Finance

# ALTMAN MODEL VERIFICATION USING A MULTI-CRITERIA APPROACH FOR SLOVAKIAN AGRICULTURAL ENTERPRISES

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**Abstract:** The Altman model is still one of the most widely used predictive models in the 21st century, and it aims to highlight the differences between bankrupt and healthy enterprises. This model has been modified several times; its most well-known forms are from 1968, 1983 and 1995. However, the use of the Altman Z-score for Slovak enterprises is more than questionable. The unsuitability of the model for the conditions of Slovak companies has been confirmed by several empirical surveys. The objective of this study was to verify the validation of these three variants of the Altman model, depending on how an unprosperous company is identified, using a sample of 996 agricultural enterprises operating in the Slovak Republic. Four indicators were selected for the identification of an unprosperous enterprise – economic results, total liquidity, equity, and economic value added – and they were monitored over the last year or, as the case may be, over the last three years from 2014 to 2016. Using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Coefficient of variation (CV) methods as an objective method for weight determination, a combination of the Altman model from 1968 and the negative total liquidity in the last reference year was determined to be the best. One of our main findings is that the way in which an unprosperous enterprise is identified is a significant factor affecting the overall reliability of the Altman model. The Altman model from 1968 and 1983 confirmed the differences resulting from the natural conditions in which the enterprises operate. The economic results and economic value added (EVA) proved to be inappropriate as indicators for defining an unprosperous enterprise in the conditions of the Slovak Republic.

**Keywords:** Unprosperous enterprise, Altman model, TOPSIS technique, Coefficient of variation method.

**JEL Classification:** B23, Q14.

## Introduction

In the 21st century, a prerequisite for a successful business is good knowledge of past and current trends, for the right long-term decisions to be made. According to Brealey et al. (2011), knowing where a company stands today is a necessary prelude to contemplating where the company might end up in the future. One of the options for supporting short-term and long-term decisions is financial analysis

and financial ratios. Financial ratios have traditionally been indicators of a corporate's overall performance (Rahman et al., 2017) and may help to quantify the potential impact of internal ratings on financial performance (Belas et al., 2012; Klieštik et al., 2020).

The simplest and narrowest definition of financial analysis is based on the activities that this term includes without specifying their purpose, i.e., financial analysis is an analysis of company data, which is based on accounting (Sůvová & Knaifl, 2008). It is focused on evaluating the financial health of a company and identifying its weaknesses and strengths (Mrkvička & Kolář, 2006). According to Bank et al. (2006), this assessment is dependent on the company's liquidity and short-term financial liabilities, which represent its ability to regulate sources of funding. According to Bocharov (2007), it is necessary also to consider financial analysis in the long term, i.e., as a systematic process of controlling financial resources. From a time perspective, we can divide financial analysis into retrospective ex-post analysis and ex-ante analysis focusing on prediction. The latter can identify critical factors that could threaten the survival of an enterprise, i.e., an appropriate response to the results of ex-ante analysis in the form of recovery measures can significantly affect a company's future financial situation or ensure its sustainability. Financial distress can be defined in many different ways, and similarly, the terminology referring to companies experiencing such also differs – bankrupt, insolvent, and in default (Čámská & Klecka, 2020; Alaka et al., 2018). Several prediction methods based on ex-ante financial analysis have been verified to date (e.g. Mihalovič, 2018; Gavúrová et al., 2017; Ko et al., 2017).

The aim of this study was to verify the explanatory power of three variants of the Altman model (from 1968, 1983 and 1995) depending on how a non-prosperous enterprise is identified, using a sample of 996 agricultural enterprises operating in Slovakia. To verify the outputs of ex-ante financial analysis, it is also necessary to identify prosperous and unprosperous enterprises (first part). There are usually two approaches, depending on the legislative and theoretical definitions. The legislative definition of an unprosperous enterprise is determined by the legislation of a given country; in this case, we encounter the

concept of bankruptcy. The theoretical definition is given by the quantification of a selected set of financial indicators and their subsequent scaling (see ex ante methods). In the following text, the various approaches taken by both foreign and domestic authors to defining an unprosperous enterprise are described, and the frequent penetration of individual criteria can be observed. The second part is focused on a set of our own indicators used to identify an unprosperous enterprise, i.e., methodology. The third part describes the results of our own research, i.e., the verification of the predictive ability of the Altman model applied to a sample of 996 agricultural enterprises in the Slovak Republic. The use of a multi-criterion approach in the form of the CV-TOPSIS technique as a methodological extension to the discussed approaches to the verification of the explanatory power of prediction models can be described as original and new (see Part 1). The fourth part presents a discussion of the obtained results in the context of other authors' thoughts and research. The last part presents the conclusion and an evaluation of the obtained results.

## 1. Different Approaches to Defining an Unprosperous Enterprise

In the previous section, we dealt with defining an unprosperous enterprise from different perspectives, i.e., those that can be applied to enterprises regardless of the region in which they are located. For an appropriate definition, we consider it necessary also to take into account the local conditions in which a company operates. This is then reflected in a more precise definition of the conditions under which the enterprise can be considered unprosperous.

Bakeš and Valášková (2018) proposed criteria for identifying an unprosperous company that would take into account currently valid Slovak legislation along with economic and financial aspects. Such criteria include a ratio of equity to liabilities of <0.08, a total liquidity of <1, and negative earnings after tax. Ďurica (2018) described an unprosperous enterprise as an enterprise in crisis, when the total amount of their current liabilities is higher than the value of their current assets, the ratio of equity to liabilities is less than 0.04, and the company has generated a loss (valid for analysis in 2016). Klieštik et al. (2018) and Mendelová and Bieliková (2017) identified an

unprosperous enterprise as one that meets the criterion found in applicable legislation of the Slovak Republic, i.e., the value of its liabilities due exceeds the value of its assets, or the enterprise is in negative equity.

Bieliková et al. (2014) described a more complex view, expressed by three criteria according to which an enterprise can be considered unprosperous, namely, if it:

- Meets the legislative definition of an enterprise in the Slovak Republic, i.e., the enterprise is obliged to conduct accounting procedures according to a special regulation, it has more than one creditor and the value of its liabilities exceeds the value of its assets, i.e., the enterprise is in negative equity;
- Has made a loss for two consecutive years;
- Has a negative return on sales (ROS) and total liquidity ($L_3$) less than 1.

This set of criteria was also used by Bieliková (2016), who additionally take into account the following:

- The legislative definition of a company in prolongation in the Slovak Republic, i.e., the same criterion as in the previous case;
- The European Union guidelines 2004/C 244/02 on state aid for rescuing and restructuring firms in difficulty, which define a firm in difficulty as one in which more than half of the basic capital is covered by loss and more than a quarter of that basic capital was covered by loss during the previous 12 months;
- A loss in two consecutive periods.

Boďa and Úradníček (2016) and Kráľ et al. (2016) presented a set of three criteria for identifying an unsuccessful business. These criteria include negative equity and earnings after tax (EAT <0), as well as a total liquidity (L3) less than 1. According to Valášková et al. (2018a, 2018b), an unprosperous company is one with a ratio of equity to total debt less than 0.4, a total liquidity (L3) less than 1, and negative earnings after tax (EAT). According to Kováčová and Kubala (2018), it is an enterprise that:

- Did not achieve positive equity, or in other words, the difference between assets and liabilities, including the accrual of liabilities, was negative;
- Had at least two monetary liabilities more than 30 days overdue (because we were unable to identify this information directly

from the financial statements, it has been replaced by a determination of the overall liquidity indicator threshold, i.e., $L_3$ <1);

- Exhibited the following values for the self-financing coefficient (equity and liabilities ratio): in 2016, <0.08; in 2015, <0.06; and in 2014, <0.04.

For an independent group of authors, the key criterion for assessing business prosperity is the economic value added, which represents an aggregate characteristic of a company's financial performance. This group includes Šofranková et al. (2017), Neumaierová and Neumaier (2016), Čámská (2016), Maňasová (2008) and others; in all cases, an unprosperous enterprise is one that has achieved negative economic value added in a certain period. Along with Lesáková et al. (2015), Zalai et al. (2013) and others, we consider economic value added as an important criterion, as there has been a recent shift in thinking away from traditional indicators towards the market value of a company. This is confirmed by the fact that the EVA indicator is now increasingly being used in financial management and decision-making.

## 2. The Altman Model as a Method of Multidimensional Discrimination Analysis

As a result of the recent worldwide financial crisis and economic recession, the demand for bankruptcy-prediction models and financial-risk analysis has gained strong attention. The inability to accurately predict both bankruptcy and credit risk can have devastating socio-economic effects (Antunes et al., 2017). To date, many models to predict bankruptcy have been introduced, but research in this field is ever constant (Le et al., 2018; Zelenkov et al., 2017). Several authors (Alaka et al., 2018; Karas & Režňáková, 2012; Sušický, 2011) argue that methods of multidimensional discrimination analysis are the world's most widely used methods for predicting the financial health of businesses. Among their supporters are Balcaen and Oooghe (2006) and Sun et al. (2014), who appreciate their good classification capability.

The founder and pioneer of the use of multidimensional discrimination analysis is Altman (1968). The Altman Z-score is currently the most well-known and widely used prediction model (Gavúrová et al., 2017; Delina & Packová,

2013). It is often modified and verified for the needs of national economics. In the Slovak Republic, these applications are offered by Kabát (2011a) and Boďa and Úradníček (2016, 2019); in the Czech Republic, by Schönfeld et al. (2018) and Režňáková and Karas (2015); and abroad, by Li and Faff (2019), Almany et al. (2016), Sulub (2014) and Lifschutz and Jacobi (2010).

The model was created using a sample of 33 US companies that went bankrupt between 1946 and 1965, while a second group included 33 US companies that prospered in this period (Kočišová & Mišanková, 2014). Altman (2002) considered the limited data available to be a major problem, causing the group of selected businesses to be relatively heterogeneous. The author initially worked with a set of 22 selected financial indicators from five classes – liquidity, profitability, debt, solvency and activity (Hosaka, 2019; Kabát, 2011a). Concerning Altman's Z-score, firms are grouped into the three zones of discrimination identified by Altman: the Distress Zone, Grey Zone and Safe Zone (Meggison et al., 2019). Altman's goal was to select a small number of ratio indicators that would best highlight the difference between a bankrupt and a healthy enterprise. Ratio indicators were selected based on the greatest differences in the values between the different sets of enterprises (see Tab. 1).

In this manner, Altman created a five-factor model. In the original study from 1968, he successfully classified 94% of bankrupt US enterprises and 97% of prosperous US production enterprises based on a Z-score with an annual advance. In the 30 years following the creation of the model, he tested its predictive ability, and another 86 problematic enterprises were analyzed from 1969 to 1975. From 1976 to 1995, Altman tested 110 bankrupt enterprises, and in the period from 1997 to 1999, the number of enterprises went up to 120. The threshold for problematic businesses was set at 2.67, and businesses were only tested two years before bankruptcy (Maňasová, 2008). Altman (2006) states that the main reason for the higher error rate of the model is that, at that time, US businesses were at higher risk compared to when the model was created. The higher risk level is reflected in the change in the variables $X_2$ and $X_4$. In 1983, an updated Altman Z-score model was created (for businesses that did not have publicly traded shares) and included the same ratio indicators as the original model. However, the weights of the individual ratio indicators were changed, and thus, the evaluation criteria also changed. The same changes took place in 1995, when a third model was created for the purpose of evaluating non-productive enterprises; it was also used in its own research. Even Altman's models based on multiple discriminant analysis have proved quite successful and stood up to criticism (Pereira et al., 2016). According to Klieštik et al. (2015), the limitations of the models are as follows. The models take only a normal distribution of independent variables into account, consider only homogeneity of the variation-covariation matrix, and assume only a linear relationship between the independent variables. Altman's models are accounting-based, which reduces their ability to predict financial distress and bankruptcy reliably. Li and Faff (2019) argue that under the going-concern principle, their application is limited, as predictions of a firm's future financial condition may be less informative when they are based on the firm's past performance.

**Tab. 1:**    **Average values of Altman test indicators in 1968**

| Indicator | | Healthy enterprises | Bankrupt enterprises |
|---|---|---|---|
| Working capital/total assets | $X_1$ | 0.414 | −0.061 |
| Retained earnings/total assets | $X_2$ | 0.355 | −0.626 |
| Earnings before interest and tax/total assets | $X_3$ | 0.154 | −0.318 |
| Market capitalisation/total liabilities | $X_4$ | 2.477 | 0.401 |
| Sales/total assets | $X_5$ | 1.900 | 1.500 |

Source: Altman (1968)

## 3. Research Methodology

After a theoretical overview of the different views on what constitutes an unprosperous enterprise and a specification of the basics of the Altman model, it is possible to define the aim of the presented manuscript as a verification of the Altman model's predictive ability depending on how an unprosperous enterprise is identified.

Based on the theoretical definition of the different views on what highlights an unprosperous enterprise, we present a summary overview (Tab. 2), which also serves to define its own view.

For the purposes of the further analysis of unprosperous enterprises, we will consider ones that meet:

- Separately, one of the four conditions referred to above in the last reference year, 2016 (Variants A1, A2, A3, A4);
- Separately, one of the four conditions referred to above throughout the period under review, in 2014, 2015 and 2016 (Variants B1, B2, B3, B4);
- At the same time, all four of the above conditions in the last reference year, 2016 (Variant C).

Within the framework of the presented research, we discuss the explanatory ability of three variants of the Altman model, i.e., the models from 1968, 1983 and 1995 (for more details and differences, see Kotulič et al., 2018), which are calculated as follows:

$$Z_{1968} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

$$Z_{1968} = 0.717X_1 + 0.847X_2 + 3.107X_3 + \\ + 0.420X_4 + 0.998X_5 \quad (2)$$

$$Z_{1995} = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (3)$$

where:
$X_1$ = Net working capital/total assets;
$X_2$ = Retained earnings/total assets;
$X_3$ = Earnings before interest and tax/total assets;
$X_4$ = Market value of equity/total liabilities;
$X_5$ = Sales/total assets.

As can be seen from the construction of individual models or modifications of the Altman model, the structure of the indicators used remains the same. Views on their importance has changed over the years, expressed by a change in the weights assigned to each indicator. These changes in weight were subsequently reflected in a change in the intervals/boundaries for the identification of an unprosperous enterprise, or a healthy one, as the case may be (Tab. 3).

The explanatory ability of the Altman model is subsequently verified by the calculation of the type I error ($\alpha$), type II error ($\beta$) and overall reliability, which are shown in Tab. 4.

According to Gavúrová et al. (2017) and Delina and Packová (2013), the following calculation is based on the above table for:

- Type I error, i.e., the proportion of misclassified bankrupt companies (the false-negative rate):

$$FNR = \frac{FN}{TP + FN} \quad (4)$$

**Tab. 2:** Conditions for identifying an unprosperous enterprise

| Variant | | | Condition | | Author |
|---|---|---|---|---|---|
| A1 | B1 | | 1. | Profit < 0 | Bakeš & Valášková, 2018; Ďurica, 2018; Valášková et al., 2018a, 2018b; Boďa & Úradníček, 2016; Kráľ et al., 2016; Bieliková et al., 2014 |
| A2 | B2 | C | 2. | Equity < 0 | Kliestik et al., 2018; Kováčová & Kubala, 2018; Mendelová & Bieliková, 2017; Boďa & Úradníček, 2016; Kráľ et al., 2016; Bieliková et al., 2014 |
| A3 | B3 | | 3. | $L_3 < 1$ | Bakeš & Valášková, 2018; Kováčová & Kubala, 2018; Valášková et al., 2018a, 2018b; Boďa & Úradníček, 2016; Kráľ et al., 2016; Bieliková et al., 2014 |
| A4 | B4 | | 4. | EVA < 0, (EAT − re × E) < 0 | Šofránková et al., 2017; Čámská, 2016; Neumaierová & Neumaier, 2013, 2016; Maňasová, 2008 |

Source: own

**Tab. 3:** Evaluation boundaries of individual Altman models

|  | Financial problems | Gray zone | Healthy enterprise |
|---|---|---|---|
| Z-score (1968) – A68 | <1.81 | <1.81–2.99> | >2.99 |
| Z-score (1983) – A83 | <1.2 | <1.2–2.9> | >2.9 |
| Z-score (1995) – A95 | <1.1 | <1.1–2.6> | >2.6 |

Source: Boďa and Úradníček (2016)

**Tab. 4:** Type I and II error

|  | Prediction-bankruptcy | Prediction-non-bankruptcy |
|---|---|---|
| Fact-bankruptcy | the correct result (TP) | error type I (FN) |
| Fact-non-bankruptcy | error type II (FP) | the correct result (TN) |

Source: Klepáč and Hampel (2017)

- Type II error, i.e., the proportion of misclassified prosperous companies (the false-positive rate):

$$FPR = \frac{FP}{FP + TN} \qquad (5)$$

- Overall reliability (overall accuracy), i.e., the proportion of correctly classified enterprises:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \qquad (6)$$

The data for the analyses were drawn from data for agricultural companies (balance sheets and profit and loss statements) provided by the Ministry of Agriculture of the Slovak Republic in the form of information sheets for anonymous agricultural subjects. The total file included 1,867 subjects of legal and natural persons with up to 19 and 20 or more employees in the period 2014–2016. By using the SOFINA_standard economic software for financial planning and managerial economy, we identified 996 businesses (from the total set) for which there was a continuous record of financial data for the reference period and which had full records of balance sheets and financial statements (see Fig. 1).

Differences in the economic results of these entities can also be observed with respect to the natural conditions in which they operate. Kotulič et al. (2017) divided the territory of the Slovak Republic into two groups (Fig. 2) on this basis.
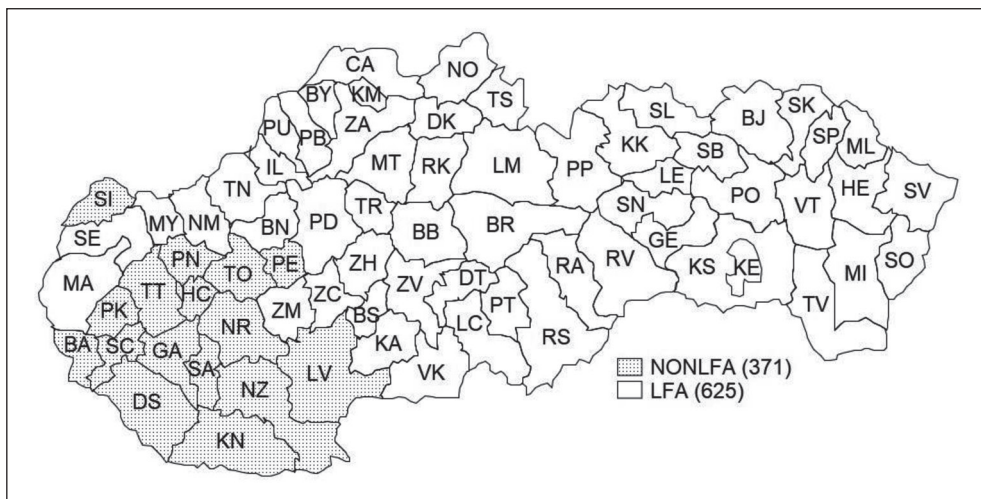
**Fig. 1:** Structure of the research sample
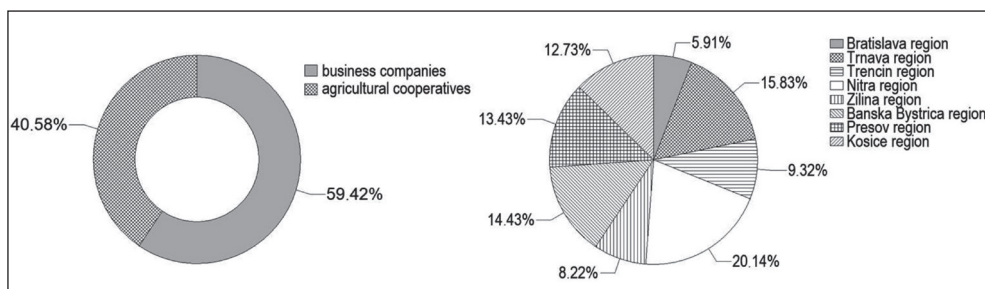


Source: own

| Fig. 2: | Spatial distribution of analyzed subjects (LFA – the districts with worse natural conditions; NONLFA – the districts with better natural conditions) |



Source: own

The method of Damodaran (2004, 2014) was used to calculate the cost of equity capital (re) according to the EVA indicator (Tab. 2); it was also applied by Šofránková et al. (2017) and Mařík et al. (2011). The analyses were performed in MS Excel, Statistica 13.4 and Statgraphics XVIII.

## 3.1 TOPSIS Technique as a Tool for Assessing the Explanatory Ability of the Model

MCDM (Multi Criteria Decision Making) methods were developed to assist decision-making regarding either ranking a known set of alternatives for a problem or making a choice from among this set while considering the conflicting criteria (Mardani et al., 2016). According to Zavadskas et al. (2014), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is one of the most widely used MCDM methods. The origin of this method can be attributed to Hwang and Yoon (1981) and Yoon (1980), who developed it as an alternative to the ELECTRE method. The result of the TOPSIS technique is described by Streimikine et al. (2012) as a solution with the shortest distance to a positive-ideal solution (PIS), in terms of Euclidean distance. The TOPSIS method offers a solution that is

the closest to the abovementioned PIS under the given conditions and, at the same time, the farthest from the negative-ideal solution (NIS) (Zavadskas et al., 2016). The TOPSIS technique was performed according to Vavrek and Bečica (2020) and Vavrek (2019).

The indicators used for the above calculation are the result of an evaluation of the Altman model's explanatory ability:

- $I_1$ = Type I error (FNR) with a minimizing character;
- $I_2$ = Type II error (FPR) with a minimizing character;
- $I_3$ = Overall reliability (ACC) with a maximizing character.

For each of the MCDM methods, the first and essential step is determining the weights of the individual indicators. Keršuliene et al. (2010) divide the approaches to weighting into four groups: subjective, expert, objective and integrated (which combines the previous approaches). Subjective methods reflect the decision-maker's personality and individual preferences. Objective methods determine weights based on a predetermined mathematical model unique to each method, with the decision-maker having no influence on the outcome. They include CRITIC (CRiteria Importance Through

Intercriteria Correlation), MW (mean weight), SD (standard deviation), SVP (Statistical Variance Procedure) and others (see Suder & Kahraman, 2018; Yalcin & Unlu, 2018, and others). For our own processing, the Coefficient of variation method (CV) was used, which was devised by Singla et al. (2017) and further described in the studies of Vavrek and Chovancová (2019) and Yalcin and Unlu (2018).

The aim of the CV-TOPSIS combination is an objective assessment of the Altman model's explanatory ability for individual variants, which would reflect the reliability of not only the model (ACC) as a whole but also specific results (FNR and FPR), which we believe should also be considered. These results are supplemented by additional mathematical and statistical methods to which we can add the Mann-Whitney test (W), Kruskal-Wallis test (Q), Levene test (LE) and Kolmogorov-Smirnov test (K-S).

## 4. Research Results

The results of our own research can be divided into several separate parts. In the first, the overall evaluation results are described and statistically compared. In the second, the evaluation of a set of 996 entities is carried out separately using each condition for identifying unprosperous enterprises in the last monitored year, 2016 (i.e., Variants A1, A2, A3, A4), one of the conditions for the last three years is fulfilled separately (i.e., Variants B1, B2, B3, B4), and all four conditions for identifying unprosperous enterprises in the last year of the period under review are then fulfilled simultaneously (i.e., Variant C). The last part is a multi-criteria evaluation of the obtained results using the CV-TOPSIS technique.

## 4.1 Overall Evaluation Results with the Altman Model

The variability of the overall evaluation of the results using the variants of the Altman model (from the years 1968, 1983 and 1995) is shown in Fig. 3, from which differences can be identified, especially when comparing the range of variation ($R_{A68}$ = 71.31, $R_{A83}$ = 50.39, and $R_{A95}$ = 162.40), which, in combination with the changing subject-classification intervals, underlines overall significant differences ($Q$ = 26.667; $p < 0.01$; $LE$ = 121.036; $p < 0.01$). However, the particular variant of the Altman model does not affect the shape of the overall results or their distribution function, because in all three cases, we can consider the results to be positively skewed and more pointed than a normal distribution.

**Fig. 3:** Overall results of the evaluation of subjects with the Altman model (Z-score)
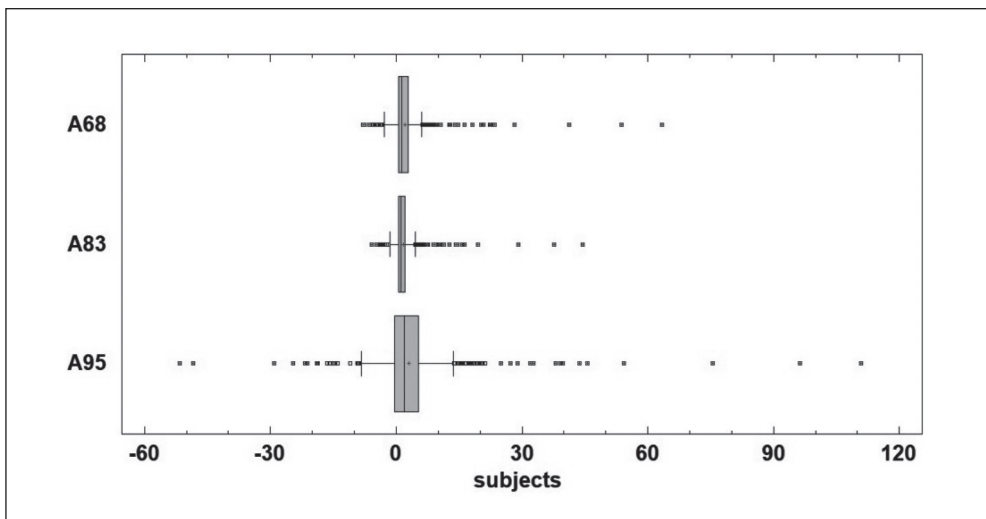


Source: own

**Fig. 4:** Classification of the financial health of subjects according to the Altman model
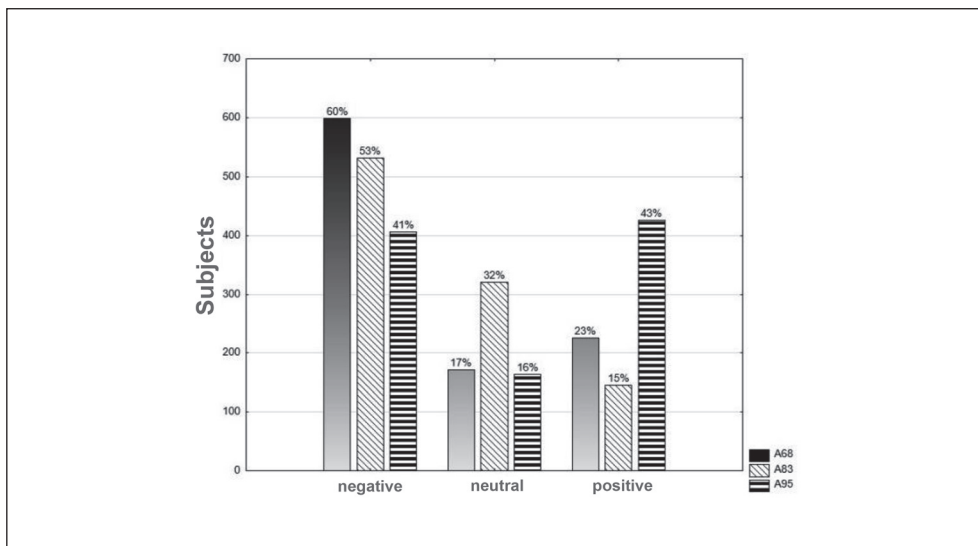


Source: own

This structure of the absolute results is reflected in a classification of the financial health of individual enterprises (Fig. 4). The Altman model from 1968 and 1983 marked the financial health of the majority of the rated entities as negative, and signaled financial problems for these entities in the upcoming period (60% or 53%, as the case may be). By contrast, the Altman model from 1995 indicated a satisfactory financial situation for up to 43% of all the entities (426).

Differences in financial health can also be observed when comparing enterprises operating in better, or worse, natural conditions (LFA/NONLFA). Statistically significant differences were found in the case of the Altman model from 1968 and 1983, when not only the

median value but also the overall structure of the results, i.e., their distribution function, was different (see Tab. 5).

The assessment of financial health through variants of the Altman model from 1968 and 1983 is determined by the quality of the soil, i.e., the natural conditions. Statistically significant differences using these variants were also demonstrated in the distribution functions, but we note their homoskedasticity. However, in the case of the 1995 model, the natural conditions did not influence this assessment. Paradoxically, subjects operating in districts with better natural conditions (NONLFA) showed a better average rating. Based on these results, we can say that even in the 21st century, the assessment of financial health using the Altman

**Tab. 5:** Comparison of results of the Altman model (LFA/NONLFA)

| Model | Medians check | Variance check | DF check | Average | |
| --- | --- | --- | --- | --- | --- |
| | | | | LFA | NON |
| Altman 68 | W = 131417 (<0.01) | LE = 0.007 (0.934) | K-S = 1.996 (<0.01) | 2.37 | 1.99 |
| Altman 83 | W = 136857 (<0.01) | LE = 0.0003 (0.985) | K-S = 2.483 (<0.01) | 1.90 | 1.51 |
| Altman 95 | W = 120612 (0.287) | LE = 0.039 (0.843) | K-S = 0.910 (0.383) | 3.18 | 3.08 |

Source: own

model is strongly influenced by the variant of the model used. For the purpose of evaluating entities working the soil in the Slovak Republic, we recommend the Altman model from the years 1968 or 1983, which identified previously confirmed differences on the basis of the natural conditions in which the entities operate.

## 4.2 Verification of the Explanatory Ability of the Altman Model

Three variants of the Altman model (from 1968, 1983 and 1995) were used to verify the explanatory ability of the model. The rating is divided according to the method used to identify an unprosperous enterprise, as follows:

- An unprosperous enterprise is one that will separately meet one of the four conditions listed in Tab. 2 in the last reference year, 2016 (variants A1, A2, A3, A4);
- An unprosperous enterprise is one that will separately meet one of the four conditions listed in Tab. 2 throughout the period under review, namely, in 2014, 2015 and 2016 (Variants B1, B2, B3, B4);
- An unprosperous enterprise is one that will meet all four of the conditions listed in Tab. 2 in the last reference year, 2016 (Variant C). When evaluating the first group of results

(Variants A1–A4), it is possible to observe high variability in the obtained results expressed by the variation range and, subsequently, also by the standard deviation or coefficient of variation (Fig. 5). From this point of view, the biggest differences were shown in terms of type I error, i.e., the proportion of misclassified unprosperous enterprises (FNR).

If, as a criterion for identifying an unprosperous enterprise, one indicator is set for the last year, the best results can be obtained by taking into account the third condition, i.e., the negative overall liquidity of the company. Thereby, an overall reliability of almost 80% can be expected when using the Altman model from 1995 (FNR = 0.1237; FPR = 0.1185; ACC = 0.8795). The average values of the monitored parameters when using individual variants of the Altman model are shown in Tab. 6.

Equally, the biggest differences in the second group (Variants B1–B4) can be observed when quantifying the type I error, which, along with overall reliability, is considerably skewed. It can be considered positive in the case of FNR (Fig. 6). For 4 out of the 12 models, the rate of misclassified unprosperous enterprises was below 10%. Like the models in the previous

| Fig. 5: | 5: FNR, FPR and ACC with identification of unprosperous enterprises under variant A (1–4) |
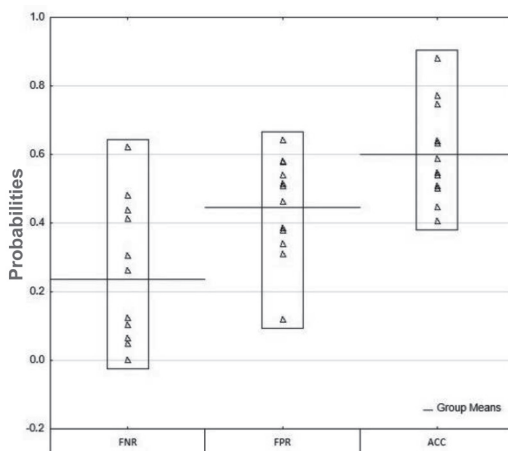


Source: own

| Tab. 6: | Differences in FNR, FPR and ACC with identification of unprosperous enterprise under variant A (1–4) | | | |

| Condition | | FNR | FPR | ACC |
|---|---|---|---|---|
| A1 | Profit < 0 | 0.3344 | 0.4467 | 0.5877 |
| A2 | Equity < 0 | 0.0213 | 0.4907 | 0.5314 |
| A3 | $L_3 < 1$ | 0.0912 | 0.2700 | 0.7982 |
| A4 | EVA < 0 | 0.5032 | 0.5752 | 0.4812 |

Source: own

| Fig. 6: | FNR, FPR and ACC with identification of unprosperous enterprise under variant B (1-4) |
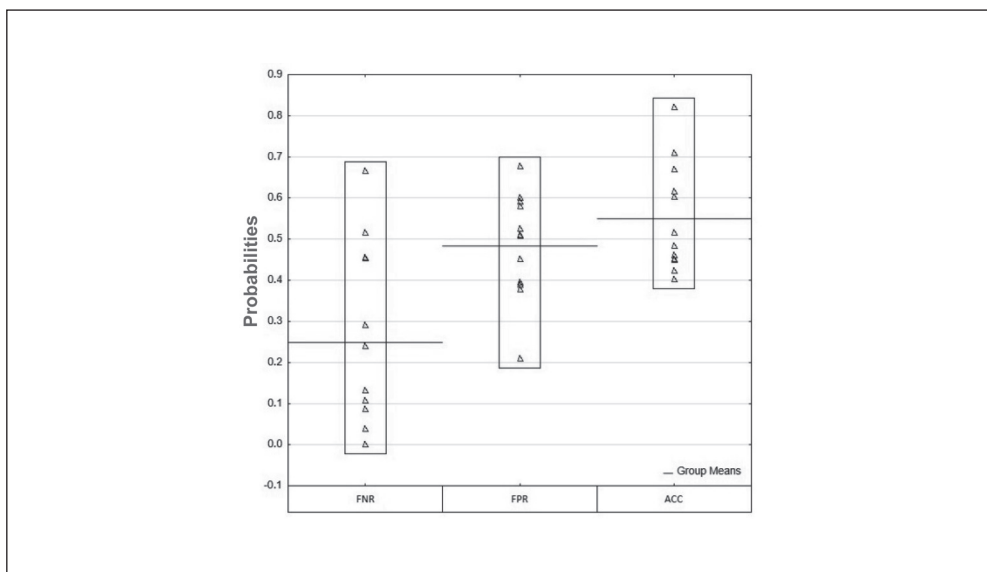


Source: own

group, even in this case, there is a frequent error in classifying prosperous enterprises, whereby at least 20.82% of businesses are badly labeled in this way.

If we follow the years 2014, 2015 and 2016 when identifying unprosperous enterprises, the overall reliability of the Altman model does not exceed 75% in any case. The fourth criterion, the EVA indicator, was clearly inappropriate. In most cases, the model using the EVA indicator also incorrectly identified a bankrupt company as a prosperous enterprise (Tab. 7). Within this group, the Altman model from 1995 achieved

the best scores (FNR = 0.1069, FPR = 0.2082 and ACC = 0.8213). The average values of the monitored parameters when using individual variants of the Altman model are shown in Tab. 7.

Monitoring all four indicators during the last year (Variant C, the most difficult variant) showed a low type I error, which did not exceed 5%. However, the problem within this group was the high error rate in identifying prosperous enterprises, which was also reflected in the low overall reliability of the model (Fig. 7).

| Tab. 7: | Differences in FNR, FPR and ACC with identification of unprosperous enterprise under variant B (1–4) |

| Condition | | FNR | FPR | ACC |
|---|---|---|---|---|
| B1 | Profit < 0 | 0.3276 | 0.4930 | 0.5264 |
| B2 | Equity < 0 | 0.0435 | 0.5032 | 0.5074 |
| B3 | $L_3 < 1$ | 0.0770 | 0.3456 | 0.7326 |
| B4 | EVA < 0 | 0.5451 | 0.5944 | 0.4341 |

Source: own

| Fig. 7: | FNR, FPR and ACC with identification of unprosperous enterprise according to variant C |
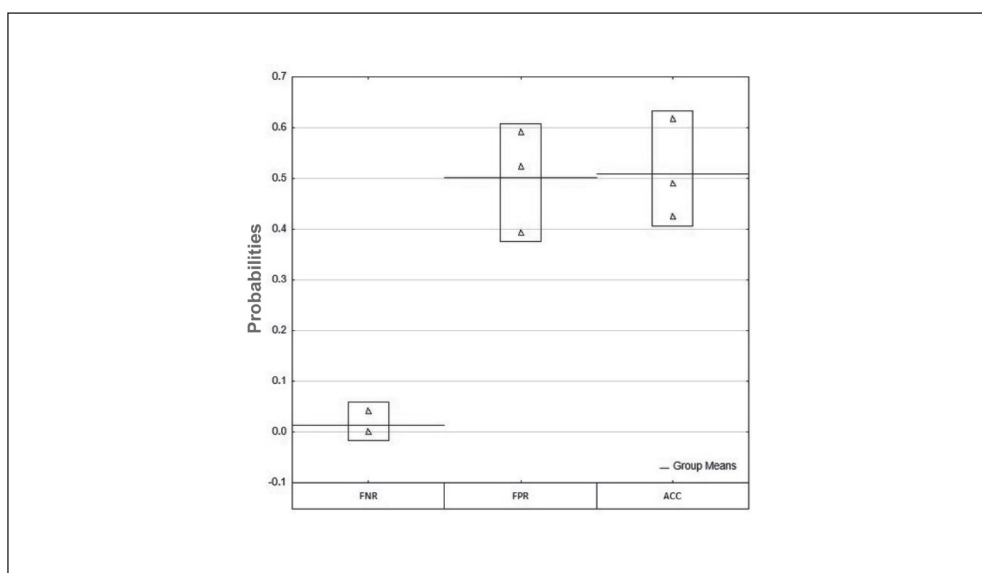


Source: own

## 4.3 Common Multi-criteria Evaluation of the Altman Model's Explanatory Ability

The differences resulting from the method of defining an unprosperous enterprise were described in the previous chapter. Here, we identified the combinations with a lower type I error, i.e., the proportion of misclassified enterprises in bankruptcy (FNR) or lower type II error, i.e., the proportion of misclassified prosperous enterprises (FPR) or higher overall reliability (ACC). To clearly identify the best combination for the needs of enterprises

working the soil in the Slovak Republic, it is necessary to take into account all the above attributes simultaneously. To this end, a total of 27 variants were evaluated together.

The overall variability of the input indicators mirrored the partial variability described in the previous section. The biggest differences can again be observed in the case of type I error ($s_{FNR} = 0.2140$); the variability of the other two indicators was similar for both a relative and absolute assessment. The majority group had a below-average FNR and ACC, and an above-average FPR (Fig. 8).

**Fig. 8:** FNR, FPR and ACC as input criteria for the CV-TOPSIS technique
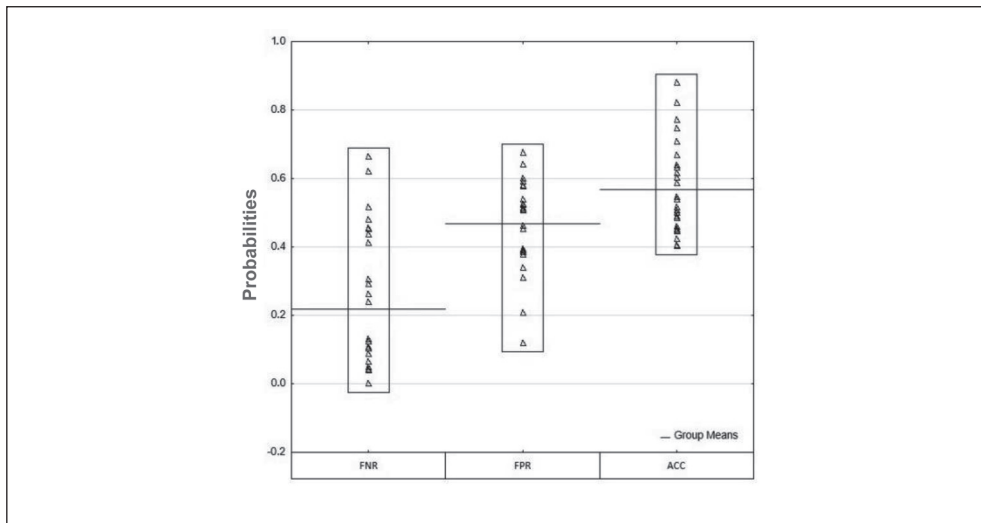
Significant differences found in the overall assessment of the combinations can be confirmed by CV-TOPSIS (Fig. 9). Two combinations did not reach a 0.1 relative distance from the PIS alternative, and one-third of them achieved $c_i > 0.8$.

The best results are obtained using the negative total liquidity ($L_3$) as an indicator for identifying an unprosperous enterprise in one year (A3) as well as three years (B3). The results thus obtained are balanced, i.e., their variability is
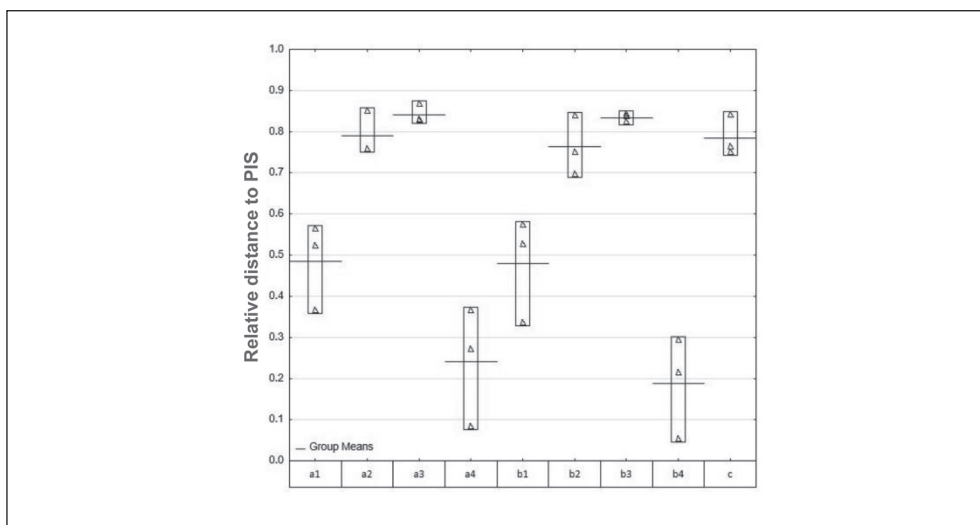
**Fig. 9:** Quantile plot of CV-TOPSIS results
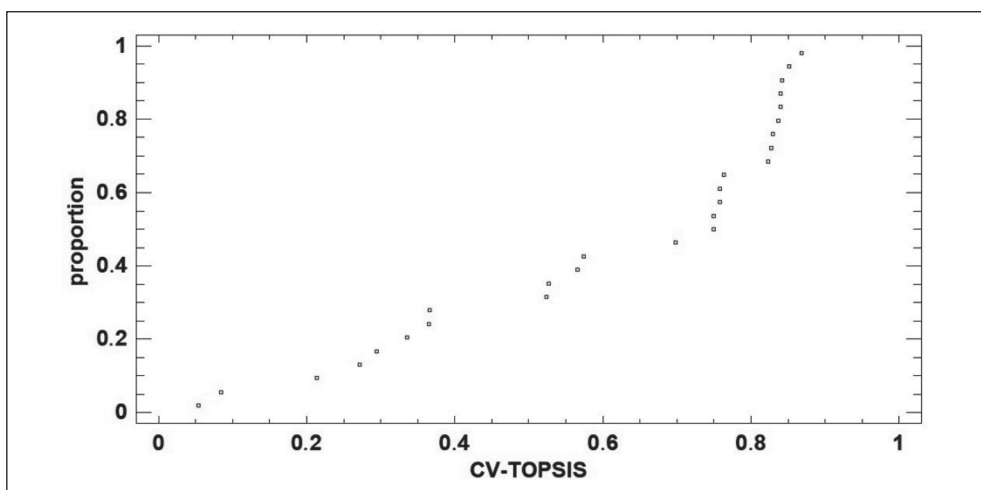
Source: own

the smallest, while the differences between the Altman model variants used are minimal (Fig. 10).

Good overall results ($c_i$) are also achieved using negative equity, as well as monitoring all the indicators simultaneously (C). In this case, the Altman model used already represents a factor affecting the overall results (see Tab. 8).

The best rated criterion for identifying an unprosperous enterprise was the Altman model from 1968 combined with the monitoring of negative total liquidity ($L_3$) in the last year. This combination produced a low proportion of misidentified enterprises in decline and had a relatively high overall reliability. The

**Tab. 8:** Overall results of the CV-TOPSIS technique

| Rank | Model | A* | FNR | FPR | ACC | $c_i$ |
|------|-------|-----|------|------|------|------|
| 1 | Altman 68 | A3 | 0.0473 | 0.3831 | 0.7449 | 0.8682 |
| 2 | Altman 95 | A2 | 0 | 0.3782 | 0.6395 | 0.8512 |
| 3 | Altman 95 | B3 | 0.1068 | 0.2082 | 0.8212 | 0.8420 |
| 4 | Altman 95 | C | 0 | 0.3930 | 0.6164 | 0.8402 |
| 5 | Altman 95 | B2 | 0 | 0.3936 | 0.6154 | 0.8397 |
| 6 | Altman 68 | B3 | 0.0379 | 0.4518 | 0.6686 | 0.8368 |
| 7 | Altman 83 | A3 | 0.1026 | 0.3084 | 0.7700 | 0.8295 |
| 8 | Altman 95 | A3 | 0.1236 | 0.1185 | 0.8795 | 0.8272 |
| 9 | Altman 83 | B3 | 0.0862 | 0.3767 | 0.7078 | 0.8234 |
| 10 | Altman 83 | C | 0.0416 | 0.5226 | 0.4889 | 0.7627 |

Source: own

Note: * a precondition for identifying an unprosperous enterprise.

combinations of the Altman model with indicators that did not make errors in identifying unsuccessful enterprises were ranked next, but their drawback was their lower overall reliability.

## Discussion

The Altman model is still one of the most commonly used prediction models. When trying to predict two years in advance, the success rate for predicting a business entity's bankruptcy has been 72–94% (Zwingli & White, 2010). Yi (2012) states that the Altman Z-score still has a high predictive ability for US companies. The study of Altman et al. (2017) offers evidence that the general Z-score model works reasonably well for most countries (the prediction accuracy is approximately 0.75), and the classification accuracy can be improved further (above 0.90) by using country-specific estimation that incorporates additional variables.

The use of the Altman Z-score for Slovak enterprises is more than questionable. Its unsuitability for the conditions of Slovak companies has been confirmed by several empirical surveys. In particular, Kabát (2011b) pointed out that the model was derived from the special conditions of the American market; different legislation and content definitions could make its use for Slovak enterprises problematic. Using a sample of 700 Slovak enterprises, Gavúrová et al. (2017) found that the Altman model was less accurate than Czech models, which better reflect the conditions in this region (FNR = 22.86%; ACC = 77.14%). From the research of Mihalovič (2018), conducted on a sample of 1,280 enterprises (evenly divided into bankrupt and prosperous enterprises), it can be seen that the model of multidimensional discriminatory analysis exhibited a type I error of up to 54.38%, confirming the unacceptability of using such a model. Delina and Packová (2013) analyzed a sample of 1,560 Slovak enterprises from 1993 to 2007, of which 103 were in bankruptcy during this period. The Altman model showed the worst results. The incorrect prediction of bankruptcy was 87.62%, the accuracy of the prediction of bankruptcy was 12.38%, and the return of the forecast was 51.46%. On this basis, they noted that the Altman model was not suitable for use in the Slovak economy. The aforementioned authors uniformly pointed out that the main drawback was the fact that the model was created in a different, specific environment and time that differs from the current Slovak business environment. On the other hand, Boďa and Úradníček (2016) argued that the Altman Z-score was suitable for the economic conditions of Slovak enterprises and could be a useful tool for predicting their decline.

## Conclusion

Based on these analyses, we can state that the way of defining an unprosperous enterprise is a significant factor affecting the overall reliability of the Altman model; monitoring a longer period for defining an unprosperous enterprise does not automatically mean better results (reflected in the fact that 4 of the top 10 combinations followed the indicator for more than one year). The Altman model from 1968 and 1983 confirmed the differences resulting from the natural conditions in which the enterprises operate. If the aim of the research is to identify a combination with the smallest type I error, the smallest proportion of misclassified bankrupt enterprises, we recommend using the Altman model from 1968 or 1995, using negative equity as an indicator to monitor, for determining an unprosperous enterprise, i.e., a company in trouble. However, if the aim the research is to identify a combination with the smallest type II error, the smallest proportion of misclassified prosperous enterprises, we recommend using the Altman model from 1995, using negative total liquidity as an indicator to monitor, for determining an unprosperous enterprise. In this case, the enterprise creates uncovered debt, which means that it is undercapitalized, i.e., part of the fixed assets are covered by short-term resources, and the golden rule of funding is thereby not met. The same combination of the Altman model from 1995 and negative total liquidity can be recommended to achieve the highest overall reliability for the model. The economic results and economic value added (EVA) proved to be inappropriate as indicators for defining an unprosperous enterprise in the conditions of the Slovak Republic.

The above conclusions should be seen within the limits of this research. In our opinion, it is not possible to unequivocally reject or recommend the use of the Altman model for the evaluation of entities working the soil in the Slovak Republic. To supplement this conclusion, it is necessary to identify the explanatory ability of other models, e.g., the Taffler model or Bonity index, which are also often used in

this region. In addition, we plan, in the future, to verify the predictive abilities of the Gurčík index and Chrastinova model, which were designed expressly for the needs of Slovak farms. Another limitation is the territory of the Slovak Republic. In order to increase the objectivity of the research results, we recommend extending the research sample to subjects working the soil in other V4 countries and comparing them.

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