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Predicting Financial Distress of Slovak Agricultural Enterprises[1]

*Martin BOĎA – Vladimír ÚRADNÍČEK**

Abstract

The paper focuses upon the predictive validity of Chrastinová's CH-Index and Gurčík's G-Index devised for predicting financial distress of Slovak agricultural enterprises and confronts them with Altman's bankruptcy formula. Its aim is to verify whether these out-dated models preserve their usefulness in newer conditions of Slovak agribusinesses and whether they may be improved by redefining the cut-off points used in separating distressed and non-distressed enterprises. Using a data sample on Slovak agricultural enterprises for the period from 2009 until 2013, it is ascertained that the G-Index with redefined cut-off points may be tentatively recommended for financial distress prediction showing a balanced trade-off between distress and non-distress prediction accuracy.

Keywords: *G-Index, CH-Index, Altman's Z-score, Slovak agricultural enterprises, financial distress, prediction accuracy*

JEL Classification: G33, Q00

Introduction

Albeit bankruptcy or financial distress prediction in Slovak economic conditions is up to some rare occasions founded upon foreign prediction models, it seems that these models are not importable without uncertainty and doubts about their reliability (see e.g. Boďa and Úradníček, 2015; Harumová and Janisová, 2014, pp. 522 – 524). An alternative to this might be utilization of prediction models developed for, and tailored to, the needs of the Slovak enterprise environment. Nonetheless, to the best knowledge of the authors there have been only

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three such domestic bankruptcy or financial distress prediction models published in academic literature with a sufficient degree of credibility: the M-model developed by Harumová and Janisová (2014), the CH-Index of Chrastinová (1998) and the G-Index of Gurčík (2002). The construction of the last two models respected both the general industry-specific character of agricultural production and the competitive vulnerability of the Slovak agricultural sector. In spite of their specialization on Slovak agricultural enterprises they have not gained wider acclaim in corporate or industrial analysis of agricultural enterprises where the Z-score bankruptcy formula developed by Altman (1968; 1983) is fairly proliferated and prevails. Odd as it may be, Altman's Z-score seems to dominate corporate use no matter that it was derived and estimated from a sample of US manufacturing enterprises compiled for the period from 1946 until 1996. The CH-Index and G-Index are mostly encountered only in research academic literature (e.g. Lososová and Zdeněk, 2014; Steklá a Náglová, 2014). Notwithstanding the obvious limitations of Altman's Z-score model, it is questionable to which extent this model is apt for predicting financial distress of Slovak agricultural enterprises and whether the CH-Index and G-Index are equal to the task. The issue of classification reliability and validity has not been given a thorough examination with respect to none of these three models, and they are utilized either by practising analysts or by the academic sphere merely on trust. This point becomes even more blatant when considering the changes through which the Slovak economy has had to go in the past 15 years. The accession to the European Union, the euro adoption or the global economic downturn are not phenomena tallying with gradual economic development. Especially agricultural enterprises were furthermore greatly affected by structural harmonization with the rules of the Common Agricultural Policy and volatility of the climatic situation in Slovakia where dry weathers alternated with other unfavourable natural conditions.

Although the intention of the original authors was not to anyhow confine temporal usability of their prediction models, they all three were developed for an economic environment that no longer exists, and it is then uncertain as to whether their utilization can be at liberty extended to the contemporary period. The standard position and popularity of Altman's Z-score, the CH-Index as well as the G-Index in the practice and theory of Czecho-Slovak corporate finance evaluated in confrontation with their seeming temporal validity begs the research interest that underlies this paper. As is cautioned by Harumová and Janisová (2014, p. 524) with an emphasis on Altman's bankruptcy formula, these models should be constantly updated so that they can be safely applied to enterprises undertaking in a specific industrial environment (see also Bellovary, Giacomino and Akers, 2007, p. 3). Oddly enough, there has recently been an interest in the validation of „older“ models of bankruptcy or financial distress prediction for agricultural enterprises, e.g. Purves, Niblock and Sloan (2015) for Australia, Rajin, Milenković and Radojević (2016) and Stojanović and Drinić (2017) for Serbia, or Karas, Rezňáková and Pokorný (2017) for Czechia. Concerning Slovak agricultural enterprises, this issue has been sort of overlooked and no research has been devoted to this topic using a satisfactory sample of genuine Slovak data.

Led by this input and building on these considerations, the aim of the paper is verify as to whether Altman’s bankruptcy formula (as a prediction model favoured by practitioners) and Chrastinová’s CH-Index and Gurčík’s G-Index (as prediction models preferred by academicians) are, or continue to be, valid for predicting financial distress of Slovak agricultural enterprises. To this end a data sample of Slovak enterprises sectorally affiliated with the agricultural industry for the period from 2009 until 2013 is used, and the research interest is further augmented by investigating as to whether the predictive ability of these three prediction models can be improved by redefining the cut-off points that mark off three classification zones: the zone of probable financial distress, the zone of ignorance (the gray area) and the zone of presumable financial health. This redefinition is done not only for the Z-score, the CH-Index and G-Index themselves but also for their components. Each of these prediction models is constructed by linear discriminant analysis as a linear combination of five suitably selected financial indicators serving as predictors of corporate financial status. In consequence of non-constant temporal and econo-geographical conditions, it is possible that the coefficients that define these linear combinations are no longer „optimal“ and single component predictors alone may yield better prediction performance than the three prediction models. Hence, in tune with the observation of Harumová and Janisová (2014, p. 524), the paper redefines the cut-off points of the three prediction models and sets (new) cut-off points for their component predictors in the hope that an insight is gained into what constitutes the core of financial condition of agricultural enterprises nowadays and what predicts it best.

All in all, there are two overlapping directions of research in the paper: In the first instance, using a relatively recent data sample of Slovak enterprises the paper seeks to establish predictively good classification zones of the 15 financial ratios that are used in the definitions in the Z-score, CH-Index and G-Index and also for these three prediction models themselves. Then, in the second instance, the paper assesses the prediction performance of the individual predictors and the modified three prediction models, and compares it with the prediction performance of the Z-score, CH-Index and G-Index with the originally formulated classification zones. The prediction models and predictor variables under consideration are reviewed and inspected not only using standard measures of classification performance, but also by means of the tests based on the odds ratio and on Cohen's kappa. In this effort, the ambition of the paper is not to develop a new prediction model but to operate with what is well-established in the field of financial distress prediction and to put it to test or to improve it. By critical revisiting of the prediction accuracy of the three financial distress prediction models proliferated amongst Slovak agricultural enterprises or proposed for them, the paper makes a recognizable input to the theory and practice of Slovak corporate finance The reason being, not only does it challenge the credibility of traditional tools of corporate finance, it also identifies factors crucial to financial condition of Slovak agricultural enterprises.

The remainder of the paper is organized into four more sections. The next section makes short notes on the three prediction models and explains certain unavoidable methodological inaccuracies that go with using them in practice. Another section describes the data set used in the analysis and clarifies the statistical procedures used in the paper, and is followed by the section that gives the results. The last two sections first discuss the results and then conclude.

Financial Distress Prediction Models for Slovak Agricultural Enterprises

It is but coincidental that there has recently been an emergence of interest in the academic community in a possibility of importing financial distress prediction models developed in foreign conditions into domestic economic practice or in a possibility of utilizing older models long after the period to which they related. Relevant examples are inquiries of Rezňáková and Karas (2015) and Čámská (2016). The study by Rezňáková and Karas (2015) investigates usability of Altman's Z-score model in predicting bankruptcy of Visegrád Group enterprises and finds that except Hungary there are some gains in redefining the loadings carried by predictors and adjusting the cut-off values. The paper by Čámská (2016) is an investigation into the accuracy of diverse prediction models (inter alia, of American, Swiss, Czech, Baltic provenience) in predicting bankruptcy of Czech metal manufacturing enterprises. In most cases, sufficient and satisfactory accuracy was detected resulting in the statement that there is no need for a new model.

Apparently, only three models of bankruptcy or financial distress predictions have been presented in the extant literature for use in the corporate conditions of Slovak agriculture. Alongside Altman's Z-score, it is the CH-Index and G-Index, and these were specially developed for, and tailored to, Slovak agricultural enterprises. They also happen to be advertised in standard textbooks on financial analysis such as those by Kotulič, Király and Rajčániová (2010, pp. 121 – 122) or Kalouda (2015, pp. 73 – 74). The fact that their books devoted to financial analysis or management focus on a general audience is suggestive that these models are considered as standard, though specifically oriented on agricultural enterprises. This is one of the reasons for which these two models are highlighted for Slovakia also in an in-depth study by Prusak (2018) reviewing bankruptcy prediction research in European Post-Communist economies.

Nonetheless, it is perhaps only Altman's Z-score model that is actually employed in bankruptcy predictions of Slovak agricultural enterprises owing to its general proliferation, and the CH-Index and G-Index remain more of academic proposals than instruments of practical analysis. Both these models as well as Altman's Z-score model are founded on the methodology of linear discriminant analysis and they are presented here in this section together with notes on their correct use. For clarity of presentation, the formulas of the model and classification rules for classification of agricultural enterprises are organized in Table 1. The following notes encompass a brief, yet essential discussion on difficulties with defining the actual distress condition they attempt to predict.

T a b l e 1

Z-score, CH-Index and G-Index

Prediction model and formula	Predictor variables
Z-score of Altman (1983) $Z = 0.717 \cdot A1 + 0.847 \cdot A2 + 3.107 \cdot A3 + 0.420 \cdot A4 + 0.998 \cdot A5$ $Z \leq 1.23 \Rightarrow$ the enterprise being at risk of bankruptcy $1.23 < Z \leq 2.90 \Rightarrow$ the enterprise being in the grey area $Z > 2.90 \Rightarrow$ the enterprise is probably financially healthy	A1 – working capital/total assets A2 – retained earnings/total assets A3 – earnings before interest and taxes/ total assets A4 – equity/liabilities A5 – sales/total assets
G-Index of Gurčík (2002) $G = 3.412 \cdot X1 + 2.226 \cdot X2 + 3.277 \cdot X3 + 3.149 \cdot X4 – 2.063 \cdot X5$ $G \leq –0.6 \Rightarrow$ an unprosperous agricultural enterprise $–0.6 < G \leq 1.8 \Rightarrow$ a mediocre (average) agricultural enterprise $G > 1.8 \Rightarrow$ a prosperous agricultural enterprise	X1 – retained earnings/total assets X2 – earnings before taxes/total assets X3 – earnings before taxes/revenue X4 – cash flow/total assets X5 – inventories/revenue
CH-Index of Chrastinová (1998) $CH = 0.37 \cdot Y1 + 0.25 \cdot Y2 + 0.21 \cdot Y3 – 0.1 \cdot Y4 – 0.07 \cdot Y5$ $CH \leq –5 \Rightarrow$ an unprosperous agricultural enterprise $–5 < CH \leq 2.5 \Rightarrow$ a mediocre (average) agricultural enterprise $CH > 2.5 \Rightarrow$ a prosperous agricultural enterprise	Y1 – earnings after taxes/total assets Y2 – earnings after taxes/sales Y3 – cash flow/payables Y4 – 365 × payables/sales Y5 – liabilities/total assets

Source: The authors based on Altman (1968; 1983); Chrastinová (1998); Gurčík (2002).

It is customary to compare a new prediction method in terms of classification accuracy with the Z-score model developed by Altman (1968; 1983). Albeit this model is rightly subjected to a massive critique when used outside the home US environment for which it was developed under completely different circumstances (for criticism consult e.g. Boďa and Úradníček, 2015, and for vindication see e.g. Kalouda, 2010), it is used as a yardstick (see e.g. Grice and Ingram, 2001, p. 53). Altman's Z-score was also employed for the purpose of comparison by Chrastinová (1998) and Gurčík (2002) or later by Kopta (2006; 2009). This exceptional status follows from the fact that Altman's Z-score was the first multivariate prediction model and exhibited high predictive accuracy (see Bellovary, Giacomino and Akers, 2007, p. 4). Altman (1968) first proposed his model for manufacturing enterprises with publicly traded shares and later in a monograph of his (Altman, 1983, pp. 121 – 123) extended its scope to manufacturing enterprises with shares non-listed on the capital market. As argued e.g. by Boďa and Úradníček (2015), this revised Z-score model is more reasonable than the original Z-score model. Besides, it was also employed by Chrastinová (1998) and Gurčík (2002) in the comparison of their models.

Ignoring some methodological inaccuracies stemming from the changing definition of items declared in financial statements or their incompatibility owing to different accounting standards and practices, neglecting the issue of credibility of financial and non-financial information disclosed with financial statements, and believing in universal applicability or generalizability of the method across diverse territories and/or periods, there is still one issue of outstanding and it is that it is not certain what these models actually predict. There are well understood differences between financial distress and bankruptcy and these two different notions of enterprise economic condition can easily be isolated. Despite being conscious of this distinction, when predicting financial condition these two terms are frequently interpreted loosely and their meaning is interchanged. Interestingly, Grice and Ingram (2001, p. 53; 55) note that bankruptcy models are perhaps more suited to predicting financial distress than to predicting bankruptcy. The claim of Grice and Ingram (2001) that bankruptcy or financial distress prediction models should be interpreted in relation to financial distress is accepted in this paper. For the adopted definition of financial distress the paper then investigates the predictive accuracy of the Z-score, CH-Index and G-Index, and examines these three models and their 15 component indicators for a possible redefinition of classification zones. These aspects are elucidated in the next section.

Data and Methodology

The economic rule for classification of enterprises as financially distressed or non-distressed is constructed as a definition of financial distress and rests upon two principal characteristics of financial condition: the ability to attain and retain profitability, and the ability to maintain liquidity. The former characteristic comes from observation that bankrupt agricultural holdings tend to suffer from long-term negative profitability and from drops of current earnings which is a factor hindering long-term asset renewal (cf. Kopta, 2006, p. 1065; Střeleček, Lososová and Zdeněk, 2011, p. 104; Lososová and Zdeněk, 2013, p. 552). This characteristic is treated here by means of two definitional criteria for a financially distressed enterprise: (i) its equity must be negative, and (ii) its earnings after taxes must also be reported negative. Condition (ii) means that in a given fiscal year the enterprise is loss-making and temporarily short of cash-flow generating capability. Condition (i) under normal circumstances occurs when the enterprise accumulated a considerable amount of loss relative to its common stock over past years and captures past long-term negative profitability. Conditions (i) and (ii) jointly reflect long-term negative profitability, both historical and current. The second characteristic stresses the importance of liquidity and refers to the ability of an enterprise to settle its liabilities which are due at present or in a near future. This follows from the fact that an enterprise with decreased liquidity is putting itself at risk of insolvency. The second characteristic is then mirrored in another condition for a financially distressed enterprise: (iii) its current ratio (defined as current assets/current liabilities) must attain a value lower than 1. Normally, this indicator should be around 2 or 2.5 and too low values are critical for preserving a state of solvency (see e.g. Střeleček, Lososová and Zdeněk, 2011, p. 112; Lososová and Zdeněk, 2013, p. 559). Conditions (ii) and (iii) were also considered also by Šnircová (1997, p. 16) who investigated financial distress of Slovak enterprises, though in a more general context and not restricted to the agricultural industry. Some useful insights in this regard are also intermediated by the study by Jakubík and Seilder (2009) who investigates the macro-determinants of insolvency of Czech enterprises. One of the majors factors confirmed is the level of debt taken, and justifies condition (ii).

The data set on economic results of Slovak agricultural enterprises for the analysis was obtained from the leading Slovak corporate analytical agency CRIF – Slovak Credit Bureau, s. r. o. The data sample related to the fiscal periods from 2009 to 2013 and involved 5 legal forms of enterprises usual in Slovakia, i.e. co-operatives, general partnerships, limited partnerships, private limited companies, and joint-stock companies. All these companies had the majority of their activities sectorally registered with agriculture (under division 01 Agriculture, hunting and related service activities as specified by NACE Rev. 2). One property of the data set is that it did not emerge as a random drawing from the population of Slovak enterprises, which prohibits rigorous statistical testing and inference. Yet, the manner in which it was obtained nohow affects the classification of enterprises into a group of financially distressed entities and a group of financially non-distressed entities.

The adopted definition of financial distress was applied with respect to a prediction horizon of one fiscal year. Hence, the analysis to come required that financial statements in two consecutive fiscal years for every enterprise be available. Whilst the information in financial statements in the later year was used to determine the financial condition of enterprises, the information reported in financial statements of the earlier year was used for the purpose of prediction. The requirement that financial statements in two consecutive years are available reduced a larger sample of agricultural enterprises, in which it was naturally imperative that in the initial year an enterprise not be in financial distress condition. In the year of prediction the enterprise might be in either condition. The matching of financial statements in two subsequent years led to 164 enterprises for the two-year period from 2009 to 2010, 324 enterprises for the period from 2010 to 2011, 648 enterprises for the period from 2011 to 2012, and – finally – 886 enterprises for the last two-year period from 2012 to 2013. Following the three definitional criteria of financial distress,

- out of 164 non-distressed enterprises in 2009 only 8 were found in financial distress in the next year (representing thus 4.88%),
- from 324 non-distressed enterprises in 2010 just 27 were found distressed in 2011 (representing thus 8.33%),
- from 648 non-distressed enterprises in 2011 as many as 50 were found distressed in 2012 (representing a share of 7.72%), and
- from 886 non-distressed enterprises in 2012 a total of 130 enterprises were in distress condition in 2013 (which is a share of 14.67%).

Proceeding similarly as Altman (1968); Chrastinová (1998) or Kopta (2006; 2009), the data for these enterprises were pooled in one data set totalling 2022 enterprises, out of which 215 were considered distressed (amounting thus to a share of 10.63%). For illustration, Altman (1968) had a sample of 66 enterprises, Chrastinová (1998) employed data on 1123 agricultural enterprises, Gurčík (2002) made use of a data set counting 60 agricultural enterprises. A sample of 112 enterprises was used by Kopta (2006) and of 117 enterprises by Kopta (2009).

For each agricultural enterprise in the sample the financial ratios Y1 – Y5, X1 – X5 and A1 – A5 were computed alongside the CH-Index, G-Index and Z-score as defined in expressions (1), (2) and (3). For brevity, the CH-Index is in the tabular and visual displays contracted to CH, the G-Index abbreviated as G and Z-score is denoted as Z. As announced in the earlier text, each of these prediction variables (i.e. the 15 financial ratios and 3 composite prediction indicators) were investigated for their univariate prediction capacity in the spirit similar to the analysis of Beaver (1966) but allowing for the gray area (or the zone of ignorance). Assuming inevitably therewith that there are differences between non-distressed and distressed enterprises and expecting that these differences appear in the mean level of prediction variables (and not in their variability), two cut-off points were determined to separate predictively the class of distressed enterprises from the class of non-distressed enterprises. The real axis was divided by two points into three parts. An agricultural enterprise which attained the value of the respective prediction variable in the left-end part (i.e. the value lower than or equal to the smaller cut-off point) or in the right-end part (i.e. the value greater than the larger cut-off point) was classified either non-distressed or distressed. Otherwise, if the value of the prediction variable was found in the middle part (being greater than the smaller cut-off point but not greater that the larger cut-off point), the agricultural enterprise in question found itself in the gray area of indeterminacy. For each prediction variable, the cut-off points were determined by a systematic two-step search procedure performed exhaustively for the range of observed values. The real axis was divided by the midpoints of observed values for each prediction variable and these midpoints conjointly with the actually observed values were treated as potential candidates for cut-off points. Under normal circumstances, the means of observed values for non-distressed enterprises and distressed enterprises should suffice in specifying which group is the „lower" one and which group is the „upper" one. Bearing in mind that the arithmetic mean as a statistical descriptor of location is sensitive to anomalous observations appearing as outliers, classification of distressed and non-distressed enterprises on the basis of means calculated separately for either group may be misguiding, which comes from the fact that the ordering of group means on the real axis may be expected to be gravely affected by a presence of outliers in observed values. Although a priori economic reasoning might be put to work, an atheoretical data mining approach was entertained instead in the spirit of the trial-and-error method. Distressed enterprises were first considered to constitute the lower group (with values up to the cut-off point) and non-distressed enterprises the upper group (with values above the cut-off point). Then this arrangement was reversed and the predictively better performing option was continued with. As concerns the employed two-step procedure, in the first step by systematic going over the range of cut-off point candidates the real axis was divided into two parts and one cut-off was found by dividing enterprises into the non-distress group and the distress group. With these classifications two errors are made: Whereas the Type I error rate is given by the proportion of wrong classifications of distressed enterprises as non-distressed to the number of distressed enterprises, the Type II error rate is defined as the proportion of wrongly classified non-distressed enterprises labelled as distressed to the number of non-distressed enterprises. In accordance with Wu, Gaunt and Grant (2010), the cut-off point was determined so that the sum of Type I error and Type II error rates was minimal. In the second step a possibility of the gray area was accommodated and the neighbourhood of the first-step cut-off point (± 25% of observed values) was investigated exhaustively for two cut-off points delimiting the gray area. Also this second-step search was conducted with the desire to minimize the sum of Type I error and Type II error rates. The described two-step procedure was applied and the prediction accuracy was calculated with the use of the entire sample. No hold-out sample was allocated, but to ameliorate the biases of this whole-sample procedure, the cross-validation approach was utilized in a conventional style (see e.g. Ripley, 1996, pp. 69 – 72) in order to measure uncertainty associated with quantification of prediction accuracies. This uncertainty is measured by root mean square error (RMSE). The analysis in its entirety was undertaken in program R (R Core Team, 2013) and its library pROC (Robin et al., 2017).

The comparison in terms of prediction accuracy was effected with respect to the CH-Index, G-Index and Z-score with the original cut-off zones declared beneath expressions (1), (2) and (3) and with respect to the three-zone simple prediction models developed in a univariate style for the 15 financial ratios as well as for the CH-Index, G-Index and Z-score. In order to differentiate the original prediction models CH, G and Z from their improved counterparts with redefined cut-off zones, the improvements are indicated typographically by asterisks and denoted as CH*, G* and Z*, respectively. The results are reported in the following section. They instruct on the performance accuracy of the original prediction models, their improvements and the developed three-zone univariate prediction models based each upon one financial ratio for the available sample of Slovak agricultural enterprises. Another aspect is that they help evaluate as to which of the predictors is most useful in the process of identifying distressed agricultural enterprises. The last remark is that statistical testing was avoided as the data sample was not secured through a random sampling design.

Results

An insight into the stand-alone classification ability of the predictor financial ratios Y1 – Y5, X1 – X5 and A1 – A5 as well as of the CH-Index, G-Index and Z-score is provided by Table 2. This table conveys information on the location and dispersion of the individual predictors aggregated separately for the group of 1807 non-distressed enterprises and the group of 215 distressed enterprises. Structured for individual predictor variables, Table 2 reports for both groups of enterprises mean values and standard deviations (abbreviated as StdDev), medians and median absolute deviations (tagged as MAD) alongside minimum and maximum values. Whilst the mean and standard deviation are used as classic non-robust measures of location and variability, the median and mean absolute deviation act here as their robust counterparts. Difference in location is vital to the task of discriminating between non-distressed and distressed enterprises. Ideally, group means (or medians) of predictor variables relative to group variability should be sufficiently distant from each other, which is not the case here. With most predictor variables, means are too close and notional intervals „mean ± standard deviation“ tend to overlap. Even so, this cannot be attributed to a presence of outlying values insomuch as the same scheme is observed when medians and median absolute deviations are considered instead. In this case, there is little or no practical difference with each predictor variable. Furthermore, it is especially the predictor variables Y4, CH, X3, X5, G, partially A4, and Z that suffer from high variability. A higher level of variability in the CH-Index, G-Index and Z-score is just a consequence of larger heterogeneity of its components. This finding of pronounced variability of financial indicators and agrees with what is reported e.g. by Gurčík (2002, p. 376); Kopta (2006, pp. 1061 – 1063; 2009, pp. 120 – 123). In summary, the differences between non-distressed and distressed enterprises captured by dint of the considered 18 prediction variables are factually negligible and what is apparent is a rather high level of within-group variability with some variables, which indicates that the resulting univariate classifiers may be less performing.

Using the pooled data set of 2022 agricultural enterprises and the methodology elucidated in the preceding section, for each prediction variable two cut-off points were determined and univariate prediction models were thus defined. The cut-off values found for the 15 financial ratios and newly established for the CH-Index, G-Index and Z-score by minimizing the sum of Type I error and Type II error rates are reported in Table 3. On an eye-ball tests, they mostly do not differ much and are located very closely on the real line, but they delimit a good many enterprises that are subsequently classified in the gray zone as follows from the numbers of grayly classified enterprises. It is notable that the classification boundaries that came originally with the prediction models were to a great extent redefined. Operating with rounded numbers, for the CH-Index the cut-off points were substantially altered from –5 and –2.5 to –55 and –39, for the G-index from –0.6 and 1.8 to –0.25 and 0.64 and for the Z-score from 1.23 and to new 0.95 and 1.24. The change in cut-off points registered at the CH-Index is obviously a consequence of large magnitudes of the Y4 indicator that measures days payable outstanding. Table 3 then also reports on the number of classifications of enterprises in both groups into the class of non-distressed enterprises (indicated as ND), distressed enterprises (shown as D) or falling into the gray zone (shown as G).

These numbers of classifications serve as the inputs in calculating total, non--distress and distress accuracy of predictions that are reported as percentages in Table 3 as well. Whilst total prediction accuracy measures the number of correct classifications relative to the number of all classifications, non-distress and distress prediction accuracy capture the proportion of correctly classified enterprises amongst non-distress and distressed enterprises, respectively. Incidentally, non--distress prediction accuracy is one minus Type II error rate and distress prediction accuracy coincides with one minus Type I error rate. Table 3 states classification results not only for the 18 prediction variables with sought-after or redefined cut-offs (i.e. the financial indicators X1 – X5, Y1 – Y5 and A1 – A5, the indices CH, G and the score Z), but also for the prediction models with original cut-offs (i.e. the models with asterisks reported as CH*, G* and Z*).

The prediction performance of the 21 prediction models summarized in Table 3 varies. One should be aware in inspecting these results that the ultimate goal of this study is to find out how the CH-Index, G-Index and Z-score, their versions with redefined classification zones and their component financial indicators fare in predicting financial distress when put to test with a more recent data on Slovak agricultural enterprises. Attention should therefore be oriented upon distress prediction accuracy as the key indicant of a model's classification quality, which is not meant to belittle the role of total prediction accuracy in assessment of prediction performance.

A better picture of the prediction performance delivered by the models summarized in Table 3 is given in Figure 1, which displays for them total prediction accuracy beside distress prediction accuracy. The CH-Index with original classification zones (shown as CH*) records the highest distress accuracy (96%), which is but owing to its propensity to designate any agricultural enterprise in the sample as distressed and its high distress prediction accuracy is compensated with high Type II error. A satisfactory level of prediction accuracy of distressed enterprises is then found for the gross return on revenue ratio X3 (81%), the debt ratio Y5 (77%), the days payables outstanding ratio Y4 (70%) and for the CH-Index with redefined cut-off values (70%). This extraordinary ability to detect financial distress goes at the cost of increased Type II error rates since the total prediction accuracy of these models in question is relatively small.

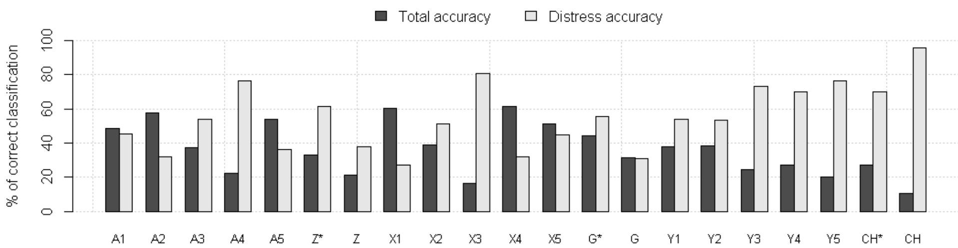
Nonetheless, first and foremost this suggests that the most important predictors of financial distress in the sample of Slovak agricultural enterprises are X3, Y4 and Y5 and what really helps in predicting their distress condition rests in three areas of their financial performance. Firstly, it is their gross (i.e. before-taxes) profit margin, which captures the capacity of an enterprise to make revenue in excess of expenses and to retain a fraction of its revenue in the form of profit (before tax deductions which should be objectively beyond the control of the enterprise). Secondly, it is the average number of days it takes an enterprise to pay its own outstanding invoices through which this enterprise can improve on its working capital and increase free cash-flow (with impacts overstepping cash management and outreaching liquidity management). Thirdly, it is the capital structure and the amount of debt relative to assets exerting its influence over debt cost management deciding whether an enterprise appears risky to its creditors. All the three factors have their links to solvency of agricultural companies and can be traced easily through economic relationships to (il)liquidity or (in)solvency. Naturally, the fact that the CH-Index is a function of Y4 and Y5 propagates itself to good distress prediction performance of the CH-Index with both redefined cut-offs (CH) and original cut-offs (CH*). A similar behaviour of Chrastinová's CH-Index (with original cut-offs) is also recorded in the studies of Kopta (2006, p. 1060; 2009, p. 123) who reports that it has a tendency to classify enterprises into the gray zone or into the group of distressed enterprises and finds reasons for this behaviour with Y4.

As regards total prediction accuracy, the best predictors on a comparative basis for distinguishing between distressed enterprises and non-distressed enterprises seem the retained earnings to total assets ratio X1 (60%) and the retained earnings to total assets ratio A2 (58%).

Their prediction power works undoubtedly through retained earnings, though their representation is a different balance-sheet item as was adverted to earlier (retained earnings in A2 comprise current earnings whereas retained earnings do not). Insomuch as their high total prediction accuracy is attained by means of high non-distress prediction accuracy, it is clearly accumulated profitability (or rather accumulated retained earnings) that is instrumental in identifying non-distressed agricultural enterprises and helps unidirectionally to separate a non-distressed enterprise from any agricultural enterprise.

F i g u r e 1

Comparison of Classification Accuracy for the Predictor Variables



Source: The authors.

In general, the prediction variables whose performance is summarized in Table 3 and compactly displayed in Figure 1 can be broken down into three categories: predictors that are more suitable for identification of financial distress (such as A3, A4, Z*, Z, X2, X3, G*, Y1, Y2, Y3, Y4, Y5, CH* and CH), predictors that are more apt in differentiation of non-distressed enterprises (such as A2, A5, X1, X4) and neutral predictors with balanced distress and non-distress prediction accuracy (such as A1, X5 and G). The extraordinary high performance of both versions of Chrastinová's CH-index, i.e. CH* and CH, stems from the fact that this index is constructed as a linear combination of variables that belong to the first recognized category.

Table 3 also equips the prediction accuracies for the 18 prediction variables when cut-off values were sought-after or redefined with an RMSE measure of uncertainty as detailed in the earlier section. Each RMSE is stated after an ± sign enclosed in parentheses and is expressed in percentage points (pp). Being estimated by the 10-fold cross-validation procedure in the process of determination of cut-off points, the RMSE measures in Table 3 suggest that – as a whole – non--distress prediction accuracy and distress prediction accuracy have a tendency to display higher uncertainty than total prediction accuracy has. The reported total prediction accuracies are estimated to deviate on average from the actual accuracy level from 3 to 28 percentage points, whilst for non-distress prediction accuracy these deviations vary from 2 to 30 percentage points and for distress prediction accuracy they are in the range from 7 to 52 percentage points. This complies with the fact that distressed enterprises form a share of only 10.63% and due to their distress condition their economic behaviour as captured by individual financial indicators serving as predictors is burdened with a fair amount of heterogeneity. The RMSE measure casts also some doubt upon the reliability of the favourably high distress prediction accuracy rate of the ratio X3 as the estimated error is 26 percentage points.

However, for the ratios Y5 and Y4 as well as for the CH-Index with redefined cut-off values these estimated errors are much lower (9 or 16 percentage points). In this respect, a more credulous total prediction accuracy rate is estimated for the ratio A2 (with an error of 5 percentage points) than for the ratio X1 (showing an error of 14 percentage points). All the same, it is not possible to compare the calculated degrees of prediction uncertainty with other studies as they did not engage in cross-validation to assess the effect of observational variability on prediction accuracy.

The tabular report in Table 4 is assistant in assessing stationarity of prediction accuracy. Prediction accuracy was derived in Table 3 with the use of the pooled sample covering all the four biannual periods between 2009 and 2013 and it may suffer from structural changes that might have happened in the individual years of this period. Notwithstanding, this is not the case because when prediction accuracy is measured for the individual biannual periods – viz. 2009/2010, 2010/2011, 2011/2012 and 2012/2013 – differences in total prediction accuracy as well as in non-distress and distress prediction accuracy as exhibited by each prediction variable are negligible and minute. This is a statistical complement to Table 3 giving an insight into the validity of results. Treating the aspect of (un)certainty of prediction accuracy rates, it is indicative that the prediction accuracy of the prediction variables is stable and free of structural fluctuations over time.

It is of further interest to examine the statistical significance of the 18 predictor variables and to explore their overall prediction accuracy that follows from shifting or readjusting the cut-off points. Significance testing in this situation must reflect two circumstances. First, the data set does not represent a random sample, which prohibits using statistical tests that are frequently used in a predictive context. Second, the prediction variables being analyzed were not identified or established by virtue of a model-building procedure that would be based on the statistical assumption of a data generating process for the data set at hand. The prediction variables X1 – X5, Y1 – Y5 and A1 – A5 are financial ratios suggested by economic reason, and the definitions of the three composite prediction indicators CH-Index, G-Index and Z-Index are here pre-determined and appear as linear combinations with fixed coefficients. Nonetheless, although testing in a usual regression-like fashion is not possible, it is possible to analyze the prediction information that is dispersed along Table 3. Toward this end, the predicted counts of enterprises in Table 3 are converted to classification tables and two approaches to testing the significance of predictors are applied in parallel, viz. the test based on the odds ratio and the test based on Cohen's kappa. The tests are described in sufficient detail in Fleiss (1981, pp. 61 – 71; 212 – 220) or in Agresti (1990, pp. 54 – 55; 366 – 367).[2]

The results are now reported in Table 5. As was also suggested from the preceding results, the predictor variables fundamental to predicting financial distress of Slovak agricultural enterprises do not display satisfactory discriminatory power. Both tests point to the same finding and suggest that only the CH-Index is of statistical significance in regard to its prediction capacity and all the other predictors are convincingly insignificant. So far the prediction accuracy was assessed for one particular choice of cut-offs points. Such cut-offs are reported in the last columns of Table 3. By changing these values one makes a compromise between Type I and Type II errors, which is usually plotted as an ROC (receiver operating characteristic) curve, and the overall prediction accuracy is quantified by the area under the [ROC] curve (AUC). AUC represents a summary measure of the predictive power of a predictor variable or a model and ranges normally between 0.5 and 1. A value of 0.5 means that the predictions were no better than random guessing. For the case when one cut-off value is considered (and a gray zone is not allowed), the associated AUCs are reported for each predictor variable in the last columns of Table 5, first for the individual biannual periods and eventually for the pooled entire sample.

Useful statistical details on the ROC analysis are detailed in Hanley and McNeil (1982) or Bradley (1997). The estimated AUCs reveal that the predictive performance of all the predictor variables – no matter whether inspected for the biannual periods or for the entire period – is poor or even substandard with the exception of the predictor variables A3, X2, X3 and Y1 for the first biannual period 2009/2010 when the AUCs suggest fair performance. This merely proves that albeit the cut-off scores declared in Table 3 may be optimal in some sense, there is not much room for improvement of these prediction rules by finding other cut-offs since for any choice the resulting performance might be expected disappointing.

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[2] A classification table is a fourfold table whose rows are observed conditions and columns are predicted conditions arising from a dichotomous classification into distressed enterprises and non--distressed enterprises. The cells of the classification table are formed by true positives (TP = the number of distressed enterprises correctly classified), false negatives (FN = the number of distressed enterprises classified wrongly as non-distressed), false positives (FP = the number of non--distressed enterprises classified wrongly as distressed) and true negatives (TN = the number of non-distressed enterprises classified correctly). The conversion from the information from Table 2 necessitates that the FN and FP categories be extended respectively by the number of distressed and non-distressed enterprises assigned to the gray zone. Then the conversion is complete and exhausts the entire data sample.

The following notation is further espoused: P_{act} = TP + FN and N_{act} = FP + TN (the numbers of actually distressed and non-distressed enterprises), P_{pr} = TP + FN and N_{pr} = FN + TN (the number of distress and non-distress predictions), and eventually $\Omega = P_{act} + N_{act} = P_{pr} + N_{pr}$ (the number of all enterprises). Then the odds ratio is estimated by the formula $\text{Odds} = (\text{TP} \times \text{TN})/(\text{FN} \times \text{FP})$. The lack of association between the observations and predictions would imply Odds ≈ 1 and the prevalence of correct predictions occurs with Odds > 1.

Therefore, the statistical significance of a predictor may be based on testing the null hypothesis for its odds ratio H_0: Odds = 1 against the alternative hypothesis H_A: Odds > 1. The χ statistic defined as $\chi = \log(\text{Odds})/\text{StdErr}$ with $\text{StdErr} = \sqrt{(1/\text{TP} + 1/\text{FN} + 1/\text{FP} + 1/\text{TN})}$ has the asymptotic standard Gaussian distribution. The test is applied here with continuity correction and all counts are simply increased by +0.50. A similar test is based on Cohen's kappa that measures to which extent the predictions are drawn at random. In this dichotomous problem, the definition is $\text{Kappa} = 2(\text{TP} \times \text{TN} - \text{FN} \times \text{FP})/(P_{act} \times N_{pr} + N_{act} \times P_{pr})$. A value of 1 indicates that the predictions are in complete agreement with reality (and are statistically significant) and negative values signify that the predictions happen by chance irrespective of actual conditions.

Thus, the testing for statistical significance of a predictor requires that the null hypothesis H_0: Kappa = 1 be confronted with the alternative H_A: Kappa < 0, which may be implemented by means of the Z statistic defined as Z = Kappa/StdErr, wherein $\text{StdErr} = [(1 - p_e)\sqrt{\Omega}]^{-1}\sqrt{(p_e + p_e^2 - D)}$ with $p_e = (P_{act} \times P_{pr} + N_{act} \times N_{pr})/\Omega^2$ and $D = [P_{act} \times P_{pr} \times (P_{act} + P_{pr}) + N_{act} \times N_{pr} \times (N_{act} + N_{pr})]/\Omega^3$. The Z statistic follows asymptotically the standard Gaussian distribution and the test is carried out one-sided.

T a b l e 2

Statistical Differences in the Predictor Variables between Non-distressed Enterprises and Distressed Enterprises

Predictor/model	Non-distressed enterprises							Distressed enterprises						
	Count	Mean	StdDev	Median	MAD	Minimum	Maximum	Count	Mean	StdDev	Median	MAD	Minimum	Maximum
Y1	1 807	0.04	0.11	0.01	0.03	–0.66	0.87	215	0.04	0.12	0.02	0.03	–0.53	0.60
Y2	1 807	0.18	3.33	0.03	0.07	–7.32	121.68	215	0.04	0.60	0.03	0.06	–7.88	2.41
Y3	1 807	1.87	5.06	0.96	0.81	–0.57	130.70	215	1.66	3.09	1.01	0.87	–0.07	36.36
Y4	1 807	686.30	4 336.40	260.04	225.35	1.67	157 939	215	498.81	1 354.6	241.86	195.71	11.22	18 092
Y5	1 807	0.49	0.26	0.46	0.32	0.00	1.00	215	0.50	0.25	0.48	0.31	0.04	0.98
CH	1 807	–68.21	433.53	–25.85	22.93	–15 793	25.94	215	–49.54	135.51	–24.15	19.41	–1 808.4	0.23
X1	1 807	0.07	0.26	0.02	0.10	–2.31	0.95	215	0.10	0.22	0.02	0.12	–0.66	0.85
X2	1 807	0.05	0.13	0.02	0.04	–0.66	0.96	215	0.06	0.13	0.02	0.03	–0.53	0.71
X3	1 807	176.19	2 992.5	0.08	0.20	–230.00	117 937	215	53.29	311.16	0.10	0.16	–9.13	2 760.00
X4	1 807	0.39	0.34	0.31	0.19	–0.41	6.20	215	0.43	0.37	0.34	0.25	–0.04	3.20
X5	1 807	276.10	9 197.00	0.76	0.69	0.00	388 363	215	21.29	279.96	0.62	0.58	0.00	4 100.60
G	1 807	9.36	19 991	0.26	3.00	–738 943	386 483	215	132.51	1 070.6	0.77	3.36	–5 512.00	9 045.10
A1	1 807	0.13	0.28	0.13	0.25	–0.77	0.99	215	0.11	0.29	0.09	0.24	–0.84	0.93
A2	1 807	0.11	0.29	0.06	0.15	–2.07	0.96	215	0.14	0.24	0.09	0.17	–0.58	0.86
A3	1 807	0.06	0.13	0.03	0.05	–0.65	0.96	215	0.06	0.13	0.04	0.04	–0.45	0.71
A4	1 807	2.98	17.98	1.15	1.34	0.00	719.58	215	2.03	2.96	1.08	1.19	0.02	22.21
A5	1 807	0.64	0.80	0.48	0.34	0.00	19.33	215	0.87	1.84	0.50	0.38	0.01	22.10
Z	1 807	2.27	7.64	1.48	1.10	–1.36	302.35	215	2.11	2.33	1.48	1.00	0.00	22.35

Source: The authors.

Table 3

Estimated Cut-off Points, Classification Results and Accuracy of Predictions for the Pooled Sample

Predictor/model	Non-distressed enterprises classified as			Distressed enterprises classified as			Total accuracy (± RMSE)	Non-distress accuracy (± RMSE)	Distress accuracy (± RMSE)	Cut-off	
	ND	G	D	ND	G	D				Lower	Upper
A1	883	200	724	92	25	98	49% (± 5pp)	49% (± 7pp)	46% (± 11pp)	0.071	0.135
A2	1 097	186	524	116	30	69	58% (± 5pp)	61% (± 6pp)	32% (± 36pp)	0.110	0.199
A3	641	243	923	71	28	116	37% (± 24pp)	35% (± 30pp)	54% (± 52pp)	0.019	0.032
A4	289	185	1 333	23	27	165	22% (± 2pp)	16% (± 3pp)	77% (± 7pp)	2.671	4.138
A5	1 018	228	561	116	21	78	54% (± 18pp)	56% (± 23pp)	36% (± 10pp)	0.538	0.658
Z*	**350**	**725**	**732**	**41**	**93**	**81**	**21%**	**19%**	**38%**		
Z	**533**	**204**	**1070**	**58**	**25**	**132**	**33% (± 3pp)**	**29% (± 3pp)**	**61% (± 16pp)**	**0.945**	**1.242**
X1	1 165	189	453	130	27	58	60% (± 14pp)	64% (± 17pp)	27% (± 18pp)	0.085	0.174
X2	678	235	894	76	29	110	39% (± 2pp)	38% (± 2pp)	51% (± 64pp)	0.007	0.017
X3	159	205	1443	18	23	174	16% (± 8pp)	9% (± 11pp)	81% (± 26pp)	–0.253	0.003
X4	1 175	195	437	124	22	69	62% (± 5pp)	65% (± 7pp)	32% (± 20pp)	0.393	0.488
X5	936	203	668	95	24	96	51% (± 9pp)	52% (± 10pp)	45% (± 16pp)	0.541	0.729
G*	**565**	**565**	**677**	**83**	**66**	**66**	**31%**	**31%**	**31%**		
G	**774**	**217**	**816**	**71**	**25**	**119**	**44% (± 5pp)**	**43% (± 6pp)**	**55% (± 24pp)**	**–0.249**	**0.635**
Y1	655	238	914	70	29	116	38% (± 11pp)	36% (± 15pp)	54% (± 31pp)	0.004	0.013
Y2	658	253	896	75	25	115	38% (± 3pp)	36% (± 3pp)	53% ± (18pp)	0.010	0.029
Y3	334	188	1 285	37	21	157	24% (± 28pp)	18% (± 36pp)	73% (± 13pp)	1.619	2.314
Y4	393	226	1 188	44	20	151	27% (± 3pp)	22% (± 3pp)	70% (± 16pp)	388.15	549.88
Y5	248	237	1 322	21	29	165	20% (± 9pp)	14% (± 12pp)	77% (± 9pp)	0.180	0.275
CH*	**8**	**98**	**1 701**	**0**	**9**	**206**	**11%**	**0%**	**96%**		
CH	393	223	1 191	44	20	151	27% (± 7pp)	22% (± 9pp)	70% (± 9pp)	–54.99	–38.74

Source: The authors.

T a b l e 4

Accuracy of Predictions in the Individual Years and for the Pooled Sample (in %)

Predictor/model	Total accuracy					Non-distress accuracy					Distress accuracy				
	2009	**2010**	**2011**	**2012**	**All years**	**2009**	**2010**	**2011**	**2012**	**All years**	**2009**	**2010**	**2011**	**2012**	**All years**
A1	48.17	48.15	46.30	50.34	**48.52**	48.72	48.48	46.32	51.06	**48.87**	37.50	44.44	46.00	46.15	**45.58**
A2	70.12	62.04	56.94	54.29	**57.67**	71.79	65.32	59.53	57.54	**60.71**	37.50	25.93	26.00	35.38	**32.09**
A3	58.54	37.04	32.25	37.47	**37.44**	57.69	36.70	29.93	34.79	**35.47**	75.00	40.74	60.00	53.08	**53.95**
A4	21.34	20.99	17.75	26.64	**22.45**	18.59	16.16	13.38	17.46	**15.99**	75.00	74.07	70.00	80.00	**76.74**
A5	82.93	61.42	50.31	49.10	**54.20**	85.90	65.32	52.01	50.13	**56.34**	25.00	18.52	30.00	43.08	**36.28**
Z*	38.41	29.94	33.02	32.84	**32.89**	36.54	28.28	30.27	27.91	**29.50**	75.00	48.15	66.00	61.54	**61.40**
Z	14.02	17.59	19.44	25.40	**21.32**	13.46	14.48	18.39	23.28	**19.37**	25.00	51.85	32.00	37.69	**37.67**
X1	69.51	63.89	60.03	57.90	**60.48**	71.79	67.34	63.38	62.70	**64.47**	25.00	25.93	20.00	30.00	**26.98**
X2	65.24	42.59	33.80	36.57	**38.97**	65.38	42.76	32.11	33.99	**37.52**	62.50	40.74	54.00	51.54	**51.16**
X3	29.88	12.04	12.35	18.62	**16.47**	26.92	7.41	6.35	7.54	**8.80**	87.50	62.96	84.00	83.08	**80.93**
X4	75.61	60.80	59.72	60.50	**61.52**	78.21	63.97	61.87	65.21	**65.02**	25.00	25.93	34.00	33.08	**32.09**
X5	57.93	48.46	53.40	48.98	**51.04**	59.62	49.49	53.51	49.74	**51.80**	25.00	37.04	52.00	44.62	**44.65**
G*	60.37	44.75	43.36	41.53	**44.16**	60.90	45.45	41.64	39.02	**42.83**	50.00	37.04	64.00	56.15	**55.35**
G	10.98	26.54	32.72	35.55	**31.21**	10.26	24.92	33.28	36.51	**31.27**	25.00	44.44	26.00	30.00	**30.70**
Y1	60.98	40.12	33.02	36.91	**38.13**	60.90	39.73	30.94	33.99	**36.25**	62.50	44.44	58.00	53.85	**53.95**
Y2	57.93	39.81	33.02	37.81	**38.23**	57.69	39.39	30.43	35.58	**36.41**	62.50	44.44	64.00	50.77	**53.49**
Y3	18.90	23.77	21.60	27.43	**24.28**	16.03	19.87	17.39	19.31	**18.48**	75.00	66.67	72.00	74.62	**73.02**
Y4	24.39	25.00	26.23	28.56	**26.90**	22.44	20.54	22.91	21.16	**21.75**	62.50	74.07	66.00	71.54	**70.23**
Y5	17.68	18.52	15.59	25.17	**20.43**	14.74	13.47	11.04	15.74	**13.72**	75.00	74.07	70.00	80.00	**76.74**
CH*	24.39	25.00	26.23	28.56	**26.90**	22.44	20.54	22.91	21.16	**21.75**	62.50	74.07	66.00	71.54	**70.23**
CH	4.88	8.02	7.72	14.67	**10.58**	0.00	0.00	0.50	0.66	**0.44**	100.00	96.30	94.00	96.15	**95.81**

Source: The authors.

Table 5

Significance of the Predictor Variables and Overall Classification Accuracy

Predictor/model	Testing based on the odds ratio				Testing based on Cohen's kappa				Area under the ROC curve				
	Odds	**StdErr**	**χ statistic**	**P-value**	**Kappa**	**StdErr**	**Z statistic**	**P-value**	**2009**	**2010**	**2011**	**2012**	**All years**
A1	0.031	0.130	0.237	**0.407**	–0.685	0.022	–30.884	**1.000**	0.500	0.546	0.510	0.542	**0.529**
A2	0.021	0.147	0.146	**0.442**	–0.643	0.020	–32.057	**1.000**	0.611	0.479	0.497	0.530	**0.528**
A3	0.050	0.122	0.407	**0.342**	–0.578	0.021	–27.664	**1.000**	0.714	0.568	0.513	0.497	**0.515**
A4	0.090	0.122	0.733	**0.232**	–0.273	0.013	–21.790	**1.000**	0.615	0.527	0.543	0.536	**0.517**
A5	0.028	0.139	0.205	**0.419**	–0.642	0.021	–30.566	**1.000**	0.656	0.511	0.535	0.533	**0.534**
Z*	0.246	0.133	1.853	**0.032**	–0.219	0.020	–11.108	**1.000**					
Z	0.051	0.121	0.417	**0.338**	–0.515	0.019	–27.584	**1.000**	0.634	0.568	0.529	0.515	**0.494**
X1	0.019	0.156	0.120	**0.452**	–0.606	0.019	–32.232	**1.000**	0.521	0.530	0.529	0.535	**0.513**
X2	0.044	0.124	0.358	**0.360**	–0.606	0.021	–28.420	**1.000**	0.743	0.554	0.492	0.501	**0.518**
X3	0.171	0.131	1.310	**0.095**	–0.133	0.009	–14.520	**1.000**	0.716	0.552	0.506	0.517	**0.507**
X4	0.023	0.147	0.156	**0.438**	–0.580	0.018	–31.443	**1.000**	0.647	0.568	0.503	0.551	**0.529**
X5	0.031	0.131	0.235	**0.407**	–0.675	0.022	–30.817	**1.000**	0.612	0.494	0.620	0.517	**0.549**
G*	0.098	0.140	0.696	**0.243**	–0.407	0.022	–18.725	**1.000**					
G	0.042	0.122	0.345	**0.365**	–0.644	0.022	–29.136	**1.000**	0.679	0.535	0.576	0.530	**0.550**
Y1	0.048	0.122	0.396	**0.346**	–0.588	0.021	–27.895	**1.000**	0.745	0.554	0.513	0.499	**0.519**
Y2	0.050	0.122	0.413	**0.340**	–0.584	0.021	–27.550	**1.000**	0.660	0.553	0.539	0.509	**0.513**
Y3	0.075	0.122	0.612	**0.270**	–0.323	0.014	–23.655	**1.000**	0.546	0.542	0.512	0.505	**0.497**
Y4	0.077	0.118	0.651	**0.258**	–0.374	0.016	–23.847	**1.000**	0.460	0.485	0.500	0.501	**0.508**
Y5	0.132	0.121	1.095	**0.137**	–0.219	0.012	–18.118	**1.000**	0.615	0.527	0.543	0.536	**0.517**
CH*	1.535	0.364	4.219	**0.000**	0.005	0.004	1.302	**0.096**					
CH	0.076	0.119	0.640	**0.261**	–0.375	0.016	–23.964	**1.000**	0.461	0.482	0.504	0.500	**0.508**

Source: The authors.

Discussion

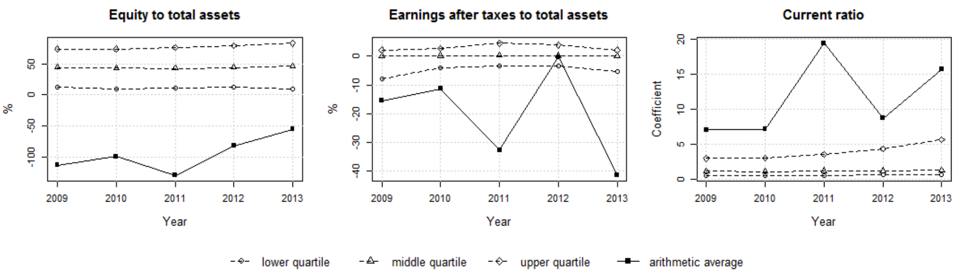
It is questionable as to whether it is possible to predict financial distress of agricultural enterprises on the basis of information comprised in their financial statements. Although an enterprise's financial statements should give a true and fair view of its financial position, they are subject to accounting manipulations and practices and they simply may not contain information needful to predicting financial distress. As every economic sector, agriculture is very vulnerable to cyclical fluctuations of the entire economy, but it is besides exposed heavily to natural and climatic conditions. Agricultural production suffers not only from sudden changes in these conditions, but also from relatively frequent epidemic diseases or plant pests. Changes in these specific factors tend to take place unexpectedly with a grave unpredictable impact, and another feature of theirs is that they are not directly readable in financial statements. Neither the three prediction models considered in the paper nor the financial ratio indicators from which they are derived take into account this sort of information. The prediction variables X1 – X5, Y1 – Y5 and A1 – A5 as well as the three resulting prediction models extract partial information disclosed in balance sheets and profit and loss statements in a priori belief that it will suffice in predicting future financial condition of agricultural enterprises. Such a prediction then for instance even ignores the extent of governmental support given to individual enterprises and the degree of their dependence on it. There is evidence that agricultural subsidies may constitute a significant factor in maintaining competitiveness and good economic position of Slovak agricultural enterprises (cf. e.g. Szabo and Grznár, 2013). The purpose of this paragraph is not to challenge this task and the sense of this effort, but it is to merely point out that it builds only on fragmented and incomplete information, which partly explains that it is a demanding task.

The discourse taken in this direction must also subsume the issue of how agricultural enterprises that find themselves in financial difficulty should be treated in predicting their financial condition. A question emerges whether one should adopt the legal view and deal with the ultimate condition of bankruptcy or he should consider the economic view and restrict himself to the worsened financial condition preceding bankruptcy. These two treatments are not identical: for general financial distress is not always a precedent of bankruptcy and, vice versa, bankruptcy is not as a rule declared after financial difficulties. An ambiguity of this sort is discernible also in intermixed use of bankruptcy models, financial distress prediction models and credibility prediction models as follows for instance from the studies of Kopta (2006; 2009) who compares their predictive reliability for predicting the legal status of bankruptcy of agricultural enterprises. Although there is a sharp boundary between bankruptcy and financial distress (or credibility), it is argued by some that it is advisable to use bankruptcy models for predicting financial distress rather than bankruptcy itself or are used to that end (consult e.g. Grice and Ingram, 2001, p. 53; Altman et al., 2017, p. 134). This is the line in which the present paper proceeds as it occupies itself with financial distress prediction and verifies viability of three prediction models in the sample of 2022 Slovak agricultural enterprises.

In operationalization of financial distress the paper specifies a triplet of definitional criteria that an agricultural enterprise must meet in order to qualify itself for distress condition. According to the view taken on in this paper, an enterprise finds itself in financial distress if (i) its equity is negative, (ii) its earnings after taxes are negative, and (iii) its current ratio is lower than 1. These three conditions stipulate altogether that an enterprise must exhibit a deterioration in long-term and current profitability and must experience difficulties with its liquidity in order to qualify itself for financial distress. It remains perhaps to defend these criteria and show that they are reasonable for Slovak agricultural enterprises. That this is so is demonstrated in Figure 2 which depicts the overall situation for the Slovak agricultural sector between 2009 and 2013.

F i g u r e 2

Three Definitional Criteria of Financial Distress during the Period 2009 – 2013 for Enterprises in the Slovak Agricultural Sector



Source: The authors based on data from CRIF – Slovak Credit Bureau, s. r. o.

The figure relates to enterprises that were registered in the division 01 Agriculture, hunting and related service activities of the NACE Rev. 2 classification and displays the industry situation for equity, earnings after taxes and current ratio for single years. Whilst equity and earnings after taxes are expressed in proportion to total assets (i.e. as shares in order to make this simultaneous comparison meaningful), current ratio is drawn in its original units as a coefficient. Each indicator is represented by industry lower quartile, middle quartile (median), upper quartile and arithmetic average and these aggregates are joined on a year-on-year basis in order to sketch trends. The first two graphs corroborate that a certain percentage of Slovak agricultural enterprises experienced difficulties with profitability. For equity to total sales, the industry lower quartiles in each year hanged closely above zero and the industry averages were considerably under zero in each year, which suggests that there were a number of enterprises whose equity was far negative. A very similar pattern is found for earnings after taxes to total sales. Both these observations testifies that for many Slovak agricultural enterprises profitability is a concern and their activities are burdened with losses proving themselves in the current period in negative earnings after taxes and in the long run in negative equity.

A special attention must be reserved to current ratio. Because agricultural production is conditional on biological reproduction cycle and its seasonality, the duration of biological reproduction cycle (e.g. the length of vegetation period, the length of animal husbandry or plant breeding) affects and predetermines the duration of agricultural production cycle. The natural duration of agricultural production can barely be shortened and depend thus on a certain level of inventory that is used up during the production cycle. The size and makeup of stocked goods must fully respect regularities of biological reproduction cycle and capital invested in inventory in an agricultural enterprise is invested for a longer period of time than it is typical for a manufacturing enterprise. In general, greater consumption of inventory then presses for higher liquidity, and agricultural enterprises should report the current liquidity ratio of about 2.5 or 3, but in situations with lengthy production cycle it is not unusual to have much larger current liquidity ratios. That high liquidity ratios are typical for many Slovak agricultural enterprises is also shown in Figure 3 which safely confirms that no less than 25% enterprises during the period between 2009 and 2013 had a value of current ratio (very much) higher than 2.5 or 3. The same point is raised by Kopta (2006, p. 1063) who stresses that many (Czech) agricultural enterprises have a current ratio well in excess of 5. The threshold 1 for current ratio can be then looked on as very critical when the level of liquidity is untenable. Though chosen arbitrarily, this reference point is also considered by Šnircová (1997, p. 16).

Conclusion

The paper verifies critically the usefulness of three predictions models that are used or were developed for predicting financial distress of Slovak agricultural enterprises and contributes in this regard to both theory and practice of Slovak corporate finance. The verification is accomplished with the use of the comparatively largest sample of enterprises committed to this purpose so far, and helps to identify factors that describe enterprise financial condition in Slovak agriculture.

The indicators that turn out to be key in predicting financial distress in the sample of Slovak enterprises are three, viz. (i) gross return on revenue, (ii) the debt ratio, and (iii) days payables outstanding. They are related to liquidity and solvency through revenue profitability, capital structure and discipline of outflows in cash management, respectively. These are clearly the economic channels through which financial distress is proliferated in agricultural enterprises and causes insolvency, which is considered as a sore and lasting aspect of doing business of Slovak agricultural enterprises (see Chrastinová, 2000). Although these ratios display a satisfactorily high level of distress prediction accuracy, their ability to correctly classify non-distressed enterprises is low, which merely implies that they are too strict and over conservative. Nevertheless, their tendency to classify an enterprise as distressed may be a legacy of the proposed two cut-off points for classification as these were chosen by minimizing the unweighted sum of Type I error and Type II error rates following Wu, Gaunt and Grant (2010). Inclusion of weights into the determination of cut-off points might make distress and non-distress prediction accuracy more balanced

The highest accuracy in classifying non-distressed enterprises have the indicators derived from retained earnings and they are the ratio of retained earnings to liabilities and retained earnings to total assets (yet, there is some imprecision as with these two indicators retained earnings are defined slightly differently). Insomuch as these two indicators are associated closely to long-term profitability, the ability of an agricultural enterprise to generate and sustain profits in accumulated form is what separates good enterprises from those mediocre or financially distressed, at least in the Slovak economic conditions.

Altman’s Z-score improved with the redefinition of cut-offs as its prediction accuracy increased for both distressed and non-distressed enterprises. Chrastinová’s CH-Index at its original cut-off values classified correctly nearly all distressed enterprises and almost no non-distressed enterprise, but after the redefinition of cut-off values, its prediction accuracy became more balanced. The distress prediction accuracy of the CH-Index declined and the non-distress prediction accuracy increased to a more acceptable level. Finally, used with the original cut-offs, Gurčík’s G-Index gave uniformly distress and non-distress prediction accuracy of about one third. With the cut-offs redefined, also the performance of the G-Index was improved for both distressed and non-distressed enterprises. Regardless of the mostly satisfactorily high distress prediction accuracies of the prediction models under consideration, the overall prediction performance is relatively low. Their poor performance is convincingly signalized also by values of the AUC measure which are low by any standard of assessment and also by the results of the testing centred upon the odds ratio and Cohen’s kappa. These results are not in controversy with the findings of Kopta (2006, p. 1060; 2009, p. 119) who performed a similar analysis for Czech agricultural enterprises.

Apart from directing attention to factors which are important for detecting distress condition of Slovak agricultural enterprises or to factors which determine their good financial position, the results are suggestive that with some level of trustworthiness it is possible to utilize the older models of bankruptcy or financial distress prediction developed by Chrastinová (1998) or Gurčík (2002) for Slovak agricultural enterprises or even the outdated model of Altman (1968; 1983) developed for a foreign economic environment. That being said, it is advisable to redefine the cut-off points in the light of new data in order to improve on classification accuracy. What is a curious question is which of these three models is most apt for financial distress prediction of Slovak agricultural enterprises. Given the trade-off between distress and non-distress prediction accuracy, Gurčík's G-Index with the redefined cut-off points seems most eligible to this end, although the idea of using of a single ratio indicator (such as the inventories in-revenue turnover ratio X5) should not be discarded.

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