AN ANALYSIS OF THE EFFECTIVENESS OF BANKRUPTCY PREDICTION MODELS – AN INDUSTRY APPROACH

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Abstract

Research background: Bankruptcy prediction models are frequently used in research. However, an industry approach is not often carried out. Due to this, this study included trends observable between the number of bankruptcies and its prediction by models.

Purpose: The aim of the paper is to verify if changes in the number of actual bankruptcy in individual industries are properly predicted by the models. Also, if analyzed models are providing consistent information according to the risk of bankruptcy between industries.

Research methodology: The data were collected from the Orbis database and the Coface reports. The period included in the study is 2014–2019. 5 Polish bankruptcy prediction models were used: these by D. Hadasik, E. Mączyńska and M. Zawadzki, M. Pogodzińska and S. Sojak, D. Wierzba and the Poznan one.

Results: The analyzed models do not properly predict changes in the number of bankruptcy in individual industries, however, 3 out of 5 correctly predicted the trend for the entire sample. Analyzed models often provide inconsistent information. Hence, it seems sensible to use more than a few models in any further analyzes.

Novelty: In the literature of the subject, there are often carried out analyses focused on the effectiveness of bankruptcy prediction models regarding individual companies. This research is focused on the prediction of changes in the number of companies to be considered as at bankruptcy risk between industries, and also on comparing these models.

Keywords: financial ratios, sectors of the economy, discriminant analysis.

JEL classification: C14, G17, G33.

Introduction

The effectiveness of a business activity might come down to success or failure. Referring to the life stages of enterprises, the management staff of each of them tries to prevent it from going into the decline phase (Lester, Parnell, Carraher, 2003). This may prove difficult, given that globalization promotes increased competition. Changes in both micro and macroeconomic areas may negatively affect the financial situation of an enterprise, leading to bankruptcy. Therefore, it is now becoming increasingly important to prevent crises in a company as soon as possible. Early warning tools used for this purpose include bankruptcy prediction models. They use financial data to help assess the company's financial condition, indicating a potential bankruptcy risk. Recently, they are used more and more often, which makes them important for business practice. Hence, the effectiveness of these models is verified by various authors. Usually, it is indicated that these models work, at least for some entities. Analyzes of the effectiveness of bankruptcy models are often carried out in relation to individual companies, not to industries. It seems, however, that this type of research may provide valuable information on average trends in individual areas of the economy. Therefore, as part of this work, it was decided to verify the effectiveness of bankruptcy prediction models through the prism of industries.

The theoretical part of the study takes into account the symptoms of bankruptcy, bankruptcy prediction models and a review of the literature related to the assessment of the effectiveness of these models. The empirical part is focused on similar verification, but with reference to industries. The research included a literature review, empirical data analysis, induction and deduction methods.

1. Bankruptcy and its economic aspects

Bankruptcy tends to be defined differently. According to the Polish law, bankruptcy is strongly connected with insolvency. This term means a loss of a company's ability to meet its required monetary obligations. Measurable symptoms of this state of affairs are a 3-month delay in the performance of these commitments or a surplus of the value of liabilities over the value of assets, lasting for more than 2 years (The Bankruptcy Law).

Entrepreneurs are trying to prevent business bankruptcies. In this context, it is important to early detect symptoms that indicate the risk of bankruptcy of a given entity. Usually, for this purpose, it relies on financial data, its changes over time and comparisons to the industry. Liquidity, debt and profitability ratios are particularly important in this context (Zeytinoglu, Akarim, 2013).

Many symptoms of bankruptcy risk were presented by P. Antonowicz (2015). He listed among them for instance lack of financial liquidity, the volatility of demand, insufficient cash of the enterprise, and limited access to financing. The increased risk of bankruptcy may also have macroeconomic reasons, such as economic policy, price levels, the exchange rate or legal regulations (Kuciński, 2013).

Apart from the financial data, there are also qualitative symptoms of a company's deteriorating financial condition. According to H. Ooghe and S. de Prijs (2006), it can be mentioned:

- 1) management with a serious deficiency in managerial and industry-related experience,
- 2) risk-seeking managers or entrepreneurs,
- 3) taking exaggerated risks and refusing to adjust the managerial and operational structure,
- 4) lack the commitment and the motivation to lead a company efficiently.

T. Korol (2017) also adds that the management staff often ignores the risk and symptoms of the poor condition of a company. A. Kücher et al. (2020) also point to the importance of the age of companies and the use of controlling in their operations among the factors influencing the risk of bankruptcy.

The realization of this type of factor may lead to the emergence and intensification of crisis situations in an enterprise. It can be generally assumed that the materialization of the qualitative causes of a company's crisis is reflected in the deteriorating financial indicators in the subsequent periods. An example sequence of events within a crisis situation in an enterprise is: strategy crisis, profitability crisis, turnover crisis, liquidity crisis, insolvency (Gurgul, 2006). It seems that all stages except the first one can be classified as identifiable through a financial analysis. Due to the possibility of quantifying a large amount of the above information, in particular with regard to financial indicators, many models of prediction bankruptcy of enterprises have been built on their basis.

2. Corporate bankruptcy prediction models

The most known methods for constructing a corporate bankruptcy prediction model are linear discriminant analysis and logit analysis. The first one is based on the estimation of a linear function that is to differentiate the two groups as much as possible – companies at risk and not at risk of bankruptcy. In this context, it is purposeful to maximize the variance between groups and

minimize within groups (Tharwat, Gaber, Abdelhameed, Hassanien, 2017). The general form of such a model is as follows (Ramayah, Ahmad, Abdul-Halim, Rohaida, Lo, 2010):

$$Z = \alpha + W_1 \times X_1 + W_2 \times X_2 + \dots + W_n \times X_n \quad (1)$$

where: Z – the value of the discriminant function, α – constant, W_i – the coefficient for the variable i , X_i – independent variable i (these are usually financial ratios).

The next one is the logit model. Its main advantage is that it not only delimits groups of companies due to the risk of bankruptcy, but also indicates the probability of such a state of affairs. This probability is given by the formula (Pociecha, Pawełek, Baryła, Augustyn, 2014):

$$P(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

where: $P(x)$ – probability, x – the value of the logit function.

With respect to these methods, the measurement of the cut-off point is crucial. This is the value that separates the two groups. The model values higher than the cut-off point indicate no risk of bankruptcy, while lower – the existence of such a threat (Jagiello, 2013).

Apart from discriminant and logit models, there are also non-parametric methods that are nowadays more often used. These include, in particular, classification trees and neural networks (Pociecha et al., 2014).

The history of business bankruptcy forecasting began with discriminatory models. The first ones were prepared by using one financial ratio as the only predictor. The construction of such a model was quite simple, although it could be characterized by decent efficiency. W.H. Beaver was the pioneer of this type of analysis (Karas, Režňáková, 2014). Probably the best-known model focused on corporate bankruptcy prediction is the one by E. Altman. He was the first to propose the use of a multivariate discriminant analysis to build a bankruptcy prediction model (Altman, 1968). The model he created became the basis and point of reference for further research in this field, and in later years it was also modified for other markets (the original one focused on the specificity of the American market). Therefore, the issue of matching models to the market seems to be important. For example, although the Z' Score model, also by E. Altman, works for many markets, its effectiveness can be improved taking into account the specificity of a given one (Altman, Iwanicz-Drozdowska, Laitinen, Suvas, 2017). Hence, the next part

of the study focused on models prepared by Polish researchers, more suited to the realities of the domestic market.

Polish models of bankruptcy began to be built and published in the 1990s. The most recognized, among others, are those by D. Hadasik, D. Gajdka and J. Stos, A. Hołda or M. Hamrol, B. Czajka and M. Piechocki (Godlewska, 2010). In the literature on the subject, there are also frequent references to models by M. Pogodzińska and S. Sojak, E. Mączyńska or D. Wierzbą. All of the mentioned models were prepared on the basis of the discriminant function, using accrual data. Worth mentioning are also research by D. Wędzki (2010) or T. Maślanka (2008). These authors included not only data from the balance sheet and the income statement, but also cash flows. In the Polish literature, one can find works systematizing the area of predicting the bankruptcy of enterprises. These include studies by B. Prusak (2007), P. Antonowicz (2015), E. Mączyńska (2015) and M. Gruszczyński (2012).

In reference to models focusing on predicting the bankruptcy of entities, it is important to point out their positives and negatives. The advantages of these models include especially these focused on the indicator analysis – its simplicity, speed of analysis and also common knowledge of financial indices (Gabrusewicz, 2014). Interpretation of the values of these models is also simple and straightforward.

On the other hand, bankruptcy prediction models cannot be considered universal, because of their negatives. For example, the grey zone problem is one of the main issues connected with the topic (Karas, Režňáková, 2014). Further, referring to the stages of a company crisis previously mentioned, not all of them might be quantified quite simply (Gurgul, 2006). For instance, the crisis of the strategy is difficult to estimate based on accounting or even market data. This is one of the disadvantages of using bankruptcy prediction models, based on the accounting data – it is impossible to capture all the events that contributed to the deterioration of a company's situation by using them. Taking everything into account, it should be emphasized that using bankruptcy prediction models may be useful in a process of making decisions, due to their advantages, however, it should not be the only way to determine the bankruptcy risk.

3. Verification of the effectiveness of bankruptcy prediction models – a literature review

A common view in the literature on the subject is that the predictive models lose their value over time. Hence, the effectiveness of these models is often verified based on the latest financial data. The results of that type of research are quite differentiated – on the basis of some samples, it is indicated that the effectiveness of the models decreases over time, while on the

basis of other studies it can be concluded that it is not true. In general, effectiveness might be perceived as the percentage of companies correctly classified by the model, which could be expressed as:

$$\text{Effectiveness of the model} = \frac{(\text{number of entities that go bankrupt, identified by the model as at risk of bankruptcy in the previous period} + \text{number of entities that did not bankrupt, identified by the model as not at risk of bankruptcy in the previous period})}{\text{number of analyzed entities}} \quad (3)$$

It is essential to verify the validity of the models in the example of Polish companies, because of the specificity of the domestic market. Research of this type was carried out, among others, by J. Wojnar (2014). Each of the 9 models analyzed as part of the study was effective at a level exceeding 80%. Thus, it can be concluded that in relation to the proposed sample, these models turned out to be quite effective. W. Lichota (2020), on the basis of research focused on 25 models of bankruptcy prediction, indicated that 10 of them were effective at the level above 90%, 9 – within the range (75; 90%), and 6 – below 75%. He also concluded that the newer models are not more effective than others. Similar conclusions were put forward by G. Gołębiowski and K. Żywno (2008). Most of the 26 models analyzed by them were quite effective. The result of this study also negated the claim that the newer models are more effective than older ones. Likewise, T. Maślanka (2012) stated that the models prepared by him a few years earlier did not lose their prognostic ability with time. The study by J. Kisielińska and A. Waszkowski (2010) drew attention to the weaker effectiveness of some models. Moreover, the authors pointed out that the models using more financial indicators in their structure turned out to be more effective. Further, J. Kisielińska (2016) indicated the advisability of using more than one bankruptcy predicting model for a given enterprise.

In general, it seems that the majority of Polish business bankruptcy prediction models are quite effective despite the passage of time. It is worth mentioning, however, that most studies verifying the effectiveness of these models focus on predicting the bankruptcy of individual business entities. This work, in turn, takes into account tendencies observed among industries that can provide useful information about the risk of bankruptcy in particular groups of enterprises.

4. The methodology of the research

The models analyzed in the empirical part of the study are these prepared by D. Hadasik, E. Mączyńska and M. Zawadzki, M. Pogodzińska and S. Sojak, D. Wierzba, M. Hamrol and B. Czajka and M. Piechocki (the Poznan model). The cut-off point for each of them, except

for D. Hadasik's model (cut-off point -0,374), is 0. Values below this point indicate a risk of bankruptcy, while positive values – lack such risk. The specific forms of these models are as follows:

1. Model by D. Hadasik (1998):

$$Z = 0,365425 \times X_1 - 0,765526 \times X_2 - 2,40435 \times X_3 + 1,59079 \times X_4 + 0,00230258 \times X_5 + 0,0127826 \times X_6 + 2,36261 \quad (4)$$

where:

$$X_1 = \frac{\text{Current assets}}{\text{Current liabilities}}; X_2 = \frac{\text{Current assets} - \text{Stock}}{\text{Current liabilities}}; X_3 = \frac{\text{Liabilities}}{\text{Assets}};$$

$$X_4 = \frac{\text{Working capital}}{\text{Assets}}; X_5 = \frac{\text{Receivables} \times 365}{\text{Sales revenues}}; X_6 = \frac{\text{Stock} \times 365}{\text{Sales revenues}}.$$

2. Model by E. Mączyńska and M. Zawadzki (2006):

$$Z = 9,498 \times X_1 + 3,566 \times X_2 + 2,903 \times X_3 + 0,452 \times X_4 - 1,498 \quad (5)$$

where:

$$X_1 = \frac{\text{EBIT}}{\text{Assets}}; X_2 = \frac{\text{Shareholder's funds}}{\text{Assets}};$$

$$X_3 = \frac{\text{Net income} + \text{Depreciation} + \text{Amortization}}{\text{Liabilities}}; X_4 = \frac{\text{Current assets}}{\text{Current liabilities}}.$$

3. del by M. Pogodzińska and S. Sojak (1995)

$$Z = 0,644741 \times X_1 + 0,912304 \times X_2 \quad (6)$$

where:

$$X_1 = \frac{\text{Current assets} - \text{Stock}}{\text{Current liabilities}}; X_2 = \frac{\text{Gross income}}{\text{Sales revenues}}.$$

4. del by D. Wierzba (2000):

$$Z = 3,26 \times X_1 + 2,16 \times X_2 + 0,3 \times X_3 + 0,69 \times X_4 \quad (7)$$

where:

$$X_1 = \frac{\text{EBIT} - \text{Depreciation} - \text{Amortization}}{\text{Assets}}; X_2 = \frac{\text{EBIT} - \text{Depreciation} - \text{Amortization}}{\text{Sales revenues}};$$

$$X_3 = \frac{(\text{Current assets})}{\text{Liabilities}}; X_4 = \frac{\text{Working capital}}{\text{Assets}}.$$

5. The Poznan model (Hamrol, Czajka, Piechocki, 2004):

$$Z = 3,652 \times X_1 + 1,588 \times X_2 + 4,288 \times X_3 + 6,719 \times X_4 - 2,368 \quad (8)$$

where:

$$X_1 = \frac{\text{Net income}}{\text{Assets}}; \quad X_2 = \frac{\text{Current assets} - \text{Stock}}{\text{Current liabilities}}; \quad X_3 = \frac{\text{Fixed capital}}{\text{Assets}}; \\ X_4 = \frac{\text{Sales result}}{\text{Sales revenues}}.$$

The models presented above were used for the assessment of bankruptcy risk between industries. Financial data was collected from the Orbis database, while information about bankruptcy among industries – from the Coface reports. Joint-stock companies and limited liability companies for which all the data needed to calculate the value of the models were available were analyzed. The number of entities included in the research was 8,414. It is needed to note that the outliers (~2.8% of observations) were excluded from the sample (e.g. due to the fact that companies achieving them were characterized by unnatural values of individual financial ratios). The period included in the study covers 2014–2019. The number of analyzed entities differs, due to the availability of data.

In the first part of the empirical analysis, numbers of bankruptcies and restructurings among industries by years were taken into account. Further, changes in the number of companies at risk of bankruptcy according to the models mentioned were compared with the actual data for the next year (for example, changes in this number between 2017 and 2018, according to the models, with the actual changes between 2018 and 2019). Finally, the conformity of the classification of individual enterprises by models was compared. The hypothesis can be formulated as follows: the analyzed models make it possible to predict trends (increase/decrease) in the number of bankruptcies in a given industry; besides, these constructs provide quite consistent information.

5. Empirical study

In the case of Poland, in the period 2015–2019, the number of bankruptcies and restructurings systematically increased, exceeding 1,000 in 2019. This was related to the good, but still gradually deteriorating economic situation. The industries such as manufacturing, construction, wholesale and retail trade, transportation had the largest share among the failing

companies. Due to this, the remainder of the work focuses especially on these sectors. The number of bankruptcies and restructuring in these fields of the economy is presented below:

Figure 1. Number of bankruptcies and restructuring in selected industries in the period 2015–2019

Source: author's own work based on the Coface reports.

The tendency, identical to the trends for the entire sample, was observed in the case of wholesale and retail trade. The number of failing companies from this industry was growing in the period 2015–2019. In the case of the remaining ones, except the construction industry, some fluctuations were observable. However, regarding the number of bankruptcies in any of these industries, it can still be pointed out as being an upward trend, on the basis of the period 2015–2019. The opposite tendency applied to the construction industry, where the number of bankruptcies in 2019 was significantly lower than that observed in 2015.

Given the increasing number of bankruptcies and restructurings, it seems that bankruptcy prediction models in the corresponding period should indicate a growing number of companies at risk of bankruptcy in a given industry (and decreasing for the construction one). In the beginning, the focus was on the model by D. Hadasik. The specific numbers of enterprises considered by the model as threatened and not threatened with bankruptcy are shown Table 1.

This model flawlessly indicated the trends observed for the manufacturing industry and for the entire sample – the increase in bankruptcies from year to year. In the case of the trade and transport industry, correct changes (for instance, increase in the number of entities classified as at risk of bankruptcy in 2016–2017 in comparison to changes predicted by the model based on the data for 2015–2016) were observed in 3 cases out of 4, and in the construction industry – only 1 in 4. The tendencies that could be determined on the basis of the value of this model did

not fully coincide with the actual trends observed in individual industries. Hence, it seems that this model is not the best predictor of bankruptcy risk among given sectors.

Table 1. Number of entities classified due to the risk of bankruptcy by the model by D. Hadasik¹

Industry		2014	2015	2016	2017	2018
Manufacturing	N+	1,889	1,984	2,015	2,229	2,297
	N–	180	176	178	265	276
Construction	N+	713	766	777	969	1,023
	N–	48	58	63	108	117
Wholesale and retail trade	N+	722	765	775	917	925
	N–	54	64	60	82	104
Transportation	N+	150	154	160	178	179
	N–	14	13	17	30	32
Together	N+	5,114	5,387	5,462	6,489	6,659
	N–	476	495	519	813	907

Source: author's own work.

The next model being analyzed is the one by E. Mączyńska and M. Zawadzki. According to this model, the numbers of companies at risk of bankruptcy are as in Table 2.

Table 2. Number of entities classified due to the risk of bankruptcy by the model by E. Mączyńska and M. Zawadzki

Industry		2014	2015	2016	2017	2018
Manufacturing	N+	1,676	1,751	1,765	1,929	2,000
	N–	311	323	344	468	476
Construction	N+	612	677	641	821	873
	N–	164	168	209	289	289
Wholesale and retail trade	N+	624	678	686	771	788
	N–	158	156	152	239	253
Transportation	N+	134	143	143	161	163
	N–	31	26	35	48	50
Together	N+	4,543	4,784	4,788	5,674	5,820
	N–	1,104	1,173	1,249	1,737	1,831

Source: author's own work.

¹ N+, N– – means, in sequence, the number of companies that were recognized by the model as not endangered/at risk of bankruptcy (the model value exceeds/is lower than the cut-off point).

This model was found to be 75% effective in most industries (manufacturing, construction, wholesale and retail trade industries). For the transport one, it was 50%. However, for the entire sample, the tendencies predicted by this model were consistent with the real ones, observed in the next years. The assessment of this model is similar to that of the previous one by D. Hadasik. Both constructs correctly predicted the trend in the entire sample, but in individual industries, their effectiveness was lower.

Similar numbers, classified by the model by M. Pogodzińska and S. Sojak, are as follows:

Table 3. Number of entities classified due to the risk of bankruptcy by the model by M. Pogodzińska and S. Sojak

Industry		2014	2015	2016	2017	2018
Manufacturing	N+	1,925	2,002	2,043	2,284	2,357
	N–	56	62	55	98	110
Construction	N+	726	783	791	999	1,070
	N–	35	41	49	78	71
Wholesale and retail trade	N+	741	792	815	960	978
	N–	35	37	20	39	53
Transportation	N+	162	162	172	205	207
	N–	2	6	5	4	4
Together	N+	5,334	5,586	5,712	6,913	7,133
	N–	256	297	269	391	441

Source: author's own work.

This model was 25% effective for the construction and transportation sector, 50% for the manufacturing sector, and 75% for the trade sector and the entire sample. It is the first of the analyzed models, which did not fully correctly predict the trends observed in the entire group of the companies taken into account. In the case of this model, the very low number of companies from the transport sector deemed at risk of bankruptcy is also particularly surprising. This model seems to be less effective than the previous ones. This proves their advantage over the model of M. Pogodzińska and S. Sojak, so this model is weaker compared to them in terms of the effectiveness of bankruptcy risk assessment among industries.

The next one is the model by D. Wierzba. The distribution of companies, considered to be at risk of bankruptcy or not, by this model, is presented in Table 4.

Table 4. Number of entities classified due to the risk of bankruptcy by the model by D. Wierzba

Industry		2014	2015	2016	2017	2018
Manufacturing	N+	1,832	1,913	1,958	2,185	2,268
	N–	156	162	151	216	211
Construction	N+	723	784	797	1,016	1,062
	N–	54	61	54	99	103
Wholesale and retail trade	N+	720	774	783	921	939
	N–	63	62	56	93	107
Transportation	N+	142	146	156	178	182
	N–	23	23	22	31	32
Together	N+	5,057	5,330	5,423	6,559	6,792
	N–	595	630	617	868	878

Source: author's own work.

This model also predicted trends for the entire sample not entirely correctly (in 75%). In the case of individual sectors, the effectiveness was even lower – 50% for the construction and trade industries and 25% for the manufacturing and transport industries. The efficiency of this model is very similar to the previous one, by M. Pogodzińska and S. Sojak, and cannot be considered as satisfactory either.

The last model taken and included in this research is the Poznan one. The numbers consistent with the previous models, according to this one by M. Hamrol, B. Czajka and M. Piechocki, are as follows.

Table 5. Number of entities classified due to the risk of bankruptcy by the Poznan model

Industry		2014	2015	2016	2017	2018
Manufacturing	N+	1,722	1,804	1,827	1,996	2,081
	N–	259	260	271	386	384
Construction	N+	653	706	702	863	906
	N–	108	118	138	214	234
Wholesale and retail trade	N+	625	659	684	782	776
	N–	151	170	151	217	253
Transportation	N+	143	150	154	177	177
	N–	21	17	23	31	34
Together	N+	4,774	4,983	5,058	5,971	6,152
	N–	816	899	923	1,331	1,414

Source: author's own work.

This model accurately predicted trends for all units (for instance, signalization of an increase in the number of entities at bankruptcy, based on the data for 2014–2015, was reflected in actual change between 2016 and 2015). In relation to individual sectors, it achieved 75% (for manufacturing, wholesale and retail trade, transport ones) or 25% (for the construction sector) efficiency. It seems that this model can be ranked on a par with the structures of D. Hadasik and E. Mączyńska with M. Zawadzki, due to the correct classification of the trend for the entire sample.

Summarizing this part of the analysis, it can be stated that, in relation to the entire sample, the trends were unmistakably predicted by the models of D. Hadasik, E. Mączyńska, M. Zawadzki, and the Poznan one. These models were also, on average, more effective in terms of sectors than the other 2, by M. Pogodzińska with S. Sojak and D. Wierzba. Therefore, it seems that these 3 models can be useful in assessing the overall risk of bankruptcy in a given sample. However, with regard to individual sectors, only D. Hadasik's model for the manufacturing sector was faultless. Therefore, it seems that the analyzed models are unlikely to be the correct predictors of the increase/decrease in bankruptcy risk in a given industry. Therefore, they are not able to sufficiently accurately inform about threats in the area of profitability, liquidity, debt or others, which may have both micro- and macroeconomic sources. Especially the predictions for the construction sector are also worth emphasizing – they were correct only in 40% of indications. Therefore, the risk of bankruptcy of companies belonging to this sector probably could not be effectively predicted using the models considered. The reason for this may be the opposite tendencies observed in this sector and the entire sample.

The next part of the research is focused on the differences between the analyzed models, in reference to the percentage of companies that considered them to be at risk of bankruptcy. This can provide valuable information in terms of comparing it with the effectiveness of models in forecasting trends. Such indications for the individual sectors are presented below.

As it can be seen, the indications of individual models differ significantly. For each sector, the model of M. Pogodzińska and S. Sojak considered a lower percentage of companies at risk of bankruptcy than forecasted by the other models. Therefore, it seems that this model was too lenient in assessing some companies, hence it turned out to be ineffective in the context of predicting the trends outlined earlier for industries. It is worth noting that this model contains only 2 financial indicators. In the context of this analysis, models with 4–5 indicators looked better. This conclusion, according to which the models built on the basis of a greater number of explanatory variables are more effective, is consistent with that by J. Kisielińska and A. Waszkowski (2010). However, the models that proved successful in predicting trends for the entire sample classified significantly different the percentages of companies as being at risk of bankruptcy. It, therefore,

seems that there is not much of a correlation between the percentage of firms considered at risk of bankruptcy and the effectiveness of the models in predicting trends in their number.

Table 6. Percentage of manufacturing companies considered by the models to be at risk of bankruptcy²

	2014	2015	2016	2017	2018
H	8.70	8.15	8.12	10.63	10.73
MZ	15.65	15.57	16.31	19.52	19.22
PS	2.83	3.00	2.62	4.11	4.46
W	7.85	7.81	7.16	9.00	8.51
PZN	13.07	12.60	12.92	16.20	15.58

Source: author's own work.

Table 7. Percentage of construction companies considered by the models to be at risk of bankruptcy

	2014	2015	2016	2017	2018
H	6.31	7.04	7.50	10.03	10.26
MZ	21.13	19.88	24.59	26.04	24.87
PS	4.60	4.98	5.83	7.24	6.22
W	6.95	7.22	6.35	8.88	8.84
PZN	14.19	14.32	16.43	19.87	20.53

Source: author's own work.

Table 8. Percentage of wholesale and retail trade companies considered by the models to be at risk of bankruptcy

	2014	2015	2016	2017	2018
H	6.96	7.72	7.19	8.21	10.11
MZ	20.20	18.71	18.14	23.66	24.30
PS	4.51	4.46	2.40	3.90	5.14
W	8.05	7.42	6.67	9.17	10.23
PZN	19.46	20.51	18.08	21.72	24.59

Source: author's own work.

² H, MZ, PS, W, PZN – in sequence: model by D. Hadasik, E. Mączyńska and M. Zawadzki, M. Pogodzińska and S. Sojak, D. Wierzba, the Poznań one; “[%]+”; “[%]–” means, in sequence, the percentage of companies for which the values of the model exceeds/are below its cut-off point.

Table 9. Percentage of transportation companies considered by the models to be at risk of bankruptcy

	2014	2015	2016	2017	2018
H	8.54	7.78	9.60	14.42	15.17
MZ	18.79	15.38	19.66	22.97	23.47
PS	1.22	3.57	2.82	1.91	1.90
W	13.61	12.36	14.83	14.95	16.29
PZN	12.80	10.18	12.99	14.90	16.11

Source: author's own work.

Based on the above data, the real percentage of failing companies among all entities can be expected to increase. The chart below illustrates the ratio of entities going bankrupt in year $n + 1$ to the number of commercial companies in year “ n ” (data taken from the Central Statistical Office [CSU]).

Figure 2. The ratio of the number of bankrupt entities in the year $n + 1$ (period 2015–2019) to the number of commercial companies in a given sector in the year n (period 2014–2018).

Source: author's own work based on the Coface Reports and CSU data.

As it can be noticed, in the period 2015–2019 there was an increase in the share of entities and bankruptcy among all commercial companies on average, which might be considered as a confirmation of the conclusions based on tables 6–9. The same trends can be observed on the basis of comparing the number of failing entities to the number of all types of enterprises in a given sector. The main difference concerned the construction sector, in which the share pointed out above decreased in the analyzed period. It was not accurately predicted by the models.

It also makes sense to investigate what percentage of companies are classified agreeably according to particular model pairs. For this purpose, a total number of companies classified as to be at risk of bankruptcy by all analyzed models were added to the number of entities recognized by the models as not at risk of bankruptcy. This amount was divided by the total number of enterprises included in the research (for which all of the data needed to compute the values of the analyzed models were available). The results of such calculations are as follows.

Table 10. Compatibility of the classification of an entity as at risk of bankruptcy or not, between the models (%)³

Industry	Manufacturing	Construction	Wholesale and retail trade	Transportation	Together
H-MZ	84.21	78.27	81.51	79.94	79.84
H-PS	93.54	88.15	91.50	88.57	88.49
H-W	92.35	91.54	92.41	84.47	88.02
H-PZN	87.05	82.40	80.75	85.33	83.23
MZ-PS	85.90	81.03	82.81	81.66	82.80
MZ-W	86.97	82.21	84.62	83.60	83.40
MZ-PZN	92.74	89.19	91.23	89.21	90.41
PS-W	93.06	91.45	93.26	87.70	90.32
PS-PZN	89.05	86.63	82.81	88.13	87.46
W-PZN	89.30	84.79	84.62	87.27	85.98
Mean	89.42	85.57	86.55	85.59	86.00

Source: author's own work.

The highest classification compliance is observed in the case of manufacturing companies, where 4 pairs of models are consistent in over 90% of cases. The model of D. Hadasik and E. Mączyńska with M. Zawadzki shows the lowest classification agreement (below 80%). Based on the entire sample, the following models are quite compatible: E. Mączyńska with M. Zawadzki and the Poznań one, M. Pogodzińska with S. Sojak and the model by D. Wierzba (over 90%). It seems that this compliance is quite satisfactory, but it is also worth checking its level in relation to the 5 analyzed models in total. The percentage of jointly classified into one of the groups due to the risk of bankruptcy, among all of the analyzed

³ H, MZ, PS, W, PZN – in sequence: model by D. Hadasik, E. Mączyńska and M. Zawadzki, M. Pogodzińska and S. Sojak, D. Wierzba, the Poznań one. H-W means compatibility between the models by D. Hadasik and D. Wierzba etc.

models, is as follows (the calculation methodology used is analogous compared to the one in Table 10).

Figure 3. The percentage of compliant classifications of companies as at risk of bankruptcy or not, by all of the analyzed models

Source: author's own work.

Again, the highest classification consistency is observed in the manufacturing industry, although it is below 80%. The rest of the analyzed sectors are characterized by significantly lower compatibility. Therefore, it can be concluded that the analyzed models often lead to different conclusions, based on the classification of individual entities in terms of their bankruptcy risk. In this context, it makes sense to use more models to find out if the company or industry is considered to be at risk of bankruptcy on the basis of multiple signals, especially in industries other than a manufacturing one.

Conclusions

In general, some models (like the ones by D. Hadasik, E. Mączyńska and S. Sojak, the Poznań one) appear to be able to correctly predict general trends in the number of bankruptcies. However, in relation to individual industries, the analyzed models were not able to forecast trends correctly (except for D. Hadasik's model in the case of the manufacturing industry). As for the number of companies considered by particular models as threatened by bankruptcy, the smallest percentage was generated by the model by M. Pogodzińska and S. Sojak, and the largest – by the model by E. Mączyńska and M. Zawadzki. The compliance of the classification of individual enterprises by models, whether at risk of bankruptcy or not, was close to 70%, although it

was higher for each pair of models. However, this compatibility is generally quite low, which indicates the advisability of using more models in assessing the risk of bankruptcy in a given industry. In the context of this study, it also seems that models with a greater number of financial indicators are more effective (models with 4 or 5 ratios were more effective than the model by M. Pogodzińska and S. Sojak, which contains only 2 explanatory variables).

Taking everything into account, it seems that the analyzed models are not able to correctly predict the changes in risk of bankruptcy between companies in individual industries. What is more, these models often provide information that is quite different. Thus, the hypothesis can be considered as a rejected one. However, it is worth bearing in mind that this may be due to the selection of specific models, although they are among the most frequently described in the Polish literature on the subject. Referring to the research of other authors, it could be pointed out the similarity of the obtained result with the analyzes of J. Kisielińska and A. Waszkowski (2010) and J. Kisielińska (2016), who pointed to the relatively weak discriminatory power of the bankruptcy forecasting models analyzed in this study. The study by J. Wojnar (2014) led to different conclusions, which indicated the effectiveness of the analyzed models at a level significantly exceeding 80%, and in some cases higher than 90%.

For potential research involving industry bankruptcy risk assessments, more models, as well as other industries, might be worth considering. A longer-term analysis can also provide valuable information. It also seems reasonable to compare the obtained results with the study taking into account the specificity of the years 2020-2021, as characterized by the occurrence of extraordinary events in the form of the COVID-19 world pandemic. Such research will be conducted further.

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