14th International Scientific Conference "Business and Management 2024"
May 16–17, 2024, Vilnius, Lithuania

NEW TRENDS IN CONTEMPORARY ECONOMICS, BUSINESS AND MANAGEMENT

ISSN 2029-4441 / eISSN 2029-929X
eISBN 978-609-476-363-2
Article Number: bm.2024.1302
https://doi.org/10.3846/bm.2024.1302



# THE ACTUAL PREDICTIVE POWER OF BANKRUPTCY MODELS IN TERMS OF TIME USE

Michal KUBĚNKA*, Irena HONKOVÁ, František SEJKORA, Martin MLÁZOVSKÝ

*Institute of Economy and Management, Faculty of Economics and Administration, University of Pardubice, Studentská 84, 532 10 Pardubice, Czech Republic*

Received 29 February 2024; accepted 14 April 2024

**Abstract.** The quality of bankruptcy models is habitually based on how well they can predict the financial health of a business a year in advance. However, corporate accounting data is publicly available usually with one year delay. So, the research question is not how accurate the prediction is one year in advance, but two years in advance. Therefore, an analysis of 7 models was performed to compare the change in their accuracy depending on time. The results showed a decline in prediction accuracy over time. The found total success rate of prediction is from 67.38% to 80.64%, which confirms that some of these models are also usable for two-year prediction of the financial health of the company.

**Keywords:** bankruptcy model, financial distress, accuracy of prediction, accounting data, time factor.

**JEL Classification:** G32, G33, C52, C53, C58.

## 1. Introduction and literature background

There has always been an effort to estimate the imminent bankruptcy of the company. Such information can be of great benefit and allows management to take preventive measures in time and business partners to consider co-operation with a risky partner. The reason is that in the field of business, ignorance and unpreparedness can lead to the end of a successful business.

Therefore, models for predicting financial distress have been developing since the first half of the 20th century. Of course, this has to do with the widespread use of accounting as a basic source of information for bankruptcy models. However, they only came to the attention of the professional public thanks to Beaver (1966) and especially Altman (1968), who created his world-famous bankruptcy prediction model called Z score and thus popularized the issue of bankruptcy models.

Various methods for creating models were gradually tried. Beaver and Altman used multiple discriminant analysis method. Next followed, for example, logit analysis, which was first used by Ohlson (1980), later, for example, by Platt et al. (1994) or Wang (2004). Probit analysis applied by Hanweck (1977) or Zmijewski (1984) or Lennox (1999) was also tested more or less simultaneously. A number of other methods followed, some of which were able to increase the predictive power of the bankruptcy model.

Among the newest tested methods are artificial neural networks, for example models of Tam and Kiang (1992). According to the findings of the authors Chih-Fondg and Chihli (2014) or Kim and Park (2012), this method can create prediction models that are several percent more accurate than older methods. The problem, however, is that the algorithm of these models is unknown, respectively its form is purely electronic and therefore such models are difficult to disseminate and verifiable by the professional public.

Regionally broad universal models are also created, for example for the whole of Europe, Asia, South America and others, for example models by the authors of Alaminos et al. (2016); Eling and Jia (2018); Jones (2017); Jones and Wang (2019).

Most authors of bankruptcy models have concluded that a model achieves greater accuracy if it is created for a specific region. And not only specific market conditions play a role. Kuběnka and Myšková (2022) claim that different accounting systems in different countries affect the structure of financial data as well

* Corresponding author. E-mail: michal.kubenka@upce.cz

as the value of accounting items (also Charalambous et al., 2020; Jabeur, 2017; Mousavi et al., 2019). This is also confirmed by other authors (Honková & Výbora, 2015), who claim that accounting systems operate on the basis different rules that are established in the legislation of the given country. That is why accounting systems in different countries show certain differences (Honková, 2015).

Regional models, respectively models focused on a specific state, are the majority. Therefore, this study will also focus on testing the accuracy of regional models, specifically models created in the Czech Republic or Slovak Republic because the economy and accounting systems are very close to each other. The authors base this on the fact that the accuracy of the models is reported for their ability to predict bankruptcy 1 year in advance. In fact, the information needed to apply the model is usually available only in the third or fourth quarter after the end of the financial year of the tested company. Therefore, reporting model accuracy on an annual basis is inappropriate.

From the point of view of applicability, it is therefore advisable to follow the accuracy of the model on a two-year basis. Evaluating the accuracy of the model on a two-year basis has not yet been a subject of interest for experts, yet some of the authors of the models analyzed the prediction power in a period of several years before bankruptcy. Usually, they found that as the number of years preceding bankruptcy increases, the accuracy of the model decreases (see e.g., Jabeur, 2017; Karas & Režňáková, 2014; Zhang et al., 2010).

However, even these analysts, when creating their models, constructed the model in such a way as to maximize the accuracy of the prediction for 1 year ahead and not for 2 years ahead. This ensured the maximum accuracy of the model, but unfortunately with a time usage of several months. The authors assume that analysts in the Czech Republic are not the only ones with a similar problem with the time availability of models.

The aim of this analysis was to identify which of the latest Czech od Slovak models is the most precise in bankrupt prediction in a 2-year time horizon.

## 2. Data, methodology, and models

### 2.1. Data

The authors used 7 of the latest publicly available models, which have been created in the Czech Republic or Slovakia.

Selected bankruptcy models were tested on a sample of 823 financially stable enterprises (did not show signs of financial problems at time t + 2), the structure of this sample is in Table 1 and 138 bankrupt enterprises (went bankrupt at time t + 2), the structure of this sample is in Table 2. So, a total of 961 enterprises operating in the Czech Republic in the processing industry. Therefore their 2016–2019 financial statements were used. These enterprises were in 2019 either bankrupt or financially stable. Data were gathered from the Bisnode's MagnusWeb (2024) database.

Table 1. Sample structure of non-bankrupt companies (2-years horizon) (source: own data processing from Bisnode's MagnusWeb, 2024)

| | Min | Average | Median | Max |
|---|---|---|---|---|
| Assets | 111 090 | 1 059 148 | 571 843 | 16 440 868 |
| Equity | 9578 | 537 918 | 267 753 | 7 168 654 |
| Sales | 224 907 | 1 354 973 | 738 270 | 15 810 200 |
| ROE | –31.75% | 29.71% | 24.77% | 190.72% |
| ROA | –10.92% | 8.53% | 6.70% | 53.36% |
| Liquidity L3 | 0.47 | 2.08 | 1.51 | 16.03 |
| Asset turnover | 0.46 | 1.58 | 1.40 | 5.14 |
| Total indebtedness | 10.03% | 51.07% | 51.12% | 95.73% |

Table 2. Sample structure of bankrupt companies (2-years horizon) (source: own data processing from Bisnode's MagnusWeb, 2024)

| | Min | Average | Median | Max |
|---|---|---|---|---|
| Assets | 308 | 90 173 | 25 100 | 1 268 545 |
| Equity | –1 148 908 | –8 788 | 648 | 105 183 |
| Sales | –17 184 | 83 562 | 32 544 | 828 307 |
| ROE | –163.64 | 63.30% | 22.68% | 244.23% |
| ROA | –50.91% | –6.77% | 1.10% | 18.07% |
| Liquidity L3 | 0.01 | 0.91 | 0.77 | 2.13 |
| Asset turnover | 0.00 | 1.62 | 1.27 | 11.73 |
| Total indebtedness | 37.64% | 119.38% | 94.12% | 257.75% |

### 2.2. Methodology

The predictive power of the models will be evaluated using the standard methodology used for example in Huijuan (2015) or Berzkalne and Zelgalve (2013).

The model indicates an enterprise as bankrupt or non-bankrupt in a 1-year or more time horizon. For us, it is crucial to monitor which models have the greatest accuracy not only over a 1-year, but also over a 2-year time horizon. From this point of view (Table 3), four combinations of the successfulness of prediction can occur. The Table 3 presents them.

Table 3. Method of prediction power evaluation (source: own processing)

| | | Prediction | |
|---|---|---|---|
| | | Bankrupt | Non-bankrupt |
| Fact | Bankrupt | TRUE I. | ERROR I. |
| | Non-bankrupt | ERROR II. | TRUE II. |

Accuracy of prediction could be consequently evaluated separately in two areas. As success rate of bankruptcy prediction for the financially unstable (bankrupt) enterprises, we can express the accuracy as follows.

$$\text{Success Rate of Bankruptcy } (SRB) = \frac{\text{TRUE I.}}{\text{TRUE I.} + \text{ERROR I.}}. \quad (1)$$

As success rate of non-bankruptcy prediction for the financially stable enterprises, we can express it as follows:

$$\text{Success Rate of Non-bankruptcy } (SRN) = \frac{\text{TRUE II.}}{\text{ERROR II.} + \text{TRUE II.}}. \quad (2)$$

So, the total success rate (*TSR*) of a concrete model can be calculated as an arithmetical average of *SRB* and *SRN* as follows.

$$\text{Total Success Rate } (TSR) = \frac{\text{SRB} + \text{SRN}}{2}. \quad (3)$$

Comparison of the 2-years and 1-years accuracy of SRB and SRN will be performed with taking into account a possible error in relation to the sample size. For this purpose, confidence intervals of the 2-year determined values of SRB and SRN will be also calculated. According to Kuběnka (2018), the confidence interval can be calculated as follows:

$$P\left(p - z_{1-\frac{\propto}{2}} * \sqrt{\frac{p(1-p)}{n}} < \pi < p + z_{1-\frac{\propto}{2}} * \sqrt{\frac{p(1-p)}{n}}\right) = 1 - \alpha, \quad (4)$$

where: $p$ – determined 2-year *SRB* or *SRN* of a model; $n$ – size of the base (size of the tested sample); $\alpha$ – etermined at the level of 5%, $z_{1-\frac{\propto}{2}}$ – is the quantile of normal distribution.

## 2.3. Models

The authors set themselves the goal of testing the predictive power of 7 Czech or Slovak bankruptcy models on a sample of Czech businesses. These models will then be evaluated according to their ability to predict bankruptcy 1 year and especially 2 years before this negative event.

**$P_j$ model**

Kuchina created $P_j$ model in 2013 using logit regression using data from 94 bankrupt businesses and 94 financially healthy businesses. According to Kuchina (2013), the model contains four share indicators and is defined by the following equation:

$$P_j = \frac{1}{1 + e^{-(2.337 - 7.958X_1 - 0.568X_2 - 6.744X_3 + 0.521X_4)}}, \quad (5)$$

where: $X_1$ – EBIT / total assets; $X_2$ – revenues / total assets; $X_3$ – retained earnings / total assets; $X_4$ – net working capital / liabilities.

According to the author, the overall prediction success rate of the model is 89.7% one year before bankruptcy and 75.8% two years before bankruptcy.

**Ycz model**

Model was created in 2018 by team consists of Klieštik, Vrbka and Rowland. They named the model as the model Ycz. The authors applied a multiple discriminant analysis when creating the work. They analysed a total of 62,794 Czech enterprises, of which 50,058 were financially stable and 12,736 were insolvent. These companies come from different branches (in the fields of commerce, production and services). The model created uses 10 variables. The authors note that the total accuracy of the model is 84.8%. The model is formulated in this equation (Klieštik et al., 2018):

$$Y_{cz} = -1.016 + 0.007\,Y_2 - 0.884\,Y_4 + 2.168\,Y_7 - 0.343\,Y_8 + 2.526\,Y_{10} + 0.416\,Y_{12} - 0.592\,Y_{21} - 2.561\,Y_{27} + 0.352\,Y_{28} - 1.075\,Y_{35}, \quad (6)$$

where: $Y_2$ – current assets / current liabilities; $Y_4$ – net income / equity; $Y_7$ – earnings after taxes / total assets; $Y_8$ – working capital / total assets; $Y_{10}$ – liabilities / total assets; $Y_{12}$ – cash & cash equivalents / total assets; $Y_{21}$ – non-current liabilities / total assets; $Y_{27}$ – EBIT / total assets; $Y_{28}$ – EAT / equity; $Y_{35}$ – EBIT / sales.

**V4 model**

The same authors created another model usable for V4, which was based on the data of tens of thousands of enterprises from the states in the V4 grouping, i.e., Slovakia, Hungary, Poland and the Czech Republic. It is therefore a universal, or a more widely usable model than the $Y_{cz}$ model. According to (Klieštik et al., 2018), the V4 model equation is this:

$$\text{V4} = -1.470 + 0.024Y_2 - 0.589Y_4 - 1.158Y_7 + 1.870Y_{10} - 0.452Y_{11} + 0.613Y_{12} + 1.030Y_{15} - 0.012Y_{22} + 0.731Y_{27} + 0.173Y_{28} - 0.475Y_{35} + 0.244CZ + 0.522SK, \quad (7)$$

where: $Y_{11}$ – current assets / total assets; $Y_{15}$ – current liabilities / total assets; $Y_{22}$ – cash / current liabilities; $CZ = 1$, $SK = 0$.

The authors report an overall V4 model prediction accuracy of 85.7%.

**Model 1**

The Model 1 was created by Slavíček and Kuběnka (2016). They used only 33 companies to create the model, 11 of them were bankrupt. This is unequivocally the smallest sample of the evaluated models, nevertheless, the model is among the most accurate, as will be seen later. Logistic regression was used to create. The model operates on 4 variables. According to the authors, the accuracy of bankruptcy predictions was 91% and the accuracy of non-bankruptcy predictions 95%.

$$\text{Model 1} = 0.0173\,V_1 - 4.7107\,V_2 + 0.0412\,V_3 + 0.0918\,V_4 - 7.5378, \quad (8)$$

where: $V_1$ – inventories / (sales / 360); $V_2$ – financial property / current liabilities; $V_3$ – operating profit / total assets × 100; $V_4$ – (liabilities / total assets) × 100.

**Pav model**

In 2015, Pavlík created a model for one-year prediction. The authors did not set the name, we will call it the Model $P_{av}$. The author specifies the total accuracy of the model as 83.97%. The author used the logistic regression for the creation of the model. 2,061 enterprises were tested for the model construction within the period from 2005 to 2013. The model works with six variables.

The equation of the model according to Pavlík (2015) is:

$$\text{Model } P_{av} = \frac{1}{1+e^{-(0.0068-0.5160R3-0.0559R9+0.6346R14-3.8307R17-1.1347R19-0.0016R29)}}, \quad (9)$$

where: $R_3$ – current assets / current liabilities; $R_9$ – total assets / equity; $R_{14}$ – foreign resources / total assets; $R_{17}$ – cash flow / external sources; $R_{19}$ – equity / liabilities; $R_{29}$ – financial assets x 360 / sales.

**Model DA**

In 2016, the authors Durica and Adamko created a bankruptcy model based on a multiple discriminant analysis of financial data of almost 110,000 companies. The authors did not set the name, we will call it the Model DA. The model works with five indicators, and its equation, according to the authors (Durica & Adamko, 2016), has the following form:

$$\text{Model DA} = 0.250X_1 + 0.510X_2 - 0.207X_3 + 0.282X_4 + 0.618X_5, \quad (10)$$

where: $X_1$ – current assets / current liabilities; $X_2$ – EBIT / total assets; $X_3$ – short-term debts / sales; $X_4$ – working capital / total assets; $X_5$ – equity / total debts.

The authors report that the model has an overall reliability of 82.2%.

**P' model**

Delina and Packová created the P' model using regression analysis in 2013. Data from 1,560 companies in the different fields of business, production and services were used to create this model. 1,457 enterprises were financially healthy, and 103 went bankrupt. The model contains six variables.

According to Delina and Packová (2013) the model is formulated in this equation:

$$P' \text{ model} = 2.86 - 0.0001278\,X_1 + 0.04851\,A_2 + 0.2136\,A_3 - 0.000071\,A_4 + 0.0001068\,B_1 - 0.0006116\,B_4, \quad (11)$$

where: $X_1$ – (fina000000ncial assets – short-term liabilities) / (operating expenses – depreciations); $A_2$ – retained earnings / total assets; $A_3$ – EBIT / total assets; $A_4$ – registered capital / liabilities; $B_1$ – cash flow / total liabilities; $B_4$ – EBT / operating revenues.

According to Kuběnka, et al. (2021), the model has an overall reliability of 76.52%.

## 3. Research results

The results of the tested models showed that the accuracy of the models is different depending on the length of the prediction. The accuracy of the models for estimating the financial situation one year before bankruptcy (t-1) is higher than 2 years before bankruptcy (t-2) both for non-bankrupt companies and for companies headed for bankruptcy (see Table 4). This was proven in all tested models. But the difference between the models was how accurate they are at time t-1 and how much their predictive power drops at time t-2.

Table 4. Determined accuracy for the correct prediction of non-bankrupt and bankrupt companies (source: own processing)

| Model | Classification of companies | | | | | |
|---|---|---|---|---|---|---|
| | non-bankrupt | | | bankrupt | | |
| | error II. | true II. | SRN | error I. | true I. | SRB |
| Model $P_j$ (t–2) | 356 | 467 | 56.74% | 20 | 118 | 85.51% |
| Model $P_j$ (t–1) | 354 | 469 | 56.99% | 7 | 131 | 94.93% |
| Model Ycz (t–2) | 257 | 566 | 68.77% | 13 | 125 | 90.58% |
| Model Ycz (t–1) | 251 | 572 | 69.50% | 5 | 133 | 96.38% |
| V4 Model (t–2) | 330 | 493 | 59.90% | 13 | 125 | 90.58% |
| V4 Model (t–1) | 326 | 497 | 60.39% | 5 | 133 | 96.38% |
| Model 1 (t–2) | 92 | 731 | 88.82% | 38 | 100 | 72.46% |
| Model 1 (t–1) | 87 | 736 | 89.43% | 17 | 121 | 87.68% |
| Model $P_{av}$ (t–2) | 18 | 805 | 97.81% | 87 | 51 | 36.96% |
| Model $P_{av}$ (t–1) | 13 | 810 | 98.42% | 51 | 87 | 63.04% |
| Model DA (t–2) | 6 | 817 | 99.27% | 89 | 49 | 35.51% |
| Model DA (t–1) | 3 | 820 | 99.64% | 54 | 84 | 60.87% |
| P´ Model (t–2) | 92 | 731 | 88.82% | 70 | 68 | 49.28% |
| P´ Model (t–1) | 91 | 732 | 88.94% | 34 | 104 | 75.36% |

*Note:* SRN – success rate of non-bankruptcy prediction, SRB – success rate of bankruptcy prediction.

In Table 5 is stated total success rate of tested models. The confidence intervals of TSR (t-2) were also calculated so that the sizes of the tested samples were taken into consideration in the results. No con-formity with the value of TSR (t-1) was found within these confidence intervals either.

Table 5. Total success rate of prediction (source: own processing)

| Models | TSR | TSR confidence interval |
|---|---|---|
| Model Pj (t–2) | 71.13% | (68.26%; 73.99%) |
| Model Pj (t–1) | 75.96% | x |
| Model Ycz (t–2) | 79.68% | (77.13%; 82.22%) |
| Model Ycz (t–1) | 82.94% | x |
| V4 Model (t–2) | 75.24% | (72.51%; 77.97%) |
| V4 Model (t–1) | 78.38% | x |
| Model 1 (t–2) | 80.64% | (78.14%; 83.14%) |
| Model 1 (t–1) | 88.56% | x |
| Model $P_{av}$ (t–2) | 67.38% | (64.42%; 70.35%) |
| Model $P_{av}$ (t–1) | 80.73% | x |
| Model DA (t–2) | 67.39% | (64.43%; 70.35%) |
| Model DA (t–1) | 80.25% | x |
| P´ Model (t–2) | 69.05% | (66.13%; 71.97%) |
| P´ Model (t–1) | 82.15% | x |

*Note:* TSR – total success rate of prediction.

For the tested models, the greatest decrease in accuracy between prediction t–1 and t–2 occurred in the case of Model Pav (80.73% vs. 67.38%), Model DA (80.25% vs. 67.39%) and P' Model (82.15% vs. 69.05 %). The highest prediction ability of t–1 and t–2 is achieved by Model Ycz (82.94% vs. 79.68%) and Model 1 (88.56% vs. 80.64%). Model Ycz shows a lower year-on-year decrease in accuracy (by 3.26%) compared to the decrease in accuracy in Model 1 (by 7.92%), but both TSR values at time t–1 and time t–2 are higher. Model 1 became the most suitable model for predicting financial stability and for predicting the bankruptcy of a company for a year and 2 years ahead.

## 4. Conclusions

The aim of the research was to analyse a group of bankruptcy models with the aim of determining their current ability to predict bankruptcy or financial stability 1 year and 2 years in advance. Their overall predictive power was assessed with an effort to find a model that would show high predictive quality in both years. It was found that the predictive power of some models decreased year-on-year by up to 13%, for example in the case of Model $P_{av}$, Model DA and P' model. The V4 model (decrease 3.14%) and Model $Y_{cz}$ (decrease 3.26%) showed the smallest year-on-year decrease in accuracy. In all cases, the year-on-year decrease was confirmed with statistical significance using an interval of confidence calculation. However, more important than the value of year-on-year decrease in model accuracy are the absolute values of TSR one year in advance and, given the time availability of bankruptcy model predictions, especially the accuracy of 2 years in advance.

Model 1 (TSR 88.56%) turned out to be the most accurate for predicting 1 year in advance. As the most accurate for prediction 2 years in advance, it turned out to be the same as Model 1 with an TSR accuracy of 80.64%. This model can be recommended as the most suitable for predicting the bankruptcy of Czech companies in a time horizon of 1 to 2 years.

## Funding

This paper was supported by the Student Grant Competition SGS_2024_012 of the University of Pardubice in 2024.

## Contribution

Authors are welcome to declare any involvement in writing a manuscript (e.g. conception and design of the work, acquisition of data, or analysis and interpretation of data, drafting the article or revising it critically for important intellectual content, etc.).

## Disclosure statement

The authors declare no competing financial, professional, or personal interests from other parties.

## References

Alaminos D., del Castillo A., & Fernández M. A. (2016). A global model for bankruptcy prediction. *Plos One*, *13*(11), Article e0166693. https://doi.org/10.1371/journal.pone.0166693

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, *4*(1), 71–111. https://doi.org/10.2307/2490171

Berzkalne, I., & Zelgalve, E. (2013). Bankruptcy prediction models: A comparative study of the Baltic listed companies. *Journal of Business Management*, *7*, 72–82.

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2020). Predicting corporate bankruptcy using the framework of Leland-Toft: Evidence from US. *Quantitative Finance*, *20*(2), 329–346. https://doi.org/10.1080/14697688.2019.1667519

Chih-Fondg, T., & Chihli, H. (2014). Modeling credit scoring using neural network ensembles. *Kybernetes*, *43*(7), 1114–1123. https://doi.org/10.1108/K-01-2014-0016

Delina, R., & Packová, M. (2013). Prediction bankruptcy models validation in Slovak business environment. *E&M Economics and Management*, *16*(3), 101–112.

Durica, M., & Adamko, P. (2016, September 8–10). Verification of MDA bankruptcy prediction models for enterprises in Slovak Republic. In *The 10th International Days of Statistics and Economics*. Prague. https://msed.vse.cz/msed_2016/article/253-Durica-Marek-paper.pdf

Eling, M., & Jia, R. (2018). Business failure, efficiency, and volatility: Evidence from the European insurance industry. *International Review of Financial Analysis*, 59, 58–76. https://doi.org/10.1016/j.irfa.2018.07.007

Hanweck, G. A. (1977). *Predicting bank failure* (Research Paper in Banking and Financial Economics No. 19). Board of Governors of the Federal Reserve System.

Honková, I. & Výbora, J. (2015, June 18–19). The financial results of the company depending on accounting methods (comparison CAS and IAS/IFRS). In *European Financial Systems 2015: Proceedings of the 12th International Scientific Conference*. Brno, Czech Republic. Masaryk University.

Honková, I. (2015) International financial reporting standards applied in the Czech Republic. *E+M Ekonomie a Management*, *18*(3), 84–90. https://doi.org/10.15240/tul/001/2015-3-008

Huijuan, L. (2015). Default prediction model for SME's: Evidence from UK market using financial ratios. *International Journal of Business and Management*, *10*(2), 81–106. https://doi.org/10.5539/ijbm.v10n2p81

Jabeur, S. B. (2017). Bankruptcy prediction using partial least squares logistic regression. *Journal of Retailing and Consumer Services*, *36*, 197–202. https://doi.org/10.1016/j.jretconser.2017.02.005

Jones, S. (2017). Corporate bankruptcy prediction: A high dimensional analysis. *Review of Accounting Studies*, *22*(3), 1366–1422. https://doi.org/10.1007/s11142-017-9407-1

Jones, S., & Wang, T. (2019). Predicting private company failure: A multi-class analysis. *Journal of International Financial Markets*, *Institutions and Money*, *61*, 161–188. https://doi.org/10.1016/j.intfin.2019.03.004

Karas, M., & Režňáková, M. (2014, February 4–5). Possibilities for the application of a bankruptcy prediction model for measuring credit risk of a company. In *Proceedings of Hradec economic days* (pp. 435–442). Hradec Králové, Czech Republic. University of Hradec Kárlové.

Kim, Y. S., & Park, H. I. (2012). Committee neural network for estimating preconsolidation pressure from piezocone test reset. *Engineering Computations*, *29*(8), 842–855. https://doi.org/10.1108/02644401211271618

Klieštik, T., Vrbka, J., & Rowland, Z. (2018). Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis. *Equilibrium*. *Quartely Journal of Economics and Economic Policy*, *13*(3), 569–593. https://doi.org/10.24136/eq.2018.028

Kuběnka, M. (2018). Improvement of prosperity prediction in Czech manufacturing industries. *Engineering Economics*, *29*(5), 516–525. https://doi.org/10.5755/j01.ee.29.5.18231

Kuběnka, M., Čapek, J., & Sejkora, F. (2021). A new look at bankruptcy models. *E+M Ekonomie a Management*, *24*(3), 167–185. https://doi.org/10.15240/tul/001/2021-3-010

Kuběnka, M., & Myšková, R. (2022). Implementation of standards into predictors of financial stability. *Economic Research-Ekonomska Istrazivanja*, *35*(1), 6884–6900. https://doi.org/10.1080/1331677X.2022.2053785

Kuchina, E. (2013). *Models of analysis and forecasting of the insolvency of Czech companies* [thesis, Prague University of Economics and Business].

Lennox, C. (1999). Identifying failing companies: A re-evaluation of the logit, probit and DA approaches. *Journal of Economics and Business*, *51*(4), 347–364. https://doi.org/10.1016/S0148-6195(99)00009-0

MagnusWeb. (2024). *MagnusWeb dun & bradstreet* (Database). https://magnusweb.bisnode.cz/udss/htm/index.html

Mousavi, M. M., Ouenniche, J., & Tone, K. (2019). A comparative analysis of two-stage distress prediction models. *Expert Systems with Applications*, *119*, 322–341. https://doi.org/10.1016/j.eswa.2018.10.053

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(11), 109–131. https://doi.org/10.2307/2490395

Pavlík, M. (2015). *Predictive models of insolvency risk for the corporations*. [Thesis, Masaryk University]. https://is.muni.cz/th/n49at/DP_Michal_Pav lik.pdf

Platt, H. D., Platt, M. B., & Pedersen, J. G. (1994). Bankruptcy discrimination with real variables. *Journal of Business Finance and Accounting*, *21*(4), 491–509. https://doi.org/10.1111/j.1468-5957.1994.tb00332.x

Slavíček, O., & Kuběnka, M. (2016, September 5–6). Bankruptcy prediction models based on the logistic regression for companies in the Czech Republic. In *Proceedings of the 8th International Scientific Conference on Managing and Modelling of Financial Risks* (pp. 924–931). Ostrava. https://www.ekf.vsb.cz/share/static/ekf/www.ekf.vsb.cz/export/sites/ekf/mmfr-history/cs/2018/sbornik/Soubory/Part_IIIB.pdf

Tam, K., & Kiang, M. (1992). Managerial applications of neural networks: The case of bank failure prediction. *Management Science*, *38*(7), 926–947. https://doi.org/10.1287/mnsc.38.7.926

Wang, B. (2004). *Strategy changes and internet firm survival.* [Doctoral dissertation, University of Minnesota].

Zhang, L., Altman, E. I., & Yen, J. (2010). Corporate financial distress diagnosis model and application in credit rating for listing firms in China. *Frontiers of Computer Science in China*, *4*(2), 220–236. https://doi.org/10.1007/s11704-010-0505-5

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, *22*, 59–82. https://doi.org/10.2307/2490859