# Bankruptcy Prediction Models in Prešov Region of the Slovak Republic

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**Abstract.** The current business environment, not only in the Slovak Republic, is characterized by the very frequent existence of crises of business entities. It is no different even during the pandemic, which was characterized by various measures or restrictions affecting the smooth running of companies.
If the company can adapt to the constant changes in the market and thus survive, it needs to know in which financial condition it is and what is its perspective in the market. Companies can use financial analysis, which monitors not only the company's management in the past period, but also with a view to the future. As a result, financial analysis becomes a strategic tool for company management and, with the help of indicators, represents a quantitative expression of the company's financial status. To predict the future state of the company, it performs an ex-ante analysis that uses several methods, among which we include prediction models, especially creditworthiness and bankruptcy models or models based on artificial intelligence.
The contribution is focused on predictive bankruptcy models with the aim of pointing out the financial situation and prosperity of businesses in the Prešov region carrying out their entrepreneurial activity according to SK NACE 56300 – hospitality services during the Corona virus pandemic. Emphasis is placed on the informative value of selected models applied to a selected sample of 204 companies operating in 13 districts of the Prešov Region of the Slovak Republic.

**Keywords:** Bankruptcy Prediction models, Altman model, Taffler model, Bonita Index

**JEL classification:** *C38, G33, M41*

# 1 Literary researcher

The origins of prediction models date back to the 1930s, when studies using ratios to predict future bankruptcy began to develop. One of the earliest works in this vein was P. J. Fitzpatrick's paper on identifying significant differences between successful and unsuccessful industrial businesses. This work inspired several papers into the mid-1960s. [1]

All studies up to the mid-1960s focused only on single-factor analysis. Generally, the most widespread and most widely accepted is the single-factor study by Beaver. In the study, the author used financial ratios for the first time to predict the failure of business entities. Beaver proved [2] that financial ratio can be successfully used in predicting the difficulties of business entities. He also pointed out that not all ratios have the same predictive ability. However, the use of only selected simple ratio ratios as predictors of failure has been widely questioned in practice because these can be significantly biased by managerial decisions and thus provide a distorted view of the future of the business entity. To remedy the above problem, Beaver proposed the use of the so-called dichotomous classification test. Using this method, multiple indicators with the highest predictive ability are selected and ultimately used as a single predictor with multiple degrees of freedom. [2]

It was Altman who introduced one of the multivariate methods, namely multivariate discriminant analysis, based on the ideas of Fisher (1936). Using this analysis, firms can be divided into two groups, bankrupt and non-bankrupt, based on a linear combination of characteristics that best differentiates the two groups.

Depending on how many and what factors and methods are used in the calculation of a given model to consider, there is a wide range of prediction models. Altman's (1968) model uses a 5-factor discriminant analysis, while Boritz and Kennedy's (1955) model use 14 factors. The range of factors used in the models is from one factor to 57 factors. Altman's Z-score is one of the most widely used models, and this is because its predictive accuracy is high, up to 95% one year ahead. The accuracy of the model dropped to only 72% and 49% accuracy two and five years prior to the company's bankruptcy, respectively, and 29% accuracy three and five years prior to the bankruptcy. [3]

Altman simultaneously with the development of the methodology of prediction models also investigated its reliability or error rate. He divided the erroneous assessments into two types. Error $\alpha$ - Error type I, in which non-prosperous firms are classified as prosperous, and Error $\beta$ - Error type II, in which prosperous firms are classified as non-prosperous. [3]

Thus, Altman could be termed as the father of prediction models because after his studies and research, there were further developments and not only USA but also globally. Many other researchers have applied similar methods such as Deakin (1972), Springate (1978), Marais (1979), Taffler (1982).

The application of different prediction methods to the conditions of the Slovak Republic may be questionable, and this is because different models of financial health prediction were developed in different time and space. The question is basically whether a model created based on data characterizing enterprises of one country can be successfully used to predict the financial situation of enterprises of other countries. It is also necessary to consider the classification or focus of the enterprises for which the model was developed. In fact, the accuracy of prediction models is significantly reduced if the model is used in a different industry, time, or business environment than the one in which the data used to derive the model was obtained [4]

Within the Slovak Republic, models have been developed focusing on one area of the national economy, namely agriculture. These are the Chi-index models of Chrastinova (1998) and the G-index of Gurčík (2002). A model predicting the future bankruptcy of commercial companies operating in the Slovak Republic was developed by Gulka (2016) through logistic regression, where all business entities based in the Slovak Republic were examined except for the financial sector. This method is based on finding the dependence of the logistic variable (0 - non-bankrupt business and 1 - bankrupt business) on several independent variables, i.e. financial ratios.

The aim of the present paper is to evaluate the financial situation and prosperity of enterprises during the period of the Coronavirus pandemic, which disrupted the normal operation of companies due to the impact of various measures and restrictions.

## 2 Methodology

To achieve the set goal, universal methods were used, such as the analysis of available theoretical knowledge obtained through the study of professional literature and the subsequent synthesis of the acquired knowledge. The comparison method was used to solve the problem based on the criteria set by the Commercial Code and the results of the monitored prediction models. To verify the predictive ability of the monitored models, we used ROC analysis, which is a statistical procedure for evaluating signals of correct and false positivity and correct and false negativity. ROC curve analysis describes the relationship between sensitivity and specificity at different values of the discrimination level.

In the paper, we wanted to apply a prediction model to determine the economic impact of the corona crisis on the businesses of the Prešov region and thereby determine the prosperity of the businesses of the mentioned region, which carry out their business activities according to SK NACE 56300 – hospitality services. According to the Finstat database, before the corona crisis in 2019, there were a total of 432 businesses in the hospitality sector in 13 districts of the Prešov region. Based on statistical calculations, we determined the size of the sample, on which we subsequently applied the calculations of prediction models. The sample size corresponded to 204 enterprises. We selected the corresponding number of businesses for each district of the Prešov region.

The source of data for the predictive analysis itself was the financial statements for the accounting period 2020, where it was already possible to monitor the effects of the corona crisis.

**Table 1.** Matrix of change

| District | Actual count | Sample |
|---|---|---|
| Prešov district | 131 | 62 |

| | | |
|---|---|---|
| Poprad district | 100 | 47 |
| Bardejov district | 41 | 19 |
| Vranov nad Topľou district | 35 | 17 |
| Humenné district | 33 | 16 |
| Kežmarok district | 20 | 9 |
| Sabinov district | 20 | 9 |
| Svidník district | 14 | 7 |
| Snina district | 16 | 8 |
| Stará Ľubovňa district | 10 | 5 |
| Levoča district | 5 | 2 |
| Stropkov district | 5 | 2 |
| Medzilaborce district | 2 | 1 |
| ∑ | **432** | **204** |

Source: Finstat.sk

To perform predictive analysis and evaluate the financial health of 204 companies, we chose 3 bankruptcy models: Altman's, Taffler's and Bonita Index. We specify the methodology of each model in more detail.

### 2.1 Altman index

Altman was the first to quantify the multivariate discriminant function. The Altman index is also called the Z-score. It is based on a discriminant analysis carried out in 1966 on a sample of 66 randomly selected firms, 33 of which had gone through bankruptcy proceedings in the last twenty years and 33 of which had not yet gone through bankruptcy proceedings. This model was originally designed for publicly traded companies. Under the pressure of the needs of economic practice, the index was gradually supplemented with models for joint stock companies without publicly traded shares and for nonmanufacturing companies. [5]

The basic relationship for expressing the financial situation of a company according to the Altman model:

$$Z = 1{,}2x_1 + 1{,}4x_2 + 3{,}3x_3 + 0{,}6x_4 + 1{,}0x_5 \quad (1)$$

$$x_1 = \frac{working\ capital}{total\ assets} \quad (2)$$

$$x_2 = \frac{retained\ earnings}{total\ assets} \quad (3)$$

$$x_3 = \frac{EBIT}{total\ assets} \quad (4)$$

$$x_4 = \frac{market\ value\ of\ equity}{total\ liabilities} \quad (5)$$

$$x_5 = \frac{sales}{total\ assets} \quad (6)$$

Altman identified the boundaries of the bands by which the future is predicted. [3] If:

- Z > 2.99 the firm's financial position is predicted to be good
- 1.81 < Z < 2.99 an area of indeterminate results (grey zone), bankruptcy is possible,
- Z < 1.81 financial situation is critical, bankruptcy very likely

### 2.2 Taffler model

Taffler's bankruptcy model (1977) is based on scoring approach and represents the linear regression model with four financial coefficients for the assessment of financial stability of 46 UK companies that default and 46 companies that are stable during the period between 1969 and 1975. Taffler's model incorporate the ratios that are easily defined and reflect the most significant links to the solvency of companies. [13]

Taffler's bankruptcy model consists of 4 factors and is given by the relationship:

$$T = 0{,}53R_1 + 0{,}13R_2 + 0{,}18R_3 + 0{,}16R_4 \tag{7}$$

$$R_1 = \frac{EBT}{current\ liabilities} \tag{8}$$

$$R_2 = \frac{current\ assets}{total\ liabilities} \tag{9}$$

$$R_3 = \frac{current\ liabilities}{total\ assets} \tag{10}$$

$$R_4 = \frac{Revenue}{Total\ Assets} \tag{11}$$

If the calculated T > 0.3, these are firms with a small probability of bankruptcy. If the calculated T < 0.2, bankruptcy can be expected with a higher probability. [6]

### 2.3 Bonita Index

In the German-speaking economic area of Europe, the Bonita index below is very often used. The discriminant function quantifying the Bonita index B has the form:

$$B = 1{,}5x_1 + 0{,}08x_2 + 10x_3 + 5x_4 + 0{,}3x_5 + 0{,}1x_6 \tag{12}$$

$$x_1 = \frac{cash\ flow}{debts} \tag{13}$$

$$x_2 = \frac{total\ capital}{debts} \tag{14}$$

$$x_3 = \frac{EBT}{total\ capital} \tag{15}$$

$$x_4 = \frac{\text{EBT}}{total\ revenues} \quad (16)$$

$$x_5 = \frac{\text{stocks}}{total\ assets} \quad (17)$$

$$x_6 = \frac{\text{total revenues}}{total\ capital} \quad (18)$$

The result of the Bonita index can be interpreted as follows:

- -3 < B < -2 ......the financial situation of the company is extremely bad
- -2 < B < -1 ......the company's financial situation is very bad
- -1 < B < 0 .......the company's financial situation is bad
- 0 < B < 1 ........the company is definitely in trouble
- 1 < B < 2 ........the financial situation of the company is good
- 2 < B < 3 ........the financial situation of the company is very good
- B > 3 ..............the financial situation of the enterprise is extremely good

The creditworthiness of an enterprise is higher the higher the Bonita index B.

Part of the survey was also the classification of enterprises into the group of prosperous or non-prosperous enterprises, while we were based on the current legislation of the Slovak Republic, which defines when an enterprise is in bankruptcy, or when it is threatened with bankruptcy. Furthermore, we have added to the criteria the fact that a non-prosperous enterprise has significant problems with liquidity and making a profit. We have thus identified four criteria:

- Total liquidity indicator,
- The financial autonomy indicator,
- Negative equity,
- Negative operating result.

Total Liquidity Ratio L3 is a ratio indicator of liquidity analysis, which expresses how much € of current assets excluding long-term receivables cover € 1 of short-term foreign funds. The recommended value of this ratio according to several literatures is 1.5-2.5. To our analysis, we considered firms to be illiquid if they had L3 values < 1. [14]

The financial autonomy ratio is an indicator from the group of debt ratio indicators. It expresses how many € of equity are attributable to € 1 of liabilities of the enterprise. The higher its value is above 1, the more stable the enterprise is because it finances its activities through equity. If it is less than 1, the enterprise uses more foreign capital to finance its activities. According to Act No. 513/1991 Coll., the Commercial Code has introduced the concept of a company in crisis since 1 January 2016, where it is the ratio of equity to liabilities that can reveal the reality of the crisis. Currently, after the amendment of this law, this ratio is, as of 2018, 8 to 100. [9]

Negative equity VI < 0 is the third decisive criterion for classifying a company as non-viable. According to Section 3(3) of the Bankruptcy and Restructuring Act, such an enterprise is designated as a going concern. [10]

The last criterion is the ability to hit profits. If an enterprise is unable to make a profit, it may not be able to pay its obligations, leading to insolvency.

The application of the selected prediction models in the database of Slovak enterprises allows us to compare the obtained classification of the enterprise with real data and thus verify the predictive ability of the models. The assessment of the classification and prediction ability of the observed models is performed using a ROC curve, which shows the relationship between sensitivity and 1-specificity. This is the relationship between true positivity and false positivity, which is given by the change matrix. [8]

**Table 2.** Matrix of change

| | **Predicted** | | |
|---|---|---|---|
| **Actual** | | Negative | Positive |
| | Negative | True Negative (TN) | False Positive (FP) |
| | Positive | False Negative (FN) | True Positive (TP) |

Source: Klepáč, H., Hampel, D. 2016.

The table of changes classifies businesses into thriving and non-thriving, considering four situations [8]:

1. True Positives (TP) - this is a positive match, i.e., how many thriving businesses have been correctly classified as thriving,
2. False Positives (FP) - false positive results, i.e., how many failing businesses were misclassified as thriving, also referred to as first type error.
3. False Negatives (FN) - the results of false negatives, i.e., how many thriving businesses were misclassified as failing, this is referred to as an error of the second kind.
4. True Negatives (TN) - these are negative matches, i.e., how many failing businesses were correctly classified as failing.

For an overall assessment of the models, it is necessary to consider [8]:

- Overall model accuracy, which is defined as the ratio of correctly classified entities to all entities, i.e. (TP + TN) / (TP + FP + FN + TN).
- sensitivity, which is given by the ratio of true positive cases to all positive cases, i.e., TP / (TP + FN).
- specificity, determined by the ratio of true negative cases to all negative cases, i.e., TN / (TN + FP)

Based on the calculated sensitivity and specificity values, an ROC curve can be constructed and then the classification accuracy of the models under study can be evaluated using the area under the ROC curve (denoted as AUC) as follows [8]:

- values between 0.5 and 0.75 = acceptable classification ability,
- values between 0.75 and 0.92 = good classification ability,
- values from 0,92 to 0,97 = very good classification ability,
- values between 0.97 and 1.0 = perfect classification ability of the prediction model

## 3 Results

Considering the criteria that divide businesses into prosperous and non-prosperous according to the current legislation of the Slovak Republic, we have selected a sample of businesses divided into 70 businesses that are prosperous and 134 that are not prosperous.

We performed an ex-ante analysis using selected predictive bankruptcy models. Bankruptcy models classified by companies as average, i.e., into the gray zone, it was only necessary to divide them into two groups to be able to determine their ability to speak. According to the final value of the specific model, which was achieved by each enterprise in the gray zone, we classified it between prosperous and non-prosperous according to the threshold values, whether it was closer to which group.

**Table 3** Result of prediction models

| | **Altman model** | **Taffler model** | **Bonity Index** | **Actual** |
|---|---|---|---|---|
| **Negative** | 150 | 140 | 76 | 134 |
| **Positive** | 54 | 64 | 128 | 70 |
| ∑ | 204 | 204 | 204 | 204 |

Source: own processing

### 3.1 Altman model

The Altman model applied to the sample of selected enterprises under study ranked the enterprises as follows:

**Table 4** Result of Altman model

<table>
<tr><td></td><td colspan="4">Predicted</td></tr>
<tr><td rowspan="4">Actual</td><td></td><td>Negative</td><td>Positive</td><td></td></tr>
<tr><td>Negative</td><td>134</td><td>0</td><td>134</td></tr>
<tr><td>Positive</td><td>16</td><td>54</td><td>70</td></tr>
<tr><td colspan="3"></td><td>204</td></tr>
</table>

Source: own processing

Altman's model correctly classified the non-prosperous enterprises among the non-prosperous, which means that the type I error is equal to 0%. He classified 16 enterprises defined as prosperous among non-prosperous ones, and thus the model committed error II. kind at the level of 22.86%. The proportion of truly positive to all positive observations expressed by sensitivity reached the value of 77.14%, and the proportion of truly negative observations to all negative observations expressed by specificity is 100%. Using the sensitivity and 1-specificity relationship, we constructed an ROC curve.

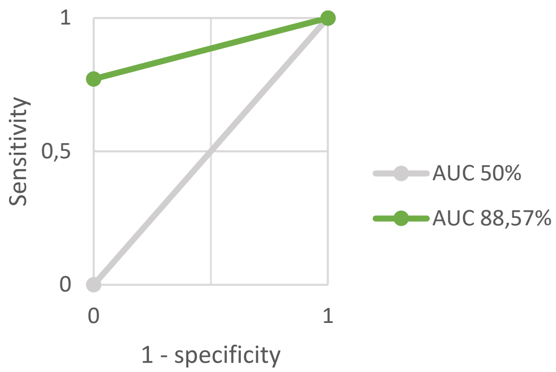


**Fig. 1.** ROC curve of the Altman model.
Source: own processing.

Fig 1. shows the ROC outcry of the Altman model of a selected sample of surveyed businesses. The area under the ROC curve of AUC is 88.57%. According to the AUC classification, the model acquired a good classification ability of the prediction model. The AUC 50% curve on the graph shows a straight line to which acceptable classification ability belongs.

### 3.2 Taffler model

Taffler model applied to the research sample of selected enterprises ranked the enterprises as follows:

**Table 5** Result of Taffler model

| | | **Predicted** | | |
|---|---|---|---|---|
| **Actual** | | Negative | Positive | |
| | Negative | 134 | 0 | 134 |
| | Positive | 6 | 64 | 70 |
| | | | | 204 |

Source: own processing

Taffler model correctly classified 134 businesses as non-prosperous. What caused us to make a Type I error at the 0% level. The high accuracy of the model is also evident in the case of classifying enterprises in the group of prosperous ones, where up to 64 enterprises were correctly classified. The model committed 8.57% error II. kind, by wrongly classifying 6 enterprises in the non-prosperous group. The proportion of truly positive to all positive observations reached a value of 91.43%. The proportion of truly negative observations to all negative observations expressed by specificity reached a value of 100%. Using the sensitivity and 1-specificity relationship, we constructed an ROC curve.

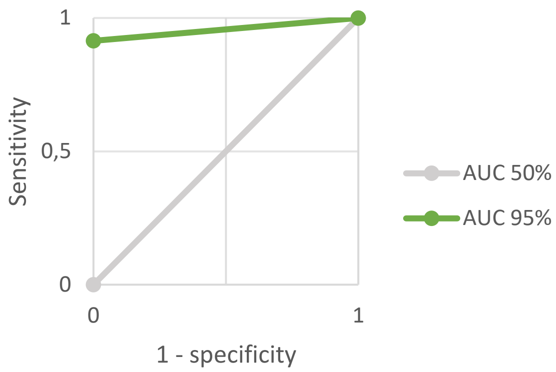


**Fig. 2.** ROC curve of the Taffler model
Source: own processing

Fig. 2 shows the ROC outcry of the Taffler model of a selected sample of surveyed businesses. The area under the ROC curve of the AUC is 95.72%, which means that the model has acquired a very good classification ability.

### 3.3 Bonita Index

The last model (Bonita Index) applied to the research sample of selected enterprises classified the enterprises as follows:

**Table 6** Result of Bonita Index model

| | | Predicted | | |
|---|---|---|---|---|
| **Actual** | | Negative | Positive | |
| | Negative | 76 | 58 | 134 |
| | Positive | 0 | 70 | 70 |
| | | | | 204 |

Source: own processing

Based on the above table, significant imperfections are identified. The model correctly identified only 76 businesses that are among the non-prosperous. Which is reflected in the high level of Type I error (43.28%) compared to previous models. What we cannot criticize the model for is the correct determination of the number of enterprises that meet the criteria of prosperous enterprises, of which there are 70. Type I error is thus at the level of 0%. The sensitivity of this model is at the level of 100%, which expresses the proportion of truly positive to all positive observations. The specificity indicator of this model is at the level of 56.72%.

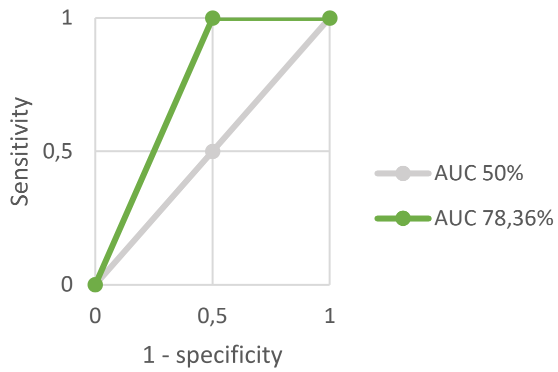


**Fig. 3** ROC curve of the Bonita Index model
Source: own processing

The figure shows the ROC curve of the Credit Index model of a selected sample of surveyed companies. The area under the ROC curve of the AUC takes on a value of 78.36%, so we can conclude that the classification ability of the prediction model is good.

## 4 Conclusion

In the presented contribution, we focused on predictive models for businesses in the Prešov region applied to a researched sample of 204 businesses in 13 districts of this region, which conduct their business activities according to SK NACE 56300 – hospitality services. For predictive analysis, we used 3 models of Altman, Taffler and Credit Index, which led us to the following conclusion. All three used models achieved a fairly high level of reporting ability. The Credit Index model has the lowest reporting ability at 74.45%. The Taffler model has the highest reporting ability, and thus, according to the AUC classification, the model is included in the category of very good classification ability of the prediction model, which corresponds to 95.72%.

**Table 7** Results of each model

| Model | Sensitivity | Specificity | Type I Error | Type II Error | AUC |
|---|---|---|---|---|---|
| **Altman** | 95.12% | 100% | 0.00% | 4.88% | 88.57% |
| **Taffler** | 100.00% | 48.89% | 51.11% | 0.00% | 95,72% |
| **Bonita Index** | 82.93% | 100.00% | 0.00% | 17.07% | 78,360% |

Source: own processing

The contribution was focused on predictive bankruptcy models with the aim of pointing out the financial situation and prosperity of companies during the Corona virus pandemic with an emphasis on the informative value of selected models applied to a selected sample of companies operating in the Prešov region of the Slovak Republic. The subject of further research, which would supplement the current contribution, is the analysis of subsidies that were provided to companies with a significant delay to mitigate the impact of the crisis. Based on the current results, we have concluded that with the help of selected prediction models such as Taffler's and Altman's model, we can predict the financial situation of companies operating in the industry we are investigating with a very good predictive ability.

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