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Identifying Symptoms of Bankruptcy Risk Based on Bankruptcy Prediction Models—A Case Study of Poland

Jerzy Kitowski, Anna Kowal-Pawul * and Wojciech Lichota

Institute of Economics and Finance, University of Rzeszów, 35-310 Rzeszow, Poland; kitowski@ur.edu.pl (J.K.); wlichota@ur.edu.pl (W.L.)
* Correspondence: annakowal@ur.edu.pl

Abstract: The article presents selected Polish early warning models (logit and discriminant models) that allow the assessment of the risk of bankruptcy of a company, and the purpose of the considerations is to indicate their prognostic effectiveness in predicting susceptible Polish companies one year before their declarations of bankruptcy. The limitations of these methods were also indicated in unpredictable situations, such as the outbreak of an economic crisis, e.g., caused by a humanitarian crisis—the COVID-19 pandemic. Another aim chosen in the article is a methodological critical assessment of the phenomenon of widespread use of foreign models (including the common Altman method) in the study of the risk of bankruptcy of Polish enterprises. Models developed on a sample of foreign enterprises without prior adaptation to domestic conditions are used all over the world, so the conclusions of the article are applicable internationally. The research was based on a query of Polish and foreign literature in the field of economic and legal aspects of bankruptcy and financial analysis, including, in particular, bankruptcy forecasting. The empirical research analyzes the financial data of 50 Polish enterprises from 2017 to 2018. The effectiveness of the selected bankruptcy forecasting models in identifying enterprises from section C of the Polish economy (industrial processing) that filed for bankruptcy in 2018 and 2019 was tested. The time frame fully allows for the identification and the assessment of the effectiveness of early warning models a year before bankruptcy.

Keywords: bankruptcy risk; early warning models; company bankruptcy; discriminant analysis; logit analysis

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1. Introduction

As stated by Joseph A. Schumpeter [1], one of the most powerful mechanisms of economic progress is the so-called creative destruction—a phenomenon in which the bankruptcy of enterprises is an integral part. This phenomenon can be considered natural, as it acts as a means of natural selection [2]. In dynamic and competitive market conditions, every business is exposed to greater or lesser risk [3,4]. From the theoretical point of view, the bankruptcy of an enterprise is part of a self-regulatory market mechanism and may be a condition for market development; however, when considered in terms of the interest of the enterprises, it becomes an unfavorable phenomenon [5]. Creditors, managers, shareholders, investors, employees, and even the local community or the economy of a given country suffer major consequences [6–8]. In particular, creditors and suppliers are at risk when debtors go bankrupt because: "failure to fulfill debt commitments by a customer may hamper the solvency of the supplier (creditors), who may become unable in turn to pay its own suppliers located in the upper level, which may lead to a chain of similar failures (domino effect) and in extreme cases result in bankruptcy avalanches" [9]. At the same time, the stronger the ties between the attacked enterprise and other domestic and foreign partners, the faster the "bankruptcy virus" spreads. Globalization intensifies the diffusion of bankruptcies. It is no coincidence, therefore, that they are escalating globally (both in absolute and relative terms) [2].

Studies of the European Commission, suggest quite a radical thesis, which is often mentioned in the literature, stating that about 50% of enterprises registered in the European Union are not able to survive their first five years, and the percentage of bankruptcies among the enterprises that close in that time frame is around 15% [10,11]. With increased financial globalization, faster economic changes, and a new dimension of increased financial risk in the context of the 2007 global financial crisis and the economic crisis caused by the COVID-19 pandemic, the question should not focus on whether bankruptcy prediction models should be used but rather on how to increase their effectiveness [12].

The article presents selected Polish early warning models (logit and discriminant models) that allow the assessment of the risk of enterprise bankruptcy, and the purpose of the considerations is to indicate their prognostic effectiveness in predicting susceptible Polish enterprises a year before their declarations of bankruptcy. The main criterion for determining a given enterprise as bankrupt was the submission of a bankruptcy petition to the territorially competent economic division (KRS) in the district court. Another purpose of the article is a methodological critical assessment of the phenomenon of widespread use of foreign models (including the popular Altman method) in the study of the risk of bankruptcy of Polish enterprises. The use of such models without prior adaptation to national conditions is common in many countries.

The research was based on a query of Polish and foreign literature in the field of economic and legal aspects of bankruptcy and a financial analysis regarding bankruptcy forecasting. The financial data of 50 Polish companies from 2017 to 2018 were used for empirical research. What was evaluated was the effectiveness of selected bankruptcy forecasting models in identifying enterprises from section C of the Polish economy (industrial processing) that filed for bankruptcy in 2018 and 2019. The time frame fully allows for the identification and assessment of the effectiveness of early warning models a year before bankruptcy. In relation to the objectives of the study, two research hypotheses were formulated and verified:

Hypothesis 1 (H1). *Despite the lapse of time, certain discriminatory and logit models show similar effectiveness of bankruptcy prediction to that indicated by their creators on the learning sample.*

Hypothesis 2 (H2). *The mechanical transfer of the Altman model (a model developed on a sample of American enterprises) onto the assessment of the risk of bankruptcy of Polish enterprises is not methodologically correct and generally does not bring reliable results.*

2. Review of the Literature

Business bankruptcy is a polysemantic concept that is associated with many related terms, including financial failure, insolvency, loss of payment capacity, execution, liquidation, legal proceedings, coercion, deprivation of rights, and even the consequences of a financial or organizational crisis [13,14]. This phenomenon is defined both in a legal and an economic sense. In legal terms, it is a phenomenon of a legal institution established in order to stop a crisis situation in an enterprise by eliminating it from the market. From an economic point of view, bankruptcy is the failure of a company to meet its financial liabilities, combined with the lack of improvement prospects in terms of the entity's economic situation [15,16]. In Poland, bankruptcy is regulated by the Act of 28 February 2003, Bankruptcy Law [17]. According to its provisions, bankruptcy is declared in relation to a debtor who has become insolvent, that is, they have lost the ability to meet due pecuniary obligations or the pecuniary obligations exceeded the value of their assets [18].

It is worth emphasizing that the bankruptcy of an enterprise is preceded by a number of causes or symptoms of an internal (endogenous, which indicate the main reasons for the failure of a significant part of enterprises) and external (exogenous) nature [19]. The internal causes include the following [20,21]:

- poor financial policy leading to a high level of indebtedness,

- loss of sales markets,
- lack of an unequivocally formed company strategy,
- too high debt, and
- insufficient financial control of concluded contracts.

The external causes are much more complex than the internal ones, as they are related to the country's situation—political, macroeconomic, and social, as well as to the internal situation of partners, investors, and clients. Internal and external causes differ in their predictability, as well as the intensity of the effects [22].

One of the tools in the process of assessing the economic and financial situation of an economic entity is undoubtedly the bankruptcy early warning system, which identifies the deteriorating financial standing and, in particular, detects elements that indicate a risk of bankruptcy. In the theory and practice of bankruptcy forecasting, a number of methods and types of predictive models (risk estimation models) have been formulated, the comprehensive classification of which was presented, among others, by McKee [23]. The assessment of bankruptcy risk is important primarily for managers when making decisions that contribute to improving the company's financial performance but also for investors considering a given company, as well as for creditors [24].

The first studies on bankruptcy prediction appeared in the United States [25]. Fitzpatrick identified significant differences between financially sound and distressed companies [26,27]. Since then, the use of bankruptcy prediction models has been widespread in developed economies. Many international researchers have tried to find an appropriate model for predicting bankruptcy using various methods in order to achieve the best prediction accuracy [28]. After the 2008 global financial crisis, the importance of predicting bankruptcy was confirmed and sparked a new wave of interest [29].

One of the most common methods is discriminant analysis. The issue of discrimination was first raised by Ronald A. Fisher [30]. In his work, he introduced the concept of the discriminant function and the method of estimating its parameters. The literature on the ideas, the formalization, and applications of Fisher's linear discriminant function is extensive. Its detailed description can be found in the works of Cornfield [31], Maddala [32], Mika et al. [33], Jajuga [34], etc. The development of discriminatory models of bankruptcy forecasting was largely due to Beaver [35], who was the first to apply one-dimensional discriminant analysis. A breakthrough in the research area was the work of an American economist Edward Altman [36], who presented the possibility of using multidimensional linear discriminant analysis to build a model for assessing the risk of enterprises' bankruptcy.

In the 1970s, many authors used models built on a game theory to forecast the bankruptcy of enterprises. In the second half of the 1970s and at the beginning of the 1980s, the first logit and probit analyses appeared in the studies in the field of forecasting enterprise bankruptcy [37]. Compared with the Western countries, in post-socialist states, research on the subject became possible more than 20 years later. However, based on the historical development of corporate bankruptcy forecasting, it can be seen that it has already caught up with the best international practice [38].

In Poland, Mączyńska [39] was the first to use linear discriminant analysis to predict the bankruptcy of enterprises, while adapting the assumptions of Jacobs [40] to Polish economic conditions [41]. In the following years, early warning models appeared, prepared by Pogodzińska and Sojak [42], Gajdka and Stos [43], Hadasik [44], and Hołda [45].

The main goal of discriminant analysis is to classify an object into one of the distinguished groups according to a specific classification factor. When examining the risk of enterprises' bankruptcy, usually, there are only two groups considered—entities not at risk of bankruptcy and entities at risk of bankruptcy. The problem is to find a classification rule that will allow for the correct classification of companies described with diagnostic variables (financial ratios) into one of the groups [46]. The linear discriminant function proposed by Fisher is as follows [47]:

$$D(X) = \alpha_0 + a_1 X_1 + \alpha_2 X_2 + \ldots + a_k X_k, \tag{1}$$

where

X—vector of independent (explanatory) variables—in the case of bankruptcy forecasting models, these are most often financial indicators;
α_0—constant of the discriminant function; and
α_1—coefficients (weights) of the discriminant function.

The statistic characterizing the general discriminant ability of the function is the Wilks lambda coefficient, which has a value in the range <0.1>. When this value is closer to zero, it indicates a high discriminant ability of the model. The most important issue is to ensure the accuracy of the classification of the units surveyed by the model. For this purpose, a classification matrix is used to compare the classification of objects on the basis of a discriminant function with their actual belonging to the appropriate group. From a practical point of view, the construction and use of the discriminant function makes sense only when the accuracy of the classifications obtained on its basis is (in a statistical sense) significantly higher than in the case of the random allocation of statistical units to a given group [48].

The logit model is the second bankruptcy prediction tool commonly used in practice. The first researcher to use the logit model for this purpose was Ohlson [49]. The variables for this model were selected on the basis of the indicated literature in the field of financial analysis. Since then, there has been a rapid development of the use of logit models for the purposes of estimating bankruptcy risk [50]. Among the many publications on the subject, the work of Zavgren [51] should be mentioned as it estimates the logit function on the basis of 45 companies that went bankrupt and 45 companies in a "safe financial situation". Another interesting example of the use of the logit function is the work of H.D. Platt and M.B. Platt [52].

Logit models for forecasting the bankruptcy of Polish enterprises have been used since the beginning of the 21st century [50]. One of the first logit models was estimated by Hołda [53]. Gruszczyński also presented extensive research. Using an expert method, he selected 23 enterprises with a good financial standing and 23 enterprises with a bad financial condition. The learning sample separated in this way was used to build logit binomial models. By selecting a 25-element group of enterprises with an unclear financial situation, Gruszczyński estimated the trinomial logit models [54]. Wędzki also presented a number of logit models of bankruptcy in the Polish economy, including a multi-branch model for industrial enterprises [55]. The presented Polish logit models are only examples of Polish bankruptcy forecasting structures. Their detailed review can be found in the work by Prusak [56].

The logit model belongs to the class of binary models in which the dependent variable takes only two values, 1 with the probability p_i and the value 0 with the probability $1 - p_i$ presented as follows [47]:

$$P(y_i = 1) = p_i,\ P(y_i = 0) = 1 - p_i. \tag{2}$$

The probability is a function of the vector of explanatory variables x_i and the vector of parameters β, therefore,

$$p_i = P(y_i = 1) = F(x_i^T \beta) \text{ for } i = 1, 2, \ldots n. \tag{3}$$

The values of the inverse function of F are called logits. Logit is the logarithm of the odds of an event happening and not happening. It is determined from the dependence

$$F^{-1}(p_i) = \ln \frac{p_i}{1-p_i}. \tag{4}$$

In relation to the discussed issue, the logit is, therefore, the logarithm of the ratio of the odds of bankruptcy and "non-bankruptcy" of the enterprise. If the odds are the same, i.e., $p = 0.5$, then logit is 0, for $p > 0.5$ the logit is positive, and for $p < 0.5$ logit is negative.

After the logit transformation, one can proceed to study the relationship between logit values and explanatory variables being the appropriate financial indicators, usually adopting a linear econometric model of the form given below [57]:

$$L = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \varepsilon. \tag{5}$$

For many years, it has been discussed in the subject literature to define the impact of the number of model coefficients on its quality. More than once, studies have shown that the number of variables in a discriminant model is not a factor determining its quality [58]. According to Mączyńska and Zawadzki, a model with a dozen or so variables does not show a spectacularly higher classification accuracy than models with a smaller number of variables [2]. Korol also rejected the hypothesis that the use of more financial ratios increases the effectiveness of the bankruptcy forecasting model [59]. The Greek researcher Sfakianakis put forward a hypothesis that one properly selected index can determine the quality of a given model [60].

Puagwatana and Gunawardana presented a different opinion by presenting a logistic regression model for predicting business failures in the technology industry in Thailand [61]. The authors found that one way to improve the model is to add more coefficients, which will make the predictability of bankruptcy more accurate. The thesis about the greater effectiveness of the logit model with a greater number of coefficients was refuted by Lichota after researching Polish enterprises [57].

Moreover, Puagwatana and Gunawardana indicated that, when constructing the model, the existing macroeconomic conditions should be taken into account [61]. A similar position was taken by Slovak scientists who stated that the logistic regression model should include information about the size of the enterprise, as it is a significant predictor of the probability of financial difficulties [62]. From a methodological point of view, it seems particularly important to include the criterion of the enterprise specificity and the variable economic conditions of its operations in synthetic methods of assessing the financial condition of an enterprise [63–65].

The limitations of these two bankruptcy prediction methods should also be mentioned. The models of discriminant and logit analysis do not take into account factors influencing the activity of enterprises, such as development opportunities, moods among employees, the company's position on the market, or the quality of management [66]. Of course, they do not work in unpredictable situations, such as the outbreak of an economic crisis, e.g., caused by a humanitarian crisis—the COVID-19 pandemic. Many companies across the EU became defaulted due to lockdowns in 2020 and 2021 [67]—discriminatory and logit models based on financial data for obvious reasons did not indicate the risk of bankruptcy a year before the event.

It is also commonly expressed that the mechanical transfer of foreign models (models developed on a sample of foreign enterprises) onto the assessment of the financial condition of enterprises from another country is not methodologically correct [2,68]. At the same time, what should be supported is the hypothesis concerning the need for an earlier adaptation of a foreign model to the conditions of a given economy. The indiscriminate use of the current model with its original assumptions does not bring reliable results [69,70]. This position was taken by Hungarian researchers [38], who do not recommend applying bankruptcy models that have been developed on samples of foreign companies to Hungarian companies, regardless of their popularity and high citation. The results are consistent with those of Serbian researchers [71–76], who prove that the existing predictive models (e.g., Altmans's Z-score, model, Taffler's Z-score model, Sandin and Porporato's model, Zmijewski's model) are not accurate in predicting the bankruptcy of Serbian enterprises because the socio-economic, institutional, and other operating conditions are significantly different than the ones in the countries where these models were developed. The Polish researcher Kitowski puts forward a blunt conclusion that "it is unacceptable, from a methodological point of view, to unauthorized modification of the most important assumptions (still known as the Altman method) and to uncritically recommend the use of this method to assess the risk of bankruptcy of Polish enterprises and to "fetish" its timeless diagnostic credibility and industry universality" [77]. Micherda [78] took a similar position.

In line with the aim of the article and the hypothesis put forward, the considerations focus on the Altman method, which is the most popular foreign method used in Polish economic practice. It is also used by statutory auditors in the process of auditing financial statements. Out of 100 randomly selected opinions, the E. Altman method was used in 82 cases to assess the risk of bankruptcy of the audited entity, including 39 cases using only this method (in 28, the E. Altman method and A. Hołda's method; in 11 opinions, the E. Altman method, the method of A. Hołda, and the method of M. Hamrol; and in 4 opinions, the method of E. Altman and the method of J. Gajdka and D. Stos) [77]. The national literature on the subject emphasizes that the results of the conducted research indicate the inadequacy of the Altman model to Polish conditions [78]. A similar position was taken by M. Hamrol, who believes that "it is difficult to imagine, for example, the use of the Altman model in a health care institution in assessing the risk of bankruptcy" [79].

This article notes that the Altman model is not only used for research purposes in Poland. The model is used in practice, with numerous errors and simplifications, which is not methodologically correct. Statutory auditors persistently use E. Altman's model, among others, to assess the financial condition of hospitals, and to make matters worse, they use the version of the model from 1968, intended for companies from the stock exchange (apart from the obvious fact that these hospitals are not joint stock companies). Particularly disturbing, from a methodological point of view, is the manner in which statutory auditors use the scheme for applying the version of the Altman method intended for unlisted joint-stock companies. In their opinions of the financial statements of the audited companies, statutory auditors uncritically duplicate errors and methodological simplifications from the literature on the subject. For example, in the opinion of the auditor, the 1968 model of the method was used for a company listed on the Warsaw Stock Exchange but with many errors. In the analyzed reports of statutory auditors, we also find errors in the cases of using E. Altman's EM-Score model (without the asset turnover ratio). Until 2015, the State Fund for Rehabilitation of Disabled Persons verified the financial condition of entities applying for subsidies for the remuneration of employees with disabilities using the E. Altman method.

In the Polish literature on the subject, the topics of methodological controversies related to the use of the E. Altman model by statutory auditors and court experts are sporadically discussed, in different judicial decisions. The analysis of court judgments containing the assessment of the reliability of E. Altman's method leads to unexpected and contradictory conclusions. The proposed direction of research seems to be of great practical utility, as it is critical of the unilateral and uncritical application of discriminatory methods (especially the Altman model) by certified statutory auditors and court experts. It is amazing that, in the Polish literature on the subject, until 2015, it was not possible to find even one example of a correct discussion of the assumptions of the ZETA Score method, published by E. Altman, R. Haldeman, and P. Narayanan in 1977 [80].

Despite the presented limitations and controversies, the discriminant and logit models are characterized by objectivity, high prediction efficiency (if selected correctly), and simplicity resulting from the limitation of the method to the most important indicators [81,82]. When used correctly, the indicators enable the comparison of the financial situation of various enterprises, as well as the assessment of the risk of bankruptcy. The advantages also include transparency and ease of interpretation of the outcomes [83].

Polish enterprises do not use modern bankruptcy forecasting methods [84]. Moreover, statutory auditors do not fully use the tools of modern financial analysis. In Poland, despite the fact that logit models and classification trees give more accurate diagnoses, discriminatory models still dominate, and their number is nearly four times higher than the number of published logit models. Decision trees and neural networks are sporadically used in research into financial health risks.

3. Materials and Methods

The article verified 10 discriminant analysis models and 10 logistic regression models available in the national and international literature, based on the financial statements of 50 companies. The discriminant and logit models used in the article differ not only in the number of financial analysis indicators used but also in the period in which they were created, the number of entities that constituted the test group when estimating the parameters (often from a specific range of the value of assets or a specific sector) or the form of legal commercial company.

Due to the fact that early warning models should be used in the country of the establishment of a given enterprise, the sample included 19 models developed for the Polish economy and only one foreign model by E. Altman. The methods for the study were selected from a sample of several available methods in terms of their diagnostic reliability estimated by individual authors and their applicability for the industrial sector. The assumptions of the methods and indicators constituting the variables in the formulas have been described in scientific articles in accordance with the given bibliography.

The following discriminant functions were used:

1. Mączyńska, 1994 [39]

$$Z = 1.5 \cdot W_1 + 0.08 \cdot W_2 + 10.0 \cdot W_3 + 5.0 \cdot W_4 + 0.3 \cdot W_5 + 0.1 \cdot W_6 \tag{6}$$

W_1—(gross profit + amortization)/liabilities,
W_2—assets/liabilities,
W_3—gross profit/assets,
W_4—gross profit/revenues from sales,
W_5—inventory/revenues from sales, and
W_6—revenues from sales/assets.

2. Mączyńska and Zawadzki, 2006 [2]

$$Z = 9.478 \cdot W_1 + 3.613 \cdot W_2 + 3.246 \cdot W_3 + 0.455 \cdot W_4 + 0.802 \cdot W_5 - 2.478 \tag{7}$$

W_1—profit from operating activity/assets,
W_2—equity/assets,
W_3—(net profit + amortization)/liabilities,
W_4—current assets/short-term liabilities, and
W_5—revenues from sales/assets.

3. Hamrol, Czajka, and Piechocki, 2004 [14]

$$Z = 3.562 \cdot W_7 + 1.588 \cdot W_{16} + 4.288 \cdot W_5 + 6.719 \cdot W_{13} - 2.368 \tag{8}$$

W_7—net profit/assets,
W_{16}—(current assets − inventory)/short-term liabilities,
W_5—(equity + long-term liabilities)/assets, and
W_{13}—profit from sales/revenues from sales.

4. Hadasik, 1999 [44]

$$Z = -1.3301 \cdot W_5 + 0.04094 \cdot W_8 - 0.0038 \cdot W_{12} + 2.16525 \cdot W_{14} + 0.0235 \cdot W_{17} + 1.6238 \tag{9}$$

W_5—liabilities/assets,
W_8—equity/tangible fixed assets,
W_{12}—inventory × 365/revenues from sales,
W_{14}—net profit/assets, and
W_{17}—net profit/inventory.

5. Appenzeller, 2004 [85]

$$Z = 1.286 \cdot W_1 - 1.305 \cdot W_2 - 0.226 \cdot W_3 + 3.015 \cdot W_4 - 0.005 \cdot W_5 - 0.009 \cdot W_6 - 0.661 \quad (10)$$

W_1—current assets/short-term liabilities,
W_2—(current assets − inventory − short-term receivables)/short-term liabilities,
W_3—gross profit/revenues from sales,
W_4—net profit/average assets,
W_5—average inventory × number of days/revenues from sales, and
W_6—liabilities/EBITDA.

6. Maślanka, 2008 [86]

$$Z = -1.44979 + 3.55401 \cdot W_4 + 2.14847 \cdot W_6 - 0.33302 \cdot W_7 + 4.81862 \cdot W_{17} + 0.05236 \cdot W_{26} + 2.52164 \cdot W_{40} \quad (11)$$

W_4—equity/assets,
W_6—net working capital/assets,
W_7—(equity + long-term liabilities)/fixed assets,
W_{17}—profit from sales/assets,
W_{26}—revenues from sales/fixed assets, and
W_{40}—(profit from operating activity + amortization)/liabilities.

7. Prusak, 2004 [87]

$$Z = 6.9973 \cdot W_1 + 0.1191 \cdot W_2 + 0.1932 \cdot W_3 - 1.1760 \quad (12)$$

W_1—profit from sales/average assets,
W_2—operating costs/average short-term liabilities without special funds and short-term financial liabilities, and
W_3—current assets/short-term liabilities.

8. Korol, 2010 [88]

$$Zb = -1.97 + 2.35 \cdot W_1 - 2.90 \cdot W_5 - 2.68 \cdot W_8 + 0.79 \cdot W_9 \quad (13)$$

$$Zn = -3.49 + 9.93 \cdot W_1 - 0.05 \cdot W_5 - 0.62 \cdot W_8 + 1.19 \cdot W_9 \quad (14)$$

W_1—profit from sales/assets,
W_5—net working capital/assets,
W_8—(net profit + amortization)/liabilities, and
W_9—operating costs/short-term liabilities.

9. Waszkowski, 2011 [89]

$$Z = 0.327 \cdot W_1 + 3.276 \cdot W_2 + 0.402 \cdot W_3 - 0.001 \cdot W_4 + 0.002 \cdot W_5 - 1.989 \quad (15)$$

W_1—revenues from sales/liabilities,
W_2—fixed assets/assets,
W_3—(net profit + amortization)/liabilities,
W_4—revenues from sales/net working capital, and
W_5—net profit/revenues from sales.

10. Altman, 1983 [90]

$$Z = 0.717 \cdot W_1 + 0.847 \cdot W_2 + 3.107 \cdot W_3 + 0.420 \cdot W_4 + 0.998 \cdot W_5 \quad (16)$$

W_1—working capital/assets,
W_2—retained earnings/assets,
W_3—EBIT/assets,
W_4—book value equity/liabilities, and
W_5—revenues from sales/assets.

The following logit models were used:

1. Korol, 2010 [88]

$$Z = 2.0 - 10.19 \cdot W_1 - 4.58 \cdot W_2 - 0.57 \cdot W_3 \quad (17)$$

W_1—profit from sales/assets,
W_2—(net profit + amortization)/liabilities, and
W_3—operating costs/short-term liabilities.

2. Wędzki, 2005—model 1 [55]

$$Z = 1.0 - W_1 - 0.256 \cdot W_2 - 0.044 \cdot W_3 - 4.373 \cdot W_4 \quad (18)$$

W_1—current assets/short-term liabilities,
W_2—interest/(gross profit + interest),
W_3—profit from sales/assets, and
W_4—gross profit/profit from sales.

3. Wędzki, 2005—model 5 [55]

$$Z = 2.0 - 2.0 \cdot W_1 - 0.323 \cdot W_2 \quad (19)$$

W_1—current assets/short-term liabilities and
W_2—interest/(gross profit + interest).

4. Wędzki, 2005—model 7 [55]

$$Z = -4.0 - 6.0 \cdot W_1 + 9.37 \cdot W_2 - 2.088 \cdot W_3 + 1.317 \cdot W_4 + 0.04 \cdot W_5 - 4.217 \cdot W_6 \quad (20)$$

W_1—current assets/short-term liabilities,
W_2—liabilities/assets,
W_3—interest/(gross profit + interest),
W_4—leverage index,
W_5—short-term receivables $\times$ number of days/revenues from sales, and
W_6—profit from sales/revenues from sales.

5. Wędzki, 2005—model 8 [55]

$$Z = -4.0 - 4.0 \cdot W_1 + 11.441 \cdot W_2 - 2.0 \cdot W_3 \quad (21)$$

W_1—current assets/short-term liabilities,
W_2—liabilities/assets, and
W_3—interest/(gross profit + interest).

6. Gruszczyński, 2003—model 3 [54]

$$Z = 22.8748 \cdot W_1 - 5.5926 \cdot W_2 - 26.1083 \cdot W_3 + 4.3515 \quad (22)$$

W_1—gross profit/revenues from sales,
W_2—liabilities/assets, and
W_3—inventory/revenues from sales.

7. Gruszczyński, 2003—model 7 [54]

$$Z = 1.2458 \cdot W_1 + 13.1907 \cdot W_2 - 4.4523 \cdot W_3 \quad (23)$$

W_1—current assets/short-term liabilities,
W_2—profit from operating activity/assets, and
W_3—liabilities/assets.

8. Stępień and Strąk, 2004—model 1 [91]

$$Z = -19 - 11 \cdot W_1 + 6 \cdot W_2 + 40 \cdot W_3 + 19 \cdot W_4 \quad (24)$$

W_1—liabilities/assets,
W_2—(current assets − inventory)/short-term liabilities,
W_3—profit from sales/assets, and
W_4—revenues from sales/operating costs.

9. Stępień and Strąk, 2004—model 2 [91]

$$Z = 5.83 + 4.27 \cdot W_1 + 2.00 \cdot W_2 - 7.78 \cdot W_3 \quad (25)$$

W_1—gross profit/assets,
W_2—net working capital/assets, and
W_3—liabilities/assets.

10. Hołda, 2006 [18]

$$Z = 1.659 + 16.609 \cdot W_1 + 2.442 \cdot W_2 - 5.40 \cdot W_3 \quad (26)$$

W_1—profit from sales/operating costs,
W_2—current assets/short-term liabilities, and
W_3—liabilities/assets.

4. Results

In Tables 1 and 2, the results of correct indications of the risk of bankruptcy of companies are presented using the discriminatory and logit models presented in the methods chapter. The research sample consisted of 50 industrial processing companies in Poland. The financial data of the companies were taken from the EMIS database and were included in the sample on the basis of the highest asset value criterion.

Table 1. Values of discriminant functions one year before the bankruptcy of individual enterprises.

Company/Author	1	2	3	4	5	6	7	8	9	10
1	−2.53	−4.58	−5.26	−0.97	−1.05	−5.18	−3.70	4.90	1.26	3.48
2	−5.50	−4.79	−8.77	−4.78	−5.62	−3.94	−3.24	3.76	−1.26	−3.04
3	−6.84	−7.47	−7.22	−1.95	−1.81	−6.19	−4.88	5.95	−1.02	−3.28
4	−27.42	−16.20	−48.27	−4.37	−2.25	−14.69	−9.75	13.03	0.11	−12.19
5	−9.41	−8.81	−0.45	−1.82	−0.75	−3.67	−2.98	0.32	−0.03	2.07
6	−9.68	−9.01	−6.57	−2.03	−2.03	−5.04	−5.20	5.92	−0.96	−0.45
7	−117.47	−3.07	−1.10	−0.06	5.53	−21.22	−0.83	2.42	−1.69	−2.00
8	−248.00	−4.12	−1.34	−0.72	11.13	−7.75	−8.06	8.42	1.89	3.17
9	−0.62	1.12	−0.18	0.58	0.34	0.25	−1.12	0.91	0.70	3.78
10	−9.32	−6.16	−8.82	−7.88	−2.55	2.54	−5.62	5.92	−1.02	−0.51

Table 1. *Cont.*

Company/Author	1	2	3	4	5	6	7	8	9	10
11	−85.84	−93.26	−57.36	−23.66	−22.33	−45.78	−43.58	35.50	0.77	−39.94
12	−3.83	−4.59	−3.69	−0.80	−0.80	−3.21	−3.70	3.54	−1.08	0.46
13	−3.53	−3.95	4.63	−177.45	−1.16	−4.92	−5.51	6.43	−1.46	−3.47
14	−2.32	−4.58	−0.64	−0.92	−0.92	−4.26	−1.38	2.15	1.26	−1.47
15	−24.58	−64.90	−113.20	−175.59	−196.34	−16.03	−12.90	19.89	−1.90	−66.05
16	−9.53	−4.91	−5.66	−25.72	−0.71	−5.54	−2.18	4.46	1.20	−4.64
17	−16.38	−7.16	−14.99	−1.99	−1.70	−1.84	−4.56	4.48	−2.01	−0.97
18	−12.17	−10.34	−8.61	−1.22	−2.26	−6.88	−6.48	8.36	−0.32	0.32
19	−9.71	−5.83	−15.01	−1.73	−1.54	−5.46	−4.07	5.33	−0.79	−3.81
20	9.84	−12.57	5.79	−3.09	−1.55	−12.64	−5.06	7.03	−0.47	−10.90
21	−7.24	−10.72	−12.75	−3.48	−2.47	−15.87	−9.81	13.62	1.91	−6.23
22	−2.02	−82.79	−101.54	−30.10	−1.85	−111.12	−39.64	66.35	−0.63	−136.33
23	−13.81	−10.79	−29.54	−5.03	−3.68	−12.21	−6.35	9.23	−0.77	−12.85
24	−4.64	−58.12	−66.94	−20.16	−0.20	−19.37	−2.91	2.45	−1.54	−38.43
25	0.29	−0.58	1.08	0.17	−0.90	−0.67	−0.89	1.17	0.39	0.93
26	−2692.1	−10.41	−3212.4	−1.86	119.51	−8.67	−6.25	6.91	−3.16	−5.06
27	−6860.2	−138.86	−154.97	−39.85	284.24	752.25	−58.56	54.87	−4.83	−115.56
28	−46.80	−78.85	−70.70	−25.23	−14.14	1982.7	−52.56	66.41	−1.86	−62.49
29	−3.73	−4.14	−3.45	−9.99	−0.71	−4.06	−4.07	4.04	−0.28	1.39
30	−0.52	−0.54	−1.07	0.26	0.01	−1.26	−1.81	1.36	−0.20	2.17
31	−9.50	−13.35	−10.51	−3.85	−2.83	−3.99	−7.31	7.70	−1.81	−5.16
32	1.85	1.85	−2.17	−0.07	0.26	−2.42	−1.86	1.55	−1.22	3.45
33	−10.13	−10.63	−8.21	−3.12	−2.99	−9.76	−9.05	9.77	−0.34	1.03
34	−4.95	−3.94	−2.71	−0.38	−0.68	−2.76	−3.57	3.26	−0.53	3.57
35	−5.61	−5.78	−4.03	−1.01	−1.39	−2.05	−3.85	3.26	−1.06	1.30
36	−30.47	−7.16	−70.42	−9.64	−10.61	−6.69	−4.30	5.82	−0.55	−4.89
37	−1.46	−1.08	−0.91	0.23	−0.13	−1.09	−1.52	0.97	0.48	2.09
38	−0.37	0.33	−0.75	0.40	−0.06	−1.08	−1.38	0.86	0.64	2.60
39	−0.18	−1.87	−204.53	0.21	−0.57	−2.02	−1.37	2.73	0.74	−0.44
40	−19.45	−6.58	−18.82	−6.95	−5.95	−9.16	−5.64	8.62	−0.85	−8.62
41	−3.45	−1.96	−4.75	−0.90	−0.47	3.63	−2.64	2.84	−1.52	1.38
42	0.44	−0.96	−2.18	0.21	−0.50	−1.48	−1.87	1.52	−0.81	0.50
43	−2.38	−1.29	−0.35	0.83	−0.22	−2.08	−1.09	1.34	0.60	1.21
44	0.40	−1.50	0.37	−0.47	0.07	−1.55	−0.65	0.65	0.50	0.39
45	−5.40	−7.30	−10.42	−3.02	−1.95	−12.14	−5.35	9.55	0.40	−9.17
46	−4.96	−4.93	−8.98	−1.86	−1.77	−7.76	−4.25	7.47	0.07	−6.22
47	−7.17	−12.45	−14.64	−6.29	−2.57	−20.89	−6.96	12.10	0.21	−13.19
48	0.57	−0.29	1.25	0.62	0.67	−0.35	−1.07	0.68	−0.44	1.61
49	16.41	13.22	1.81	2.82	3.01	8.57	3.73	−14.49	3.35	11.50
50	0.68	2.47	3.99	0.88	2.66	1.78	−0.20	−1.16	0.71	3.97

Source: own study; explanation: the models are assigned in the table according to the numbering in Section 3.

Table 2. Values of logit models one year before the bankruptcy of individual enterprises.

Company/Author	1	2	3	4	5	6	7	8	9	10
1	1.27	7.34	10.58	−11.39	−7.86	−22.34	−7.46	−6.85	−2.36	−0.14
2	2.82	4.92	0.89	27.27	9.68	−107.10	−6.85	−15.70	−6.69	−11.13
3	5.40	1.82	1.06	14.26	13.76	−12.28	−10.98	−27.99	−11.25	−8.58
4	9.36	17.69	1.74	63.00	24.92	−101.59	−21.61	−66.10	−22.02	−25.94
5	1.93	0.82	−1.31	−7.63	3.03	−12.00	−11.87	−12.57	−6.00	−1.77
6	7.99	3.03	0.61	−25.25	5.21	−17.88	−11.11	−26.76	−5.35	−6.93
7	3.21	103.08	0.57	74.28	7.46	−540.35	−4.68	−32.41	−3.91	−98.25
8	16.41	215.99	−1.92	210.69	7.69	−1140.0	−5.16	−82.34	−4.76	−94.68
9	1.60	−0.10	−0.43	−2.46	−3.20	−4.62	−0.66	4.00	1.97	0.92
10	4.91	0.94	1.04	12.20	16.08	−9.83	−13.07	−29.21	−14.60	−8.20
11	23.30	10.59	1.98	64.10	76.37	−85.89	−126.36	−150.29	−93.90	−41.86
12	4.29	0.92	0.42	−7.63	5.43	−10.76	−7.48	−19.30	−4.33	−4.20
13	3.62	1.33	1.23	1241.4	1526.5	−753.52	−599.29	−1481.7	−1039.7	−722.36
14	1.65	1.69	1.83	5.79	12.51	−8.25	−7.61	−18.65	−6.59	−6.80
15	2.37	51.01	1.74	2387.0	203.72	−3238.5	−81.33	−218.58	−148.63	−112.92
16	2.54	9.30	3.47	10.68	23.12	−41.65	−7.33	−21.73	−8.69	−11.90
17	5.94	10.91	0.30	62.32	5.71	−80.32	−9.03	−30.84	−5.06	−12.93
18	11.94	3.72	0.57	13.07	2.44	−22.23	−12.11	−42.69	−3.92	−8.34
19	4.25	7.56	1.12	81.36	10.60	−58.60	−8.20	−32.35	−6.89	−15.21
20	4.01	−9.80	1.46	−57.73	31.42	41.64	−16.68	−80.42	−21.87	−50.36
21	10.14	1.10	1.66	20.21	25.93	−14.68	−20.28	−64.25	−22.34	−14.50
22	2.95	2.20	1.95	233.76	260.10	−131.24	−103.65	−261.40	−218.84	−127.89
23	3.82	11.93	1.57	37.69	28.04	−116.24	−14.63	−50.57	−21.05	−25.59
24	2.04	3.04	0.54	185.19	177.69	−100.40	−72.95	−160.76	−120.34	−84.40
25	1.25	0.12	0.23	2.06	0.80	−10.60	−2.12	−4.83	0.07	−0.10
26	6.90	2350.8	0.84	2773.5	15.47	−12.30	−13.57	−52.03	−10.43	−23.82
27	4.11	5936.8	1.90	2837.3	217.02	−31.15	−181.98	−230.28	−181.30	−119.24
28	45.48	2.37	1.85	115.93	139.60	−76.80	−113.99	−310.30	−115.16	−70.82
29	4.51	0.66	0.65	−5.50	6.17	−4.33	−8.39	−21.60	−4.88	−4.23
30	1.60	0.19	0.22	8.47	1.71	−5.42	−3.15	−8.83	−0.65	−0.98
31	8.07	2.82	0.86	17.29	21.46	−36.83	−18.50	−53.18	−17.24	−15.16
32	2.92	−0.82	−0.98	−0.08	−1.33	−13.92	−0.03	−16.38	0.79	−2.08
33	10.73	0.88	1.10	11.60	16.25	−10.56	−20.21	−58.60	−14.75	−9.64
34	5.81	0.47	−0.54	0.03	−1.86	−10.86	−5.78	−21.18	−0.25	−1.15
35	3.89	0.89	0.60	−7.19	5.92	−7.30	−9.81	−16.99	−5.30	−3.55
36	4.66	26.74	1.24	132.21	13.49	−301.57	−9.80	−40.97	−9.81	−22.68
37	0.86	0.46	0.49	8.56	2.05	−1.71	−3.88	−4.88	−0.95	−0.64
38	0.47	0.46	0.74	13.42	3.65	−3.75	−2.89	−7.38	−0.73	−0.93
39	2.75	1.08	1.45	171.13	6.56	−12.14	−3.51	−0.85	−1.66	−18.20
40	2.90	1.54	1.60	26.21	33.58	−21.73	−14.62	−38.00	−33.21	−15.86

Table 2. *Cont.*

Company/Author	1	2	3	4	5	6	7	8	9	10
41	4.21	0.49	−0.07	−1.02	6.24	−10.23	−7.67	−23.78	−5.01	−4.51
42	1.08	0.02	0.27	35.71	3.10	−13.03	−3.34	−10.24	−2.22	−1.65
43	1.70	0.64	0.26	58.83	3.80	−5.85	−5.34	−13.26	−2.60	−2.85
44	0.52	−0.21	−0.14	0.72	2.85	−6.98	−3.32	−1.97	−2.62	−1.05
45	6.05	1.96	1.70	20.34	25.17	−20.69	−16.85	−48.45	−19.78	−15.47
46	5.04	2.45	1.57	12.62	15.29	−22.54	−11.19	−33.89	−11.80	−11.63
47	7.06	1.28	1.74	40.37	49.79	−26.27	−28.89	−74.97	−38.80	−25.26
48	1.10	−0.41	−0.46	10.04	−0.79	−1.13	−1.52	−0.03	0.18	0.48
49	−23.74	−0.78	0.37	58.17	3.72	−0.08	14.94	40.61	2.77	0.29
50	−0.41	−2.35	−4.50	−15.74	−15.51	−6.24	3.20	8.85	5.06	8.62

Source: own study; explanation: the models are assigned in the table according to the numbering in Section 3.

The calculations presented in Table 3 show that the highest overall efficiency was presented by B. Prusak's model, 100%; a slightly lower discriminant and logit model by T. Korol, 96% and 98%; logit model 3 of M. Gruszczyński, 98% and model 7, 96%; model 1 of Stępień and Strąk, 94%; A. Hołda's model, 92%; and Mączyńska and Zawadzki's model, 90%. It is worth noting that these models were constructed by the authors in the years 2003–2010, i.e., several years ago. Thus, it can be argued that the models do not lose their prediction capabilities over time. The average effectiveness was demonstrated by the models D. Appenzeller—78%, E. Mączyńska—84%, M. Hamrol—86%, T. Maślanka—88%, D. Wędzki, from 78% to 88%, and Stępień and Strąk 2—88%. In turn, the lowest prognostic value was shown by Waszkowski's model, 62%, which was the youngest in the research sample; E. Altman's model with correct indications at the level of 70%; and D. Hadasik, 74%.

Table 3. Efficiency of individual models.

Discriminant Models/Author	1	2	3	4	5	6	7	8	9	10
Effectiveness according to the authors	no data	85%	96%	88%	85%	92%	98%	87%	89%	no data
Effectiveness according to the conducted study	84%	90%	86%	74%	78%	88%	100%	96%	62%	70%
Logit Models/Author	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Effectiveness according to the authors	93%	69%	69%	74%	78%	93%	97%	80%	84%	82%
Effectiveness according to the conducted study	98%	86%	82%	78%	88%	98%	96%	94%	88%	92%

Source: own study.

It should also be noted that the models were estimated on the basis of a certain group of companies from various industries and with a specific value of assets. Therefore, there may be a mismatch between the enterprise and the model, which makes it even more important to use several models to exclude such a possibility. When verifying the effectiveness of models, it is worth considering the reasons for the incorrect classification of a given enterprise. In the case of the sample in question, there may be a variety of reasons, for example:

- some models constructed several years ago, in different economic conditions than today, may have lost their quality, but these are isolated cases in a research sample;
- the examined enterprise does not correspond to the test sample made by the author of the model in terms of the industry, revenues, or assets;
- the model was developed on the basis of a learning sample of enterprises from another country;
- the bankruptcy of the enterprise does not result from growing, long-term financial problems, but is the result of a specific, unforeseen factor, e.g., loss of the only recipient of the products or services.

When analyzing the three companies to which the models reacted the least. i.e., companies 9, 49, and 50, it should be noted that

- company no. 9 recorded a net loss of approximately EUR 150,000 while the other financial ratios, not taking into account the net result, were at the optimal level. Moreover, the company depreciated fixed assets in the amount of approximately EUR 70,000, which meant that the ratios taking into account the net profit adjusted for depreciation had a lesser impact on the value of the function.
- company no. 49 lost liquidity due to two unprofitable investments. Moreover, the company's management board resigned, which started the company's problems.
- company no. 50 did not generate a net loss, but the costs of purchasing materials were very high. Operating expenses accounted for 98.5% of sales revenues, and activity became unprofitable.

5. Conclusions

The aim of the article was to verify the diagnostic reliability of selected discriminant and logit models, which are included in the early warning systems of the risk of enterprise bankruptcy. Moreover, the phenomenon of widespread use of foreign models was critically assessed, including in particular the Altman method in the study of the risk of bankruptcy of Polish enterprises. Foreign models without prior adaptation to domestic conditions are used not only in Polish economic practice but also by scientists, statutory auditors, and financial directors and managers in many countries. As it results from the review of the literature on the subject and the presented research, such an uncritical transfer of a foreign model with original assumptions does not bring reliable results. The same conclusions were made by E. Altman himself [92]. Altman's model verified on a research sample of Polish enterprises proved to be effective at the level of 70%, and it was one of the lowest values; therefore, hypothesis 2 (H2) was positively verified. Contradictory conclusions can be drawn especially from studies in which this method was incorrectly applied [70]. In this article, it was noted that the Altman model is not only used for research purposes in Poland. The model is used in practice, with numerous errors and simplifications, which is not methodologically correct.

On the basis of the obtained research results, it was also found that most of the models used in the article correctly indicated the risk of bankruptcy of enterprises, regardless of whether the model was developed a few or several years ago; thus, hypothesis 1 (H1) was positively verified. Due to the fact that some models accurately identified the risk of bankruptcy of all or almost all enterprises, e.g., the Prusak's, Korol's, Gruszczyński's model (3 and 7), and some of them incorrectly classified several surveyed enterprises, e.g., Waszkowski's model (19 out of 50). It is suggested to use as many discriminant and logit models as possible to assess the risk of bankruptcy, as well as other available methods of assessing the financial condition of the enterprise, e.g., risk scoring methods and traditional ratio analysis. For this reason, further research should be undertaken to verify the effectiveness of the prediction of the indicated methods.

When analyzing the models that were used to assess the financial situation of companies, it was determined that the selection of indicators that make up a given function is very important, e.g., the results of D. Hadasik's method depend in particular on changes in the level of inventories and receivables in a given year. Other authors, however, pay a lot of attention to indicators based on the operating result or the result of sales, assigning them sufficient significance. The weight of individual indicators is also important, e.g., an increase in the balance sheet total, which will cause a decrease in the overall debt ratio, while at the same time the high importance of this indicator means that the value of the discriminant function increases, in spite of the remaining indicators responding in the direction determined by other functions, i.e., reducing the value of the discriminant function. The mathematical sign applied to the indicator's weight is also important. In the case of the functions of D. Appenzeller and K. Szarzec, the subtraction of the "debt/EBITDA" ratio is justified, because the greater the debt, the worse the financial condition of the enterprise. On the other hand, in the case of an operating loss that cannot be covered by depreciation, the ratio is also negative. When performing mathematical calculations, it turns out that a significant operating loss increases the value of the discriminant function, and consequently, it can be concluded that the company's situation is improving [93].

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