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Predicting Bankruptcy: Insights from Polish Non-Public Companies (2019–2022)

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Abstract:

Purpose: *This study aims to develop bankruptcy prediction models tailored for Polish non-public companies, using linear discriminant analysis applied to data from 208 companies that filed for bankruptcy between 2019 and 2022.*
Design/Methodology/Approach: *Fisher's linear discrimination is an empirical method of classification. It gives a set of multivariate observations on sets known with certainty to come from two or more populations. The problem is to establish certain rules that assign successive individuals to the correct population of origin with minimal probability of misclassification. We use a survey covered 208 Polish non-public companies that filed for bankruptcy with the court in years 2019 - 2022. These companies (in equal proportions) belong to trade, manufacturing, and service sectors. For each bankrupt, a going concern company with a similar amount of assets was selected. Therefore, the whole set amounted 416 enterprises was created as choice-based and matched sample.*
Findings: *The results demonstrate that models constructed on pandemic dataset are more accurate than pre-pandemic models, with sector-specific models outperforming general ones. Key predictors include the value of assets, financial audits, and management's going-concern assessments. The findings underscore the importance of incorporating both financial and non-financial indicators into bankruptcy prediction and highlight the effectiveness of tailoring models to economic and sectoral conditions.*
Practical implications: *The financial performance of companies has been heavily influenced by the post-COVID-19 economic landscape and geopolitical challenges, including the ongoing Ukrainian conflict. Many businesses have faced disruptions, labor shortages, and inflationary pressures, leading to increased bankruptcy filings, particularly among small and medium-sized enterprises.*
Originality/Value: *This empirical research contributes to advancing predictive tools for corporate financial distress, offering insights for businesses and policymakers to mitigate bankruptcy risks.*

Keywords: *Bankruptcy prediction, financial distress, Polish non-public companies.*
JEL codes: *G17, G33, G39.*
Paper type: *Research article.*

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1. Introduction

The financial performance of companies post-COVID-19 and amid the ongoing Ukrainian conflict has been significantly impacted. Many businesses faced supply chain disruptions, labor shortages, and increased operational costs due to inflation and geopolitical tensions. Sectors like travel, hospitality, and retail struggled to recover, while others, such as technology and e-commerce, experienced growth.

Bankruptcy filings have risen, particularly among small and medium-sized enterprises that lacked the financial cushion to weather these challenges. Additionally, consumer behaviour changes have forced companies to reassess their strategies and offerings. Companies have had to adapt quickly to changing market conditions, often requiring innovative solutions and strategic pivots to remain competitive.

Coping mechanisms for financial distress in companies can include implementing cost-cutting measures, such as reducing overhead expenses and renegotiating contracts with suppliers. Companies can also explore alternative financing options, such as loans, grants, or equity financing to improve cash flow.

Additionally, restructuring debt and engaging in proactive financial planning can help manage liabilities more effectively.The number of bankruptcies in the EU has been increasing since 2020. In Poland, although the reported number of bankruptcies in 2021 and 2022 decreased compared to 2020, the total number of bankruptcies, restructuring proceedings and out-of-court proceedings increases significantly.

Restructuring carried out in enterprises forced by significant changes in economic conditions carries high operational risk.

Therefore, it becomes important to protect these entities against the risk of bankruptcy. The two pillars of financial security of enterprises are financial liquidity and equity. First one refers to the ease at which an asset or security can be converted into ready cash without affecting its market price. Equity is aimed to protect creditors against loss of capital and companies from failure.

However, practice has shown that monitoring liquidity and the level of equity capital is insufficient for early identification of financial problems of entities. Predicting financial distress in companies involves analyzing various financial and non-financial indicators. By monitoring these indicators and using predictive models, companies and stakeholders can take proactive steps to mitigate the risk of financial distress.

The aim of the article is to construct bankruptcy prediction models for Polish non-public companies. The survey covered 208 Polish non-public companies that filed for bankruptcy with the court in years 2019-2022. We used linear discrimination as an empirical method of classification. Discriminant functions were estimated using raw and winsorized data.

The results suggest that models estimated during the pandemic outperform pre-pandemic models in accurately identifying bankruptcies. Sector-specific models are more effective than general ones due to varying operating conditions across sectors. The value of assets, is a critical determinant in classification. Including non-financial variables like independent financial audits and management's going concern assessments enhances classification accuracy. The study's novelty lies in using non-financial variables, tailoring models to economic and sectoral conditions, and comparing their effectiveness.

2. Literature Review

Research on predicting corporate bankruptcy has a history of almost a century. A milestone was the work of Altman (1968), who was the first to apply multivariate linear discriminant analysis, combining an indicator based assessment of companies with mathematical and statistical methods. Altman's model, also known as the Z-score, was constructed under the specific conditions of the US market (Altman, 2000).

The diverse conditions accompanying the operation of companies in different regions are the reason why the problem of bankruptcy forecasting cannot be generalised and requires an individual research approach based on the use of empirical data relating to a specific economy or group of economies with similar operating conditions (Jaki and Ćwięk, 2021; Rupeika-Apoga *et al.,* 2018; Thalassinos *et al.,* 2013; 2015).

Authors such as Lichota (2018), Matsumaru *et al.* (2019), Jaki and Ćwięk (2020), and Siciński (2021), and Ahmed *et al.* (2021) emphasise the need to take into account the impact of industry specificity in forecasting corporate bankruptcy, as for example, a different average value of financial statement items will be characterised by manufacturing companies and a different one by service companies.

Nevertheless, authors such as Kopczynski (2022), Valaskova *et al.* (2023), Kušter (2023), Hamdi *et al.* (2024) conducted work on industry-mixed data, which may be dictated by the desire to match the developed solutions to the needs of business practice, where the use of a single universal model allows simplification and standardisation of analytical processes.

The definition of bankruptcy[4] adopted in the study is also important for the

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[4]*The term bankruptcy does not have a uniform definition. According to Bernstein at al. (2023), the prerequisites for bankruptcy include significant liquidity problems, leading to an inability to pay obligations on time. Pasternak-Malicka at al. (2021), on the other hand,*

predictive effectiveness of the models. In the work of Valaskova *et al.* (2018), companies whose solvency ratio value was less than 0.4, current ratio was less than 1, and net income took a negative value. It should be added that the above-mentioned criteria had to occur simultaneously.

In the work of Kliestik *et al.* (2018), bankruptcy was defined as the cessation of a company's operational activities. Authors such as Radovanović and Haas (2023), Kušter (2023) considered business entities that formally filed for bankruptcy. In contrast, the work of Kopczynski (2022) considered entities that filed for bankruptcy as bankrupts.

The definition of bankruptcy adopted in the study determines which entities will be classified as bankrupt firms. Different interpretations of the term may result in the use of different datasets, directly affecting the on the representativeness of the survey sample and the possibility to generalise the results obtained.

Currently popular methods for bankruptcy forecasting include linear discriminant analysis, logistic regression, classification trees, artificial neural networks, random forest and support vector machines (SVMs) (Shi and Li, 2019; Radovanović and Haas, 2023).

With the development of new methodologies, some authors seem to neglect discriminant analysis. Hamdi *et al.* (2024) used different methods to predict bankruptcy. Although, the researchers used linear discriminant analysis, they did not present model estimates, limiting themselves to present only the set of variables used. In addition, the paper lacks information on whether the presented results of the models' classification effectiveness refer to the learning or the test set, which makes it difficult to fully assess the reliability and generalisation of the results obtained.

Analogous deficiencies are noticeable in the work of Matsumaru *et al.* (2019). This dismissive attitude may be due to the belief that using a newer methodology allows for higher predictive performance than using linear discriminant models. According to Nehrebecka and Derlatka (2016), future improvements in predictive models should focus on improving data quality and not necessarily on changing methodologies.

Criticising discriminant analysis as an ‘outdated’ method therefore seems unjustified if its results are still competitive under the appropriate research and practical conditions. Ultimately, the choice of classification method should depend on the purpose of the study, the available data and the analytical context, and not solely on the pressure to use the latest technology.

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defines bankruptcy as a state in which a company is in a situation where it is unable to continue operations without external financial support.

According to Kopczyński (2022), discriminant analysis still retains its relevance and use in predicting corporate insolvency, despite the development of newer methods.

3. Research Methodology

Fisher's linear discrimination is an empirical method of classification. It gives a set of multivariate observations on sets known with certainty to come from two or more populations. The problem is to establish certain rules that assign successive individuals to the correct population of origin with minimal probability of misclassification.

More precisely, in the case of two classes, let $\boldsymbol{\bar{X}_1}$ and $\boldsymbol{\bar{X}_2}$ be vectors of mean values of discriminant variables representing objects belonging to the two classes, respectively. The direction of the hyperplane depends on the distribution of the data vectors for each class and, in the basic form of the procedure, passes through the midpoint of the averages of the two classes. Linear discrimination function can be written as follows (Aczel, 1989; Warner, 2007):

$$D(x) = a_0 + a_1 \cdot x_1 + a_2 \cdot x_2 + \cdots + a_k \cdot x_k \tag{1}$$

where: for *i*=0, 1, 2,…, *k*, a_i - discriminant coefficients, x_i - diagnostic discriminant variables describing attributes of objects.

Discriminant analysis involves the estimation of one-dimensional linear functions of observations (discriminant functions), on the basis of which a group of objects is distinguished. In practice, the classification function is often determined for each group of objects. Parameters of the function (1) are evaluated using so-called training dataset. Classification accuracy, on the other hand, is assessed applying testing set of data.

Knowing the pattern of object recognition, classification errors can be evaluated by comparing elements that should belong to the groups Rp with elements of classes Cp, where Cp stands for classes constructed from the results of classification experiments. The general classification error is then defined as follows (Witkowska, 2023):

$$E = \frac{BN}{N} \cdot 100\% \tag{2}$$

In many analyses, misclassification of objects belonging to different classes has different costs. For example, classifying a bankrupt into a group of well-functioning companies can result in more dire consequences than misidentifying a well-functioning company and considering it a potential bankrupt. Therefore, it is necessary to analyze how classification error is distributed among distinguished classes. Assuming that higher costs appear by misclassification to the first class, it is possible to distinguish the classification error of the first type as following:

$$E_1 = \frac{BN_1}{N_1} \cdot 100\% \tag{3}$$

and the classification error of the second type is expressed by the formula:

$$E_2 = \frac{BN_2}{N_2} \cdot 100\% \tag{4}$$

where:
N_1, N_2 - the count of objects belonging to the first and the second classes respectively ($N_1 + N_2 = N$),
BN_1, BN_2 - the count of objects misclassified to the first and the second classes respectively ($BN_1 + BN_2 = BN$),
N - the count of all objects,
BN - the count of all misclassified objects.

In further considerations, we use error complements up to 100% indicating the proportion of correctly classified objects to assess the correctness of the classification (as it is presented in Aczel, 1989) which for the general classification W is as follows:

$$W = 100 - E \tag{5}$$

where:
E - general classification error.

4. Research Results and Discussion

The survey covered 208 Polish non-public companies that filed for bankruptcy with the court in years 2019 - 2022. These companies (in equal proportions) belong to the trade, manufacturing, and service sectors. For each bankrupt, a going concern company with a similar amount of assets was selected. Therefore, the whole set amounted 416 enterprises was created as choice-based and matched sample.

The source of the data used in the study was the Emerging Markets Information Service EMIS, which includes information from financial reports, minutes of shareholders' meetings, management reports and resolutions, audit reports and additional information. The financial data collected covers one year and two years prior to the bankruptcy filing.

The training set contains 80% of enterprises whereas the test set - 20%. In order to maintain the representativeness of industry participation in the survey for the entire population, the sampling was carried out separately in each industry: trade, manufacturing and services, which allowed for symmetry between the number of available observations and industry participation. In the research, enterprises for the test set were selected at random, using a random number generator in Excel.

The results of the sampling from each industry were then aggregated, creating a balanced test set that reflects the industry structure of the available database, which should translate into greater reliability and effectiveness of the models. The process of evaluating the models is based on analysis of the data from the training set, and verification focused on identifying classification errors, which are calculated for both the learning and test sets.

Table 1. *Models estimated for for all companies in years 2019-2022*

	Percentage of correctly recognized companies		
	Bankrupt	Non-bankrupt	General
Models estimated for companies which filed for bankruptcy in 2019-2022 – 84 observations in the test set			
D1*= 0.067·Z03 + 0.289·W02 + 0.788·W03 + 0.001·R10 + 0.081·S20 – 2.012·N03 – 1.929	82.50	80.00	81.25
D2*= -0.144·R02 - 0.887·W03 + 0.091·R09 + 2.133·N03 + 2.220	75.00	85.00	80.00
D3 = -0.104·R02 - 0.699·W03 + 0.068·R09 + 2.278·N03 + 1.615	70.00	85.00	77.50
D4#= 0.019·Z03 + 0.286·W02 + 0.612·W03 + 0.001·R10 + 0.061·S20 – 2.187·N03 – 1.291	75.00	77.50	76.25
D5*= 1.210·W03 + 0.002·R10 -3.842	70.00	82.50	76.25
D6*#= 0.125·Z03 + 0.277·W02 + 1.099·W03 + 0.003·R10 + 0.117·S20 + 0.070·B01 + 0.321·B02 - 3.772	70.00	80.00	75.00
D7##= -0.001·Z02 + 0.077·Z03 + 0.000·R01 + 0.130·R02 + 0.000·R05 – 0.065·S03 + 0.000·S07 – 0.050·W01 + 0.357·W02 + 0.000·D01 + 0.035·Z04 + 0.783·W03 – 0.001·D02 + 0.000·S09 – 0.182·B01 – 0.003·B02 – 2.085	75.00	72.50	73.75
Model estimated for companies which filed for bankruptcy in 2019-2020 – 32 observations in the test set			
D8 = 2.341·N03 – 0.170·Z03 – 0.805	56.30	86.70	71.50
Model estimated for companies which filed for bankruptcy in 2021-2022 – 52 observations in the test set			
D9 = 1.560·N03 + 0.000·S11 – 0.087·R02 + 0.247·P04 + 0.198·Z05 + 0.024·R07 – 1.170·W03 + 3.001	76.90	88.50	82.70
D10 = 2.047·N03 + 0.000·S11 – 0.183·R02 + 2.106·P04 + 2.106·Z05 + 0.053·R07 – 2.181	76.90	96.20	86.55

Note: **denotes that the discriminant function was estimated using winsorized data applying and the two-sided Tukey criterion, #denotes that selection of discriminant variables was made using backward step method, ##denotes that selection of discriminant variables was made using Hellwig method to select so-called isolated variables[5].*
Source: *Own calculation.*

[5]*For the method description see Witkowska (2002).*

The concept of errors estimated on the training set, can be analogously contrasted with the evaluation of an econometric model, which is based on the analysis of empirical residuals for the set estimated (Gruszczyński, 2012; Witkowska, 2023). This method of sampling, unfortunately, is still subject to sampling error so-called choice-based sample bias. This means a situation in which objects (enterprises) are selected for the set on the basis of prior information on the dependent variable, for example, initially data is collected on a group of bankrupts.

To bankruptcy prediction, discriminant variables must describe the situations of the analysed enterprises thus in our research we collect data concerning 56 financial indicators and some nonfinancial characteristics of assessed companies that create the preliminary set of variables. For the models' construction, discriminant variables were selected from this set, using large-sample test for the difference between two populations means for variable selection[6]. Since many variables were characterized by outlier observations, both raw data and data after winsorization[7] applying the three-sigma rule and the two-sided Tukey criterion were used to determine the parameters of the discriminant function.

Tables 1-2 contains information[8] about the best performing models which were estimated for:

- the whole data from the training set, i.e., for companies from all sectors and the whole time span,
- two separated training sets containing data for companies from all sectors but filed for bankruptcy in years 2017-2019 which is considered as a pre-pandemic period, and the ones which might be contaminated by the pandemic, and they filed for bankruptcy in years 2020-2022,
- three separate training data covering the whole time span but containing companies from three distinguished economic sectors.

It is worth noting that for all the models presented in Tables 1 and 2, their specification was carried out separately for each training data set. In presented models, discriminant variables denote:

B01 and B02 - Industry of operation,
D01 - Revenue dynamics,
D02 - Dynamics of equity capital,
N02 - Financial statements audited by an independent auditor,
N03 - Management's assessment of going concern,
P04 - Working capital share in assets,

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[6]*In fact, several methods of variable selection were used. Description of the test for the difference between two populations means can be found in (Aczel, 1989).*
[7]*See (Warner 2007; Pociecha et al. 2014; Witkowska 2023).*
[8]*For some variables, the discrimination coefficients are less than 0.001, which is recorded in the model that the value of the function parameter equals 0.000.*

R01 – EBITDA,
R02 - Operating profitability of total assets,
R05 - Return on equity,
R07 - Operating profit to total assets ratio,
R09 - Average gross profit to total assets,
R10 - Return on average current assets,
R13 - Average return on operating assets,
S03 - Inventory to operating costs ratio,
S07 - Conversion ratio of receivables,
S09 - Ratio of operating costs to net sales revenue,
S11 - Short-term liabilities turnover ratio in days,
S19 - Adjusted short-term liabilities to operating costs ratio,
S20 - Adjusted turnover ratio of total assets,
W01 - Asset structure,
W02 - Logarithm of asset structure,
W03 - Logarithm of assets,
Z02 - Equity to debt ratio,
Z03 - Long-term debt to equity ratio,
Z04 - Equity share in total balance sheet,
Z05 - Short-term liabilities share in total balance sheet,
Z06 - Fixed assets share in total balance sheet.

The best predictive models are understood to be those that correctly identify at least 70% of the companies in both groups. At the same time, in the case of some training sets it was not possible to find such good models (e.g. the models D15, D18-D20). On the other hand, using the entire training set, there were many more such models (21 out of 52 constructed using different methods of variable selection).

Of all the models estimated from the data without considering the division of companies by industry (Table 1), the best predictions were generated by models D9 and D10, which applied to companies during the pandemic period. Both models correctly identified 76.9% of bankrupts and 88.5% and 96.2% of non-bankrupts, respectively.

The best of the models estimated considering the entire period under study - i.e., model D1*correctly recognized 82.5% of bankrupts and 80% of non-bankrupts. It should be noted that models D6*# and D6## include binary variables that identify the industry in which the company operates.

Evaluating the models estimated separately for each industry (Table 2), companies in the trade industry are most correctly recognized, while those in industry and services are somewhat less correctly recognized. Some models (e.g. D18-D20) recognize bankrupts much better, and others (e.g.. models D11-16) recognize non-bankrupts better. Nevertheless, the most effective of the sectoral models give better classification results than models estimated from the whole set.

Table 2. *Models estimated separately for each sector (trade, manufacturing, services) in years 2019-2022*

	Percentage of correctly recognized companies		
	Bankrupt	Non-bankrupt	General
Models estimated for trade companies – 30 observations in the test set			
D11 = 0.972·W03 + 0.002·R13 - 3.072	78.60	92.90	85.75
D12**= 1.021·W03 + 0.002·R13 - 3.224	78.60	92.90	85.75
D13 = -0.915·W03 + 0.002·R13 + 0.277·N02 - 2.938	78.60	92.90	85.75
D14*= 1.484·W03 + 0.001·R13 - 0.225·N02 - 4.598	71.40	100.00	85.70
Model estimated for manufacturing companies – 26 observations in the test set			
D15 = -1.670·S03 + 0.001·S19 - 0.503·W03 + 2.187·N03 + 0.982	69.20	92.30	80.75
D16*= -1.745·S03 - 0.502·W03 + 2.356·N03 + 1.110	76.90	92.30	84.60
Model estimated for service companies– 28 observations in the test set			
D17 = 1.057·Z06 + 0.706·W03 + 0.006·R09 - 1.899·N03 - 2.032	76.90	76.90	76.90
D18 = 0.638·Z06 + 0.963·W03 + 0.079·R09 - 0.596·N02 - 3.093	84.60	61.50	73.05
D19*= 2.587·Z06 + 0.825·W03 + 0.029·R09 - 1.398·N03 - 2.724	100.00	69.20	84.60
D20*= 2.902·Z06 + 1.001·W03 + 0.064·R09 - 0.891·N02 - 3.555	84.60	61.50	73.05

Note: **denotes that the discriminant function was estimated using winsorized data applying the two-sided Tukey criterion, ** denotes that the discriminant function was estimated using winsorized data applying the three-sigma rule.*
Source: *Own calculation.*

The novelty of our approach is employing nonfinancial characteristics of companies (represented by binary variables B01, B02, N02 and N03) in discriminant models. Among all discriminant variables, W03 is the one which appears nearly in all presented models (in 19 among 20), the second the most frequently appearing variable is N03 (12 times) and the third ones are R02 and R09 (6 times).

5. Conclusions, Proposals, Recommendations

The research presented in the article deals with bankruptcy forecasting of Polish companies, defining companies that have filed for bankruptcy as bankrupts. The adoption of such a definition was dictated, on the one hand, by the long period of processing the said applications by the courts, and, on the other hand, bankruptcy forecasting models are to generate warning forecasts for companies, so they must be estimated on current data. The aforementioned assumptions represent certain research limitations.

The results discussed were obtained using a linear discrimination model, without making comparisons with alternative bankruptcy forecasting methods, which is due to the volume of the article, but at the same time ignores the issues of using "more modern" methods.

In this article, we have shown that the issues of appropriate set design (training and testing) and the selection of diagnostic variables are crucial in the construction of models with the assumed efficiency of classifying companies into bankrupt and non-bankrupt groups.

The results of our research allow us to draw several conclusions. Economic turmoil reinforces the differences between going concern companies and those that have filed for bankruptcy with the court. Therefore, models estimated for the pandemic period (i.e., the models D9 and D10) are more effective than those estimated for the pre-pandemic period (i.e., D8), especially when identifying bankrupts correctly.

Models estimated on an aggregate set that does not take into account their economic sector variation (i.e., the models D1-D7) appear to be less effective in classification than those constructed for individual sectors (i.e. the models D11-D14, D16, D19), because the operating conditions of companies in different sectors vary.

The value of assets is one of the key determinants for classifying companies, as indicated by the presence of a variable W03 describing them in almost all estimated models. The inclusion of non-financial variables, such as N02 - Financial statements audited by an independent auditor and N03 - Management's assessment of going concern, positively affects the efficiency of recognizing both groups of companies.

The novelty of our research is the use of non-financial variables in discriminant models and the construction of models for differently defined sets that take into account changes in economic conditions and sectoral variation, and the comparison of their effectiveness in recognizing the situation of companies.

References:

Aczel, A. 1989. Complete Business Statistics. Boston: Irwin, Homewood.

Ahmed, S., Majeed, M.E., Thalassinos, E., Thalassinos, Y. 2021. The impact of bank specific and macro-economic factors on non-performing loans in the banking sector: Evidence from an emerging economy. Journal of Risk and Financial Management, 14(5), 217.

Altman, E. 1968. Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy. The Journal of Finance, 23(4), 589-609.

Altman, E. 2000. Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA Models. New York.

Bernstein, S., Colonnelli, E., Homan, M., Iverson, B. 2023. Life After Death: A Field Experiment with Small Businesses on Information Frictions, Stigma, and Bankruptcy. The International Journal of Finance, 12(2), 34-48.

Hamdi, M., Mestiri, S., Arbi, A. 2024. Artificial Intelligence Techniques for Bankruptcy Prediction of Tunisian Companies: An Application of Machine Learning and Deep Learning-Based Models. Journal of Risk and Financial Management, 17(132), 1-14.

Jaki, A., Ćwięk, W. 2020. Bankruptcy Prediction Models Based on Value Measures. Journal of Risk and Financial Management, 14(6), 1-14.

Kliestik, T., Vrbka, J., Rowland, Z. 2018. Bankruptcy Prediction in Visegrad Group Countries Using Multiple Discriminant Analysis. Equilibrium Quarterly Journal of Economics and Economic Policy, 1(3), 569-588.

Kopczyński, P. 2022. Prognozowanie upadłości przedsiębiorstw. Łódź: Wydawnictwo Uniwersytetu Łódzkiego.

Kušter, D. 2023. Construction of Bankruptcy Prediction Model Using Discriminant Analysis and Financial Ratios. Ekonomija: teorija i praksa, 1, 1-22.

Lichota, W. 2018. Weryfikacja skuteczności predykcyjnej wybranych modeli analizy dyskryminacyjnej na przykładzie przedsiębiorstw funkcjonujących w specjalnych strefach ekonomicznych w Polsce. Acta Scientifica Academiae Ostroviensis, Sectio A, Nauki Humanistyczne, Społeczne i Techniczne, 12(2), 402-414.

Matsumaru, M., Kawanaka, T., Kaneko, S., Katagiri, H. 2019. Bankruptcy Prediction for Japanese Corporations using Support Vector Machine, Artificial Neural Network, and Multivariate Discriminant Analysis. International Journal of Industrial Engineering and Operations Management, 1(1), 78-96.

Nehrebecka, N., Derlatka, K. 2016. Determinanty wskaźnika predykcji bankructwa: przegląd modeli i metaanaliza. Ekonomista, 4, 433-468.

Pasternak-Malicka, M., Ostrowska-Dankiewicz, A., Dankiewicz, R. 2021. Bankruptcy – an Assessment of the Phenomenon in the Small and Medium-Sized Enterprise Sector - Case of Poland. Polish Journal of Management Studies, 24(1), 250-267.

Pociecha, J., Pawełek, B., Baryła, M., Augustyn, S. 2014. Statystyczne metody prognozowania bankructwa w zmieniającej się koniunkturze gospodarczej. Kraków: Fundacja Uniwersytetu Ekonomicznego w Krakowie.

Radovanović, J., Haas, C. 2023. The Evaluation of Bankruptcy Prediction Models Based on Socio-Economic Costs. Expert Systems with Applications, 227, 1-18.

Rupeika-Apoga, R., Zaidi, S.H., Thalassinos, Y.E., Thalassinos, E.I. 2018. Bank stability: the case of Nordic and non-Nordic banks in Latvia. International Journal of Economics and Business Administration, 6(2), 39-55.

Shi, Y., Li, X. 2019. An Overview Of Bankruptcy Prediction Models for Corporate Firms: A Systematic Literature Review. Intangible Capital, 15(2), 114-127.

Siciński, J. 2021. Systemy wczesnego ostrzegania przedsiębiorstw przed ryzykiem upadłości na przykładzie branży transportowej. Sopot: Centrum Myśli Strategicznych.

Thalassinos, E.I., Venediktova, B., Staneva-Petkova, D., Zampeta, V. 2013. Way of banking development abroad : branches or subsidiaries. International Journal of Economics & Business Administration, 1(3), 69-78.

Thalassinos, E., Venediktova, B., Zampeta, V. 2015. Applications of GARCH Model for the Selection of Securities of Banks Investment Portfolio. Applied Economics and Finance, 2(2), 1-13.

Valaskova, K., Gajdosikova, D., Belas, J. 2023. Bankruptcy Prediction in the Post-Pandemic Period: A Case Study of Visegrad Group Countries. Oeconomia Copernicana, 14(1), 253-293.

Valaskova, K., Kliestik, T., Svabova, L., Adamko, P. 2018. Financial Risk Measurement and Prediction Modelling for Sustainable Development of Business Entities Using Regression Analysis. Sustainability, 10(7), 1-15.

Warner, R. 2007. Applied Statistics: from Bivariate through Multivariate Technique. Los Angeles: Sage Publications, Inc.
Witkowska, D. 2002. Sztuczne sieci neuronowe i metody statystyczne. Wybrane zagadnienia finansowe. Warszawa: C.H. Beck.
Witkowska, D. 2023. Wybrane metody ilościowe w finansach. Łódź: Wydawnictwo Uniwersytetu Łódzkiego.