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Application of Taxonomic Measures to Bankruptcy Prediction*

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Abstract:

Purpose: *The paper aims to propose new method of bankruptcy prediction. In our research we construct composite measures of financial efficiency using taxonomic distance to the distinguished pattern.*
Design/Methodology/Approach: *In our study we use the sample of 136 Polish manufacturing non-public companies. Half of them are bankrupts (i.e. filed for bankruptcy with the court in years 2019 – 2022), whereas the rest of them run their business and are companies with a similar amount of assets as bankrupts. Data used in research has been acquired from the Emerging Markets Information Service EMIS, which contains financial reports information one year prior to the bankruptcy filing. According to the value of these measures calculated for all analyzed companies they are classified to two classes.*
Findings: *The study shows that taxonomic measures are useful for predicting corporate bankruptcy. Identifying a grey zone improves classification accuracy within specific clusters, even though it slightly lowers overall model performance. The results also highlight company size—measured by asset value and structure—as a key factor distinguishing bankrupt firms from those that remain solvent.*
Practical Implications: *The results of our experiments show that level of recognition of both groups of companies is quite high but it depends on the selected pattern.*
Originality/Value: *The study highlights that the taxonomic measures applied are simpler than many other bankruptcy prediction methods, making them more accessible. Their straightforward nature enables use by managers of smaller firms that do not have dedicated financial staff. As a result, these measures offer a practical tool for monitoring bankruptcy risk in resource-constrained organizations.*

Keywords: *Bankruptcy prediction, financial distress, Polish non-public companies, taxonomic measures.*

JEL Classification: *G17, G33, G39.*

Paper type: *Research paper.*

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1. Introduction and Literature Review

The prediction of corporate bankruptcy remains a vital subject in financial economics, risk management, and corporate governance. The failure of firms not only incurs direct losses for shareholders, creditors and employees, but also imposes broader systemic costs—undermining investor confidence, credit markets and, in some cases, macro-economic stability. Because of this, substantial academic and practical efforts have been devoted to developing models and tools that can identify distressed firms in advance and help stakeholders mitigate risk.

Historically, bankruptcy prediction research has progressed through several distinct phases. Early work focused on accounting-ratio analyses and simple matched-sample designs. In 1968, Edward I. Altman (1968) developed the Z-score model using multivariate discriminant analysis—marking one of the first formal quantitative bankruptcy prediction models.

Over time, logistic regression, neural networks, support-vector machines and other machine-learning techniques have enriched the toolkit of corporate failure forecasting. A recent systematic review by Shi and Li (2019) found that the number of studies in the field has increased markedly, especially after the 2008 global financial crisis, and that logistic regression and neural networks remain the most commonly applied methods.

Polish researchers studying corporate bankruptcy prediction have mainly applied an approach based on pairing bankrupt and non-bankrupt companies. Early studies, such as those by Gajdka and Stos (1996) and Hołda (2001), covered relatively small samples of firms from various industries, usually consisting of several dozen observations.

In later years, these studies were expanded by authors such as Hamrol *et al.* (2004), Mączyńska and Zawadzki (2006), and Pociecha (2007), who analyzed larger datasets and included longer time horizons. The classification accuracy of these models ranged from about 75% to over 96%, confirming their high predictive power, although independent test samples were often lacking.

In more recent research, there has been a noticeable trend toward sectoral specialization and the inclusion of non-financial and macroeconomic variables. Authors such as Pociecha *et al.* (2014) focused on the manufacturing sector, Jaki and Ćwięk (2020) examined the construction industry, while Moskal *et al.* (2023) analysed the transport and energy sectors.

At the same time, researchers including Ptak-Chmielewska and Matuszyk (2018) began incorporating non-financial factors such as company size, location, legal form, and number of employees, as well as macroeconomic variables like GDP, inflation, and unemployment.

Despite significant progress, several gaps and challenges remain in the literature, which motivate the present research. First, many conventional bankruptcy-prediction models rely on parametric assumptions (e.g., linearity, distributional forms, independence) which may not hold in heterogeneous real-world firms or across different countries and industries.

Second, the interrelationships among multiple financial indicators, such as liquidity, profitability, market variables, governance, macro-factors, are often simplified or treated in isolation, whereas corporate distress is inherently a multivariate phenomenon that might benefit from holistic classification approaches.

Third, many models focus on binary classification (bankrupt vs non-bankrupt) under balanced data assumptions, whereas in practice the number of failing firms is much smaller (leading to severe class-imbalance issues) and the time horizon, industry context and macroeconomic environment vary (Gnip *et al.,* 2025).

In light of these considerations, taxonomic measures appear as a promising alternative or complement to classical approaches. Taxonomic techniques allow the simultaneous evaluation of many attributes without strong parametric constraints and can produce ranking or clustering of firms in terms of distress risk rather than simply binary labels.

As Welc and Sobczak (2017) showed, a non-parametric multivariate taxonomic ranking method outperformed logistic regression in discriminating between bankrupt and healthy firms. The adoption of such taxonomic methods remains relatively limited compared with mainstream statistical or machine-learning models, which presents a methodological gap.

The paper aims to propose different attitude towards bankruptcy prediction. Our hypothesis states that it is possible to construct the measure of firm effectiveness and/or bankruptcy indicator applying the concept of taxonomic distance.

2. Research Methodology

Bankruptcy prediction using pattern recognition models (such as discriminant or logistic regression models) involves:

- estimating model parameters based on a training sample that contains information on whether the analyzed firm is bankrupt,
- verification of the model's correctness and classification effectiveness what is carried out on the basis of a test sample.

Therefore, data sets containing information on a significant number of companies are required. This sometimes results in data from a relatively long period with varying operating conditions. Also significant are problems related to failure to meet the formal assumptions of the model estimation methods used. Another, equally important, issue is the observation that the literature uses various definitions of bankruptcy, while in practice, forecasts are intended to indicate potential threats to companies.

This results in varying expectations regarding the effectiveness of prediction models. It should also be noted that some formal corporate bankruptcies are not the result of existing difficulties, but are instead an attempt to avoid debt repayment—so-called "false bankruptcy".

In order to avoid at least some of the difficulties presented, an attempt is made to apply taxonomic measures to assess enterprises (Witkowska and Kompa, 2022; 2025) and indicate which of the analyzed companies can be recognized as bankrupt. Such a measure, being a firm efficiency and/or the bankruptcy indicator is constructed without prior knowledge of whether the company is bankrupt or continues to operate. No assumptions are needed regarding the consistency of the distribution of diagnostic variables with theoretical distributions.

A relatively small sample (in comparison to model estimation) can be used to build them, e.g., data containing information on bankruptcies observed in the recent period, which ensures that current economic conditions are taken into account and provides information about companies operating in a homogeneous environment. It is also easy to distinguish companies whose bankruptcy is unjustified in the light of their general operating conditions. The construction of popular taxonomic measures is simple and the only way to assess its effectiveness is through classification errors.

A modern approach to assessing the economic and financial condition of enterprises is applying the multidimensional comparative analysis methods. These methods allow to construct aggregated measures on the basis of many different variables, describing the condition of the company. In other words, to examine the state of the enterprise, its major economic and financial factors such as financial liquidity, level of debt, management efficiency, profitability, etc. are taken into account.

Our hypothesis states that it is possible to construct the measure of firm effectiveness and/or bankruptcy indicator applying the concept of taxonomic distance. To verify this hypothesis the popular measure, based on Euclidian distance of the considered objects from the benchmark in multidimensional space, is used:

$$d_i = \sqrt{\sum_{k=1}^{K}(z_{ik} - z_{0k})^2} \tag{1}$$

where, d_i - Euclidean distance of the k-th (k=1, 2,…, K) normalized diagnostic variable observed in the i-th (i=1, 2,…, N) company z_{ik} from the k-th normalized diagnostic variable in the benchmark z_{0k}.

One of the most popular normalization methods is standardization of variables:

$$z_{ik} = \frac{y_{ik} - \bar{y}_k}{S_k} \tag{2}$$

where, y_{ik} - observations of the k-th raw diagnostic feature in the i-th company, $\bar{y}_k$, S_k - average and standard deviation of the k-th raw feature evaluated for all firms, respectively.

In other words, $\bar{y}_k$ represent so called branch average for each considered financial indicator. Standardized variables are characterized by zero mean and standard deviation equals one.

Therefore, the object with all standardized diagnostic variables z0k=0 represents the hypothetical "average" company for which the existing operating conditions seem to be optimal. Therefore, it is assumed that such "average" company is a benchmark in the formula (1).

To normalize distance measure (1), the scaling factor d_0:

$$d_0 = \max_{i=1,2,\ldots,N} \{d_i\} \tag{3}$$

is used. The bankruptcy indicator is then as following:

$$BI_i = 1 - \frac{d_i}{d_0} \tag{4}$$

Values of the bankruptcy indicator (4) belong to the interval [0;1] and may be used to rank analyzed objects although BI has no economic interpretation. Here a question arises how divide the set of objects - companies into two classes i.e., bankrupts and healthy enterprises. In our research we use quartiles to classify companies to each of the class.

We assume that in the first quartile are bankrupts whereas in the third one healthy ones. In other words, it is assumed that companies whose diagnostic variables are closer to sector (industry, branch) averages have a greater chance of continuing their operations than those whose characteristics differ significantly from these averages.

However, as values of BI approach the median from both quartiles, considered firms enter the so-called gray zone, which is characterized by the fact that it is increasingly difficult to recognize the class to which the analyzed objects belong.

Therefore, several intervals are taken into account. In other words, basing on quartiles and quartile deviation the following limits for both classes of enterprises are established:

for healthy companies:

$$Q_3 - \alpha \cdot Q \tag{5}$$

for bankrupts: $Q_1 + \alpha \cdot Q$ (6)

where: Q1, Q3 – the first and the third quartile, respectively, $\alpha \in [0; 1]$ – scaling factor, Q - quartile deviation:

$$Q = \frac{Q_3 - Q_1}{2} \tag{7}$$

It is obvious that for $\alpha = 0$, the upper and lower quartiles, and for $\alpha = 1$ median are determined as limits for both clusters of objects. It is noticeably that for median all companies are classified whereas for other two quartiles half of enterprises belong to the grey zone and are not recognized. Referring to the interpretation of Altman's Zeta Score model, in the above considerations, three clusters are defined into which the surveyed companies can be classified:

- the highest cluster (i.e., with the highest BI values) is equivalent of safe zone with low probability of bankruptcy,
- the lowest cluster is equivalent of distress zone with high likelihood of financial failure,
- grey zone characterized by problems of classification thus further analysis of these companies is required.

Efficiency (performance) of classification to the highest and lowest clusters is evaluated according to the following formulas:

$$EE = \frac{NR}{NG} \tag{8}$$

$$EEB = \frac{NRB}{NGB} \tag{9}$$

$$EEH = \frac{NRH}{NGH} \tag{10}$$

where, *NRB* and *NRH* - number of correctly identified bankrupts and healthy companies in the lowest and highest clusters, respectively, *NGB* and *NGH* - number of all objects in both clusters, *NR=NRB+NRH* - number of all correctly identified companies in the lowest and highest clusters, *NG=NGB+NGH* - number of all objects in both clusters which might differ from the number of all analyzed objects in the sample because of the grey zone (GZ) presence.

It is worth mentioning that classification efficiency (performance) measures (9)-(10) are not the same as the commonly used ones, which are of the form:

$$E = \frac{NR}{N} \tag{11}$$

$$EB = \frac{NRB}{NB} \tag{12}$$

$$EH = \frac{NRH}{NH} \tag{13}$$

where, NB and NH - number of bankrupts and healthy companies in the considered sample of objects, respectively. In other words, NB and NH are the numbers of both types of firms whose class is known, N=NB+NH – number of all companies in the sample.

However, the procedure we propose does not rely on prior knowledge of the classes to which the surveyed companies should belong. Therefore, it may be used to analyze enterprises without such knowledge. It should be noticed that number of all objects is:

$N=NG+NU=NGB+NGH+NU$

where, NU is the number of unclassified objects, i.e., companies belonging to the grey zone.

Thus, the general performance measure (8) is the same as commonly used (11) when all objects from the sample are classified what takes place if the grey zone is empty. Such situation appears when only one limit (e.g., median or simple average) is used to divide all considered objects into two classes. The same situation appears for performance measures recognizing bankrupts (9) and (12) and companies which continue their operations (10) and (12).

In order to examine the state of the enterprises, its major economic and financial factors such as financial liquidity, level of debt, management efficiency, profitability, size are taken into account.

The selection of financial indicators for the bankruptcy indicators (BIs) was made based on their discriminatory power (Kokczyński 2025; Kokczyński *et al.,* 2024). This decision made it possible to compare the classification ability of the constructed BIs with the classification ability obtained using a linear discriminant function. Detailed formulas for financial ratios are given in Table 1.

Our research covered 136 non-public Polish companies from production service. We collected from the Emerging Markets Information Service (EMIS) financial reports for the period 2017-2021. Data from financial reports were used to calculate financial ratios for two group of companies. First group consists of companies which filed for bankruptcy. Second one covered going concern companies, which have as similar as possible scale of activity as companies belonging to first group.

Table 1. *Financial ratios used in bankruptcy indicators (BI)*

Ratio	BI 1	BI 2	BI 3	BI 4
total current assets / total current liabilities				+
fixed assets/total assets	+			
long-term debt/equity	+	+		
EBITDA	+			
EBITDA/assets	+			
net profit/equity	+			
net profit/assets				+
inventory/operating costs	+			
revenue/short-term receivables	+			
fixed assets/current assets	+			
log (fixed assets/current assets)	+	+	+	+
log (assets)		+	+	+
net profit/average current asstets		+	+	+
net working capital cycle				+
renenue/average assets		+	+	+

Source: *Authors' elaboration.*

3. Research Results and Discussion

This part includes the results, tables, figures, formulae with references, data source references, evaluation of validity for calculations and discussion. This part may be divided in balanced sub-parts.

In this section, the results of the conducted research are presented, with the bankruptcy indicators (BIs) shown in order of increasing classification ability. BI 1 (see Table 2), which included the indicators of liquidity, indebtedness, profitability, and size, correctly classified between 66.7% and 83.3% of bankrupt companies into the appropriate cluster.

With minor exceptions, it can be observed that a decrease in the adopted alpha coefficient improves the model's classification ability. In other words, as the size of the grey zone increases, the overall classification ability also improves — both for bankrupt companies and for entities continuing their operations.

Table 2. *Efficiency (performance) of classification for bankruptcy indicator 1*

BI 1							
α	1	0.95	0.9	0.8	0.75	0.5	0
EE	70.6%	69.9%	70.4%	73.9%	74.8%	77.0%	79.4%
EEB	70.6%	69.2%	66.7%	68.5%	70.6%	73.3%	83.3%
EEH	70.6%	70.6%	73.8%	78.7%	78.3%	80.0%	76.3%
NRB	48	45	40	37	36	33	25
NRH	48	48	48	48	47	44	29
NGB	68	65	60	54	51	45	30
NGH	61	60	58	57	54	50	32
GZ	0	2	7	17	21	32	68
E	70.6%	68.4%	64.7%	62.5%	61.0%	56.6%	39.7%
EB	70.6%	66.2%	58.8%	54.4%	52.9%	48.5%	36.8%
EH	70.6%	70.6%	70.6%	70.6%	69.1%	64.7%	42.6%

Notes: *Symbols as in the methodological section of the article.*
Source: *Authors' elaboration.*

The classification results of the BI 2, which included indicators of indebtedness, size, profitability, and operational efficiency, are presented in Table 3. This model demonstrated a classification ability to clusters ranging from 76.5% to 82.4%. Similar to BI 1, the expansion of the grey zone led to an improvement in the model's classification ability to clusters.

Table 3. *Efficiency (performance) of classification for bankruptcy indicator 2*

BI 2							
α	1	0.95	0.9	0.8	0.75	0.5	0
EE	76.5%	78.5%	80.3%	80.3%	81.0%	82.6%	82.4%
EEB	76.5%	78.5%	79.7%	79.4%	80.6%	82.1%	82.4%
EEH	76.5%	78.5%	81.0%	81.4%	81.4%	83.0%	82.4%
NRB	52	51	51	50	50	46	28
NRH	52	51	51	48	48	44	28
NGB	68	65	64	63	62	56	34
NGH	68	65	63	59	59	53	34
GZ	0	6	9	14	15	27	68
E	76.5%	75.0%	75.0%	72.1%	72.1%	66.2%	41.2%
EB	76.5%	75.0%	75.0%	73.5%	73.5%	67.6%	41.2%
EH	76.5%	75.0%	75.0%	70.6%	70.6%	64.7%	41.2%

Notes: *Symbols as in the methodological section of the article.*
Source: *Authors' elaboration.*

BI 3, which utilized indicators of size, profitability, and operational efficiency, allowed for the correct classification of 77.9% to 88.2% of entities into the defined clusters (see Table 4). A decrease in the alpha coefficient leads to an increase in the model's classification ability. It is also worth noting that the classification ability for going concerns is higher than for bankrupt ones.

Table 4. *Efficiency (performance) of classification for bankruptcy indicator 3*

BI 3							
α	1	0.95	0.9	0.8	0.75	0.5	0
EE	77.9%	79.4%	81.1%	81.3%	83.2%	82.1%	88.2%
EEB	77.9%	77.3%	79.7%	80.6%	80.3%	79.3%	88.2%
EEH	77.9%	81.5%	82.5%	82.0%	86.2%	85.4%	88.2%
NRB	53	51	51	50	49	46	30
NRH	53	53	52	50	50	41	30
NGB	68	66	64	62	61	58	34
NGH	68	65	63	61	58	48	34
GZ	0	5	9	13	17	30	68
E	77.9%	76.5%	75.7%	73.5%	72.8%	64.0%	44.1%
EB	77.9%	75.0%	75.0%	73.5%	72.1%	67.6%	44.1%
EH	77.9%	77.9%	76.5%	73.5%	73.5%	60.3%	44.1%

Notes: *Symbols as in the methodological section of the article.*
Source: *Authors' elaboration.*

The best classification results were obtained using BI 4 (see Table 5). This model correctly classified between 80.9% and 89.7% of companies into the defined clusters. It is also noteworthy that, in the case of bankrupt companies, the classification ability to clusters (for alpha = 0) exceeded 90%.

Table 5. *Efficiency (performance) of classification for bankruptcy indicator 4*

BI 4							
α	1	0.95	0.9	0.8	0.75	0.5	0
EE	80.9%	81.3%	82.2%	84.0%	85.2%	86.5%	89.7%
EEB	80.9%	80.6%	80.0%	83.1%	83.1%	85.2%	88.6%
EEH	80.9%	82.1%	84.4%	85.0%	87.5%	88.0%	90.9%
NRB	55	54	52	49	49	46	31
NRH	55	55	54	51	49	44	30
NGB	68	67	65	59	59	54	35
NGH	68	67	64	60	56	50	33
GZ	0	2	7	17	21	32	68
E	80.9%	80.1%	77.9%	73.5%	72.1%	66.2%	44.9%
EB	80.9%	79.4%	76.5%	72.1%	72.1%	67.6%	45.6%
EH	80.9%	80.9%	79.4%	75.0%	72.1%	64.7%	44.1%

Notes: *Symbols as in the methodological section of the article.*
Source: *Authors' elaboration.*

The results obtained for all constructed BIs across different values of the parameter α reveal a consistent relationship between model efficiency, structural complexity, and generalization performance. In all cases, lowering the α value from 1.0 to 0 led to a noticeable increase in efficiency indicators (EE, EEB, EEH).

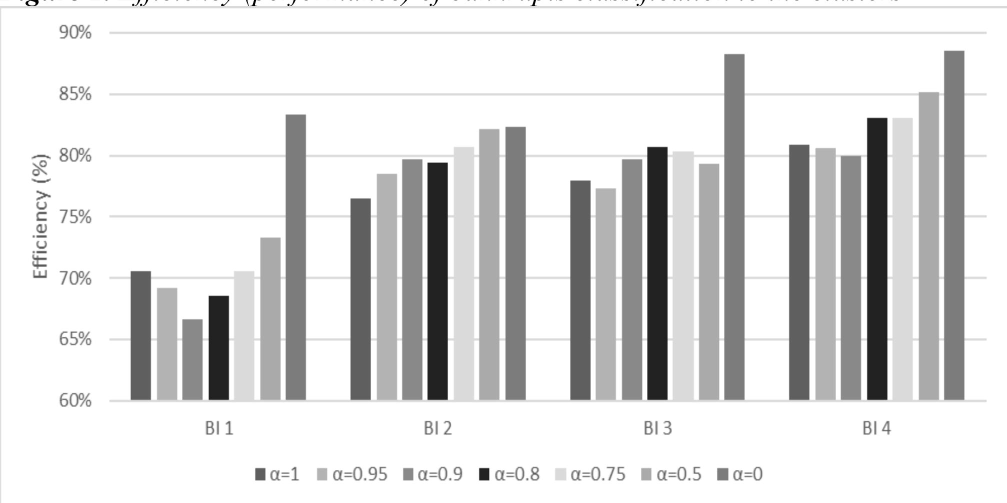
Comparative analysis across the four indicators highlights that BI 1 demonstrates the lowest efficiency values (EE ≈ 70–79%), while BI 2 and BI 3 exhibit more stable and higher performance levels (EE ≈ 80–88%). BI 4 achieved the best overall results, reaching up to 89.7% efficiency for $\alpha = 0$, indicating a strong capability to adapt under less restrictive parameter settings. Nevertheless, all models show a similar trade-off - as α decreases, efficiency increases, but generalization deteriorates.

The analysis of the number and composition of financial indicators used in the BIs in relation to their classification ability suggests that company size, measured by the value and structure of assets, is an important factor differentiating going concerns from bankrupt companies. BI 1, despite the relatively large number of financial indicators used in its construction, exhibited a lower classification ability than the BI containing fewer financial indicators, which included value-related ratios. The best results were obtained for the model based on indicators of size, liquidity, operational efficiency, profitability, and the net working capital cycle.

4. Conclusions, Proposals, Recommendations:

The results of the presented research indicate the usefulness of taxonomic measures in predicting corporate bankruptcy. The summarized results of the classification ability of bankrupt companies to the cluster for all four BIs are presented in Figure 1. The obtained results are comparable to, and often exceed, the classification accuracy achieved on the same research sample using a linear discriminant function (Kokczyński, 2025).

Figure 1. *Efficiency (performance) of bankrupts classification to the clusters*



Source: *Authors' elaboration.*

An important issue in the study is the identification of the grey zone (GZ), where companies with average financial indicator values are located. Such an approach reduces the overall classification ability of the models (E, EB, EH), but significantly improves the ability to classify within the defined clusters (EE, EEB, EEH). Considering the goal — that is, the accurate classification of companies at risk of bankruptcy — this approach appears justified. Additionally, one of the key factors differentiating going concerns from bankrupt companies is the inclusion of the entity's size, measured by the value and structure of its assets.

It is also worth noting that the taxonomic measures used in the study are relatively simple compared to other models and methods applied in bankruptcy prediction. This simplicity allows them to be easily used by managers of smaller entities that lack financial departments or positions responsible for monitoring the financial situation of companies from the perspective of bankruptcy probability.

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