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The Use of Discriminant Analysis to Assess the Risk of Bankruptcy of Enterprises in Crisis Conditions Using the Example of the Tourism Sector in Poland

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Abstract: The aim of this article is to use multiple discriminant analysis (MDA) and logit models to assess the risk of bankruptcy of companies in the Polish tourism sector in the crisis conditions caused by the COVID-19 pandemic. A review of the literature is used to select models appropriate to analyze the risk of bankruptcy of tourism enterprises listed on the Warsaw Stock Exchange (WSE). The data are from half-year financial statements (the first half of 2019 and 2020, respectively). The obtained results are compared with the current values of the Altman EM-score model and selected financial ratios. An analysis allowed the estimation of the risk of bankruptcy of enterprises from the tourism sector in Poland as well as the assessment of the prognostic value of these models in the tourism sector and the risk of a collapse of this market in Poland. The article fills the research gap created by the negligible use of solvency analysis of the tourism sector and constitutes the basis for estimating the risk of collapse of the tourism sector in a crisis situation.

Keywords: discriminant analysis; tourism enterprises; bankruptcy risk

JEL: G01; G32; G33

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1. Introduction

The tourism sector is one of the industries most affected by the coronavirus pandemic. The sharp decline in global demand for tourism services is a factor; the COVID-19 pandemic reduced the turnover of the global tourism sector by more than 50% in the first half of 2020. An important consideration in the context of the second wave of the pandemic, lockdowns, and restrictions on the activities of tourism enterprises is the risk of bankruptcy of businesses in this sector and the risks for the tourism industry, the share of which in the GDP of Poland in 2019 exceeded 6.3%. In particular, the bankruptcy of tourism firms could cause serious losses for the government and businesses involved, hindering economic development (Li et al. 2013). In fact, the tourism sector is extremely vulnerable to any crises because fixed costs are usually high.

In Poland, the entire tourism market is worth approximately PLN 30.9 billion and has grown at a rate of approximately 7% annually in the last three years. The growth was driven by, among other factors, increasing consumption, a rise in household income, and social benefits such as Family 500+, a program of monthly child benefits implemented in Poland from April 2016 (PMR 2019). The SARS-CoV-2 pandemic, however, disturbed these conditions. The three-month lockdown in the first half of 2020, travel restrictions, prohibitions on the organization of large events, fairs, and conferences, and the total paralysis of tourism have left many companies struggling to maintain liquidity. Another economic lockdown in early January 2021 may cause many of them to collapse.

Financial distress is one of the most important threats facing firms, regardless of their size and operations (Charitou et al. 2004). Fitzpatrick (1932) and Beaver (1966) were the first to use single variable analysis in the assessment of the possibility of firm bankruptcy. Fitzpatrick pointed out that the development of selected corporate indicators differs for a long time in groups of insolvent and solvent companies before financial distress occurs (Kliestik et al. 2018).

Altman (1968), in his Z-score model, used multiple variable analyses in evaluating bankruptcy risk. Using financial data from 33 prosperous and 33 nonprosperous companies, 22 variables were considered in the construction of the model. The model correctly classified 70% of the companies. In 1977, the Z-score model was expanded by Altman et al. (1977) to improve its accuracy (Zeta model). Both the Z-score and Zeta models are specific forms of multiple discriminant analysis (MDA), with all its assumptions and limitations (Li et al. 2013).

Default risk prediction of restaurants was first explored by Olsen et al. (1983) using ratio analysis. Gu (2000) and Gu and Gao (1999) indicated that MDA can be used successfully in forecasting the default risk in tourism. Other authors have used logit to predict the default risk for hotels and restaurants, e.g., Cho (1994), Kim and Gu (2006). As Kim and Gu (2006) have shown, MDA and logit models have the same effectiveness in predicting the bankruptcy of restaurants.

The use of MDA and logit models to assess the bankruptcy of companies in the tourism sector in Poland is rare. Gołębiowski and Pląsek (2018) investigated 20 MDA and logit models forecasting default risk on a sample of 30 companies (18 solvent and 12 insolvent) from the tourism industry in Poland. The highest $t-1$ and $t-2$ accuracy were found in domestic models: the Wędzki model ($t-1$ accuracy = 91.67%), the Prusak model ($t-2$ accuracy = 83.33%), and the Gajda and Stos model ($t-2$ accuracy = 81.94%). The most accurate foreign model for predicting bankruptcy was the Altman model for emerging markets (Altman EM-score).

In addition to MDA, artificial neural networks (ANNs) are also used (Atiya 2001). ANNs do not have the statistical constraints of discriminant analysis. In addition, their ability to represent nonlinear relationships makes them well-suited to modeling the frequently nonlinear relationship between the likelihood of bankruptcy and commonly used variables (i.e., financial ratios) (Laitinen and Laitinen 2000). ANNs allow us to determine the significance of variables in the model and to use big data (Agosto and Ahelegbey 2020; Cerchiello et al. 2020). The efficiency of classification using ANNs is often compared with the effectiveness of other methods (discriminant analysis, logit models) and the ANN method is becoming extremely popular. However, the limitation of these methods is the necessity to choose the right tool (Alaka et al. 2018; Chung et al. 2008).

The aim of this study is to assess the risk of bankruptcy of companies in the tourism sector in Poland in the crisis conditions caused by the COVID-19 pandemic using discriminant analysis. As we will prove, the COVID-19 pandemic has significantly influenced the risk of bankruptcy of enterprises from the tourism service sector in Poland.

This article fills the research gap created by the negligible use of discriminant analysis on the tourism sector in Poland and constitutes the basis for estimating the risk of collapse of the tourism sector in a crisis. The problem is new and important because the impact of the pandemic on the tourism sector is extremely significant, and there are no such studies on the Polish tourism sector yet. It is obvious that there are likely to be some comprehensive studies in the future, but our article already signals some problems that the crisis caused by the pandemic will surely aggravate.

2. Results

We estimated the value of the Z function for the surveyed companies using three models: Prusak, Gajdka and Stos, and Altman's EM-score. Table 1 presents the results for the first half of 2019.

Table 1. The value of the discriminant functions in the first half of 2019.

Company	Prusak		Gajdka and Stos		Altman EM-Score	
	Z	Classification Rule	Z	Classification Rule	Z	Classification Rule
Novaturas AB	−0.285	GZ	0.208	GZ	4.153	GZ
Rainbow Tours SA	−0.698	GZ	0.171	GZ	4.563	GZ
AmRest Holdings	−1.350	DZ	0.180	GZ	3.473	DZ
CFI Holdings SA	−1.649	DZ	1.111	SZ	4.438	SZ
Interferie SA	−1.173	DZ	0.875	SZ	11.267	SZ
Mex Polska SA	0.471	SZ	0.268	GZ	2.611	DZ
Sfinks Polska SA	−1.037	DZ	−1.069	DZ	0.428	DZ
Tatry Mountain Resorts	−1.409	DZ	0.414	GZ	4.407	GZ
Benefit Systems SA	−1.090	DZ	0.391	GZ	3.290	DZ

The value of the Z function for the Prusak model indicates that in the first half of 2019, six out of nine of the companies that were analyzed were at risk of bankruptcy, two were in the grey zone, and only Mex Polska SA was in a good financial situation. In the case of the Gajdka and Stos model as well as Altman's EM-score model, seven companies were in the grey zone or were at risk of bankruptcy. On the other hand, both Gajdka and Stos and Altman's EM-score indicate no risk of bankruptcy for CFI Holdings SA and Interferie SA. Figure 1 presents the number of enterprises in each classification, according to the different models.

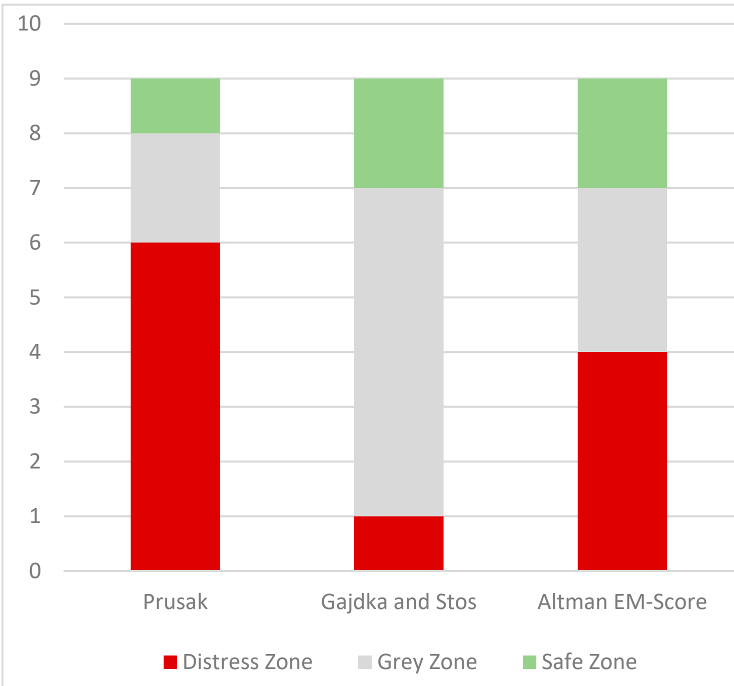

Figure 1. The classification of companies according to the discriminant models in the first half of 2019.

Table 2 shows the results obtained for the same companies based on the data for the first half of 2020.

Table 2. The value of the discriminant functions in the first half of 2020.

Company	Prusak		Gajdka and Stos		Altman EM-Score	
	Z	Classification Rule	Z	Classification Rule	Z	Classification Rule
Novaturas AB	−1.5438	DZ	−0.099	GZ	0.904	DZ
Rainbow Tours SA	−1.3438	DZ	−0.012	GZ	3.725	DZ
AmRest Holdings	−1.9475	DZ	−0.446	GZ	1.011	DZ
CFI Holdings SA	−1.7167	DZ	0.514	SZ	5.959	SZ
Interferie SA	−1.9276	DZ	−0.769	DZ	7.083	SZ
Mex Polska SA	−1.9155	DZ	−0.205	GZ	1.919	DZ
Sfinks Polska SA	−1.8202	DZ	−1.469	DZ	−1.857	DZ
Tatry Mountain Resorts	−1.3795	DZ	0.352	GZ	4.305	GZ
Benefit System SA	−1.4219	DZ	0.027	SZ	2.571	DZ

The value of the Z function for the Prusak model for the first half of 2020 indicates a risk of bankruptcy (distress zone) for all companies. According to the Gajdka and Stos model, only CFI Holdings was in a good financial situation. Using Altman's EM-score, CFI Holdings can also be considered safe. It also indicates that Interferie SA was in a good financial situation. Figure 2 presents the number of enterprises in each classification, according to the different models.

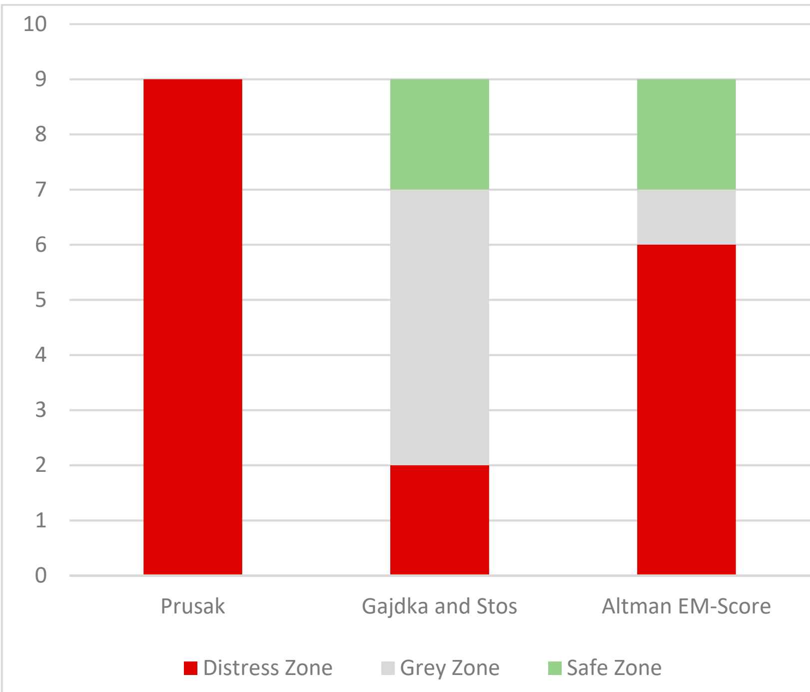

Figure 2. The classification of companies according to the discriminant models in the first half of 2019.

As shown by the discriminant analysis, the risk of bankruptcy of the surveyed enterprises increased significantly in the first half of 2020, compared to the same period in 2019. According to the Prusak model, all nine of the companies that were analyzed were at risk of bankruptcy. The other two models indicate a lower number of companies at risk of bankruptcy. However, it is worth emphasizing that the value of the Z function for all companies decreased. This proves the deterioration of the financial situation of the enterprises that were analyzed, compared to the same period in 2019. This is also confirmed by the analysis of the dynamics of operating profit and fixed assets (Table 3).

Table 3. Dynamics of EBIT and fixed assets for the audited companies (First half of 2019–first half of 2020).

Company	EBIT Growth (+) Decrease (−) in %	Fixed Assets Growth (+) Decrease (−) in %
Novaturas AB	(−) 260.57	(+) 2.88
Rainbow Tours SA	(−) 150.95	(+)27.30
AmRest Holdings	(−) 125.12	(+) 3.25
CFI Holdings SA	(−) 23.60	(+) 15.75
Interferie SA	(−) 115.54	(+) 20.37
Mex Polska SA	(−) 149.71	(−) 2.0
Sfinks Polska SA	(−) 105.89	(−) 32.8
Tatry Mountain Resorts	(+) 24.32	(+) 10.7
Benefit Systems SA	(−) 87.0	(−) 1.0

The value of fixed assets over the period studied rose for six companies, which means that these companies increased their fixed assets. The largest decrease in the value of fixed assets was recorded by Sfinks Polska SA (a decrease of 32.8%). Although there was a decline in the value of fixed assets at Mex Polska SA and Benefit Systems SA, it was small (1–2%).

Only Tatry Mountain Resorts obtained operating profit, achieving an EBIT increase of 24.32% from the first half of 2019 to the first half of 2020. A similar situation occurred in the case of CFI Holdings SA—the company generated operating profit, but in 2020, compared to 2019, there was a 23.6% decrease in EBIT. In the case of Benefit Systems SA, the company achieved operating profit in both periods, but in 2020, EBIT decreased by 87%. The remaining companies, analyzed in the first half of 2019, generated an operating profit, but for the same period of 2020, they suffered an operating loss. The greatest decrease in operating profit, by 260.57%, was recorded by Novaturas (see Table 3). Table 4 presents the following indicators: current liquidity, debt ratio, coverage ratio II, and the sales cash performance index for the surveyed companies in 2019–2020 (first half of the year).

Table 4. The value of the selected financial indicators for surveyed companies.

Company	Current Liquidity		Debt Ratio		Coverage Ratio II		Sales Cash Performance Index	
	2019	2020	2019	2020	2019	2020	2019	2020
Novaturas AB	0.77	0.72	0.69	0.68	0.80	0.73	−0.022	−0.284
Rainbow Tours SA	1.05	0.95	0.75	0.80	1.11	0.93	0.063	−0.320
AmRest Holdings	0.59	0.30	0.80	0.87	0.91	0.61	0.159	0.148
CFI Holdings SA	1.90	1.71	0.28	0.31	1.05	1.04	0.337	0.125
Interferie SA	2.63	0.45	0.14	0.22	1.13	0.90	0.098	−0.009
Mex Polska SA	0.41	0.57	0.80	0.87	0.80	0.84	0.153	0.051
Sfinks Polska SA	0.20	0.15	1.02 [1]	1.22 [1]	0.60	0.38	0.262	0.232
Tatry Mountain Resorts	1.73	1.65	0.79	0.78	1.08	1.05	0.339	0.138
Benefit Systems SA	0.53	0.60	0.69	0.71	0.89	0.89	0.201	0.257

[1] The value of liabilities, in both 2019 and 2020, exceeds the balance sheet total. This is due to the negative value of equity, which is affected by the amount of net loss and losses from previous years.

The analysis of the current liquidity ratio shows that all companies, except CFI Holdings SA, had problems with financial liquidity in the first half of 2020 as the value of the ratio does not fall within the range of 1.2–2.0. It is also worth emphasizing that in the first half of 2020, compared to the corresponding period in 2019, the value of the ratio was reduced, which proves a decrease in the financial liquidity of these enterprises. The exception is Benefit Systems SA, as the current liquidity ratio slightly increased (but not enough for the company to regain financial liquidity).

The analysis of the debt ratio in 2019–2020 indicates a very high level of indebtedness for most of the companies (ratios above 0.67). The analyzed ratio was below 0.57 only in the cases of CFI Holdings SA and Interferie SA, which proves the low indebtedness of these enterprises. Moreover, the value of the debt ratio for Sfinks SA, in both 2019 and 2020, was at 1.02 and 1.22, respectively, which was influenced by the negative value of equity (net loss and loss from previous years).

In the first half of 2019, the value of coverage ratio II in the cases of Novaturas AB, AmRest Holdings, Mex Polska, Benefit Systems SA, and Sfinks Polska was below 1.0, which proves that some parts of the fixed assets of the companies were financed with short-term liabilities. For the remaining companies, the value of the indicator was over 1.0. The situation changed in the first half of 2020 because only two companies—CFI Holdings and Tatry Mountain Resorts—had a ratio above 1.0, which means that their fixed assets were financed by fixed capital. The remaining companies did not meet this rule, which may indicate long-term financial instability.

The value of the sales cash efficiency index for all the surveyed companies decreased, which proves a decrease in the amount of cash generated by sales revenues. This decrease indicates a growing risk of losing financial liquidity. It should also be emphasized that three companies—Novaturas AB, Rainbow Tours SA, and Interferie SA—recorded a nega-tive balance in cash flows from operating activities in the first half of 2020.

We also estimated the value of the Z function for the Wędzki logit model. Table 5 presents the results for the first half of 2019 and 2020.

Table 5. Values and interpretation in the Wędzki logit model.

Company	Z	Classification Rule	Z	Classification Rule
	First Half of 2019		First Half of 2020	
Novaturas AB	0.963	DZ	1.518	DZ
Rainbow Tours SA	0.332	SZ	3.482	DZ
AmRest Holdings	3.023	DZ	5.959	DZ
CFI Holdings SA	−7.334	SZ	−5.737	SZ
Interferie SA	−17.704	SZ	4.146	DZ
Mex Polska SA	4.647	DZ	3.295	DZ
Sfinks Polska SA	8.089	DZ	8.797	DZ
Tatry Mountain Resorts	−8.301	SZ	−7.563	SZ
Benefit Systems SA	4.322	DZ	3.906	DZ

Based on the analysis of the logit model, we find that in the first half of 2019, 55% of the surveyed companies were at risk of bankruptcy, and another 45% were in a good financial situation. This changed in the first half of 2020 when only two companies—CFI Holdings SA and Tatry Mountain Resorts—showed a good financial situation and were not threatened by bankruptcy. The remaining companies were at risk of bankruptcy.

3. Discussion

It should be noted that MDA models have some limitations (Altman and Narayanan 1997). They assume that financial ratios are normally distributed and that the variance–covariance structures of insolvent and solvent firms are equivalent. In practice, both of these assumptions rarely hold up (Ezzamel et al. 1987). Logit regression models do not have these assumptions but can produce biased estimates, especially in small-sample studies (Firth 1993). Wu et al. (2010), Grice and Dugan (2001), and Pitrova (2011) have shown that the accuracy of the prediction of MDA models is significantly reduced when the model is used in another industry, at another time, or in a different trading environment than the data used to derive the model. Therefore, it is essential to develop a model for each country, accepting its economic, political, and entrepreneurial uniqueness. On the other hand, according to Mandru, Lidia 2010. The diagnosis of bankruptcy risk using score function (), Altman's model is still solid and durable, despite being formed more than 30 years ago. This view has been confirmed by other studies (Li and Ragozar 2012; Satish and Janakiram 2011).

When it comes to debt ratios, the financial structure of a firm is assumed to be a significant failure-related factor in the hospitality business (Geng et al. 2015; Gu 2000; Kim and Gu 2006; Sun et al. 2017; Zhou 2013). Nevertheless, it should be noted that financial structure was found to be significantly correlated with Spanish hotel failures (Lado-Sestayo et al. 2016) but not with failures of large Spanish hotels (three-star or higher; Gemar et al. 2016).

Although early research tended to ignore cash-based ratios, these ratios also demonstrated predictive capacity in a number of studies (Gilbert et al. 1990; Sung et al. 1999; Ravisankar et al. 2010). Kim and Gu (2006) showed in their study that a hospitality firm is more likely to fail when its operating cash flows are low and total liabilities are high.

All of the models that we used showed a visible deterioration in the financial situation of the enterprises that were analyzed. The number of companies at risk of bankruptcy increased significantly (an average of three companies for the first half of 2019 and five for the first half of 2020). Selected financial ratios also deteriorated.

As the situation of almost all of the companies in the sector has deteriorated dramatically, the Polish government should consider the default risk of tourism companies before making important decisions, such as creating anticrisis solutions for the tourism sector. It is necessary to monitor the economic stability of the industry as well as to invest and grant loans. As the crisis persists for an extended period, the industry will require fiscal support to avoid mass defaults. Regulatory forbearance on debt can ease the solvency of the tourism industry; on the other hand, it may create long-term risks as it is not helpful in improving structural issues. Lockdowns will strain the tightening economic conditions due to rising healthcare costs and unemployment. Tax deferrals will reduce the amount collected by the exchequer, and providing subordinated loans and equity support will be a significant drag on public funds. However, if there is no intervention, bankruptcies on an unprecedented scale may occur in this sector (Jamal and Budke 2020; Hoque et al. 2020; Rodríguez-Antón Jose Miguel 2020)

We do recognize the limitations of our research. Understandably, the risk of internal and external factors, other than the pandemic, that may affect the risk of bankruptcy cannot be excluded. On the other hand, external factors can have a synergic effect on bankruptcy—usually, external factors enhance the possibility of internal factors manifesting. Mackevičius et al. (2018) have shown that even in the case of successfully operating enterprises, negative external factors can have a huge negative impact. Finally, as indicated by Narkunienė and Ulbinaitė (2018), some comparative analysis with nonfinancial performance indicators that complement financial indicators should be used.

The future direction of the research is its continuation based on the results for the entire year of 2020, with an analysis of the effectiveness of the presented predictions. The research should be extended to include other enterprises from the sector and not only companies listed on the WSE. Future research should also measure the impact of government initiatives to support the recovery of tourism.

4. Materials and Methods

As seen in the results from the research in the literature, in the case of enterprises from the tourism industry, the most effective models among Polish discriminant models are by B. Prusak (Prusak 2005) and J. Gajdka and D. Stos (Gajdka and Stos 2003), alongside the logit model by D. Wędzki (Wędzki 2005). In the case of foreign models, the Altman model for emerging markets (Altman EM-score) is of the highest quality (Altman and Hotchkiss 2005; Gołębiowski and Pląsek 2018). Thus, these three models were used to assess the financial condition of companies listed on the WSE. In order to standardize and transparently interpret the results of the study, the same nomenclature for the classification rules was adopted: safe zone (financially sound), grey zone (uncertain status), and distress zone (at risk of bankruptcy). In addition to discriminant models, we also used a single-branch, noncollinear logit model by D. Wędzki. The form of the models used, with the interpretation of the Z function, is presented in Appendix A (Table A1).

All of the companies we examined were from the WSE sector—travel agencies, hotels and restaurants, and recreation and leisure. There were six companies from the Hotel, Restaurant, Catering/Café (HoReCa) sector, two companies from the travel agency group, and one company from the recreation and leisure sector. The analysis was based on data from financial statements for the first half of 2019 and the first half of 2020. In the case of Tatry Mountain Resorts SA, the financial statements were prepared for the period 1 January 2018–30 April 2019 and 1 November 2019–30 April 2020, and an analysis was made for this time range.

In order to deepen the analysis of the bankruptcy risk of the surveyed enterprises, apart from the discriminant models and the logit model, we used the analysis of selected financial indicators. For this purpose, we used the debt ratio, the coverage ratio II, the current liquidity ratio, and the sales cash efficiency index as measures of dynamic liquidity and the dynamics of operating profit (Jagiełło 2013; Podstawka 2017; Sierpińska Maria 2020; Sierpińska and Wędzki 2010). Calculation formulas and interpretation of selected indicators are included in Appendix A (Table A2).

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The mathematical form of the models and the interpretation of the Z function.

Model	Mathematical form of the Model	Interpretation of the Z Function
Prusak	$Z_P = 1.4383x_1 + 0.1878x_2 + 5.0229x_3 - 1.8713$ $x_1 = \frac{net\ profit + depreciation\ and\ amortization}{total\ liabilities}$ $x_2 = \frac{operating\ costs}{current\ liabilities}$ $x_3 = \frac{gross\ margin}{total\ assets}$	$Z_P \geq -0.295$ safe zone (SZ) $-0.7 \leq Z_{BP} \leq 0.2$ gray zone (GZ) $Z_P < -0.295$ *distress zone* (DZ)
Gajdka and Stos	$Z_{GS} = -0.0005x_1 + 2.0552x_2 + 1.726x_3 + 0.1155x_4$ $x_1 = \frac{current\ liabilities}{cost\ of\ production\ sold}$ $x_2 = \frac{net\ profit}{total\ assets}$ $x_3 = \frac{gross\ profit}{total\ revenue}$ $x_4 = \frac{total\ assets}{total\ liabilities}$	$Z_{GS} > 0$ safe zone (SZ) $-0.49 < Z_{GS} < 0.49$ grey zone (GZ) $Z_{GS} < 0$ distress zone (DZ)
Altman EM-Score	$Z_A = 6.56x_1 + 3.26x_2 + 6.72x_3 + 1.05x_4 + 3.25$ $x_1 = \frac{(current\ assets - current\ liabilities)}{total\ assets}$ $x_2 = \frac{retained\ earnings}{total\ assets}$ $x_3 = \frac{EBIT}{total\ assets}$ $x_4 = \frac{book\ value\ of\ equity}{total\ liabilities}$	$Z_A > 5.85$ safe zone (SZ) $5.58 > Z_A > 4.15$ grey zone (GZ) $Z_A < 4.15$ distress zone (DZ)
Wędzki	$Z_{DW} = 8.366 - 9.9x_1 + 0.032x_2$ $x_1 = \frac{current\ assets}{current\ liabilities}$ $x_2 = \frac{receivables}{total\ revenue} \times time$	$Z_{DW} > 0.5$ distress zone (DZ) $Z_{DW} \leq 0.5$ safe zone (SZ)

Source: own study based on Gajdka and Stos (2003), Prusak (2005), and Altman and Hotchkiss (2005).

Table A2. Financial indicators—calculation formula and interpretation.

Financial Ratio	Calculation Formula	Interpretation
Debt ratio (DR)	$DR = \frac{total\ liabilities}{total\ assets}$	The indicator should be in the range of 0.57–0.67. A value above 0.67 means a high credit risk. A low value indicates a high share of equity in liabilities.
Coverage ratio II	$\frac{equity + non-current\ liabilities}{non-current\ assets}$	*coverage ratio II* < 1 means that fixed capital (equity + long-term liabilities) does not cover fixed assets.
Current liquidity ratio	$\frac{current\ assets}{current\ liabilities}$	The correct value of the indicator should be in the range of 1.2–2.0.
Sales cash performance index	$\frac{net\ cash\ from\ operating\ activities}{total\ revenue}$	An increase in the value of the ratio over time means more cash from sales and higher security of maintaining financial liquidity.

Source: own study based on Sierpińska Maria (2020), Sierpińska and Wędzki (2010), and Podstawka (2017).

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