9	53,026.9
R_{Poland}	0.1	0.0	0.0	1.0	0.0	1.0	0.3	2.9	6.5	0.1
$\text{R}_{\text{Czech Republic}}$	0.2	0.0	0.0	1.0	0.0	1.0	0.4	1.7	0.8	0.2
$\text{R}_{\text{Slovenia}}$	0.0	0.0	0.0	1.0	0.0	0.0	0.1	8.1	65.0	0.0
$\text{R}_{\text{Hungary}}$	0.0	0.0	0.0	1.0	0.0	0.0	0.1	8.1	65.0	0.0
R_{Slovak}	0.0	0.0	0.0	1.0	0.0	0.0	0.2	5.6	29.9	0.0
Business and Economics	0.7	1.0	0.0	1.0	0.0	1.0	0.5	−0.7	−1.6	0.7

The population variable is characterized by a relatively high variability. Table 5 presents the estimated model of the citation regression count together with model diagnostics.

Table 5. The results of the regression model.

Variables	Coefficient	Std. Error	*t*-Ratio	*p*-Value
const	2.25339	0.776356	2.903	0.0053 ***
$\text{Publication}_{\text{Years}}$	0.142455	0.0576817	2.470	0.0167 **
Method	−1.64165	0.801645	−2.048	0.0454 **
Period	−0.0175148	0.0342043	−0.5121	0.6107
Sample	-6.27488×10^{-6}	3.64220×10^{-5}	−0.1723	0.8638
R_{Poland}	−0.760874	1.09228	−0.6966	0.4890
$\text{R}_{\text{Czech Republic}}$	−0.539631	0.805635	−0.6698	0.5058
$\text{R}_{\text{Slovenia}}$	40.0911	116.007	0.3456	0.7310
R_{Slovak}	−1.23644	2.29480	−0.5388	0.5922
Business and Economics	−0.495428	0.818482	−0.6053	0.5475
Model Diagnostics				
Mean dependent var		1.73	S.D. dependent var.	3.15
Sum squared resid.		250.67	S.E. of regression	2.13
R-squared		0.61	Adj. R-sq.	0.54
F(9, 55)		9.42	*p*-value(F)	1.69×10^{-8}
Log-likelihood		−136.10	Akaike criterion	292.20
Schwarz criterion		313.94	Hannan–Quinn	300.78

*** $p < 0.01$, ** $p < 0.05$. Model: OLS, using observations 1–65. Dependent variable: TC_Year. Heteroskedasticity-robust standard errors, variant HC1.

The model fit rates are not necessarily well-fitting, but this is not an obstacle to sample identification because the method is robust and depends primarily on the difference in the coefficients of the original model and the reduced model. Table 6 demonstrates the leverage points (articles) for which the value of the test statistic surpassed the reference point, while Table 7 shows the distribution by country.

The selected sample includes all the articles in multiple domains and all the control variables are represented, including articles not assigned to domains.

Table 6. Leverage papers.

No.	First Author	Error u	Leverage 0 <= h <= 1	Year	Ref.
1	Altman, E.	0.4773	0.445 *	2018	(Altman 2018)
2	Altman, E.	0	1.000 *	2017	(Altman et al. 2017)
3	Siekelova, A.	-9.6782×10^{-16}	1.000 *	2015	(Siekelová et al. 2015)
4	Adeleye, T.	−0.13068	0.310 *	2013	(Adeleye et al. 2013)

* Leverage observation.

Table 7. Distribution of the leverage papers by country, areas, and citation count.

No.	First Author	Poland	Czech Republic	Slovenia	Hungary	Slovak Republic	Business and Economics	Citation WoS
1	Altman, E.	0	0	0	0	0	1	0
2	Altman, E.	1	1	1	1	1	1	54
3	Siekelova, A.	0	0	0	0	1	0	0
4	Adeleye, T.	0	0	0	0	0	0	6

5. Robustness of Results

The results provided earlier are subject to sampling bias due to the applied methodology. In order to verify the stability of the results, we applied an alternative approach both in terms of the sample selection and the source of the citations.

We cross-checked our results using the following procedure. Using the Google Scholar service, we compared the references of the sample to other papers and verified the potential application of the models developed in the sample (Table 8).

Table 8. Distribution of the leverage papers by country, areas, and citation count.

No.	First Author	Citation WoS	Citation Google Scholar	Cross-Validation
1	Altman, E.	0	2	Yes
2	Altman, E.	54	177	Yes
3	Siekelova, A.	0	0	No
4	Adeleye, T.	6	13	No

The cross-validation relates to the original Altman model. Diep, Tung, and Phung (Tung and Phung 2019) reapplied the Altman model on Vietnam's economy.

The revised procedures do not affect our conclusion, except for the Altman model. None of the other models has been cross-applied on a third economy.

We then selected the random sample consisting of 10% of the revised population count and treated them as the home papers. Next, we replicated the host paper check (Table 9).

No cross-validation has been identified. None of the procedures affects our conclusion, and thus the results support the stability of the findings presented in Section 4.

Table 9. Robustness check random sample specification.

No.	First Author	Title	Year	Citation WoS	Cross-Validation	Ref.
1	M. I. Javaid	Efficacy of going concern prediction model for creditor oriented regime via liquidation	2018	0	No	(Javaid and Javid 2018)
2	B. Singh	Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies	2016	6	No	(Singh and Mishra 2016)
3	E. Rim	Classifying manufacturing firms in Lebanon: An application of Altman's model	2014	7	No	(Rim and Roy 2014)
4	J. K. Bae	Predicting financial distress of the South Korean manufacturing industries	2012	15	No	(Bae 2012)
5	K. Männasoo	Patterns of firm survival in Estonia	2008	11	No	(Männasoo 2008)
6	D. Faems	The effect of individual HR domains on financial performance: Evidence from Belgian small businesses.	2005	30	No	(Faems et al. 2005)

6. Discussion and Conclusions

The basic result of our analysis is that at the stage of the construction of the prediction models the verification (testing) sample is likely to include different economies (Altman et al. 2017), while subsequent cross-country validation by other authors than the original ones is infrequent. Our results indicate that most bankruptcy prediction models are built for a local purpose. It is rare, for example, that a model built and tested on Spanish data was also tested on Polish data. Researchers usually specify the details of models in the literature review. The Altman models are the exception. This observation supports the data dependency of the models. However, we are unable to fully reject our null hypothesis that "the manufacturing insolvency models are reapplied on other economies" as Altman models are reapplied across the world. Thus, we conclude that our results, besides the Altman models, indicate the lack of cross-border verification of the developed models.

The finding presented in this study extends the prior research syntheses of Altman (Altman 1984; Dimitras et al. 1996; O'Leary 1998; Calderon and Cheh 2002; Daubie and Meskens 2002; Bellovary et al. 2007; Ravi Kumar and Ravi 2007; Alaka et al. 2018; Shi and Li 2019) by identifying the need for cross-country validation of insolvency prediction models. The presented results do not conflict with any of the prior synthesis research but rather extend the context of failure research.

This study extends the (Staszkiewicz 2019a, 2019b) citation count methodology of population reduction with the mechanism of leverage papers citation mining. It allows to verify not only a paper directed hypothesis but also the derivatives hypothesis which relates to the paper's literature impact. Contrary to prior research the fit of the regression count model is substantially higher than 20%, we understand this phenomenon to be the result of the homogeneity of the population in terms of the research issue. However, this study does not provide evidence to verify our understanding and it probably provides a good starting point for further extended research

Our approach is limited. The citation count regression does not pick up the most cited papers in a population, and thus the reference check suffers from the completeness risk. For example, (Harhoff et al. 1998) was cited 145 times, (Grice and Ingram 2001) 103 times, and (Ding et al. 2008) 128, however, these are relatively old papers published in 1998, 2001, and 2008, respectively. Another limitation of the presented approach is a publication bias. We searched for cross-country applications of the models, where the results may not necessarily be of sufficient importance to attract the audiences of the top tier journals indexed by the WoS. Due to the nature of the identification of the papers' populations, some of the papers not closely related to manufacturing insolvency prediction were omitted (Staszkiewicz and Morawska 2019; Prusak et al. 2019; Karkowska 2019; Nocoń and Pyka 2019). The independent variables in the model follow the original methodology and are not standardized, nevertheless the methodology is less subjective than literature review based on researcher experience, and thus our conclusion remains most robust.

To conclude the research: this study identified a research gap in respect of the cross-country validation of the developed insolvency prediction models for the manufacturing industry. The findings are robust in terms of the different specifications of the sample selection methods. The identified gaps indicate a practical and systematic risk for the application of the prediction model in international companies. The centralization of risk management and risk model verification can result in a substantial model risk when models developed on local heterogenic data are used at the cross-national and cross-subsidiary level.

Supplementary Materials: The data for the regression count citation model calculation are available online at doi:10.17632/4nck5pg6b3.1.

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Tax Arrears Versus Financial Ratios in Bankruptcy Prediction

Oliver Lukason * and Art Andresson

Faculty of Economics and Business Administration, University of Tartu, Liivi 4, 50409 Tartu, Estonia; art@taust.ee
* Correspondence: oliver.lukason@ut.ee

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Abstract: This paper aims to compare the usefulness of tax arrears and financial ratios in bankruptcy prediction. The analysis is based on the whole population of Estonian bankrupted and survived SMEs from 2013 to 2017. Logistic regression and multilayer perceptron are used as the prediction methods. The results indicate that closer to bankruptcy, tax arrears' information yields a higher prediction accuracy than financial ratios. A combined model of tax arrears and financial ratios is more useful than the individual models. The results enable us to outline several theoretical and practical implications.

Keywords: bankruptcy prediction; tax arrears; payment defaults; financial ratios

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1. Introduction

In the year 2018, half a century had passed from the foundational multivariate bankruptcy prediction study conducted by Altman (1968). During this time, hundreds of financial ratio-based prediction models have been published (see e.g., reviews by Ravi Kumar and Ravi 2007; Sun et al. 2014; Alaka et al. 2018). The area has especially flourished with the advances in artificial intelligence, and substantial amount of new tools are being introduced annually. Although high prediction accuracies have been achieved with financial ratios, due to several reasons, they can never be fully relied on in bankruptcy prediction.

The first set of reasons includes the availability and accuracy of financial reports. Financial reporting delays or non-submission of reports are fairly common in case of SMEs, especially for financially distressed firms (Clatworthy and Peel 2016; Luypaert et al. 2016). The latter is characteristic to Estonia as well (Lukason 2013; Lukason and Camacho-Miñano 2019). In addition, as annual reports of SMEs are usually non-audited, they are at a higher risk of including faulty information (Altman et al. 2010). Thus, the financial ratios needed for prediction might be incorrect or not available.

The other substantial reason concerns how capable financial ratios are in signaling future bankruptcy of firms. It is an established fact that a fair share of firms regardless of their age can follow a failure process, where (serious) financial problems or performance declines are not observable in the last financial report before bankruptcy (Lukason et al. 2016; Lukason and Laitinen 2019). In addition, a remarkable number of firms perform poorly, but will never fail, and therefore, cannot be distinguished from their bankrupting counterparts, leading to a Type II error in classification models (du Jardin 2017).

Because of these reasons, an ongoingly important research question is whether there is a substitute for financial ratios in bankruptcy prediction. Various attempts have been utilized in this area, for instance using information about corporate governance, business environment, past payment defaults, and audit resolution (Lussier 1995; Back 2005; Ciampi 2015; Liang et al. 2016; Iwanicz-Drozdowska et al. 2016; Munoz-Izquierdo et al. 2019; Ciampi et al. 2019). Such studies have concluded that variables other than financial ratios can be individually better predictors or can at least provide some incremental value, when applied with financial ratios.

Relying on the aforementioned general motivation, this study aims to find out how accurately future bankruptcy can be predicted by using tax arrears information and whether the accuracy exceeds the level of a financial ratio-based model. In the following literature review section, we synthesize the past findings of failure (prediction) studies in order to lay a foundation for the follow-up empirical part of the paper. The literature review section is followed by a thorough explanation of our dataset, variables calculated, and methods used. Then, empirical results with relevant discussion are presented, succeeded by both theoretical and empirical implications. This is followed by a separate section about the study's limitations and the paper ends with conclusive remarks, while also including multiple novel research directions.

2. Literature Review

2.1. Firm Failure Process Leading to Bankruptcy

The general theoretical foundation for the choice of variables for bankruptcy prediction is firm failure process, i.e., a pathway to bankruptcy. A firm failure process depicts in a certain timeframe how managerial actions in certain environmental conditions lead to an outcome such as poor profitability or illiquidity of a firm (Crutzen and Caillie 2008; Ooghe and Prijcker 2008). The theoretical models of firm failure processes (e.g., Weitzel and Jonsson 1989; Crutzen and Caillie 2008; Amankwah-Amoah 2016) have broken the pathway to bankruptcy into multiple consecutive stages, and concluded that in the earlier stages, problems might not be signaled through financial reports, and thus, finally bankrupting firms might not be (well) distinguishable from poorly performing, but finally surviving firms. Therefore, empirical studies have concluded that in the longer time horizon, financial ratios are not accurate in bankruptcy prediction (du Jardin 2017) and variables other than financial ratios would be beneficial (Iwanicz-Drozdowska et al. 2016).

Recent studies have indicated that the pre-bankruptcy problems indicated through the values of financial ratios or failure risk might not be observable enough through the pre-bankruptcy annual reports of SMEs more than one year before bankruptcy is declared. For instance, Lukason and Laitinen (2019) showed that for 73% of analyzed European SMEs, bankruptcy risk became over 50% and known financial ratios obtained negative values only in the last annual report before bankruptcy. Still, the latter result was obtained when looking at the median values of respective variables, and thus, a fair share of firms might not witness any observable problems in the last financial report (see e.g., Lukason et al. 2016).

A practical issue when using information from annual reports is the delay in information disclosure. Multiple studies (e.g., Altman et al. 2010; Luypaert et al. 2016) have vividly pointed to the issue that firms in (high) failure risk tend to delay the presentation of negative information. In the worst scenario, this can mean not submitting the pre-bankruptcy annual report at all, while the delay of the annual report beyond a deadline set in law (e.g., in Estonia 6 months after the fiscal year) becomes more like a "rule" rather than an exception (Lukason 2013).

2.2. Financial Ratios as Predictors of Bankruptcy

A vast amount of studies exploiting financial ratios for bankruptcy prediction have been composed so far with largely varying results (see e.g., literature reviews by Dimitras et al. 1996; Ravi Kumar and Ravi 2007; Sun et al. 2014; Alaka et al. 2018). As the situation of bankruptcy points to either a shortage of cash (liquidity crisis) and/or liabilities exceeding assets (solidity crisis) (Uhrig-Homburg 2005), the theoretical explanations of which ratios could be useful rely on both of them. The cash flow-based explanation to predictors' choice originates from Beaver (1966) idea of firm as a reservoir of liquid assets, while a (negative) equity-based explanation is most vividly explained in the probabilistic theory of bankruptcy developed by Scott (1981). Still, since the earlier multivariate contributions (e.g., Altman 1968; Ohlson 1980), the financial ratios for bankruptcy prediction have mostly been chosen on empirical grounds, without focusing on the mechanism leading to corporate collapse. The usual ratio domains applied in bankruptcy prediction, although occasionally phrased differently, concern liquidity, solidity, capital/financial structure, profitability, and turnover (Lukason et al. 2016; du Jardin 2017).

The recent cross-sectional studies using very large populations of European firms and t-1 period for bankruptcy prediction have indicated that areas under the curve (AUCs) remain on an average level, namely in the range of 0.7–0.9 and only on rare occasions exceed 0.9 (Laitinen and Suvas 2013; Altman et al. 2017). In a meta-analysis of bankruptcy prediction studies, du Jardin (2017) found the average t-1 classification accuracy to be 85%. Recently, studies have shown that prediction accuracies can be enhanced by accounting for the financial dynamics and patterns occurring before bankruptcy (e.g., du Jardin 2015, 2017, 2018), but still the misclassification rates have remained at 10–20%. This provides a clear indication that financial ratios have inherent problems (see also Section 2.1), which cannot be overcome by using more sophisticated classification methods.

2.3. Payment Defaults as Predictors of Bankruptcy

A domain in the literature scantly developed is the usage of past payment defaults to predict bankruptcy. The few available studies (e.g., Laitinen 1999; Back 2005; Altman et al. 2010; Wilson and Altanlar 2014; Iwanicz-Drozdowska et al. 2016; Ciampi et al. 2019) have all indicated that past payment behavior can be valuable in bankruptcy prediction and lead to either higher classification accuracies individually or at least provide an increment to classification accuracies, when applied with financial ratios.

Despite substantial contribution to the area, the available studies have treated payment defaults in a rather simple way: by accounting their presence, number and size. Still, the extant studies do not pay attention to defaults in the longer time horizon, i.e., their exact dynamic behavior in respect to what pattern they follow. Another substantial issue in the portion of extant literature is that the applied payment defaults are permanent, namely they are a logical precedent to the future bankruptcy. Such application can lead to using de facto insolvency to predict de jure insolvency, reducing the practical applicability of such models, i.e., they do not lead to remarkable benefits for creditors aiming to reduce their misclassifications. Therefore, the practical usage of relevant prediction models can be enhanced by taking into account temporary payment defaults as well. In addition, to our knowledge tax arrears as a type of payment default has so far not been applied in bankruptcy prediction, although their existence has successfully been used as a dependent variable with financial ratios being independent (see Höglund 2017).

2.4. Research Propositions

We would argue that as many SMEs do not witness financial problems one year before bankruptcy portrayed through the annual report, but in turn start witnessing temporary liquidity problems, models based on tax arrears are more accurate than models based on financial ratios in the short-run. Further away from bankruptcy, liquidity problems are equally frequent for future bankrupt and non-bankrupt firms, and thus, financial ratio-based models are more beneficial in the long-run. As different types of variables are beneficial in the short- and long-run, their conjoint usage should logically lead to the highest classification accuracy. Relying on the latter theoretical explanations and past achievements in the literature, we phrase three research propositions for the empirical part of the paper, while we consider one specific type of payment defaults, i.e., tax arrears, in this study:

P1: *A model based on payment defaults leads to a higher accuracy in bankruptcy prediction than a model based on financial ratios only in the short-run.*

P2: *The accuracy of a model based on payment defaults decreases further away from bankruptcy.*

P3: *A model incorporating both payment defaults and financial ratios leads to a higher accuracy than the individual models incorporating these variables.*

3. Data and Methods

3.1. Dataset and General Setting of the Study

The dataset of this paper includes all Estonian bankrupted firms from 2013–2017, in case of which the following restrictions have been applied. First, all firms must have information available to calculate variables outlined in Sections 3.2 and 3.3. Second, we demand the financial report of a bankrupted firm to be not older than two years from the moment of bankruptcy declaration. With this restriction, we guarantee that the annual report portrays pre-bankruptcy financial situation homogenously for firms included in the analysis and is available for comparative purposes with payment defaults. On average, the financial report in the dataset portrays financial situation one year before bankruptcy declaration. In total, 512 bankrupted firms are included in the analysis, which are all SMEs.

Concerning survived firms, 4003 firms are used which are functional at the time of the analysis. All firms which have financial information available from 2011 to 2015 are chosen, irrespective of how well they perform. The latter is important to avoid a bias of discriminating only in between bankrupt and "successful" survived firms. The time 2011–2015 is determined by the fact that the reports of bankrupted firms originate from the same time interval. In the viewed period, Estonia had recovered from the consequences of the global financial crisis and these years were characterized by stable economic growth. Thus, the viewed period is not subject to any abnormal performance of firms due to economic recession.

For calculating financial ratios of bankrupt firms, we use the last available annual financial report before bankruptcy. In case of survived firms, we calculate the financial ratios for all firms for all five years incorporated to the analysis. In Estonia, firms are responsible for submitting an annual report in maximum six months after the end of the fiscal year, which for the vast majority of firms overlaps with the calendar year.

Concerning taxes, firms need to submit tax reports and pay taxes twice in the month following the month that the taxes were incurred. Specifically, on the 10th day of the month for taxes concerned with salaries and on the 20th day of the month for value added tax. Estonia is among a few countries in the world where profit is not taxed on an accrual basis, but only when dividends are paid. When dividends are paid, the respective income tax is subject to the same principles as salaries. When tax arrears (i.e., unpaid tax debt due) occur, this is observable live on the Estonian Tax and Customs Board database. From the latter database, we have obtained the values of tax arrears for the whole population for each month end in the viewed period of 2011–2017. The usage of the month end is a more suitable option when compared with for instance one day delay of paying taxes. This is because a few days' delays of paying taxes is common in Estonia and are more subject to administrative or diligence reasons, rather than pointing to a temporary liquidity crisis. Thus, tax arrears' information can be used dynamically to view the emergence of problems up to the exact month when bankruptcy occurred. As the annual reports are up to 2 years old, in case of tax arrears data, we consider a 24 month long period before bankruptcy is declared. For survived firms, we use multiple 24 month long periods within the years from 2011 to 2016.

We do not apply other payment defaults (i.e., to private creditors, such as banks and suppliers) in this study for multiple reasons. First, in Estonia no single database incorporates all payment defaults to private creditors. Second, some of such defaults might not be documented, for instance because of their small size or creditors executing their claims in a different way (e.g., suing managers who have guaranteed the credit). Third, such defaults might not be documented precisely in respect to their start or end period, e.g., due to the fact that creditors could be delaying the execution of a claim because of groundless promises by debtors to pay the debt.

To provide an answer in which period tax arrears' information is more useful than financial ratios, we consider different pre-bankruptcy periods concerning tax arrears. The usage of financial information in this study has been consolidated into Table 1.

Table 1. The logic of calculating financial ratios and variables portraying tax arrears in this study.

Information Sources for Calculating Financial Ratios in This Study	
Bankrupted firms	Last annual report (not older than two years from bankruptcy moment)
Survived firms	All annual reports from 2011 to 2015
Information sources for calculating tax arrears variables in this study	
Bankrupted firms	12 month long periods before bankruptcy, where the respective numbers indicate month x to month y before the bankruptcy declaration month: 1–12, 4–15, 7–18, 10–21, 13–24. A single 24 month long period before bankruptcy, where the respective numbers indicate month x to month y before the bankruptcy declaration month: 1–24.
Survived firms	12 month long periods are used as six full years from 2011 to 2016. A single 24 month period is used as five two-year periods: 2011–2012, 2012–2013, 2013–2014, 2014–2015, 2015–2016. As there are proportionally much less bankruptcies from 2017, then in case of survived firms that year is neglected from the analysis.

Source: own elaboration.

3.2. Financial Ratios Portraying Different Domains

The financial ratios for this study have been chosen based on their previous usage for bankruptcy prediction and taking into account that all important financial ratio domains would be covered (see the formulas and ratio domains in Table 2). Firm leverage is reflected by the total debt to total assets ratio (DA). This ratio in its different forms (e.g., total equity to total assets or total equity to total debt) might be the most common and useful failure predictor. The ratio has a strong intersection with legislation, as business and insolvency codes in different countries often set minimum requirements for firms' equity. Profitability is captured with two ratios, i.e., net income to total assets and net income to operating revenue. The former is a more common profitability ratio in bankruptcy prediction and was used already in the Altman (1968) model, although having EBIT instead of net income in the numerator. Static liquidity is portrayed with two ratios, namely either the quotient of cash minus current liabilities to total assets or the quotient of current assets minus current liabilities to total assets. These ratios have been frequently used in the form of cash to current liabilities (quick ratio) and current assets to current liabilities (current ratio), but the usage of such ratios is problematic. Namely, as among survived firms there might be a fair amount of companies with no or very low level of current liabilities, such ratios would obtain extreme values or the value cannot be calculated at all. Moreover, the division with total assets helps us to have a better overview how large the surplus or deficit of cash or current assets is in comparison to all assets a firm possesses. A firm's cash flow creation is portrayed with two ratios reflecting the quotient of operating cash flow to either operating revenue or total assets. The productivity (efficiency) of a firm's assets is reflected by the quotient of operating revenue to total assets. Finally, the burden of interest paid on debt is proxied with two ratios, specifically the quotient of total financial revenues minus total financial expenses to either total assets or operating revenue. The latter two variables (with similar, but not necessarily identical formulas) have been often classified as solvency (solidity) ratios.

The ten applied financial ratios reflect the most usual domains used in previous bankruptcy prediction studies, i.e., profitability, cash flow creation, leverage, liquidity, solidity, and profitability. We acknowledge that many more financial ratios have been applied in previous studies, but they are mostly very similar (or mere modifications) to the ones used, and thus, would evidently provide only a marginal surplus (if at all) to classification accuracies. In addition, the calculation of very specific financial ratios is altered by the availability of financial information, as the financial reports of SMEs are often quite brief. Because of the latter, we can for instance use the difference of financial revenues and financial expenses, rather than specific types of those revenues/expenses. In case of all applied financial ratios, the general rule is that higher values should reduce the bankruptcy probability on a univariate principle. The exception is DA, where the situation is the reverse.

Table 2. Financial ratio abbreviations, domains, and formulas used in this study.

Ratio Abbreviation	Domain	Formula
CCLA	liquidity	(cash—current liabilities)/total assets
CACLA	liquidity	(current assets—current liabilities)/total assets
NIA	profitability	net income/total assets
NIOR	profitability	net income/operating revenue
DA	leverage/solidity	total debt/total assets
ORA	productivity	operating revenue/total assets
FREOR	interest burden	(financial revenues—financial expenses)/operating revenue
FREA	interest burden	(financial revenue—financial expenses)/total assets
OCFA	cash flow creation	operating cash flow/total assets
OCFOR	cash flow creation	operating cash flow/operating revenue

Source: own elaboration.

3.3. Variables Portraying Tax Arrears

Unlike with financial ratios, there are no uniform guidelines on how to calculate variables portraying the dynamics and content of tax arrears. Still, past theoretical and empirical research provides hints that larger and/or more frequent payment defaults increase the likelihood of failure. Derived from that logic, both of those dimensions should be incorporated into the analysis. To capture the scale of tax arrears, we calculate the maximum of tax arrears occurring in the viewed period. As large tax arrears can occur only episodically (e.g., only during one month in the sequence of 12 months), we extend the scale variable to incorporate frequency context as well by calculating the median of tax arrears in the viewed period. The frequency of tax arrears is captured by a variable counting the month ends when tax arrears were present. Still, the latter variable might be limited, because tax arrears can occur for instance every second month, i.e., they occur frequently, but still episodically. In order to enhance the frequency analysis by also incorporating the severity of ongoingness of payment defaults, we also introduce a variable measuring the longest sequence of month ends when tax arrears occurred. Thus, the four applied tax arrears' variables (see Table 3) also incorporate both the scale and frequency of payment defaults in a combined manner.

Table 3. Abbreviations and calculation explanations of variables portraying tax arrears in this study.

Variable Abbreviation	Calculation Explanation
TMAX	Maximum tax arrears in the viewed sequence on month ends
TMEDIAN	Median tax arrears in the viewed sequence of month ends
TCOUNT	Number of month ends with tax arrears in the viewed sequence
TCONSMON	Length of the longest sequence of month ends with tax arrears

Source: Own elaboration; Note: we consider the presence of tax arrears as over 100 euros unpaid tax debt, as tax authority does not add a disclaimer of owing taxes in case of very small arrears, and also, managers can occasionally forget paying very small tax arrears.

3.4. Methods

We apply one classical statistical (i.e., logistic regression, noted as LR) and one machine learning (i.e., multilayer perceptron with two hidden layers, noted as MP) tool for composing the prediction models. In case of using only one method, the results could be biased towards that specific method, and therefore, not generalizable. These two methods are probably the most exploited classical and novel methods in bankruptcy prediction, thus their choice is fairly justified based on the developments in previous research. We acknowledge that there is nowadays a myriad of different methods (especially in the area of machine learning) available for failure prediction. Still, as the first and foremost aim of the paper is to show whether and in what context the information about tax arrears can be exploited in bankruptcy prediction, we find the usage of two methods a sufficient choice. In addition, based on the results in the empirical section, we thoroughly explain why the usage of additional methods would probably not have provided a surplus to the obtained results.

In bankruptcy prediction, there are different streams concerning how to use observations in the analysis. The classical studies have used (rather) equal samples for bankrupted and survived firms. This definitely guarantees that the analysis reaches a clear conclusion how accurately bankrupted and survived firms can be discriminated from each other. Still, such selection of survived firms should be avoided, as there is a serious risk of creating a bias, i.e., the sample of survived firms does not represent the population it originates from. Moreover, when for instance a credit analyst is solving a practical classification problem, a firm under consideration originates from the whole population without any preselection. Thus, if available, the population of survived firms should be used irrespective of their characteristics. Therefore, our dataset (see Section 3.1) incorporates all bankrupted firms and all their survived counterparts, for which the respective annual reports were available.

There are different options on how to use LR and MP. When the frequencies in two groups (i.e., bankrupted and non-bankrupted firms) are very imbalanced (which is the usual case and also applies for this study), algorithms can result in classifying a majority group (i.e., non-bankrupt firms) as correctly as possible, at the same time creating (huge) misclassification errors in case of the minority group (i.e., bankrupt firms). Therefore, we administer a procedure frequently used in bankruptcy prediction research (see e.g., Altman et al. 2017) by weighting the two groups of firms to be equal in the analysis. In case of LR, the weights for observations are calculated as 0.5 divided by the share of respective group in the population used. In case of MP, we achieve the same by making synthetic observations. Such a method, i.e., a synthetic minority oversampling technique (SMOTE), has been frequently used in case of machine learning classification applications for bankruptcy prediction (Kim et al. 2015). SMOTE is achieved by repeating the observations of bankrupt firms as long as their population size equals that of non-bankrupt firms. We acknowledge that different weights could be applied in this study, but this is specifically dependent on how large the misclassification costs of (non-)bankrupt firms are (in practice). Likewise with majority of previous studies in the area, we do not incorporate misclassification costs in the analysis.

In order to understand what are the prediction abilities of individual variables, we first provide the results in case of LR by using only single variables from Tables 2 and 3. After that, we conduct three types of analyses: (a) using all financial ratios together for LR and MP, (b) using all tax arrears' variables together for LR and MP, (c) using financial ratios and tax arrears' variables together for LR and MP. When the comparison of (a) and (b) enables us to outline the individual prediction abilities of the specific variables through the two applied methods, then (c) introduces a joint analysis. Results are provided for both test and hold-out samples.

4. Results and Discussion

4.1. Univariate Prediction Abilities of Variables

We first outline the univariate prediction abilities of the applied variables (see Table 4), while the descriptive statistics of the variables have been provided in Appendix A Tables A1–A3. The results in Table 4 have been presented for descriptive purposes and obtained from LR by applying each variable individually. The most useful financial ratio on a univariate principle is DA, which is a fairly common and useful predictor in previous studies (usually also in the form of total equity to total assets ratio). Still, the accuracy (77.1%) of this solidity ratio remains modest, closely followed by a liquidity ratio CCLA with 75.7% accuracy.

The tax arrears' variables indicate better predictive performance. For instance, when calculated for the period 1–12 months before bankruptcy declaration, all of them outperform DA. When further away from bankruptcy, the individual predictive power of tax arrears' variables deteriorates. For instance, when the period 13–24 months before bankruptcy prediction is applied, the most accurate tax arrears variable is TMAX, indicating that the largest tax arrears in that period obtains the same predictive power as DA, i.e., 77.1%. Thus, the univariate results provide an initial indication that tax arrears have remarkable predictive power and this result is further elaborated with multivariate analysis in the next section.

Table 4. Univariate prediction accuracies (%) of variables.

Financial Ratios			
CCLA	75.7	ORA	60.5
CACLA	70.1	FREOR	59.5
NIA	61.4	FREA	63.6
NIOR	59.5	OCFA	49.3
DA	77.1	OCFOR	42.2
Tax Arrears Variables			
TMAX1–12	85.3	TMAX10–21	77.6
TMEDIAN1–12	78.5	TMEDIAN10–21	71.5
TCOUNT1–12	84.9	TCOUNT10–21	76.3
TCONSMON1–12	85.1	TCONSMON10–21	76.9
TMAX4–15	82.1	TMAX13–24	77.1
TMEDIAN4–15	74.8	TMEDIAN13–24	70.3
TCOUNT4–15	81.6	TCOUNT13–24	74.7
TCONSMON4–15	81.0	TCONSMON13–24	75.4
TMAX7–18	79.3	TMAX1–24	85.9
TMEDIAN7–18	73.5	TMEDIAN1–24	74.0
TCOUNT7–18	77.9	TCOUNT1–24	83.0
TCONSMON7–18	79.0	TCONSMON1–24	83.8

Source: own elaboration; Note: Tx-y indicates tax arrears variable from period month x to month y before bankruptcy is declared.

4.2. Multivariate Approach with Logistic Regression and Multilayer Perceptron

The classification accuracies of the logistic regression and multilayer perceptron models are quite similar, although the logistic regression models are somewhat more precise on holdout sample when tax arrears' variables are applied. The higher accuracy in case of non-bankrupt firms observable in Table 5 for tax arrears' models can be explained by a simple financial logic. Type I error (i.e., bankrupt firms classified as non-bankrupt) is caused by a certain proportion of bankrupt firms having no tax arrears during the viewed period. The survived firms normally do not witness tax arrears, or at least not in such scale and frequency as the bankrupt firms. Thus, when using tax arrears in bankruptcy prediction, no sophisticated logic about the occurring patterns is necessary, and rather, their existence with a certain frequency and magnitude is a sufficient proof of potential serious financial problems.

The few percentage points superiority of the LR models over the MP models in case of tax arrears' variables could mostly be explained by the MP models overtraining the relationship in between independent and dependent variables, i.e., it is considered to be more sophisticated than it actually is.

The prediction abilities of tax arrears' models gradually decrease when looking at periods further away from bankruptcy declaration. The logistic regression model TA10–21 and the multilayer perceptron model TA7–18 are the first ones being not able to outperform financial ratios in bankruptcy prediction. In case of the LR model, the latter means that when looking at the time before bankruptcy, then at a certain point in between the 7th and 10th month before the bankruptcy declaration, the usage of financial ratios becomes more beneficial than tax arrears' information. Thus, tax arrears' information is especially useful for predictive purposes in the short-run before a firm becomes bankrupt.

We find support for all three research propositions set for this study. Payment defaults' dynamics portrayed by tax arrears can lead to a higher bankruptcy prediction accuracy than financial ratios in the short-run (P1), but that accuracy reduces further away from bankruptcy (P2) and at a certain point is overrun by the accuracy of a model based on financial ratios. In addition, the model incorporating both variable domains leads to the highest accuracy (P3). The prediction accuracy of the financial ratios' model is similar to the findings in previous studies (e.g., Altman et al. 2017; du Jardin 2017), while the tax arrears' models obtain higher accuracies than previous models based on payment defaults (e.g., Back 2005; Ciampi et al. 2019). In addition, as suggested by previous studies (e.g., Iwanicz-Drozdowska et al. 2016; Ciampi et al. 2019), a combined model of financial ratios and payment defaults leads to the highest possible accuracy.

Table 5. Prediction accuracies (%) of composed multivariate models.

Variables	Logistic Regression				Multilayer Perceptron				
	Test Sample	Holdout Sample	AB	ANB	Training Sample	Test Sample	Holdout Sample	AB	ANB
Financial ratios	79.9	79.5	80.4	78.7	81.8	80.6	81.9	85.4	78.4
TA1–12	86.9	89.5	83.3	95.7	86.8	86.9	86.7	84.6	88.9
TA4–15	83.6	85.2	75.5	94.9	83.5	83.9	84.7	79.7	89.8
TA7–18	80.4	82.1	69.6	94.5	80.2	79.8	80.6	71.9	88.9
TA10–21	78.9	78.6	62.8	94.5	78.2	78.8	78.5	68.0	89.0
TA13–24	77.4	78.0	61.8	94.2	78.1	78.0	77.8	67.1	88.4
TA1–24	86.7	89.9	84.3	95.4	86.8	86.5	86.7	88.6	84.9
Financial ratios and TA1–24 combined	90.2	91.3	89.2	93.4	87.7	87.6	87.5	90.8	84.3

Source: Own elaboration; Note: TAx–y means tax arrears variables' model from period month x to month y before bankruptcy is declared. AB and ANB refer respectively to accuracies among bankrupt and non-bankrupt firms in the hold-out sample.

4.3. Theoretical Implications

The main theoretical implication from the study is that the dynamics of payment defaults can be very useful as a bankruptcy predictor shortly before bankruptcy. In addition, the finding complements previous studies (see Section 2.3) applying different types of payment defaults in a more simple manner. While tax arrears as a type of payment default have not been applied in previous studies, this study showed that they have remarkable value in bankruptcy prediction. Finally, we agree with the previous studies suggesting that variables other than financial ratios should be applied in SME failure prediction, but with a substantial extension. Namely, the individual usage of such variables could lead to a better predictive performance of models in the short-run or these variables could be used conjointly with other variables, such as financial ratios, in the long-run.

4.4. Practical Implications

This study provides multiple guidelines for various stakeholders, such as builders of insolvency prediction models, lenders (e.g., banks or trade credit providers), or credit information bureaus.

First, when used dynamically, past temporary payment defaults can include valuable individual and incremental information when aiming to build more accurate bankruptcy prediction models. In this respect, both the size and duration of payment defaults can matter.

Second, financial ratios are not very useful in predicting future bankruptcy, as when implementing models based on them for SMEs in practice, it is difficult to achieve accuracy levels that would avoid substantial losses for creditors.

Third, and maybe the most substantial practical implication, the usage of payment defaults is a vital substitution when annual reports of firms are not available in time or at all. Payment defaults are usually available on a live principle, as they are submitted by creditors, not by the firm itself.

4.5. Limitations

There are several limitations of this study that should be acknowledged. First, this study focused on a specific type of payment defaults, i.e., tax debt not paid when due, in one country. The tax laws and their practical application, i.e., enforcing tax claims by the relevant authority, can vary through different countries. Thus, when replicating the ideas proposed in this article in other environments, the country-specific tax laws and practice of dealing with tax arrears is of high essence.

Second, using payment defaults to other stakeholders, such as banks, trade credit providers, or employees could even enhance the prediction abilities. The incorporation of this information has proven to be valuable in previous relevant studies (e.g., Wilson and Altanlar 2014; Ciampi et al. 2019). Due to the variation in firms' business models, tax arrears might emerge not at all before bankruptcy, but other payment defaults might in turn be present.

Third, although tax arrears are not remarkably subject to the information disclosure issue compared to financial ratios, they are not fully free from it. Namely, some firms might engage in illegal practices, e.g., not submit tax declarations at all or provide false information in them.

5. Conclusions

This study aimed to compare the usefulness of tax arrears and financial ratios in bankruptcy prediction. The models created indicate that shortly before bankruptcy, tax arrears' models outrun the financial ratio-based models in terms of accuracy. Still, this accuracy reduces when further periods before bankruptcy declaration are considered. The highest accuracy is obtained by using tax arrears and financial ratios simultaneously.

The study provides important implications for the relevant research area. It indicates that the dynamic usage of only a certain type of payment defaults, i.e., tax arrears, can substantially outrun the accuracies of financial ratio-based models. Thus, despite the availability of hundreds of financial ratio-based prediction models, future researchers should pay more attention to payment default variables, which incorporate substantial possibilities to increase prediction accuracies.

This study can be extended in different ways. The main extension includes relaxing the previously outlined limitations, for instance by including different types of payment defaults. In addition, tax arrears' information could be supplemented by information about the tax payment behavior of firms, as during the retrenchment of activities in the decline process, small tax arrears could have a more important role than in usual circumstances. It is important to test the usefulness of tax arrears in bankruptcy prediction in other countries as well when such information is available. Last but not least, there might be potential to enhance the prediction accuracies by including variables about the background of managers, for instance concerning their past risk behavior in other firms.

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Appendix A

Table A1. Descriptive statistics of financial ratios.

Status	Descriptive Statistic	CCLA	CACLA	NIA	NIOR	DA	ORA	FREOR	FREA	OCFA	OCFOR
NB	N	20,015									
	Mean	0.07	0.43	0.07	0.04	0.35	2.00	0.00	0.00	0.10	0.09
	Std. Deviation	0.49	0.42	0.26	0.36	0.31	2.06	0.03	0.01	0.27	0.33
	Median	0.03	0.47	0.05	0.03	0.26	1.33	0.00	0.00	0.07	0.06
	Minimum	−0.95	−0.65	−0.74	−1.30	0.00	0.03	-0.10	−0.04	−0.62	−0.92
	Maximum	0.96	1.00	0.65	0.79	1.12	8.92	0.09	0.04	0.74	0.88

Table A1. *Cont.*

Status	Descriptive Statistic	CCLA	CACLA	NIA	NIOR	DA	ORA	FREOR	FREA	OCFA	OCFOR
B	N	512									
	Mean	−0.79	−0.24	−0.31	−0.09	1.09	4.00	0.01	0.01	0.24	0.16
	Std. Deviation	0.99	1.00	1.03	0.32	1.10	5.18	0.03	0.03	1.25	0.78
	Median	−0.62	0.01	−0.01	0.00	0.87	2.39	0.00	0.00	0.04	0.01
	Minimum	−5.42	−5.08	−5.26	−1.48	0.12	0.19	−0.04	−0.07	−2.33	−0.83
	Maximum	0.27	0.80	0.57	0.31	6.29	27.57	0.11	0.10	5.58	3.60
p-value of ANOVA Welch test		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.044

Source: own elaboration. Note: B—bankrupt, NB—non-bankrupt. For non-bankrupt firms, the population size 20,015 originates from using data from 5 years (2011–2015) for 4003 firms (see Section 3.1 for more information).

Table A2. Descriptive statistics of tax arrears variables (part 1).

Status	Descriptive Statistic	TMAX1–12	TMEDIAN1–12	TCOUNT1–12	TCONSMON1–12	TMAX4–15	TMEDIAN4–15	TCOUNT4–15	TCONSMON4–15	TMAX7–18	TMEDIAN7–18	TCOUNT7–18	TCONSMON7–18
NB	N	24,018											
	Mean	0.4	0.1	0.5	0.4	0.4	0.1	0.5	0.4	0.4	0.1	0.5	0.4
	Std. Dev.	3.8	1.7	1.8	1.6	3.8	1.7	1.8	1.6	3.8	1.7	1.8	1.6
	Median	0	0	0	0	0	0	0	0	0	0	0	0
	Min.	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	187	125	12	12	187	125	12	12	187	125	12	12
B	N	512											
	Mean	59.1	36.9	7.4	7.1	48.9	29.8	6.8	6.3	41.5	23.9	6.2	5.7
	Std. Dev.	171.5	145.0	4.7	4.8	163.3	128.7	5.0	5.0	150.8	91.4	5.1	5.1
	Median	13.7	3.5	9.0	8.0	9.7	1.2	8.0	6.0	6.4	0.7	7.0	5.0
	Min.	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	2427	2396	12	12	2427	2396	12	12	2427	1462	12	12
p-value of ANOVA Welch test		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own elaboration. Note: B—bankrupt, NB—non-bankrupt. Mean, median and std. deviation presented in thousands euros for TMAX and TMEDIAN. For non-bankrupt firms, the population size 24,018 originates from using 6 years (2011–2016) for 4003 firms (see Section 3.1 for more information).

Table A3. Descriptive statistics of tax arrears variables (part 2).

Status	Descriptive statistic	TMAX10–21	TMEDIAN10–21	TCOUNT10–21	TCONSMON10–21	TMAX13–24	TMEDIAN13–24	TCOUNT13–24	TCONSMON13–24	TMAX1–24	TMEDIAN1–24	TCOUNT1–24	TCONSMON1–24
NB	N	24,018											
	Mean	0.4	0.1	0.5	0.4	0.4	0.1	0.5	0.4	0.6	0.1	0.9	0.6
	Std. Dev.	3.8	1.7	1.8	1.6	3.8	1.7	1.8	1.6	4.6	1.3	3.4	2.6
	Median	0	0	0	0	0	0	0	0	0	0	0	0
	Min.	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	187	125	12	12	187	125	12	12	187	109	24	24

Table A3. *Cont.*

Status	Descriptive statistic	TMAX10–21	TMEDIAN10–21	TCOUNT10–21	TCONSMON10–21	TMAX13–24	TMEDIAN13–24	TCOUNT13–24	TCONSMON13–24	TMAX1–24	TMEDIAN1–24	TCOUNT1–24	TCONSMON1–24
B	N						512						
	Mean	38.5	18.6	5.7	5.3	32.3	17.7	5.3	4.8	64.1	23.2	12.7	11.2
	Std. Dev.	157.6	61.9	5.1	5.0	127.7	64.6	5.1	4.9	190.4	90.0	9.0	8.8
	Median	4.9	0	5.0	4.0	3.6	0	3.5	3.0	15.6	0.7	13.0	9.0
	Min.	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	2427	872	12	12	1932	872	12	12	2427	1462	24	24
p-value of ANOVA Welch test		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own elaboration. Note: B—bankrupt, NB—non-bankrupt. Mean, median and std. deviation presented in thousands euros for TMAX and TMEDIAN. For non-bankrupt firms, the population size 24,018 originates from using 6 years (2011–2016) for 4003 firms, while for variables depicting 24 months (ending with "1–24") there are 5 periods used, resulting in 20,015 observations (see Section 3.1 for more information).

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Article

Dynamic Bankruptcy Prediction Models for European Enterprises

Tomasz Korol

Faculty of Management and Economics, Gdansk University of Technology, Narutowicza 11/12, 80-233 Gdansk, Poland; tomasz.korol@zie.pg.gda.pl

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Abstract: This manuscript is devoted to the issue of forecasting corporate bankruptcy. Determining a firm's bankruptcy risk is one of the most interesting topics for investors and decision-makers. The aim of the paper is to develop and to evaluate dynamic bankruptcy prediction models for European enterprises. To conduct this objective, four forecasting models are developed with the use of four different methods—fuzzy sets, recurrent and multilayer artificial neural network, and decision trees. Such a research approach will answer the question of whether changes in indicators are relevant predictors of a company's coming financial crisis because declines or increases in values do not immediately indicate that the company's economic situation is deteriorating. The research relies on two samples of firms—the learning sample of 50 bankrupt and 50 non-bankrupt enterprises and the testing sample of 250 bankrupt and 250 non-bankrupt firms.

Keywords: corporate bankruptcy; forecasting; fuzzy sets; artificial neural networks; decision trees

1. Introduction

The measurement of corporate bankruptcy risk is one of the major challenges of modern economic and financial research. Nowadays, with increased financial globalization, faster economic changes, and a new dimension of increased financial risk in the context of the global financial crisis that arose since 2007, we should focus on increasing the reliability of the forecasting model and on prolonging the forecasting horizon to even 10 years prior to announcement of bankruptcy.

The consequences of financial failure are enormous for financial creditors, managers, shareholders, investors, employees, and even a country's economy. That is why during the past five decades, predicting corporate bankruptcy has become a significant concern for the various stakeholders in firms. Accurate bankruptcy prediction usually leads to many benefits, such as cost reduction in credit analysis, better monitoring, and an increased debt-collection rate. Thus, bankruptcy forecasting has become of major interest and is gaining much more importance currently. Today, the question is not if we should use bankruptcy forecasting models, but how to increase the effectiveness of forecasting models.

Though the first law on bankruptcy was already written in 1542 in England during the reign of King Henry VIII, the first studies on forecasting bankruptcies took place in the 1960s, started by Beaver (1966) and Altman (1968). There are two main distinct strands of models that have been used to predict bankruptcy—statistical and artificial intelligence models.

Since the estimation of the pioneering model of multivariate discriminant analysis by Altman, numerous research studies have been carried out with the use of a wide variety of statistical methods (e.g., Alaka et al. 2018; Bandyopadhyay 2006; Barboza et al. 2017; Delen et al. 2013; Giannopoulos and Sigbjornsen 2019; Ho et al. 2013; Hosmer et al. 2013; Jackson and Wood 2013; Kieschnick et al. 2013; Kumar and Ravi 2007; Laitinen 2007; Lukason and Hoffman 2014; Lyandres and Zhdanov 2013; Mihalovic 2016; Orsenigo and Vercellis 2013; Psillaki et al. 2010). The most popular statistical techniques as noted by Balcaen and Ooghe (2006) are multivariate discriminant analysis and logistic regression models.

Although the statistical techniques have become the most commonly used in bankruptcy prediction, they are characterized by many disadvantages regarding statistical assumptions, such as linearity, normality, and independence among variables, which have been identified in many studies (e.g., Altman 2018; Balcaen and Ooghe 2006; Jardin and Severin 2011; Tian and Yu 2017; Jayasekera 2018). That is why in the last two decades, popularity of bankruptcy prediction methods has shifted from statistical to intelligent ones such as neural networks, genetic algorithms, vector support machines, fuzzy logic (e.g., Acosta-González and Fernández-Rodríguez 2014; Ahn et al. 2000; Andres et al. 2005; Atiya 2001; Brabazon and O'Neil 2004; Callejon et al. 2013; Dong et al. 2018; Garcia et al. 2019; Hosaka 2019; Jardin 2015; Jardin 2018; Kim and Kang 2010; Lensberg et al. 2006; Lin et al. 2014; Min and Lee 2005; Ptak-Chmielewska 2019; Ravisankar and Ravi 2010; Succurro et al. 2019; Sun et al. 2014; Tam 1991; Tsai 2014; Wu et al. 2010; Zapranis and Ginoglou 2000; Xiao et al. 2012). The most popular method, which has been in use since the 1990s, is neural networks.

A detailed analysis of the literature on bankruptcy prediction shows that since the first studies, the main concern in the literature was to assess which method was the most effective in making predictions. Though many novel sophisticated techniques have been proposed for effective prediction, the majority of models ensure optimal predictive ability when the forecasting horizon is short, and their accuracy decreases severely beyond three years. Regardless of the modeling technique (linear or non-linear, regression or classification), most models are based on a static snapshot of financial situation that is static values of financial ratios for a given moment of time (usually at the end of the year). These models lack a dynamic approach to indicators. The question arises whether changes in indicators are relevant predictors of a company's coming financial crisis because declines or increases in values do not immediately indicate that the company's economic situation is deteriorating. Nevertheless, by observing changes, we can distinguish between a company that has low financial ratios that improve each year and a company that has similarly low ratios that worsen each year. Static models will not detect the difference between such companies. Dynamic models can add an element that differentiates companies with a poor financial situation from companies that have a weak financial situation but are improving.

To answer this research question, the main objective of this study is to develop dynamic bankruptcy prediction models for European enterprises with the use of four methods—fuzzy sets, artificial neural networks (multilayer and recurrent), and decision trees. This paper, therefore, makes three major contributions to the bankruptcy prediction literature. First, it implements a dynamic approach to financial ratios describing the economic situation of enterprises. Second, it verifies the influence of the dynamic approach on effectiveness of models developed with the use of four different forecasting techniques. Third, it allows the analysis of which method has the smallest decrease in effectiveness in extending the forecast horizon from one to 10 years. Very few studies in the literature focus on this crucial aspect. By evaluating and identifying the predictive properties of models in longer forecasting periods, we can build a decision-support model that will give managers more time in the decision-making process and thus prevent bankruptcies.

The paper consists of five sections. In the Introduction, the author justifies the topic, the study objectives, and the contributions and innovations to the literature. Section 2 presents an overview of the limitations of bankruptcy prediction models. Section 3 introduces this study's assumptions. In Section 4, the author presents four bankruptcy prediction models and discusses the results of effectiveness tests. Section 5 concludes the paper.

2. Literature Review

A thoughtful review on limitations of bankruptcy prediction models is useful to help readers understand the research and the appropriate process of estimation of forecasting models.

The first discussion point is the definition of financial distress. The purpose of bankruptcy forecasting models should be early recognition that the company will be threatened with bankruptcy. From a methodological point of view, it is important to define the term "bankruptcy". In the literature, there are various definitions. The most common interpretation of "bankruptcy" is the criterion of the insolvency of the company. The insolvency is understood as the inability to pay debts (e.g., Crone and Finlay 2012; Deakin 1972; Foster 1986; Jardin 2017). If a company is not able to honor its short-term debt, it is considered to be technically insolvent. Technical insolvency indicates a lack of liquidity but does not yet determine the bankruptcy of the company. Lack of ability to pay current liabilities may be temporary and can be remedied by appropriate action of company management. Altman, a world authority on bankruptcy issues, finds that insolvency understood as a cause of bankruptcy is a long-term state in which the business is found if its total debt exceeds the value of all assets held (Altman 1968). In the studies of Doumpos and Zopounidis (Doumpos and Zopounidis 1999), financial distress not only contains inability to repay important obligatory payments, but also includes the situation of negative net asset value, which means an enterprise's total liabilities exceed its total assets from the view of accounting.

On the other hand, Berryman (1992) suggests a profitability criterion to define a company at risk of bankruptcy. According to him, "a company at risk of bankruptcy" is characterized by a lower long-term return on equity from the level of profitability possible to obtain in similar companies. However, such a wide interpretation of the term "bankruptcy" seems to be too broad. Even more so since research conducted by Davies (1997) on the fallen companies in the UK and France has revealed that most failed companies had positive financial results in the period preceding their bankruptcy.

An equally broad and controversial interpretation of the concept of corporate bankruptcies was presented by Watson and Everett (1999), who stated that a simple change of the owners of the company is a form of failure. In literature, the term "financial failure" is often used interchangeably with the term "bankruptcy". The criterion of continuity of ownership in the company seems to be a too far-fetched over-interpretation of the term "bankruptcy".

The second issue concerns an assessment of the effectiveness of the statistical bankruptcy prediction models such as the multivariate discriminant analysis and the logit and probit models. The allegation concerns the ability to manipulate the thresholds of these models in order to maximize the results of the classification of models. This objection is raised by Nwogugu (2007), according to whom statistical methods do not provide reliable results due to the ease of manual adjustment of the threshold so as to increase the effectiveness of the model. Such manipulation, of course, will not increase the effectiveness of the model in the general population of companies after implementation of the model, e.g., in a bank, but only in the given testing sample of the author of the model.

Another shortcoming of traditional forecasting models is their stationarity (e.g., Balcaen and Ooghe 2006; Grice and Dugan 2001; Liang et al. 2016; Mensah 1984). Bankruptcy models are usually estimated with the use financial ratios calculated with data from balance sheets and income statements. The use of ratios is as much due to their predictive power as to their availability and standardization (Jardin 2016). They generally allow for good discrimination between failed and non-failed firms. However, the way they are designed is one of their main weaknesses. The majority of the models are developed based on static values of financial ratios for a given moment of time, but bankruptcy has multiple causes and symptoms, and a model with variables that are solely measured over a single period would probably not be able to embody such diversity. The financial crisis in enterprise is a dynamic process, and it does not depend on the sole situation of a firm at a given period but is the result of many factors that often overlap. The ability of a model to capture the whole variety of negative situations is a key factor of its performance. As mentioned before, this raises the question of whether changes in the indicators are relevant predictors of the upcoming financial crisis in the company. The dynamic approach to financial ratios could help to introduce an additional element discriminating companies at risk of bankruptcy from enterprises that are in bad financial condition but improving, that is distancing them from the risk of going bankrupt. These considerations are part of the empirical analysis in next sections of the paper.

The next accusation against bankruptcy forecasting models is the issue of their obsolescence with the passage of time since their development. In the literature, it is assumed that the bankruptcy risk prediction models are working well for four to six years, after which it is necessary to modify and update them (e.g., Agarwal and Taffler 2007; Altman and Rijken 2006; Li and Faff 2019; Tian et al. 2015). It should be noted, however, that the model life cycle shown in Figure 1 is a matter of agreement. There are no strict rules that accurately define when the life of the model comes to an end. Common sense should be demonstrated in this regard. Models become outdated as a result of, for example, changes in the business cycle and changes in economic conditions, due to which mean values of economic and financial indicators are subject to change. Adding a dynamic perspective to the model could enhance the validity period of the models.

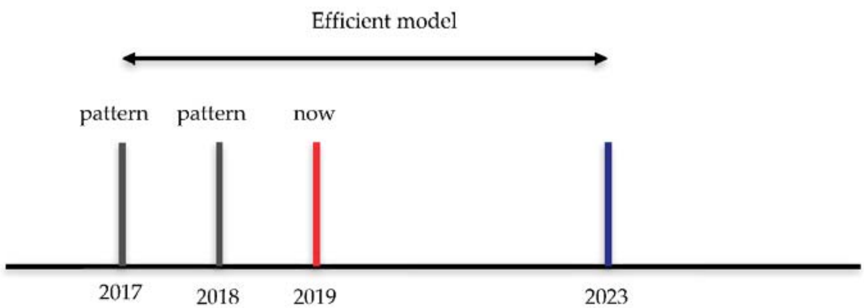


Figure 1. The life cycle of bankruptcy forecasting model. Source: Based on own studies.

Another issue arises in relation to statistical methods. As was mentioned before, there are strict assumptions regarding normal distribution of values of financial ratios used in estimating forecasting models (e.g., multivariate discriminant analysis). This assumption is usually not fulfilled due to the fact that only a few variables used in this type of model are characterized by such a distribution. However, the desire to meet this target would significantly limit the number of financial ratios that accurately reflect the economic situation of the enterprises, and thus would result in deterioration of the effectiveness of such models (e.g., Balcaen and Ooghe 2006; Kumar and Ravi 2007; Mcleay and Omar 2000).

The last important topic to consider in developing bankruptcy forecasting models is the structure of enterprises in research sample regarding their age and type of industry they operate in. In the literature, studies of individual authors (e.g., Cressy 2006) confirm the assumptions of the theoretical model developed by Jovanovic (1982). He reveals the effect of company age on the risk of bankruptcy is in the form of an inverted U shape (Figure 2).

Jovanovic suggests that after entering the market, the company begins to learn to recognize its earning potential, competitiveness, and efficiency. Research by Pakes and Ericsson (1998) has shown that the company needs time to gain that knowledge and experience to manage crisis situations. The studies of Bradley and Rubach (2002) also showed that the second and third year of existence has the highest risk of bankruptcy (52% of cases). The studies of Doyle et al. (2007) confirm that the older the company, the more established its market position but also internal financial control.

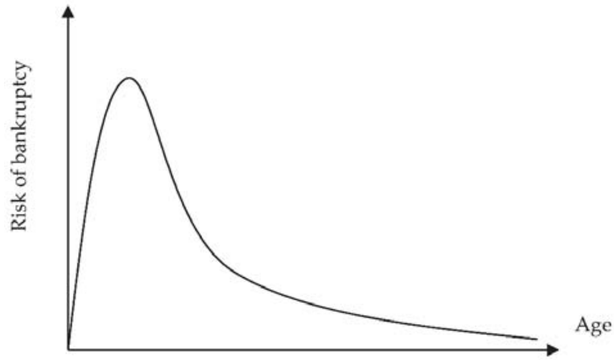


Figure 2. Age of company and the risk of bankruptcy. Source: Based on own studies.

The second demographic factor influencing the susceptibility of a company to risk of bankruptcy is the type of industry in which the company operates. According to the director of the international rating agency Standard & Poor's, the type of industry affects the risk of deterioration in financial situation of companies by such factors as (Ganguin and Bilardello 2005):

- Intensity of competition,
- Life cycle of products,
- The demand,
- Changes in consumer preferences,
- Technological change,
- Reducing entry barriers into the industry,
- Susceptibility of the industry to business cycle.

Ganguin and Bilardello (2005) emphasize that each industry has different risk parameters. In the 21st century, in an era of intense globalization, product life cycles in some industries are getting much shorter, often with increasing intensity of competition by reducing entry barriers into the industry. These authors rank industries into three risk levels:

- Riskiest sectors—industry: Metal, mining, automotive, aerospace, housing, paper,
- Medium risk industries—restaurants, retail, medical sector, tourism, transport,
- Least risky sectors—journalistic, military, pharmaceutical industry, and agriculture.

Chava and Jarrow (2004) in their studies also have demonstrated the impact of the type of industry on the bankruptcy of enterprises. They divided the population of 1461 bankrupt American joint-stock companies into 10 types of industries. Using bankruptcy prediction models by Altman, Shumway, and Żmijewski, they proved that the type of industry affects the correct coefficients in each model.

3. Data, Samples, and Modeling Methods

To address all the issues in forecasting corporate bankruptcy risk described in the previous section, the author of the paper in developing learning and the testing sample:

- Has chosen a clear definition of "bankrupt" enterprises. The enterprises at risk of bankruptcy were chosen based on the following three criteria: Information from the firm's authorities about the risk of financial failure, court judgments declaring bankruptcy, and liquidation of the company;
- Has chosen four prediction methods that do not allow manipulation of thresholds—multilayer neural network, recurrent neural network, fuzzy sets, and decision trees;
- Has calculated 20 financial ratios (Figure 3) for all the enterprises (bankrupt and non-bankrupt) for whole analyzed period of 10 years prior to bankruptcy and the dynamics for all ratios. The

assumption was to build the models with at least two variables representing the change of value of financial ratio to avoid stationarity of the created models;

- Has selected enterprises that were operating in the market for at least 10 years (to avoid the selection of new, young companies characterized with higher bankruptcy risk).

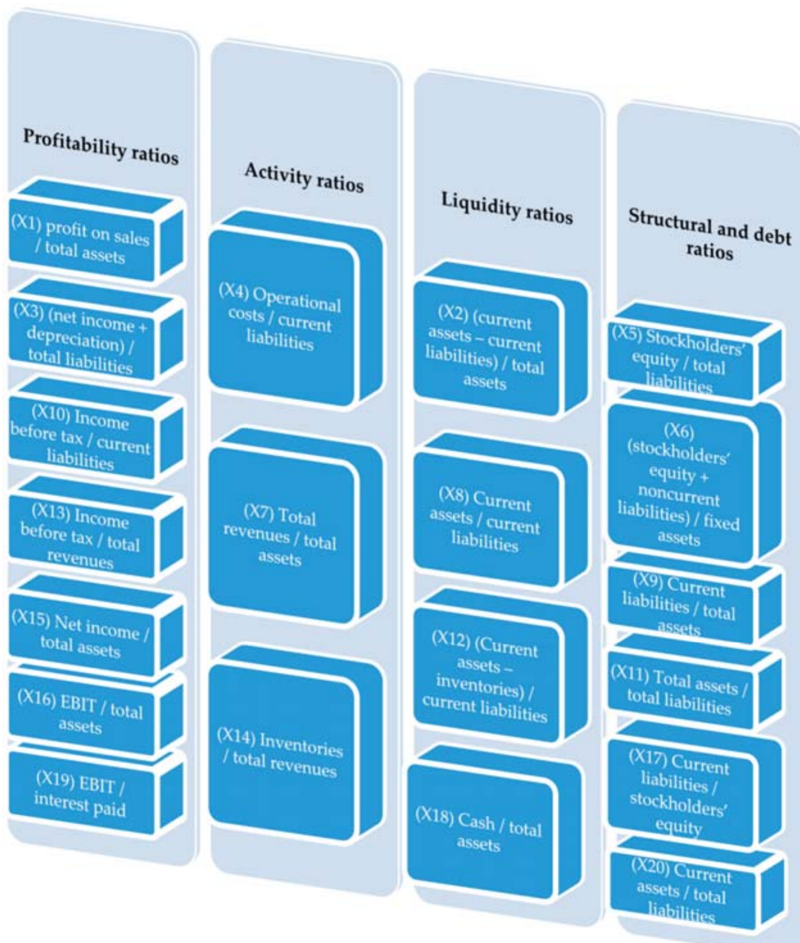


Figure 3. The financial ratios used in the study. Source: Self-study.

The forecasting horizon for all enterprises and all models comprises 10 periods: From one year to 10 years prior to bankruptcy. Such a research approach allows the identification of which model characterizes the forecast with the smallest decrease of effectiveness along the increasing horizon and verifies the influence of implementing dynamic elements to the models on its effectiveness. Depending on the enterprise, the 10-year financial statements taken for analysis covered the period from 2004 to 2017.

The learning and testing samples comprise enterprises from European countries (Germany, France, UK, Spain, Finland, Italy, Poland, Sweden, Denmark). Each testing sample includes 250 bankrupt and 250 non-bankrupt enterprises, while each learning sample includes 50 bankrupt and 50 non-bankrupt firms. Both samples consist of companies that are publicly traded, due to better availability of financial data of firms in case of such a long-term forecasting horizon (10 years prior to bankruptcy). The research contains the firms of all sizes (small, medium, and large) keeping the principle of pairing the same size and sector of bankrupt firms to non-bankrupt ones.

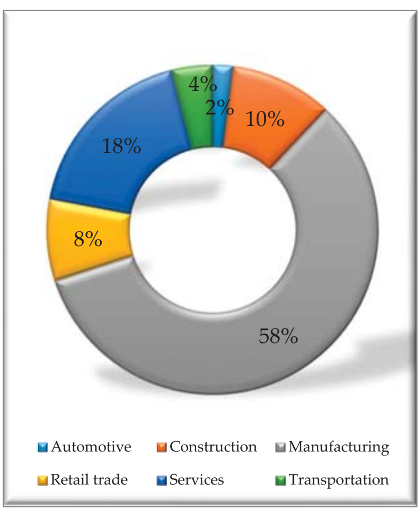
To assess the effectiveness of the created models, three evaluation metrics were calculated for each testing sample: Overall effectiveness and Type I and Type II errors. Overall effectiveness is calculated based on how many enterprises are correctly classified by the forecasting model in a given testing sample:

$$S = \{1 - [(D1 + D2)/(BR + NBR)]\} * 100\%$$

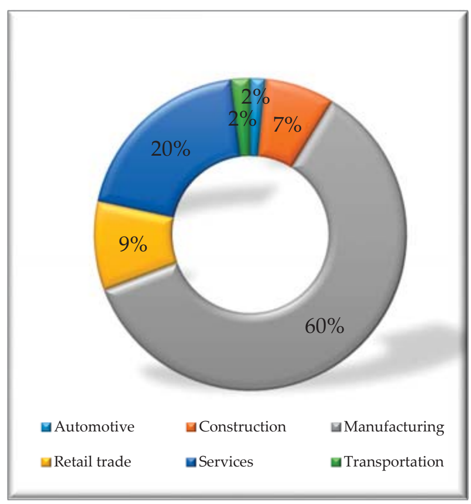
where D1 is the number of bankrupt firms classified by the model as non-bankrupt, D2 is the number of non-bankrupt enterprises classified by the model as bankrupt, BR is the number of bankrupt companies in the sample, and NBR is the number of non-bankrupt companies in the sample.

Type I error is a measure of the number of firms in which the model incorrectly classifies a bankrupt firm into a non-bankrupt class, while Type II error is a measure that accounts for the number of firms classified as bankrupt when they actually belong to a non-bankrupt class.

To ensure the reliable process of learning and testing the models, the enterprises were selected for both samples while maintaining very similar structure of belonging to sectors of industry. From Figure 4 it can be seen that the biggest number of enterprises was for manufacturing companies (58% and 60% of all firms in the learning and testing datasets, respectively). Although the automotive industry is part of manufacturing sector, it was distinguished separately from manufacturing industry as in many countries it has big influence on the whole economy, indirectly affecting also the financial situation of enterprises from other sectors. The second biggest share accounted for service companies—18% of all firms in learning and 20% of all firms in testing sample. Such a balanced number of sectors between the two samples should ensure the reliability of results.



(a)



(b)

Figure 4. The sector structure of: (**a**) learning sample and (**b**) testing sample of enterprises. Source: Based on own studies.

4. Results and Discussion

In the first stage of research, the author developed two artificial neural network models—multilayer and recurrent. Inputs to the models were chosen based on the correlation matrix by choosing only the features that were poorly correlated with each other and strongly correlated with the grouping variable, representing the information about the risk of bankruptcy. This approach ensured the selection of such features, which do not duplicate information provided by other financial ratios, while being good representatives of the ratios not selected as diagnostic. The following financial ratios were set (the formulas are given in Figure 3): X1 (profitability ratio), X6 (structural ratio), X7 (activity ratio), X8 (liquidity ratio), DX1 (dynamics of ratio X1), DX8 (dynamics of ratio X8). It can be seen that each ratio belongs to a different field of financial analysis.

The multilayer neural network is the network in which the signal flow is only in one direction, from the input (financial ratios) through the hidden layer, where the main processing of neural signals takes place, to the output, where the network provides a forecast (bankrupt/non-bankrupt). The architecture of the developed multilayer network is shown in Figure 5. At the entry layer there are six neurons, in the first hidden layer there are 12 neurons (double the number of neurons as entry ones), in the second hidden layer there are four neurons and then one single output neuron where the forecast is generated.

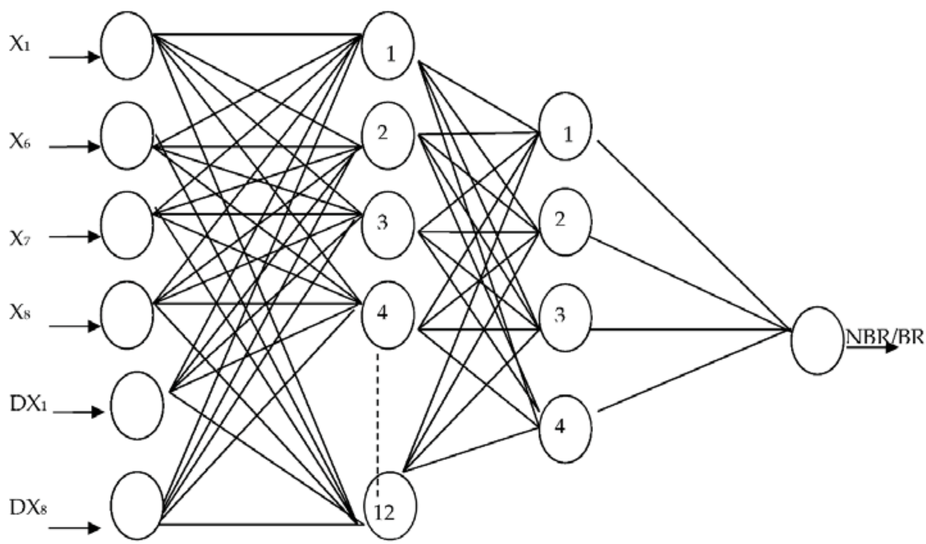


Figure 5. Architecture of artificial feedforward multilayer neural network for analysis of enterprises. Source: Based on own studies.

In topology of recurrent networks, it is acceptable to use reverse connections. The output from any neuron can be passed also to its input. Neuron state is therefore dependent not only on the value of the input signal (financial ratio), but also on the past state of any neuron, not excluding this particular neuron. The network response to specific input takes in this case an iterative character. The created architecture of the recurrent neural network for predicting risk of bankruptcy for European companies is shown in Figure 6. The developed recurrent model has the same entry layer as the previous model, but it consists of only one hidden layer with 12 neurons as the reverse connections between neurons support higher computing properties.

The next developed model was fuzzy sets model. This model requires no assumptions about the learning process and is developed based on expert knowledge and experience. The decision-making center of the fuzzy logic model is the base of rules in the form: IF-THEN, written by the author of this paper. The output of the model is a variable representing the forecast of the financial situation of the audited company. This variable has a value from 0 to 1, and it was assumed that the threshold dividing companies into at risk and not at risk of bankruptcy is 0.5. For each input, that is the financial ratio, the author defined critical value (Table 1). The fuzzy sets model consists the same entry variables as both created neural networks.

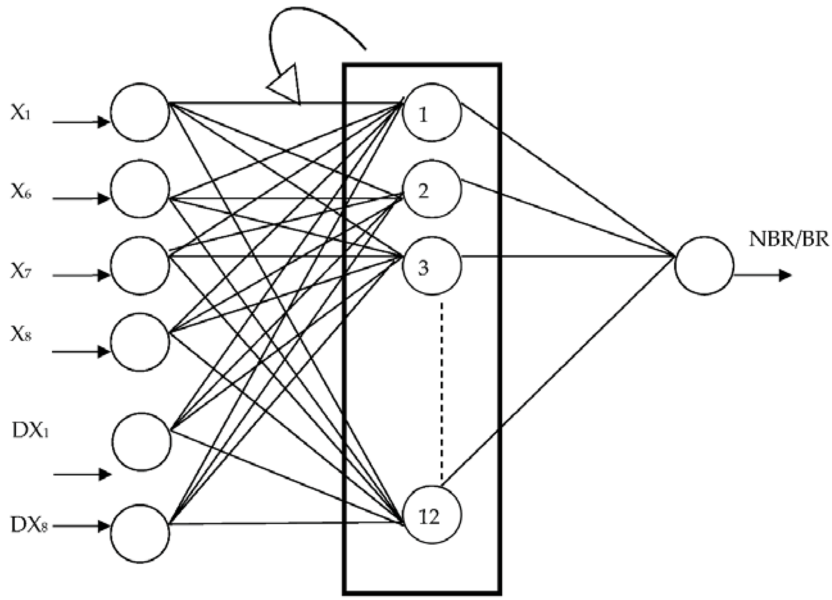


Figure 6. Architecture of artificial recurrent neural network for analysis of enterprises. Source: Based on own studies.

Table 1. Critical values of financial ratios used in the fuzzy sets model. Source: Based on own studies.

Indicator Symbol	Critical Value in Fuzzy Sets Model
$\mathbf{X_1}$	0.015
$\mathbf{X_6}$	0.9
$\mathbf{X_7}$	0.82
$\mathbf{X_8}$	1.05
$\mathbf{DX_1}$	70.0%
$\mathbf{DX_8}$	85.0%

To explain more how the fuzzy sets model functions, below is an example of fuzzy sets defined using membership functions for the ratio X8 (Figure 7).

For ratio X8, shown in Figure 7 (this ratio represents current liquidity of firms), the threshold between a positive and negative situation is the value of 1.05. All values less than 0.7 are strictly negative, i.e., they belong to the fuzzy subset "LOW" with the degree of membership of 1 and to a subset "HIGH" with the degree of membership equal to 0. All values greater than 1.3 are strictly positive and, therefore, belong to the fuzzy subset "LOW" with the degree of membership of 0 and to the subset "HIGH" with the degree of membership equal to 1. Values contained in the range from 0.7 to 1.3 belong to both fuzzy subsets with different values of membership functions, e.g., for values of X8 equal to 1.05, the value of the function of membership in the "LOW" set is 0.5 and for the "HIGH" set is 0.5. With such defined subsets, the boundary between the values considered positive or negative is fuzzificated—a certain ratio value is "partially high" and "partially low". There is no such possibility in the case of classical logic, which is bivalent and in which the value of the ratio is "high" or "low". Therefore, the use of classical logic in assessing the financial situation of enterprises negatively affects the effectiveness of forecasts. This is true particularly for values close to the border of subsets, where a slight excess in the critical values of the ratio determines the final assessment (as completely positive or negative), which is not true because both values of the ratio reflect almost the same situation in the firm.

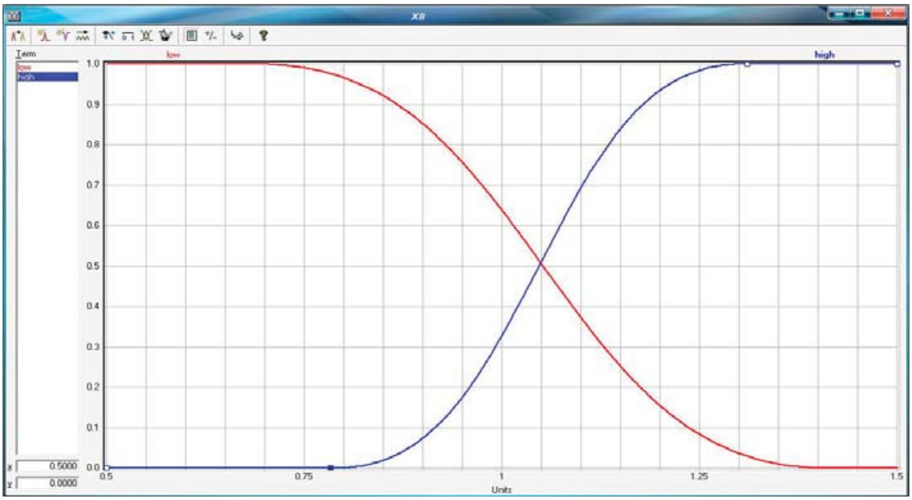


Figure 7. Fuzzy sets for ratio X8 with membership functions. Source: Own studies conducted in MATLAB.

The author has developed the following 36 decision-making "IF-THEN" rules for the fuzzy sets model:

1. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
2. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 > 70 and DX_8 <= 85 then 0
3. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 0
4. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 > 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
5. If X_1 <= 0.015 and X_6 > 0.9 and X_7 > 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
6. If X_1 > 0.015 and X_6 > 0.9 and X_7 > 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
7. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 > 0.82 and X_8 <= 1.05 and DX_1 > 70 and DX_8 <= 85 then 0
8. If X_1 <= 0.015 and X_6 > 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 > 70 and DX_8 <= 85 then 0
9. If X_1 > 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 > 70 and DX_8 <= 85 then 0
10. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
11. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 > 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
12. If X_1 <= 0.015 and X_6 > 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
13. If X_1 > 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
14. If X_1 <= 0.015 and X_6 > 0.9 and X_7 > 0.82 and X_8 > 1.05 and DX_1 <= 70 and DX_8 <= 85 then 1
15. If X_1 <= 0.015 and X_6 <= 0.9 and X_7 > 0.82 and X_8 > 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
16. If X_1 <= 0.015 and X_6 > 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
17. If X_1 <= 0.015 and X_6 > 0.9 and X_7 > 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
18. If X_1 > 0.015 and X_6 <= 0.9 and X_7 > 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
19. If X_1 > 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 <= 70 and DX_8 <= 85 then 0
20. If X_1 > 0.015 and X_6 <= 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
21. If X_1 > 0.015 and X_6 > 0.9 and X_7 <= 0.82 and X_8 > 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
22. If X_1 > 0.015 and X_6 > 0.9 and X_7 <= 0.82 and X_8 <= 1.05 and DX_1 > 70 and DX_8 <= 85 then 1
23. If X_1 > 0.015 and X_6 > 0.9 and X_7 > 0.82 and X_8 <= 1.05 and DX_1 <= 70 and DX_8 <= 85 then 1

24. If $X_1 > 0.015$ and $X_6 > 0.9$ and $X_7 <= 0.82$ and $X_8 > 1.05$ and $DX_1 <= 70$ and $DX_8 <= 85$ then 1
25. If $X_1 > 0.015$ and $X_6 <= 0.9$ and $X_7 > 0.82$ and $X_8 > 1.05$ and $DX_1 > 70$ and $DX_8 <= 85$ then 1
26. If $X_1 <= 0.015$ and $X_6 <= 0.9$ and $X_7 <= 0.82$ and $X_8 <= 1.05$ and $DX_1 <= 70$ and $DX_8 > 85$ then 0
27. If $X_1 <= 0.015$ and $X_6 <= 0.9$ and $X_7 <= 0.82$ and $X_8 <= 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 0
28. If $X_1 <= 0.015$ and $X_6 <= 0.9$ and $X_7 <= 0.82$ and $X_8 > 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 1
29. If $X_1 <= 0.015$ and $X_6 <= 0.9$ and $X_7 > 0.82$ and $X_8 > 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 1
30. If $X_1 <= 0.015$ and $X_6 > 0.9$ and $X_7 > 0.82$ and $X_8 > 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 1
31. If $X_1 > 0.015$ and $X_6 > 0.9$ and $X_7 > 0.82$ and $X_8 > 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 1
32. If $X_1 > 0.015$ and $X_6 <= 0.9$ and $X_7 <= 0.82$ and $X_8 <= 1.05$ and $DX_1 <= 70$ and $DX_8 > 85$ then 0
33. If $X_1 > 0.015$ and $X_6 > 0.9$ and $X_7 <= 0.82$ and $X_8 <= 1.05$ and $DX_1 <= 70$ and $DX_8 > 85$ then 1
34. If $X_1 <= 0.015$ and $X_6 <= 0.9$ and $X_7 > 0.82$ and $X_8 <= 1.05$ and $DX_1 > 70$ and $DX_8 > 85$ then 1
35. If $X_1 <= 0.015$ and $X_6 > 0.9$ and $X_7 <= 0.82$ and $X_8 > 1.05$ and $DX_1 <= 70$ and $DX_8 > 85$ then 1
36. If $X_1 > 0.015$ and $X_6 > 0.9$ and $X_7 > 0.82$ and $X_8 <= 1.05$ and $DX_1 <= 70$ and $DX_8 > 85$ then 1

In the last stage of the research, the author estimated the decision trees model. The structure of the model is presented in Figure 8. In this model, the following financial ratios were selected: X2 (liquidity ratio), X1 (profitability ratio), X6 (structural ratio), X9 (structural ratio). As can be seen in this model, none of variables representing the change of value of ratios (dynamics) were selected during estimation process of the model. This means it is the only static model in the proposed research.

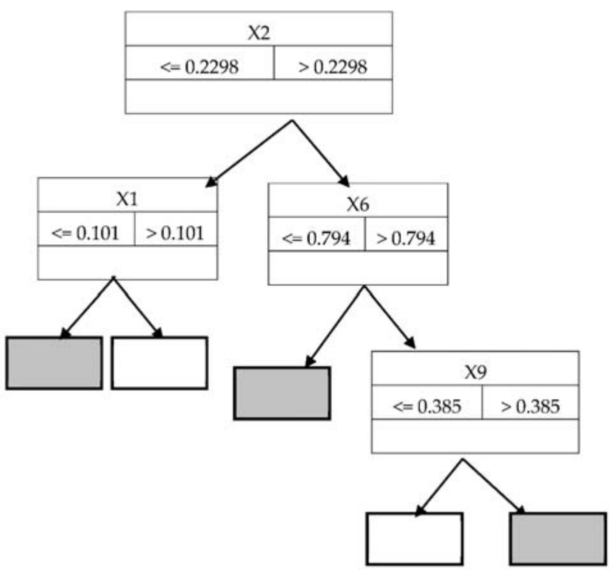


Figure 8. The structure of the Classification and Regression Tree (C&RT) model. Gray box indicates firms at risk of bankruptcy; white box, non-bankrupt firms. Source: based on own studies.

When evaluating the effectiveness of the developed models (Table 2), we can draw the following conclusions:

- During the whole analyzed period (all 10 years prior to bankruptcy) the highest effectiveness was achieved using the fuzzy sets model, with 96.2% correct classifications one year before bankruptcy, 95.4% correct classifications two years prior to financial failure, and 93.8% correct classifications three years before bankruptcy;

- The second best forecasting model is the recurrent neural network model with an effectiveness from 91.2% three years before financial crisis to up to 95.2% correct classifications one year prior to bankruptcy;
- An examination of the effectiveness of the dynamic models (fuzzy sets, multilayer and recurrent neural networks) shows that all of them stand out with very good results in the forecasting horizon of up to six years prior to bankruptcy, with an effectiveness above 80%;
- The effectiveness of the static decision tree model is smaller than the effectiveness of the dynamic models for all the analyzed years. Additionally, the model shows significantly bigger decrease of effectiveness while prolonging the period of the forecast than dynamic models;
- The fuzzy sets model as the only dynamic model maintained an effectiveness level above 70% until the eighth year prior to bankruptcy;
- Moreover, all three dynamic models have the fewest Type I errors. Such errors indicate how many bankrupt enterprises are classified as non-bankrupt firms. Type I errors, for obvious financial reasons, are far more dangerous than Type II errors.

Table 2. The results of the effectiveness of models for European firms (testing sample). Source: Based on own studies.

Years Prior to Bankruptcy	Multilayer Neural Network			Recurrent Neural Network			Fuzzy Sets			Decision Trees		
	S	E1	E2	S	E1	E2	S	E1	E2	S	E1	E2
1 year	**93.4%**	6.0%	7.2%	**95.2%**	4.0%	5.6%	**96.2%**	3.2%	4.4%	**93.0%**	8.0%	6.0%
2 years	**91.8%**	7.6%	8.8%	**93.6%**	5.6%	7.2%	**95.4%**	4.4%	4.8%	**91.2%**	10.0%	7.6%
3 years	**87.4%**	11.6%	13.6%	**91.2%**	7.6%	10.0%	**93.8%**	5.2%	7.2%	**86.8%**	14.8%	11.6%
4 years	**82.8%**	16.4%	18.0%	**87.8%**	10.4%	14.0%	**90.6%**	7.6%	11.2%	**81.6%**	19.6%	17.2%
5 years	**82.4%**	16.8%	18.4%	**82.4%**	16.8%	18.4%	**87.8%**	10.8%	13.6%	**77.2%**	24.0%	21.6%
6 years	**80.8%**	18.0%	20.4%	**81.0%**	18.4%	19.6%	**82.8%**	16.4%	18.0%	**72.0%**	30.0%	26.0%
7 years	**74.2%**	25.6%	26.0%	**77.4%**	21.6%	23.6%	**80.8%**	18.8%	19.6%	**65.0%**	35.6%	34.4%
8 years	**64.4%**	34.4%	36.8%	**65.0%**	34.4%	35.6%	**71.4%**	26.0%	31.2%	**62.8%**	38.0%	36.4%
9 years	**63.4%**	36.0%	37.2%	**64.0%**	35.2%	36.8%	**67.2%**	32.4%	33.2%	**62.4%**	38.4%	36.8%
10 years	**63.0%**	36.4%	37.6%	**63.6%**	35.6%	37.2%	**65.8%**	32.8%	35.6%	**61.4%**	39.6%	37.6%

5. Conclusions

This paper presents how to improve the effectiveness of forecasting corporate distress risk models in both the short and long horizon, exceeding five years before the announcement of bankruptcy.

The present empirical study reveals that the implementation of dynamic elements to the forecasting models positively affects the effectiveness and the stability of the forecast. The dynamic models generate a smaller number of errors, and the decrease of effectiveness of such models is smaller with extending the forecast period than in the case of static models. Additionally, this research also proved the superiority of fuzzy sets model over the other developed models, both in terms of effectiveness during all analyzed years prior to bankruptcy and in terms of the smallest decrease of predictive abilities while increasing the forecasting horizon.

The main limitation of the research is limited financial data access, especially for bankrupt enterprises (in many cases there are data available only for one to three years before the enterprise went bankrupt, which makes it difficult to conduct the research in such long horizon of 10 years prior to financial failure). That is why the studies are focused on countries with better organized financial reporting systems (EU countries). The author is going to continue the research towards the use of macroeconomic variables of selected countries in predicting the risk of bankruptcy of enterprises.

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Article

ISA 701 and Materiality Disclosure as Methods to Minimize the Audit Expectation Gap

Tomasz Iwanowicz * and **Bartłomiej Iwanowicz**

Department of Accounting, Akademia Leona Koźmińskiego, Jagiellońska 57/59, 03-301 Warsaw, Poland; biwanowicz@kozminski.edu.pl

* Correspondence: tiwanowicz@kozminski.edu.pl

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Abstract: Purpose: The main purpose of this paper is to determine how particular audit firms deal with ISA 701 requirements and the society expectations towards reporting the materiality levels. Additionally, the aim of this paper is to range the assertions in terms of the frequency of their occurrence. Design/methodology/approach: The tested sample consisted of 317 companies listed on Warsaw (158 companies) or London (159 companies) stock exchange. The analysis was divided into companies from the following ten market indexes (WIGs): construction, IT, real estate, food, media, oil and gas, mining, energy, automotive and chemicals. The research was executed based on the analysis of annual consolidated financial statements (annual reports) and independent auditor reports that were published by in-scope entities for the latest twelve-months period available as at the date of the research (mostly periods ended on 31 December 2017 and 31 March 2018). All values were denominated to euro (EUR) with use of average exchange rates published by the National Bank of Poland. All performed analyses and developed charts were supported by Microsoft Power BI data analysis tool. Findings: The general conclusion, which may be drawn from this research, is that implementation of ISA 701 and materiality disclosure limited the audit expectation gap. Detailed observations are described throughout the paper and summarized in the conclusions section. Originality/value: This study extends the prior research by providing various dimensions of the analysed matters. It contributes to understanding of the audit expectation gap and investigates on methods of minimizing it.

Keywords: ISA 701; audit expectation gap; key audit matters; materiality; Poland

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"Capitalism without bankruptcy is like Christianity without hell"

Frank Borman—American astronaut

1. Introduction

The International Auditing and Assurance Standards Board (IAASB) is a global independent standard-setting body that serves the public interest by setting high-quality international standards, which are generally accepted worldwide. The IAASB sets its standards in the public interest with advice from the IAASB Consultative Advisory Group (CAG) and under the oversight of the Public Interest Oversight Board. Changing expectations and public confidence in audits is one of the most significant environmental drivers that have shaped the IAASB's strategy for 2020–2023 (IFAC 2019, p. 7).

There is decreasing confidence and declining trust in audits, arising from continuing high levels of reported poor results of external inspections and recent high profile corporate failures in some jurisdictions. Stakeholders' expectations are also changing about what the standards should require the auditor to do, e.g., in relation to the detection and reporting of fraud, and the consideration of going concern issues.

It has already been proved that public misperceptions are a major cause of the legal liability crisis facing the accounting profession. There is a concern that auditors and the public hold different beliefs about the auditors' duties and responsibilities and the messages conveyed by audit reports (Koh and Woo 1998). This has been named as the "auditing expectation gap" which refers to the difference between (1) what the public and other financial statement users perceive auditors' responsibilities to be and (2) what auditors believe their responsibilities entail (McEnroe and Martens 2001, pp. 345–58). This gap can be divided into three elements (ICAEW 2006):

- reasonableness gap[1] (element 'A'),
- deficient standards gap[2] (element 'B'),
- deficient performance gap[3] (element 'C').

These elements can be split down further into the following key areas:

- reporting (area '1'),
- assurance being provided (area '2'),
- regulation and liability (area '3'),
- audit independence (area '4').

The auditing expectation gap is illustrated in Figure 1 below.

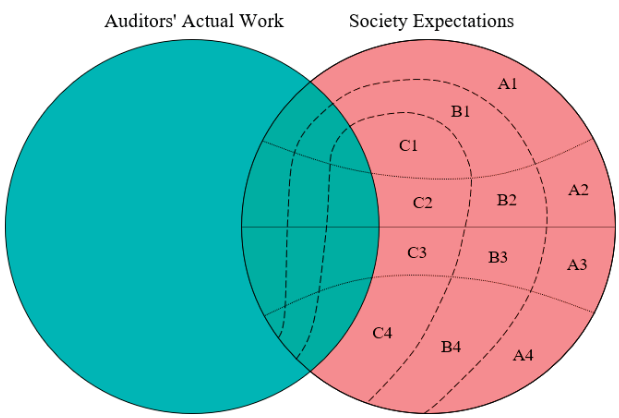

Figure 1. Auditing expectation gap divided into three elements and four key areas. Source: own elaboration based on analysed literature.

In 2015, the IAASB issued amendments to its standards. The goal of this shift was to enhance the independent auditor's reporting by making it more informative and insightful, and therefore valuable, to investors and other users of financial statements. The IAASB implemented a new International Standard on Auditing (ISA) 701, which introduced the auditor's responsibility to report on Key Audit Matters (KAM). The standard is applicable to the audit of all listed entities for periods ending on or after 15 December 2016.

Communicating key audit matters is expected to assist the users of financial statements in understanding topics, which according to the auditor were of utmost importance in the audited

1 Referring to what society expects of auditors and what can reasonably be expected of auditors to accomplish.
2 The gap between the responsibilities that society reasonably expects auditors to perform and auditors' actual responsibilities under statute.
3 The difference between the expected standard of performance of auditors and the actual performance of responsibilities by auditors.

period. Key audit matters are those matters that, in the auditor's professional judgment, were of most significance in the audit of the financial statements of the current period (IAASB 2016a, ISA 701, para. 8). At the same time, ISA 701 does not define any number of key audit matters, which ought to be identified by the auditor. The standard requires that the auditor uses his professional judgement in order to prioritize what is to be communicated within the KAM section. An attempt to determine the degree of implementation of changes in auditors' reporting for the largest companies (based on the example of the Polish market) was made in 2019 (Kutera 2019, pp. 79–94). The reports from the audit of the consolidated financial statements of the 30 largest companies listed on the Warsaw Stock Exchange for the years 2014–2016 were analyzed. The results of the analysis showed that the key audit matters mainly include estimating the impairment of assets (including deferred tax assets), revenue recognition and contingent liabilities disclosures.

Furthermore, in some jurisdictions, the auditor's report may comprise additional information going beyond the requirements of the ISA including the determination of materiality (Deloitte 2016, p. 15). The concept of materiality has received a lot of attention in recent years as high-profile accounting scandals have plagued financial reporting. ISA requires that early in an audit engagement the auditor establishes a preliminary level of materiality. This monetary value is used to determine the extent of audit testing that is to be performed. It can be changed as the audit progresses and key financial statement numbers change (Kearns 2007). Under current standards neither the preliminary nor final materiality value must be disclosed. In Poland and United Kingdom, it is permitted to disclose such additional information and therefore audit firms can decide whether or not to present this information.

The main purpose of this paper is to determine how particular audit firms deal with ISA 701 requirements and the society expectations towards reporting of the materiality levels. It compares and contrasts auditors' extent of such reporting (both KAM and materiality section) separately with regard to entities listed on Warsaw and London stock exchange and separately for analysed market indexes. Additionally, the aim of this paper is to range the assertions in terms of the frequency of their occurrence.

This study extends the prior research by providing various dimensions of the analysed matters. The article consists of an introduction, three chapters, and a summary and conclusions. The first chapter was devoted to the review of literature on the auditing expectation gap. The second chapter presents the research methodology, while the third chapter presents the results of the research.

2. Literature Review

Business failures are connected with the financial situation and non-financial factors (Ptak-Chmielewska 2019). Financial scandals have not only resulted in the loss of trust in the capital market but have also caused a crisis of credibility of auditors (Whittington and Pany 2004). There is a need to increase the usefulness of the information provided by the statutory auditors upon examination of the financial statements (Szczepankiewicz 2011). Many regulators currently debate how to increase effectiveness of supervision of public companies (Szczepankiewicz 2012, p. 25). Public expectations should go much beyond the watchdog function. The public awaits an audit to assure as to discovery of all frauds and irregularities (Gupta 2005). Absolute objectivity cannot be guaranteed since "materiality" and "material significance" are auditors' subjective concepts (Ojo 2006). A review of auditing literature shows how the auditing profession has responded to this problematic issue—including coining the phrase "audit expectation gap" (Lee et al. 2009). The expectation gap is the evolutionary development of audit responsibilities (Ebimobowei 2010, p. 129).

The audit expectation gap is a fundamental issue in every society in the world and that perception of users of financial statements as the responsibilities of auditors and the audit objective is the major cause of the gap. The gap can be addressed through (Schelluch and Gay 2006):

- emphasing the need to educate the public and reassure them about the exaggerated public outcries over isolated audit failures,
- codifying existing practices to legitimize them,

- attempting to control the audit expectation gap debate and repeatedly propounding the views of the profession,
- emphasing an awareness of the objective of the audit,
- readiness to extend the scope of an audit.

Audit definition is subject to challenges and changes according to social, economic and political developments (Jedidi and Richard 2009). Audit rules and regulations contain terms, like "reasonable", "material", and "professional scepticism" whose meanings vary in the minds of different auditors (Zikmund 2008). Independence is crucial to the reliability of auditors' reports (Salehi 2009). The literature reveals that educating the public about the objects of audit and auditors' responsibilities will help minimize the audit gap (Salehi and Rostami 2009).

The previous wording of the audit opinion no longer meets the expectations of the business community (Kutera 2018). The expanded audit report appeared to change users' perceptions about the responsibilities of management and auditors that mean users found expanded reports more useful and understandable than short-form audit reports (Aljaaidi 2009, p. 52). The professional bodies should set up new standards and renew existing ones as one of the remedies to the expectations gap (Akinbuli 2010). A common response in order to reduce the gap is to set out more auditing and accounting standards (Saeidi 2012, p. 7032). Accelerated by waves of financial crises the authorities have introduced a variety of measures to enhance the effectiveness of companies supervision (Kiedrowska and Szczepankiewicz 2011).

The IAASB implemented new ISA 701, which introduced the auditor's responsibility to report on KAM. Communicating KAMs is expected to assist the stakeholders in understanding the most important topics that occurred in the period presented in the financial statements. While determining key audit matters the auditor should consider i.a.:

- areas of higher risk of material misstatement or in which significant risks were identified (IAASB 2009e, ISA 315),
- financial statement areas, which involve substantial management judgment (e.g., accounting estimates),
- effects of significant events or transactions, which occurred during the audited period.

It must be noted that any matter giving rise to a qualified or adverse opinion (as per IAASB 2009d, ISA 705), or the existence of material uncertainty that may question the entity's ability to continue as a going concern (IAASB 2016b, ISA 570) is by its nature a KAM. However, such matters should be reported in line with applicable ISAs and the auditor should not include them in the KAM section of the report. In case when the auditor does not determine any key audit matters, he shall:

- discuss this with the engagement quality control reviewer (if appointed),
- explain in the report that there are no KAM to be reported, including the rationale for such a conclusion (IAASB 2009c, ISA 230),
- communicate this with those charged with governance.

The audit committee helps in narrowing the audit expectation gap since it is independent and non-executive and it aims to settle disputes and to reinforce external and internal audit performance. If audit committees do not play their role not more than just window dressing, then the audit expectation gap will be widened (Shbeilat et al. 2017).

An external audit of financial statements provides reasonable assurance as to whether the audited financial statements as a whole are prepared, in all material respects, in accordance with an identifiable financial reporting framework. Thus, the auditor is only responsible to detect misstatements that are material to the financial statements as a whole (IAASB 2009a, ISA 200). Misstatements, including omissions, are considered to be material if they, individually or in the aggregate, could reasonably be expected to influence the economic decisions of users taken on the basis of the financial statements

(IAASB 2009b, ISA 320, para. 2). This definition appears to be simple, however, the auditor has to distinguish between omissions and misstatements that would affect the users of financial statements and those that would not affect such users (Vorhies 2005). Additionally, there is a range of users, which makes such assessment more complex since materiality is likely to be unique to each user (Doxey 2013).

Materiality disclosures are not mandatory in Polish statutory auditing. Several foreign studies have shown that materiality disclosures in the audit report could have beneficial effects, while other studies have raised concerns about potential drawbacks. Research from a users' perspective seems to conclude that materiality should be disclosed, whilst research from the auditors' perspective is still in its fledgling stages, although it seems that auditors are rather apprehensive about disclosing materiality. This lack of consensus with regards to materiality disclosures is part of a much larger audit reporting debate that has been going on for many decades (Baldacchino et al. 2017).

3. Research Methodology

The tested sample, which was subject to the research, consisted of 317 companies listed on Warsaw (158 companies) or London (159 companies) stock exchange. The analysis was divided into companies from the following ten market indexes (WIGs): construction, IT, real estate, food, media, oil and gas, mining, energy, automotive and chemicals. The dispersion of the analyzed organizations in terms of represented WIG is illustrated in Figure 2 below.

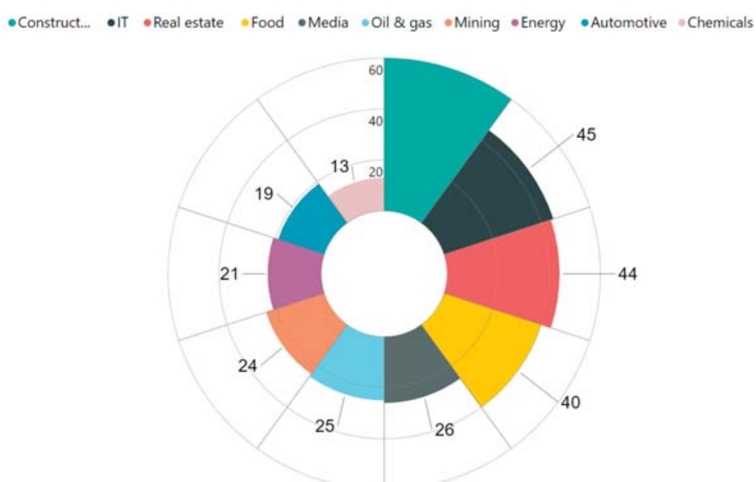

Figure 2. Tested sample by WIG. Source: own elaboration based on analyzed data.

The research was executed based on the analysis of:

- annual consolidated financial statements (annual reports)[4],
- independent auditor reports,

published by in-scope entities for the latest twelve-months period available as at the date of the research (mostly these were twelve-months periods ended on 31 December 2017 and 31 March 2018). All values were denominated to euro (EUR) with the use of average exchange rates published by the National Bank of Poland.

[4] The research was executed based on the analysis of the annual consolidated financial statements or standalone financial statements in situations where there was no capital group. The tested sample consisted of 317 financial statements (both consolidated and standalone).

All enterprises within the tested sample were public interest entities (PIE) listed on Warsaw or London stock exchange. Analyzed companies listed on the Warsaw stock exchange (158 companies) represented the entire population of PIE operating within the tested WIGs. Firms from the United Kingdom were randomly selected from respective WIGs to "mirror" the Polish ventures. The structure of the tested sample in terms of WIGs and the auditors is presented in Figure 3 below.

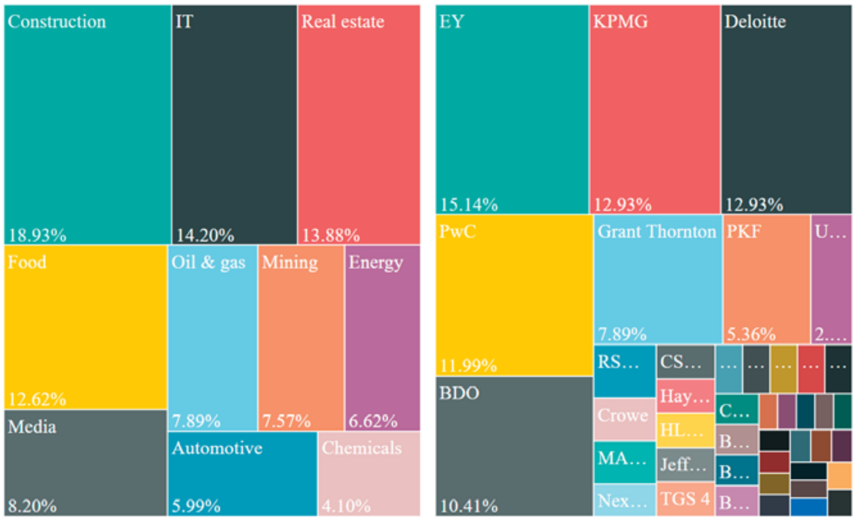

Figure 3. Structure of the tested sample in terms of WIGs and the auditors (in %). Source: own elaboration based on analyzed data.

Analyzed corporations were subject to the obligatory audits of their financial statements. The coverage of the tested sample by auditors is demonstrated in Figure 4 below.

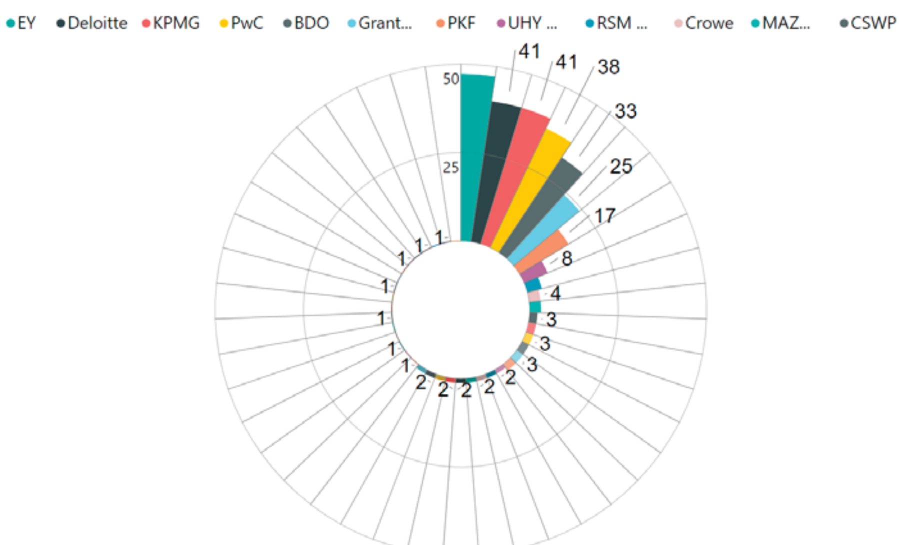

Figure 4. Structure of the tested sample in terms of the auditors. Source: own elaboration based on analyzed data.

168 of tested companies (53%) entrusted their audits to so-called "Big 4" auditing firms while the remaining (149, i.e., 47%) selected 1 of 39 other audit service providers. In the tested sample, 20 auditors (47%) were represented by a single client.

Apart from the Big 4, the auditors with the biggest share in the tested sample were:

- BDO (33, i.e., 10%);
- Grant Thornton (25, i.e., 8%);
- PKF (17, i.e., 5%).

A combined simplified balance sheet and profit and loss for the tested sample is presented in Table 1 below.

Table 1. Combined simplified balance sheet and profit and loss for the tested sample (in million EUR).

Balance Sheet	
Fixed assets	**1570**
Intangible assets	270
Tangible assets	985
Long-term receivables	36
Long-term investments	231
Long-term prepayments	48
Current assets	**641**
Inventory	168
Short-term receivables	228
Short-term investments	218
Short-term prepayments	27
Total assets	**2211**
Equity	**1013**
Provisions for liabi. and accruals	44
Long-term liabilities	701
Short-term liabilities	453
Total equity and liabilities	**2211**
Profit and Loss	
Net revenues from sales	1570
Operating expenses, incl.	1407
Amortization and depreciation	90
Other operating income	14
Other operating expenses	9
Financial income	9
Financial expenses	23
Gross profit (loss)	154
Net profit (loss)	106

Source: own elaboration based on analyzed data.

Based on the information provided in tested annual consolidated financial statements and independent auditor reports, there was a database created which contained:

- values of selected financial statements line items;
- detailed description of all KAMs reported;
- overall materiality levels and applied calculation methods.

Auditors of 317 companies, that were subjected to this test, identified a total of 793 unique KAMs. Based on their detailed descriptions they were then segmented into 36 categories (including category 'none') and finally mapped with a total of 2094 assertions from 7 types[5].

All performed analyses and developed charts were supported by Microsoft Power BI data analysis tool. With regards to presented 'sankey' type of charts, that illustrate interconnections between auditors, KAMs, assertions, WIGs, overall materiality, benchmark and Overall Materiality Rule of Thumb (OM RoT), the weights of ribbons presented were defined as number/average value of KAMs/assertions/overall materiality respectively.

4. Presentation of Research Results

In Figures 5 and 6, the KAMs' number and frequency of use and KAMs' mapping to assertions are presented, respectively. For the relationships between auditors, KAMs, assertions, and WIGs please refer to Figures 7 and 8.

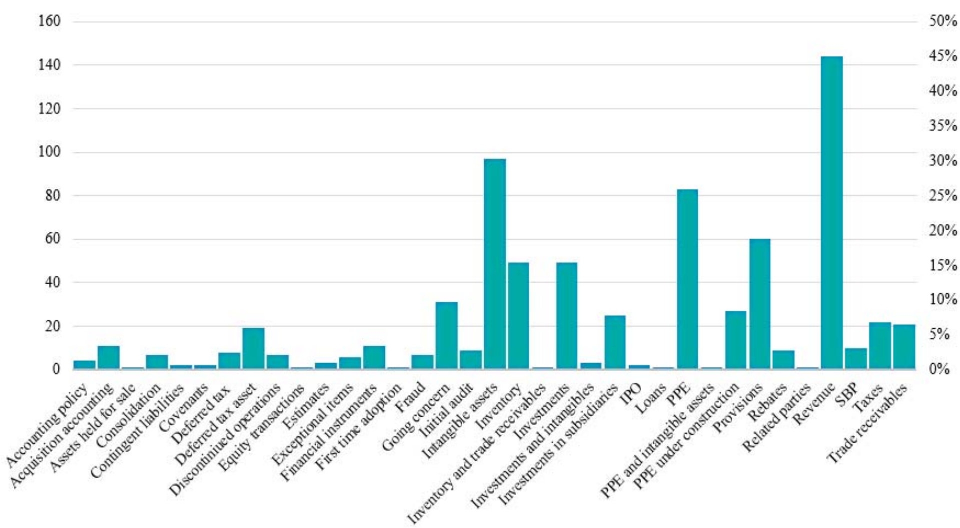

Figure 5. KAM—number and frequency of use. Source: own elaboration based on analyzed data.

5 The following types of assertions were defined and analysed: C—completeness; A—accuracy; V—valuation; CO—cut-off; PD—presentation and disclosures; E—existence; RO—rights and obligations.

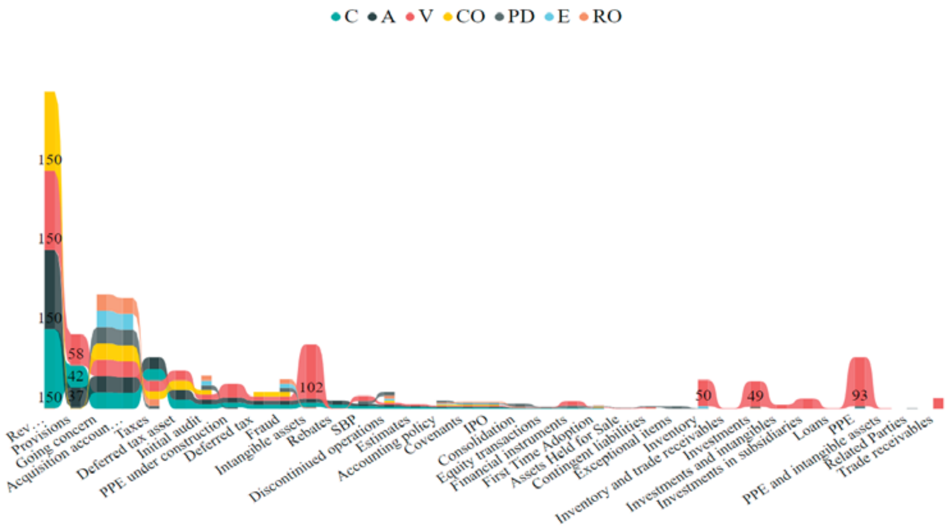

Figure 6. KAM—mapping to assertions. Source: own elaboration based on analyzed data.

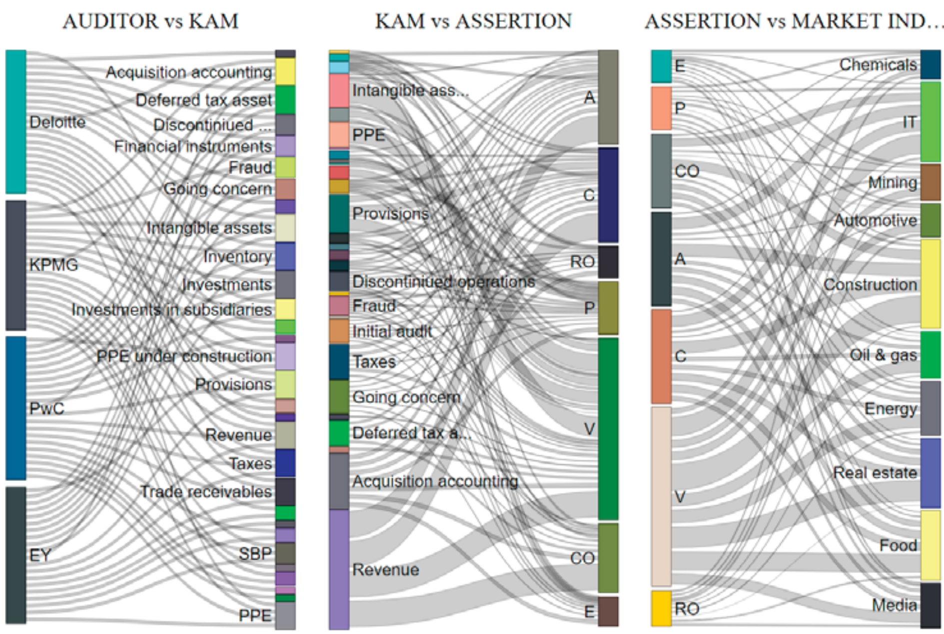

Figure 7. *Cont.*

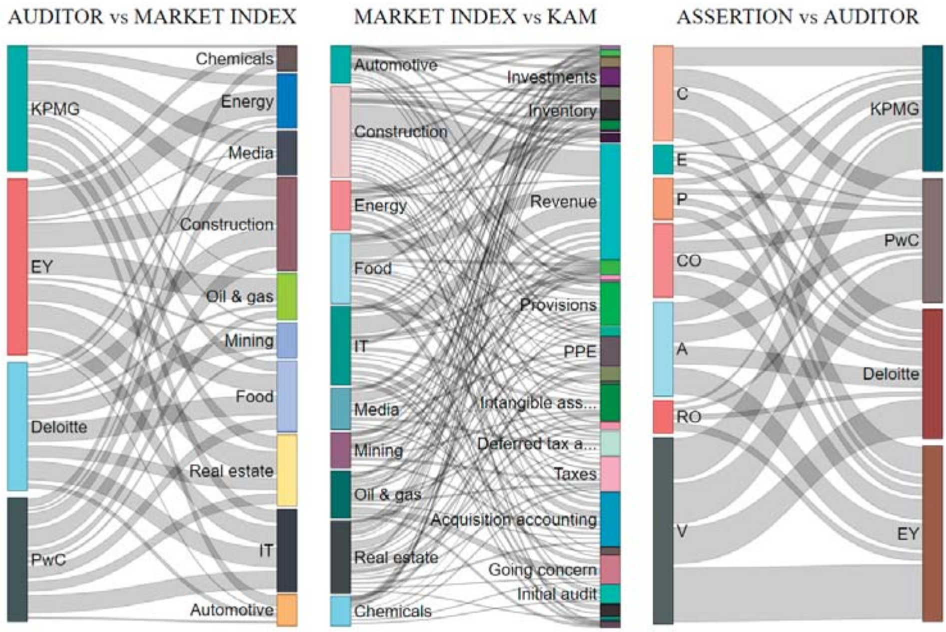

Figure 7. Relationships between auditors, KAMs, assertions, and WIGs—for Big 4 auditing firms. Source: own elaboration based on analyzed data.

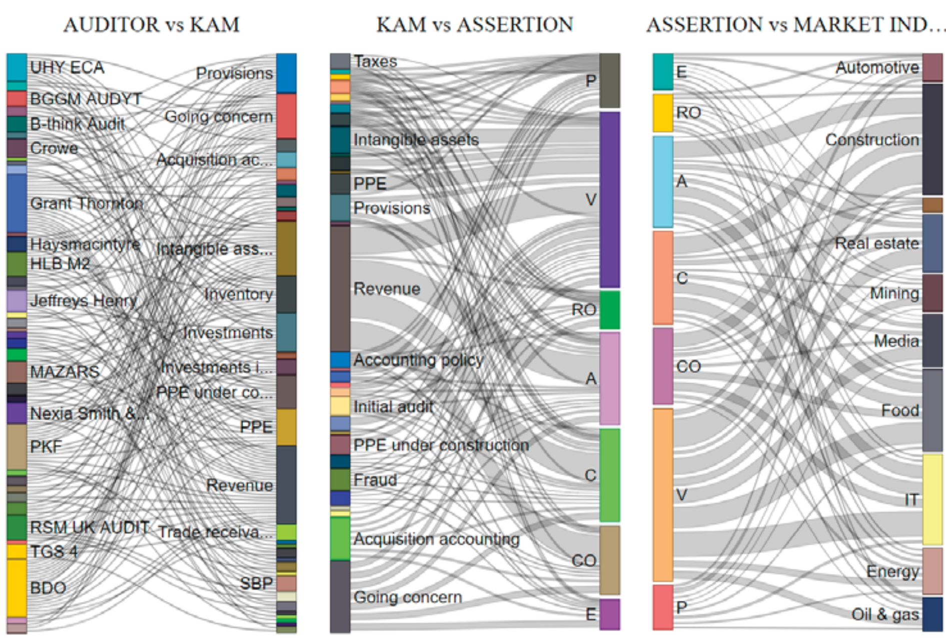

Figure 8. *Cont.*

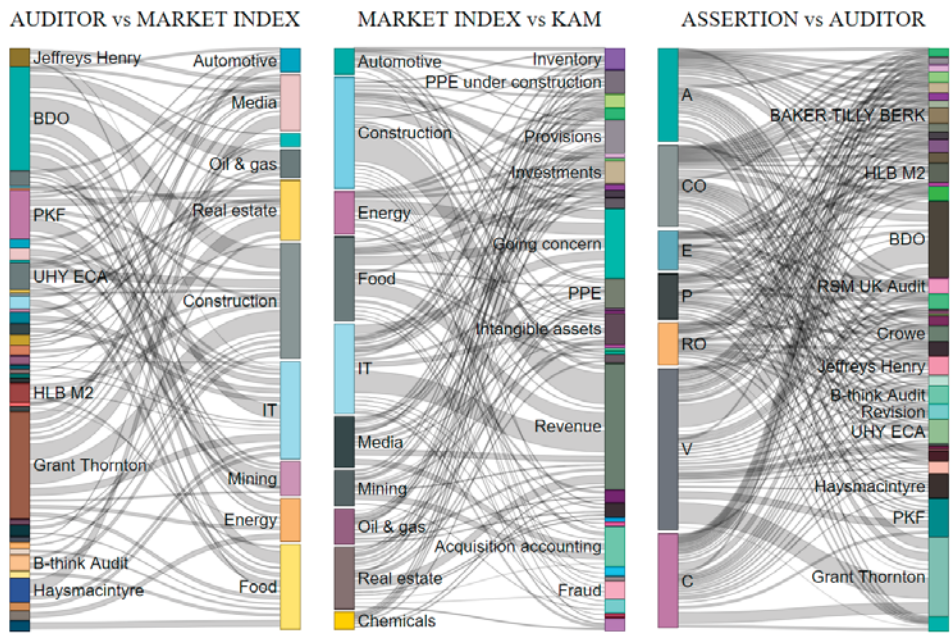

Figure 8. Relationships between auditors, KAMs, assertions, and WIGs—for non-Big 4 auditing firms. Source: own elaboration based on analyzed data.

As presented in Figures 5–8:

- for five businesses (1.6% of the tested sample) no KAMs were reported by the auditors,
- revenue is the most vastly used as a KAM category (45.3% of auditors' reports contained this KAM),
- the following 9 KAMs referred to all seven assertions: accounting policy, acquisition accounting, covenants, discontinued operations, first time adoption, fraud, going concern, initial audit and initial public offering (IPO),
- the valuation was the most frequently appearing assertion (745 items from a total of 2094, 35.6%);
- there is no clear differentiation in terms of presented patterns between Big 4 and non-Big 4 audit firms.

In Figure 9, the companies listed on the Warsaw stock exchange for which materiality levels were disclosed by auditors are presented. For the relationships between auditors, benchmarks, OM RoT, and WIGs please refer to Figures 10 and 11.

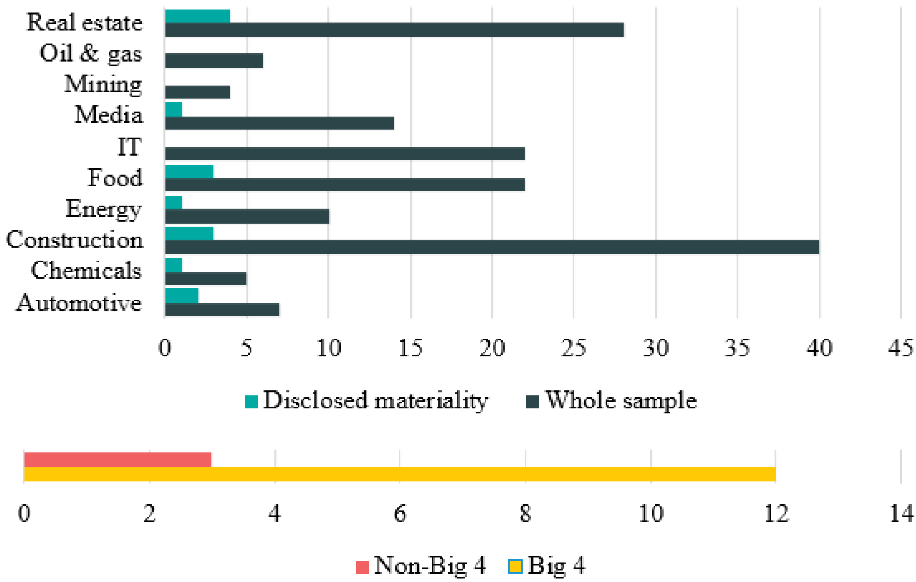

Figure 9. Companies listed on the Warsaw stock exchange for which materiality levels were disclosed by auditors—by WIG and non-Big/Big 4 auditors. Source: own elaboration based on analyzed data.

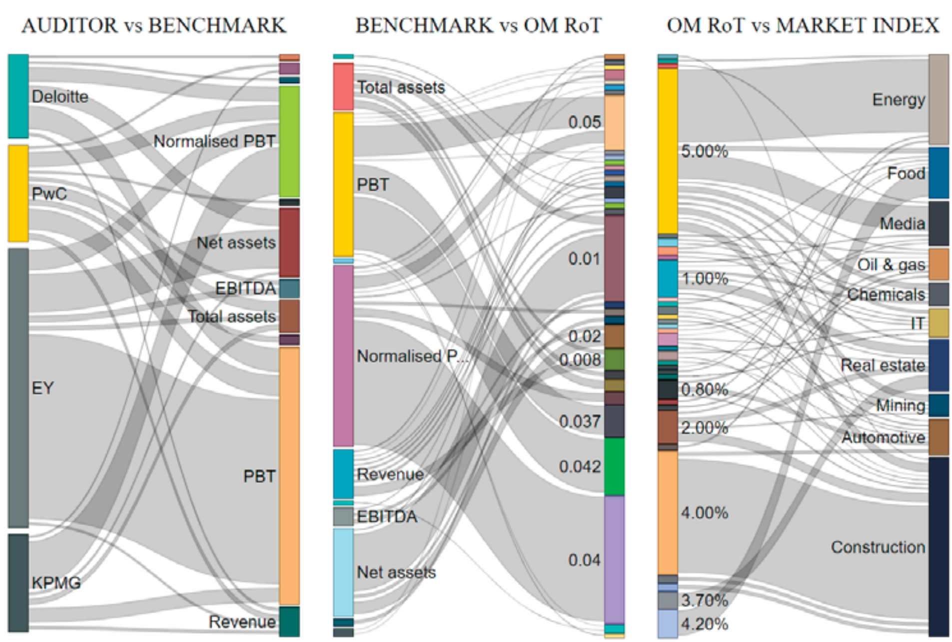

Figure 10. *Cont.*

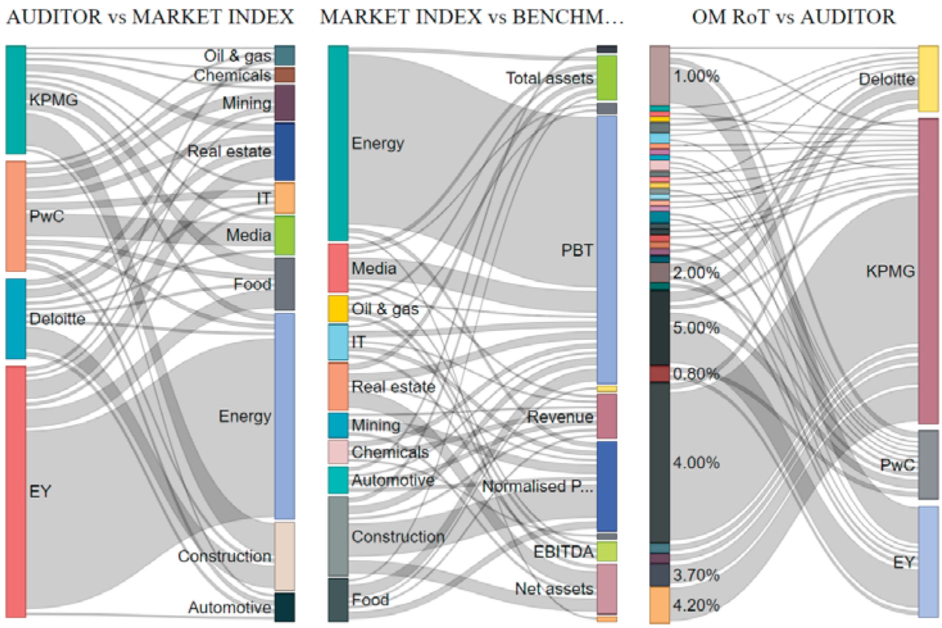

Figure 10. Relationships between auditors, benchmarks, OM RoT and WIGs—for Big 4 auditing firms. Source: own elaboration based on analyzed data.

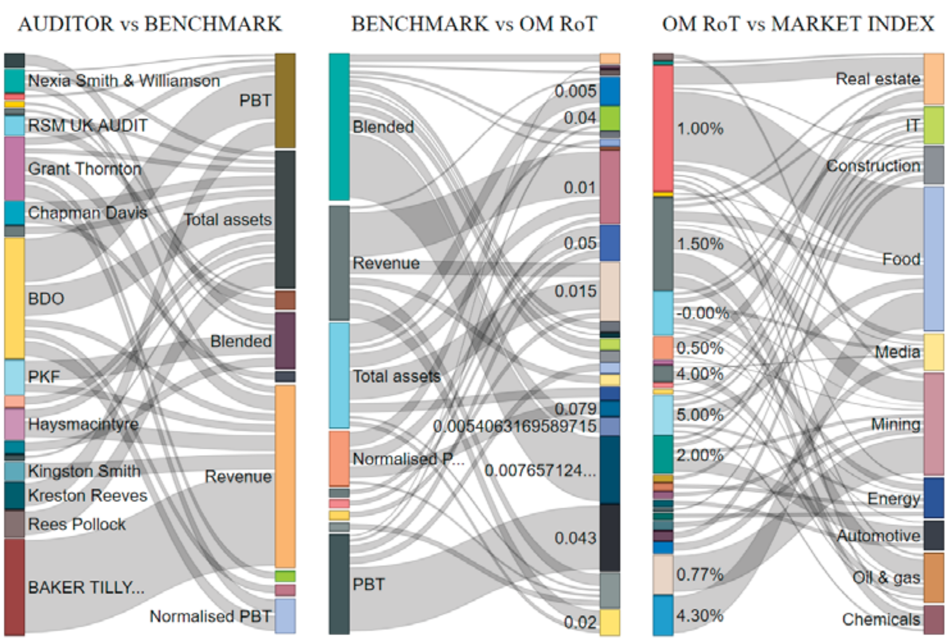

Figure 11. *Cont*.

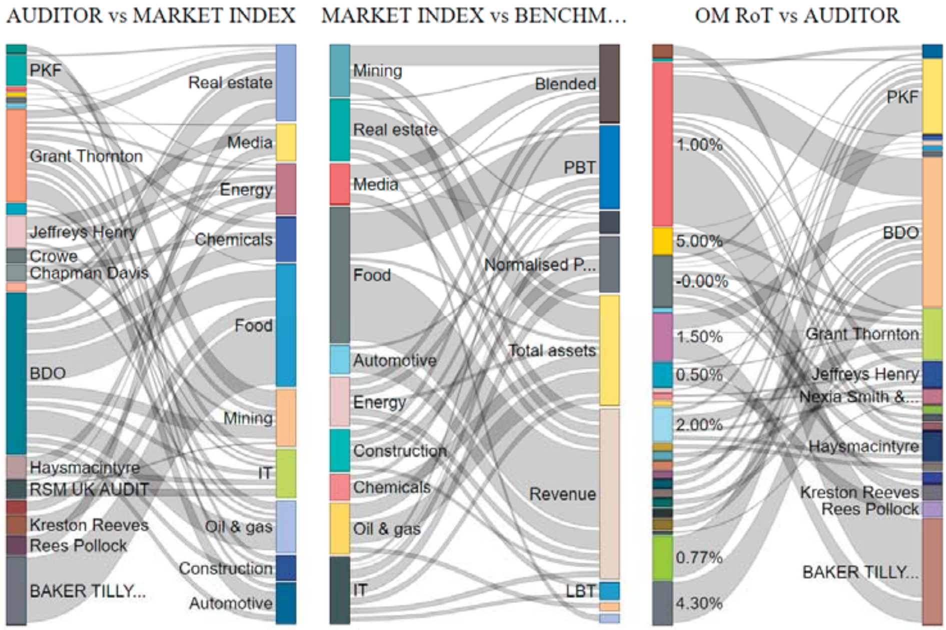

Figure 11. Relationships between auditors, benchmarks, OM RoT and WIGs—for non-Big 4 auditing firms. Source: own elaboration based on analyzed data.

All auditors of companies listed on the London stock exchange reported on the materiality levels, which they utilized for audit purposes. The information was fairly comprehensive and included: benchmark, OM RoT, overall materiality level, and de minimis materiality level. Some auditors provided also additional details about haircut and performance materiality.

As presented in Figure 9, this statistic was substantially lower for entities listed on the Warsaw stock exchange. Materiality levels were reported for 15 PIEs, which represented 9.5% of the whole population of companies operating within 10 specific industries (the Polish tested sample). It was observed that 80% of all reported materiality levels were announced by Big 4 auditors (by PwC in 11 out of 12 cases).

As presented in Figures 10 and 11:

- coverage of sectors by Big 4 representatives was fairly even, with the exception of the energy, which was dominated by EY,
- specialization of auditors may be observed (Baker Tilly's portfolio comprises mostly of food WIG) but no concentration over any particular auditor is visible within any sector,
- the most broadly used OM RoT was 4%, which was applied primarily:
    - by KPMG,
    - for normalized PBT,
    - in construction WIG;
- relatively, among Big 4, EY has the least differentiated benchmarks, with PBT being the main variable used to determine materiality,
- among Big 4, profit before tax (PBT) was the most commonly used benchmark, followed by normalized PBT, while among non-Big 4 it was revenue and total assets respectively,
- there was no other clear differentiation in terms of presented patterns between Big 4 and non-Big 4 audit firms.

The exact level of the OM is not imposed on auditors by any governing body. Its calculation is at the auditor's discretion. The auditor's determination of materiality is a matter of professional judgment and is affected by the auditor's perception of the financial information needs of users of the financial statements (ISA 320, para. 4). Determining a percentage to be applied to a chosen benchmark involves the exercise of professional judgment. There is a relationship between the percentage and the chosen benchmark, such that a percentage applied to profit before tax from continuing operations will normally be higher than a percentage applied to total revenue. For example, the auditor may consider five percent of profit before tax from continuing operations to be appropriate for a profit-oriented entity in the manufacturing industry, while the auditor may consider one percent of total revenue or total expenses to be appropriate for a not-for-profit entity (ISA 320, para. A7). The Figure below presents the OM used by Big 4 auditors in relation to those thresholds.

As presented in Figure 12, on average:

- for PBT, KPMG is 28.6% and PwC is 12.5% below the bottom threshold of 5% PBT, which means that they are even more detailed and conservative than as per the example presented in ISA 320, EY keeps it almost in the middle between the lower and upper limits, while Deloitte maintains its OM 27.3% over this base,
- for EBITDA, Deloitte stands out from the competition by getting close to the upper limit of the threshold, while the remainders keep it in the middle of the scale,
- for revenue, all Big 4 auditors except for Deloitte set up their OM below 1% revenue as per the example presented in ISA 320,
- finally, the situation for total assets is akin to the one for the revenue.

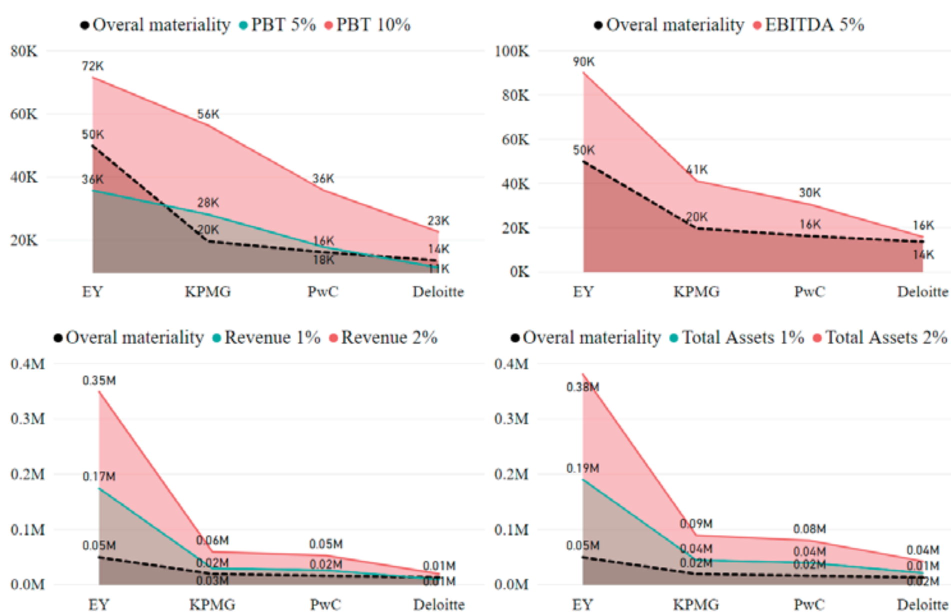

Figure 12. Overall materiality used by Big 4 auditors in relation to the percentage mentioned in ISA 320 and literature. Source: own elaboration based on analyzed data.

The Figure 13 below presents the OM used by non-Big 4 auditors in relation to those thresholds.

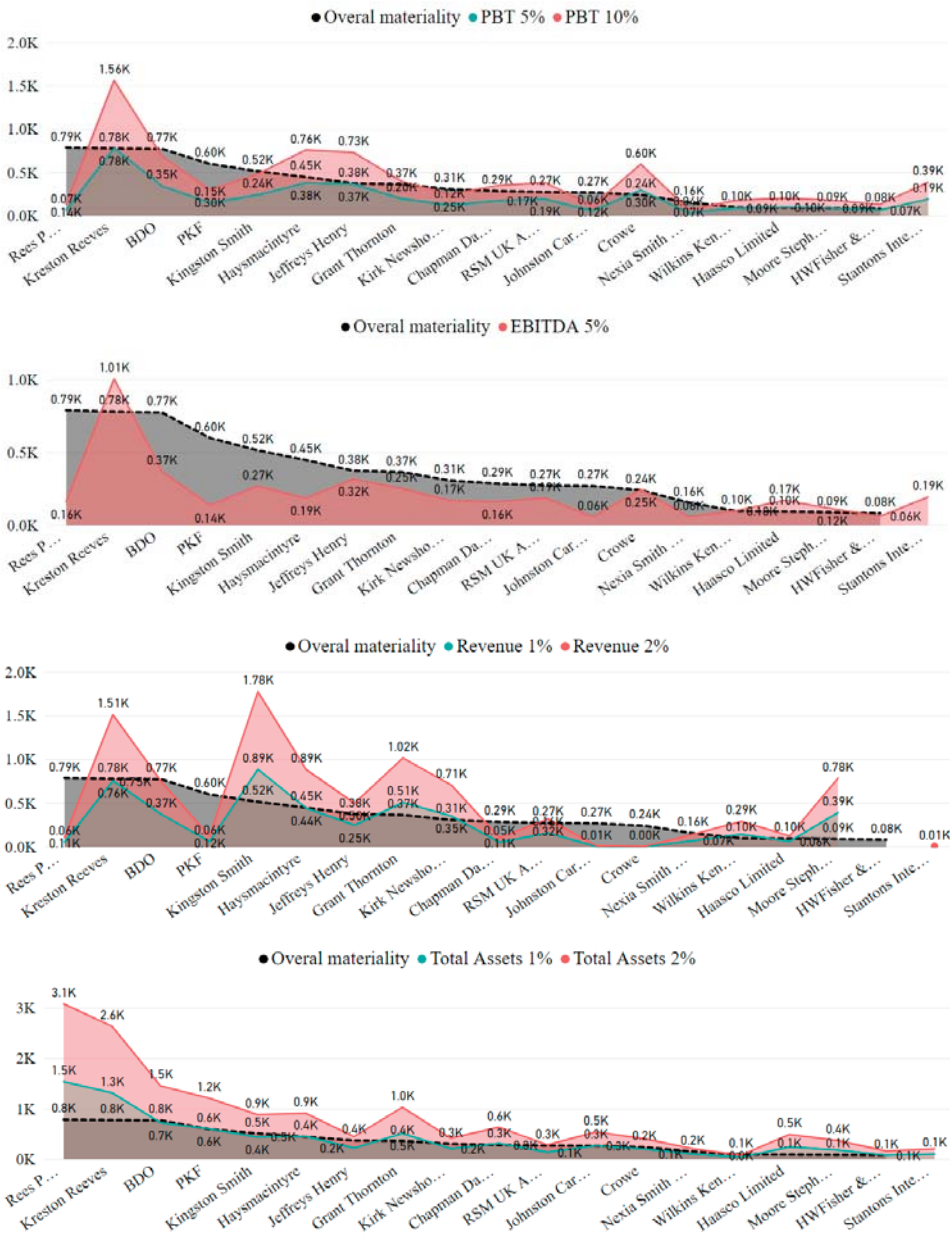

Figure 13. Overall materiality used by non-Big 4 auditors in relation to the percentage mentioned in ISA 320 and literature. Source: own elaboration based on analyzed data.

For non-Big 4 auditors it may be observed that the levels of the overall materiality, which they apply, are in general at higher stakes and in many cases, they exceed the upper thresholds as per examples presented in ISA 320.

On Figures 14 and 15 there are presented other operating income (OOI), other operating expenses (OOE), financial income (FI), and financial expenses (FE) which in some cases on average were below the OM and therefore were not audited, while they seem meaningful and vivid to the business.

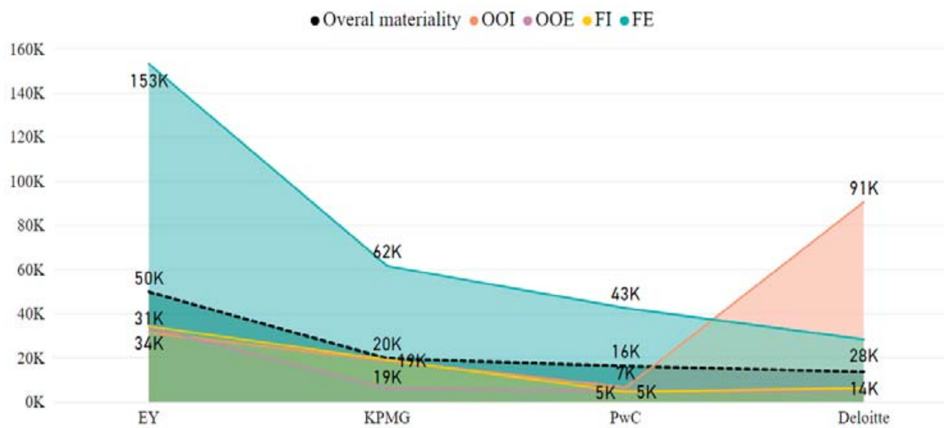

Figure 14. Average values of operating income (OOI), other operating expenses (OOE), financial income (FI), and financial expenses (FE) in relation to the OM—for Big 4 auditing firms. Source: own elaboration based on analyzed data.

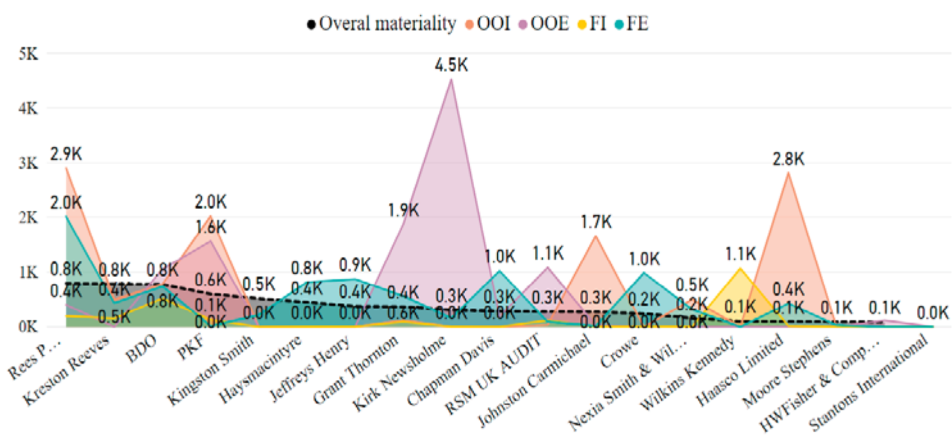

Figure 15. Average values of OOI, OOE, FI, and FE in relation to the OM—for non-Big 4 auditing firms. Source: own elaboration based on analyzed data.

As presented in Figure 14, Big 4 representatives on average do not audit OOI (except for Deloitte), OOE, and FI. The same dependencies, but for non-Big 4 auditors, are demonstrated in Figure 15, however the situation in this view is more diversified and varies by auditor. Nonetheless, it seems that there is no common approach on the market and in many cases OOI, FI, and FE are not subject to the audit of the financial statement.

5. Summary and Conclusions

Investors expect that after auditors inspect financial statements of public companies, they are complete, accurate and reliable in every significant aspect. Furthermore, as mentioned in chapter 1, investors expect that based on the auditor's reporting they will be capable of evaluating whether to invest in the entity or not. The aim of introducing ISA 701 was to further build up this confidence by ensuring that auditors, apart from "crunching numbers", also identify and pay special attention to the matters, which were the most noteworthy in the audited period and required dedicated treatment.

The performed research is the continuation of the market-wide studies conducted in this field after the implementation of the standards related to reporting on Key Audit Matters. The analysis depicted in this paper explores and re-discovers the landscape of auditing services provided to public companies in relation to the examination of their financial statements.

The general conclusion, which may be drawn from this research, is that implementation of ISA 701 and materiality disclosure limited the audit expectation gap. The study illustrates that:

- among Big 4, profit before tax (PBT) was the most commonly used benchmark, followed by normalized PBT, while among non-Big 4 it was revenue and total assets respectively,
- there were identified the following Key Audit Matters which are related with all assertions: going concern, business combination accounting, fraud risk, first-year audit and discontinued operations,
- under the current approach, some financial statement items, such as other operating expenses, are not audited at all, it should be noted that this particular category is quite capacious and can easily hide undesirable "surprises",
- although many individual Key Audit Matters were identified by auditors, they were fairly little differentiated, key categories, applied to most of the companies, were the same as benchmarks used for calculation of overall materiality,
- valuation stands out as the assertion, which is of utmost significance to the auditors, what clearly drives the way in which audit procedures are designed and performed,
- the extent of caution applied by non-Big 4 auditors, expressed by the level of overall materiality and its relation to relevant guidelines, is, in general, lower than the one exercised by their Big 4 colleagues, this means that audits performed by lesser firms may be less diligent than the ones conducted by market leaders.

The above indicates that, in general, and on average, some audits are truly commodity-like and focus only on revenues, total assets, and valuation, while other areas are not thoroughly investigated. This is especially true with regard to audit engagements performed by smaller players.

On one hand, being a commodity service is in line with the substance and the nature of the audit, which is a standardized service. On the other hand, regulators and market makers do their best to strengthen the confidence of business transactions by improving the value, which auditors create and provide to investors. In order to achieve that goal, it is necessary to re-imagine the way in which audit services are designed and delivered.

Presented results also underline the necessity to continue the discussion on the involvement of advanced tools and techniques, e.g., data analytics and visualization, machine learning (ML), blockchain, robotic process automation (RPA), and artificial intelligence (AI), to facilitate the implementation of such concepts in audit services. This idea is to be further explored in the detailed studies, which are planned to be performed following this paper. Academicians, practitioners, and regulators shall have an important insight into the current subject matter from this work. Future researchers shall also get a good base of scholarly work from this study. The proposed direction of further research is to extend the scope of the audit by including public companies listed on another European stock exchange, followed by an analysis for the next 12-month reporting periods.

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