

## PREDICTING BANKRUPTCY OF AGRICULTURE COMPANIES: VALIDATING SELECTED MODELS

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**Abstract:** Many bankruptcy prediction models have been published so far, most of them were especially designated for the manufacturing companies. According to several studies, these models are inappropriate for other industries, as such application would be connected with a significantly lower accuracy than could be expected. The aim of this paper is to analyse the current accuracy of four traditional bankruptcy prediction models in the field of agriculture. The results showed that these models are less accurate in this field in comparison with the original results. This motivates the effort of deriving new models that would be specially developed for agriculture business.

**Key words:** bankruptcy prediction models, ROC curves, agriculture

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### Introduction

In the previous decades many bankruptcy prediction models have been presented. The accuracy of these models represents a critical feature of these models and sets a limit of their practical application. A lot of attention in literature is paid to the question, whether previously created models could be still effectively used even if they were devoted for different economics or industries. In general, this this issue was a subject of the studies of Platt and Platt (1990), Grice and Dugan (2001), Niemann et al. (2008) and Wu et al. (2010). Heo and Yang (2014) came to conclusion that the accuracy of the models significantly decreases if they are used in a different environment (or a different industry). In our previous research we try to contribute this topic by analyzing the significance of same predictors in different industries (see Režňáková and Karas, 2015a or Karas and Režňáková, 2015). We found that same indicators cannot be effectively applied in different industries, as they could represent significant predictors of bankruptcy for example in case of manufacturing companies, but not in cases construction or agriculture business. Moreover, we analyse the prediction capability of bankruptcy prediction models in different environments, namely in the environment of Visegrad four countries (see Režňáková and Karas, 2015b). The result was, that the same models works in different environments with significantly different accuracies. Several researches focused on developing new bankruptcy prediction models that would be specially

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designated for agriculture companies. Bielíková et al. (2014) examined the potential of three different classification techniques for developing a new bankruptcy prediction model for agriculture companies. The mentioned study namely applies the methods of discriminant analysis, logistic regression and decision trees. The best results were obtained by using the method of decision trees. Vavřina et al. (2013) suggest the use of production function in predicting bankruptcy of agriculture companies. Furthermore, their study contains also the comparison with other methods, namely the Data Envelopment Analysis (DEA), logistic regression and Z-score. The best results were obtain by use of the logistic function, however they mentioned, that under some circumstances the method of DEA and production function could be superior to the logistic regression. In course of theirs research they analyze the current prediction ability of Altman's Z-score and come to conclusion, that the accuracy of this model in case of agriculture companies is only 62%. The mentioned studies showed on one hand that the agriculture business is specific in many features and on the other that for an effective bankruptcy prediction it is not possible to rely solely on the traditional bankruptcy prediction models. The aim of the paper is to analyze the current accuracy of the several traditional bankruptcy models in predicting bankruptcy of agriculture companies.

### Sample and Method Used

The data were obtained from AMADEUS (Analysis Major Database for European Sources). The bankrupt companies in our sample declared bankruptcy during years 2011 and 2014. The industry examined is agriculture (NACE: A Agriculture – plant production (codes 0111, 0112, 0121, 0130, 0145, 0150, 0160). The sample included only small- and medium-sized companies operating in this branch. These criteria were accommodated by 450 active companies and 25 companies in bankruptcy. In course of the research presented a following set of models was tested:

#### *A Revised Z-score Model (see Altman, 2000)*

The revised Z-score represents the original Z-score model (see Altman, 1968) adapted for non-listed companies (see Altman, 1983). The formula of the model is following (see Altman and Sabato, 2006):

$$Z = 0.717 * NWC/TA + 0.847 * RE/TA + 3.107 * EBIT/TA + 0.420 * BVE/TA + 0.998 * S/TA$$

where: NWC – net working capital (=current assets-current liabilities), TA – total assets, RE – retained earnings, EBIT – earnings before interest and taxes, BE – book value of equity, S – sales

The grey zone interval is (1.23; 2.9). For  $Z < 1.23$  the company is classified by the model as threatened by bankruptcy, for  $Z > 2.9$  is classified as not threatened by bankruptcy, i.e. financial healthy. Altman and Sabato (2006) tested the model on the sample of US SMEs over the period from 1994 to 2002. The resulted overall

accuracy of the model was 68%, while type I error (a percentage of bankrupt firms classified as non-bankrupt) 25.81%.

### ***Altman-Sabato's Model***

Altman and Sabato (2006) proposed a use of logged predictors in the model of logistic regression. They come to the conclusion, that the application of this methodology would results in a higher accuracy of the model. According to Lin (2009), who also tested this methodology, it does not necessarily improve the prediction accuracy. Altman and Sabato (2006), for the purpose of the result comparison, suggested two versions of the model: the model with unlogged predictors and the model with logged predictors. Both models were developed on the sample of US SMEs over the period from 1994 to 2002. According to the authors the accuracy on the hold out sample was, in the case of the version with logged version 87% and in the case of unlogged version 75%. The type I error was in case of the model with logged variables 11.76% and in case with unlogged variables 21%.

**a) *Altman-Sabato's model – the version with unlogged predictors*** (see Altman and Sabato, 2006)

The formula of the model is following:

$$\text{Log}(PD/1-PD) = 4.28 + 0.18 * EBITDA/TA - 0.01 * STD/BVE + 0.08 * C/TA + 0.19 * EBITDA/IE$$

where: Log(PD/1-PD) – logit or log-odds, PD – probability of default (bankruptcy), EBITDA – earnings before interest, taxes, depreciation and amortization, STD – short-term debt, C – cash, IE – interest expenses

For  $\text{Log}(PD/1-PD) < 0$  the company is classified by the model as threatened by bankruptcy, as the probability of being bankrupt is higher than 0.5. For  $\text{Log}(PD/1-PD) > 0$  is classified as not threatened by bankruptcy, i.e. financial healthy, as the probability of being bankrupt is lower than 0.5.

**b) *Altman-Sabato's model – the version with logged predictors.***

The formula of the model is following:

$$\text{Log}(PD/1-PD) = 53.28 - 4.09 * \text{LN}(1 - EBITDA/TA) - 1.23 * \text{LN}(STD/BVE) - 4.32 * \text{LN}(1 - RE/TA) + 1.84 * \text{LN}(C/TA) + 1.97 * \text{LN}(EBITDA/IE)$$

The interpretation of the model is same as in the previous version (the version with unlogged predictors).

### ***Model IN05***

The IN05 is among the tested models the only one that has been developed especially for Czech companies (see Neumaier and Neumaierová, 2005). The formula of the model is following:

$$IN05=0.13*TA/TL+0.04*EBIT/IE+3.97*EBIT/TA+0.21*OR/TA+0.09*CA/CL$$

where: TL – total liabilities, OR – operating revenue, CA – current assets, CL – current liabilities

The grey zone interval is (0.9; 1.6). For  $Z < 0.9$  the company is classified by the model as threatened by bankruptcy, for  $Z > 1.6$  is classified as not threatened by bankruptcy, i.e. financial healthy. For  $0.9 < Z < 1.6$  the predicted fate of analyzed company is not clear (it is co called grey zone).

At the time at which the model was created, its authors summarised its predication ability as follows (Neumaier and Neumaierová, 2005): *“If the index value for a given company falls beneath the lower limit, there is a 9% probability that the company is headed for bankruptcy and a probability of 76% that it will not create value. A company in the grey zone has a practically 50% probability of bankruptcy and a 70% probability of creating value. A company above the upper limit will have a 92% probability of not going bankrupt and a 95 % probability of creating value”*.

The accuracies of the models were evaluated in two ways. First, as a percentage of correctly classified bankrupt and non-bankrupt companies, with the respect to original setting of cut-off score (or generally grey zone borders). Second, by using the ROC curves and the corresponding Area Under Curve (AUC) value, regardless the setting of cut-off score.

## Results

At first we tested the accuracy of the model for the period one year prior bankruptcy. We evaluated the accuracy as the percentage of correctly classified non-bankrupt and bankrupt companies; moreover we analyzed the percentage of companies in grey zone.

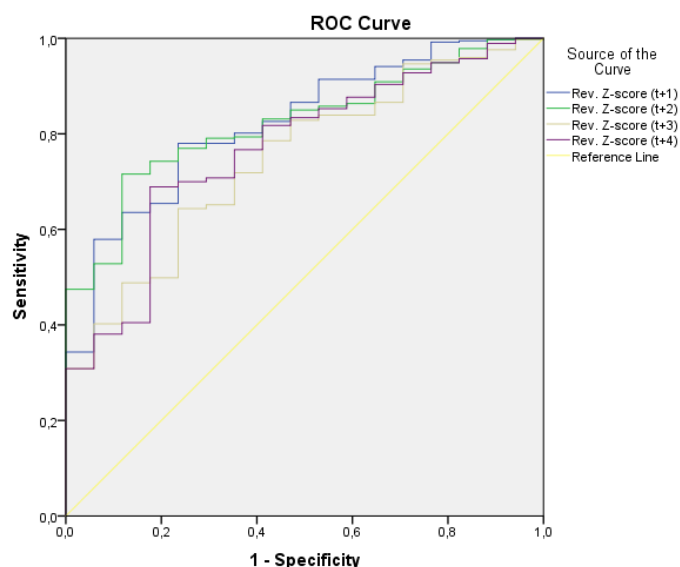
The model Rev. Z-score correctly classified 86% of bankrupt companies, however was able to correctly classified only 31% of non-bankrupt companies. Thus the produced type II error was relatively high (33% of active companies were wrongly classified as bankrupt). The model was tested on an alternative sample of Czech agriculture companies. The overall accuracy is much lower than in study Altman and Sabato (2006), namely 37.9% vs. 68%. On the other hand the type I error is much lower (5% versus 25.81%). The model AS-LN was possible to test on a limited sample of companies (only 8 bankrupt companies), as the model uses variables in form of a logarithm. This model was able to correctly classified 100% of bankrupt companies and 63% of non-bankrupt companies.

**Table 1. The accuracy of the analyzed models**  
(Own analysis of data from the Amadeus database)

Model	Observed status	Status predicted by model							
		Non-bankrupt		Bankrupt		Grey zone		Total	
		%	No.	%	No.	%	No.	%	No.
Z-rev.	Non-Bankrupt	<b>31</b>	137	33	145	36	158	440	37.9
	Bankrupt	5	1	<b>86</b>	19	9	2	22	
AS-LN	Non-Bankrupt	<b>63</b>	160	37	94	0	0	254	64.8
	Bankrupt	0	0	<b>100</b>	8	0	0	8	
AS-ULN	Non-Bankrupt	<b>93</b>	275	7	21	0	0	296	91.6
	Bankrupt	59	10	<b>41</b>	7	0	0	17	
IN05	Non-Bankrupt	<b>44</b>	193	32	141	24	105	439	45.7
	Bankrupt	29	7	<b>67</b>	16	4	1	24	

Note: Rev. Z-score – Altman’s revised Z-score model. AS-LN-Altman-Sabato’s model version with logged predictors. AS-ULN-Altman-Sabato’s model version with unlogged predictors. IN05 – IN 05 model. \*total accuracy was calculated as a weighted average of the percentage of correctly classified non-bankrupt and bankrupt companies, the number of observations was used as weights.

The overall accuracy of the model, on the analyzed sample, is 64.8%, which is again lower to the results of study Altman and Sabato (2006) which was 87%. The second version of the model (AS-ULN) correctly classified 93% of non-bankrupt companies, however only 41% of bankrupt companies, thus the model produces a relatively high type I error (59% of bankrupt companies were classified as non-bankrupt). The overall accuracy of the model was 93%, however it was mainly due to high percentage of correctly classified non-bankrupt companies. The resulted type I error is very high – 59% of bankrupt companies were classified as non-bankrupt, this is nearly three times higher than in study Altman and Sabato (2006) in which the model has been published. The IN05 model correctly classifies 44% of non-bankrupt companies and 67% of bankrupt companies. A large proportion of the non-bankrupt companies ended up in grey zone. However only limited number of bankrupt companies ended up in grey zone (only 4%), which means that the type I error produced by the model is high (29% of bankrupt companies was wrongly evaluated as non-bankrupt). The overall accuracy of the model, based on the sample of agriculture companies is 45.7%. As the accuracy of the models largely depends on the set value of cut-off score, the ROC curves were used for further analysis. The ROC curves and the corresponding AUC values analyze the accuracy of the model regardless the current value of the cut-off score. For example, the ROC curves for Altman’s revised Z-score model are following. The numbers of year prior bankruptcy are distinguished in following way: t+1 means one year prior bankruptcy, t+2 two years prior bankruptcy and so on.



**Figure 1. The ROC curve of Altman's revised Z-score model**  
*(Own analysis of data from the Amadeus database)*

The corresponding values of AUC are listed in the Table 2.

**Table 2. The values of AUC of the revised Altman's Z-score**  
*(Own analysis of data from the Amadeus database)*

Test Result Variable(s)	Area	Std. Error <sup>a</sup>	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Z-rev. (T+1)	0.822	0.044	0.000	0.735	0.909
Z-rev. (T+2)	0.823	0.038	0.000	0.749	0.896
Z-rev. (T+3)	0.747	0.053	0.001	0.644	0.851
Z-rev. (T+4)	0.768	0.053	0.000	0.665	0.872

Note: a - under the nonparametric assumption, b - null hypothesis: true area = 0.5

The AUC value of revised Z-score for the period t+1 is relatively high, namely 0.822. When analyzing the more distant periods prior bankruptcy, the AUC is lower, as expected, with the minimum of 0.768 in period t+4. In all the analyzed periods the resulted AUC value is significantly higher the 0.5, which means than the model produces better results than a random choice.

**Table 3. The values of AUC of the Altman-Sabato's model – the logged predictors' version** (*Own analysis of data from the Amadeus database*)

Test Result Variable(s)	Area	Std. Error <sup>a</sup>	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
AS-LN (T+1)	0.871	0.057	0.012	0.758	0.983
AS-LN (T+2)	0.905	0.061	0.006	0.785	1.000
AS-LN (T+3)	0.815	0.103	0.032	0.613	1.000
AS-LN (T+4)	0.835	0.090	0.023	0.657	1.000

The AUC values produced by the application of the Altman-Sabato's model (the logged predictors' version) are higher than in the case of the revised Z-score. In the period t+t the revised Z-score reached AUC value of 0.822; however the Altman-Sabato's model reached a value of 0.871. It is quit surprising, that the highest AUC value was reached not in the period t+1 (0.871) but in the period t+2 (0.905). Now to the results of model's alternative with unlogged predictors.

**Table 4. The values of AUC of the Altman-Sabato's model – the unlogged predictors' version** (*Own analysis of data from the Amadeus database*)

Test Result Variable(s)	Area	Std. Error <sup>a</sup>	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
AS-ULN (T+1)	0.761	0.095	0.005	0.573	0.948
AS-ULN (T+2)	0.841	0.082	0.000	0.680	1.000
AS-ULN (T+3)	0.701	0.074	0.031	0.557	0.846
AS-ULN (T+4)	0.784	0.053	0.002	0.680	0.888

As expected, the model with unlogged predictors reached lower AUC values, thus it reaches a lower accuracy in the comparison with its alternative with logged predictors (0.871 vs. 0.761 in period t+1). These results are in compliance with the original literature (Altman and Sabato, 2006). The highest AUC values was observed in the period t+2, not in t+1 as expected, what is a similar results to that of the model's alternative with logged predictors.

**Table 5. The values of AUC of the IN05 model** (*Own analysis of data from the Amadeus database*)

Test Result Variable(s)	Area	Std. Error <sup>a</sup>	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
IN05 (T+1)	0.656	0.088	0.030	0.483	0.829
IN05 (T+2)	0.689	0.089	0.008	0.513	0.864
IN05 (T+3)	0.568	0.078	0.345	0.414	0.721
IN05 (T+4)	0.636	0.081	0.058	0.477	0.795

The AUC values in case of the IN05 model are the lowest among analyzed models. What's more, the AUC values in periods t+3 and t+4 are not statistically significant from 0.5 at 5% level of significance, which means for this periods the model doesn't provide a better results than a random choice. The highest value (0.689) for observed for the period t+2. This value is much lower, that in case of the Altman-Sabato's model with logged predictors, which represents the most accurate model among the analyzed ones (0.689 in case of model IN05 versus 0.905 in case of the Altman-Sabato's model).

### Discussion

In course of this research, the accuracy of 4 different bankruptcy prediction models was analyzed. Two of them are based on the method of logistic regression and the other two on the method of discriminant analysis. The models based on logistic regression exhibits better results than traditional Z-score, what is in line with the results of Vavřina et al. (2013). The further analysis showed that all these models are less accurate, when applied in an alternative industry, namely in the industry of agriculture. This is in line with the results of previous studies, namely Platt and Platt (1990), Grice and Dugan (2001), Niemann et al. (2008) and Wu et al. (2010) as well as Heo and Yang (2014). The potential explanation of this could be that the branch of agriculture is specific, especially when compared with the branch of manufacturing. Čámská (2013) mentioned that: *"the agriculture sector is specific in many characteristics. The difference between agriculture and industrial sector can be defined as a strong dependency on natural conditions, time discrepancy during manufacturing process, and the work and seasonality of work* (Synek and Kislingerová, 2010 in: Čámská, 2013). In the same study another factor, which makes this industry specific is mentioned, it is the existence of subsidizing. Čámská (2013) further mentioned that: *"another difference represents high subsidizing, which softens the market mechanism"*. A different point of view to this problem is in work of Lukason (2014), who studied the reasons why and how agriculture companies fail, among other, he came to the conclusion, that there are three different failure processes characterize agricultures companies. As it is possible, that the loss of model's accuracy is due to the shift of grey zone, the ROC curves were employed. The advantage of ROC curves is that they analyse the model accuracy regardless the current set of cut-off score (or grey zone borders). We found that the, with exception of IN05 model, all the analyzed model provides, up to four years prior bankruptcy, statistically significant better results than a would be gain by a random choice. The best results (in terms of AUC) was reached by the application of Alman-Sabato's model with logged variables, however the application of logged variables lead to a significant discard of observations in the sample of bankrupt companies (only 8 from 25 bankrupt companies in the analyzed sample was possible to classify). As bankrupt companies often suffer from negative profits and consequently exhibits a negative profitability ratios, the logarithm of these values does not exist and the company



cannot be classified. Moreover, when comparing the result of model with logged predictors with the model with unlogged predictors, we agree that the use of logged predictors could lead to higher accuracy, as mentioned by Altman and Sabato (2006). For the managerial implication of the results, it is useful to analyse the results in more details, especially answer such questions as which variables of the models are most significant. In other words, which areas should managers paid more attention? At first we analyse the most accurate model, according to the results, i.e. the Altman-Sabato's model with logged variables. However, in many observations (especially on bankrupt companies) the logged variables could not be defined due to the negative values of the model's variable and as a consequence the number of observation is very limited. For that reason we had further analysed the model's version with unlogged variables.

**Table 6. The statistical significance of the Altman-Sabato's model variables**  
(Own analysis of data from the Amadeus database)

Variable	Wilk's lambda	Partial Lambda	F to rem. ((1,307))	p-value	Toler.	1-toler. (R <sup>2</sup> )
EBITDA/TA**	0.824850	0.984103	4.95929	0.026676	0.837487	0.162513
STD/BVE	0.811744	0.999991	0.00264	0.959094	0.996772	0.003228
RE/TA***	0.884685	0.917544	27.58902	0.000000	0.840800	0.159200
C/TA*	0.820620	0.989176	3.35948	0.067787	0.992223	0.007777
EBITDA/IE***	0.836130	0.970827	9.22540	0.002592	0.975761	0.024239

Note: \*\*\*significant at 1% level, \*\*significant at 5% level, \*significant at 10% level

According to above shown results, the relative value of retained earnings (RE/TA) represent the most significant variable of the model. This ratio was first applied by Altman (1968), according to whom this ratio describes the past profitability or implicitly the age of the firm, while older firms are viewed as more stable. The significance of this ratio could be interpreted as the importance of reinvesting earning back to company. The second most significant variable is the interest cover based on EBITDA (i.e. EBITDA/IE) and the third most significant variable is the return on assets based on EBITDA (i.e. EBITDA/TA). Both interest cover and return of assets are based on EBITDA, what shows that not only the profitability (in terms of EBIT) is important for agriculture companies, but also the value of depreciation as a part of operating cash flow.

## Conclusion

The presented paper represents a further step in our previous research, where we aim to derive industry-specific bankruptcy models, as the previous research made by us or by other authors showed that bankruptcy prediction model and their predictors are industry specific. We found the traditional bankruptcy prediction models, that were designated for the manufacturing companies, are not efficient in

this branch. The difference in accuracy, when compared with original results, could be explained by the possible shift of grey zone. However to verify this conclusion a further analysis is needed, what is a subject of a future research. From the results of the presented research a few practical implications for the managers could be drawn. A higher level of reinvesting the profits back to the business seems to be of high importance in case of the agriculture firms. The depreciation of fixed assets represents in the case mentioned a significant source of operating cash flow. In general, a special attention in case of agriculture business should be paid to performance indicators that are based on EBITDA (such as interest cover or assets profitability).

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### PROGNOZOWANIE UPADŁOŚCI SPÓLEK ROLNYCH: WERYFIKACJA WYBRANYCH MODELI

**Streszczenie:** Dotychczas opublikowano wiele modeli predykcji bankructwa, większość została przeznaczona dla firm produkcyjnych. Według badań, modele te są nieodpowiednie dla innych gałęzi przemysłu, ponieważ takie zastosowanie wiązałoby się ze znacznie niższą dokładnością, niż można byłoby się spodziewać. Celem niniejszego artykułu jest analiza aktualnej dokładności czterech tradycyjnych modeli predykcji bankructwa w rolnictwie. Wyniki wykazały, że modele te są mniej dokładne w tej dziedzinie w porównaniu z pierwotnymi wynikami. Motywuje to wysiłek do wyprowadzania nowych modeli, które zostałyby specjalnie opracowane dla przedsiębiorstw rolniczych.

**Słowa kluczowe:** modele predykcji bankructwa, krzywe ROC, rolnictwo

#### 預測農業公司的銀行業務：確認選定的模式

**摘要：**目前許多破產預測模型已經出版，其中大部分是特別指定的製造公司。根據幾項研究，這些模型對於其他行業是不合適的，因為這種應用將以比預期的更低的準確度來連接。本文的目的是分析農業領域四種傳統破產預測模型的準確性。結果表明，與原始結果相比，這些模型在這一領域不太準確。這促使推出新模式的努力，這將是為農業專門開發的。

**關鍵詞：**破產預測模型，ROC曲線，農業。