Possibilities for the Application of the Altman Model within the Czech Republic

MICHAL KARAS, MARIA REZNAKOVA, VOJTECH BARTOS, MAREK ZINECKER
Department of Finance
Brno University of Technology
Brno, Kolejní 2906/4
CZECH REPUBLIC
karas@fbm.vutbr.cz, reznakova@fbm.vutbr.cz, zinecker@fbm.vutbr.cz, bartos@fbm.vutbr.cz,
www.fbm.vutbr.cz

Abstract: There are currently a number of formulas that are able to predict the bankruptcy of a company (so-called "bankruptcy prediction formulas"). One of the most frequently mentioned formulas among these models is the Altman Z-score formula. The original version of the formula was intended only for companies listed on the capital market. In 2000, however, a version was published for other companies as well, which significantly broadened the applicability of this formula. The objective of this article is to verify the effectiveness of the 2000 Altman Z-score model within a different environment than which it was conducted. In this case, the environment shall be the Czech Republic or, as the case may be, a modified version of this environment. Despite our expectations, when tested, the model was proven to be significantly less accurate. For this reason we introduced a modification of the formula which has led to an increase in the total accuracy of the formula by 55% within conditions of the Czech Republic and to a decrease of 69% in the number of companies that have not been evaluated.

Keywords: Altman Index, discriminant analysis, bankruptcy prediction, model robustness

1 Introduction

The first efforts to predict bankruptcy sufficiently in advance date back to the 1960s. Beaver (1966) was the first to prove that financial indicators could be used for predicting bankruptcy. Altman (1968) built upon this work and created the first bankruptcy formula. In reaction to these works, many other bankruptcy models were created (see Deakin, 1972; Martin, 1977; Altman, 1977, 2000; Ohlson, 1980; Taffler, 1982; Zmijewski, 1984; Tam, Kiang, 1992; Shumway, 2001; Li, Sun, 2009; Sánchez-Lasheras et al, 2012; and many more). Nevertheless, Altman's model is one of the best-known. The original version of the Altman model was intended only for companies listed on the capital market. Later (see Altman, 2000), however, a modification of the model was published for corporations not listed on the capital market. This allowed greater usage of the formula and its associated popularity.

The model's popularity was summarized by Mandra et al (2010), according to whom Altman's model (see Altman, 1977) has proven to be robust despite the fact that it was invented more than 30 years ago.

Nonetheless, one can come across opposing opinions as well. There are studies (Scott, 1981; Platt, Platt, 1990; Grice, Dugan, 2001; Wu, Gaunt, Gray, 2010; Niemann et al. 2008) showing that the precision of a bankruptcy model is significantly degraded if used in a *field, period, and/or business environment* different from that in which the learning data were observed. It is therefore generally not a good idea to use models favored in the literature believing that they and their predictors will work well even within domestic conditions.

The objective of this article is to verify the effectiveness of the Altman model intended for companies not listed on the capital market within the environment of the Czech Republic. Our objective is also to propose a more effective modification of the discriminant function for the particular conditions described in this thesis, including the boundaries of the "grey zone".

2 Materials and methods

The examined sample consisted of the financial statements of 1,619 companies in the manufacturing industry operating in the Czech Republic. Of these companies, 1,432 are financially sound (active) and 187 companies were going bankrupt (one year prior to bankruptcy). The collected data are from the years 2004 to 2011. The sample included only complete observable data, i.e. data of companies whose complete financial statements were available.

Additionally, extreme variables which could degrade the explanatory value of the obtained results were removed from the sample.
The data were obtained from the AMADEUS database (Analysis Major Database for European Sources). The calculations were performed using the software program Statistica 10.

2.1. The Altman Model
The premise of the Altman Model (Altman, 1968), which applied the method of linear discriminatory analysis, included the testing of 22 variables reflecting 5 key areas of a company's financial health; liquidity, profitability, leverage, solvency and activity.
This led to the establishment of 5 indicators which, according to Altman (1968), outperform other alternatives when taking into account predictive accuracy and correlations between indicators. The Altman Model from 1968 can be calculated as follows (see Altman, 1968):

$$\text{Z-score} = 0.012 \cdot X_1 + 0.014 \cdot X_2 + 0.033 \cdot X_3 + 0.006 \cdot X_4 + 0.999 \cdot X_5 \quad (1)$$

where
- X_1 is the ratio of Net Working Capital and Total Assets
- X_2 is the ratio of Retained Earnings and Total Assets,
- X_3 is the ratio of EBIT and Total Assets,
- X_4 is the ratio of Market Value of Equity and Book Value of Liabilities,
- X_5 is the ratio of Sales and Total Assets.

Altman modified his ZETA model for the purposes of companies unlisted on the capital market (see Altman et al, 1977; Altman, 2000). This modification involved the replacement of the X_4 indicator of Market Value of Equity with the Book Value of Equity and the re-calculation of the formula coefficients, including the boundaries of the "grey zone". The significance of the adjusted predictor was somewhat lower, though it was still the third most important predictor, just as was its former variant. The model from 2000 can be calculated as follows (see Altman, 2000):

$$\text{Z-score} = 0.717 \cdot X_1 + 0.847 \cdot X_2 + 3.107 \cdot X_3 + 0.42 \cdot X_4 + 0.998 \cdot X_5 \quad (2)$$

where
- X_4 is the ratio of Book Value of Equity and Total Liabilities,

The interpretation of the formula thus follows:
- *Z<1.23* indicates that a company is at risk of bankruptcy (going bankrupt),
- *Z>2.9* indicates that a company is found to be in a state of financial health (active),
- *2.9>Z>1.23* is a range of values indicating neutral outcomes, the so-called "grey zone".

Altman (2000) presents the accuracy of this model as 90.9% for correctly classified companies that are likely to experience bankruptcy and 97% for correctly classified active companies.

2.2. Testing the Altman Model
The effectiveness of the Altman Model was tested on the data sample using the discriminant function (see Equation 2).
Effectiveness is evaluated as the ability of the model to provide a clear and proper conclusion predicting a company's likelihood of bankruptcy. Among another criteria to be assessed are the number of companies the model is not able to evaluate as risky or healthy (see "grey zone") and the model's error rate. Two types of errors can occur when applying the formula, Type I and Type II errors. Type I errors occur in a situation when a company likely to experience bankruptcy is evaluated as active, while Type II errors occur in the opposite situation. According to literary sources (Zhou, Elhag, 2007), a Type I error is two to twenty times more serious (i. e. more expensive) than a Type II error. Details can be found in the following Table 1.

Table 1, Accuracy of the Altman Model on the sample

	Active		Going bankrupt		Total	
Number	1,432	100.0%	187	100.0%	1,619	100.0%
Grey zone	564	39.4%	56	29.9%	620	38.3%
Correctly identified	710	49.6%	101	54.0%	811	50.1%
Errors	158	11.0%	30	16.0%	188	11.6%

Source: Our own analysis of data from the Amadeus database

The Altman Model managed to correctly evaluate 50.1% of the total number of the examined companies, failed to evaluate 38.3% of the companies, and errors occurred in 16% of the companies.
As far as active companies are concerned, the formula was able to correctly identify 49.6 of them, 39.4% were evaluated without definite conclusions, and 11% were wrongly identified as likely to experience bankruptcy (see Type II error).

In the case of companies with a likelihood of bankruptcy, the formula was able to correctly identify 54%, failed to identify 29.9%, and the remaining 16% were wrongly identified as active (see Type I error).
When evaluating the model's accuracy as a number of correctly evaluated companies against the number of just evaluated companies (i.e. companies outside the "grey zone"), the accuracy is higher. To be precise, 81.8% of active companies were correctly identified, 77.10% of companies likely to experience bankruptcy were correctly identified. Regardless of which method is used to assess the accuracy, it is significantly lower when compared with the accuracy claimed by its author (see Altman, 2000).
Moreover, the amount of companies which ended up in the grey zone also leads to a significant limitation to the practical usage of the model.
Therefore, it is necessary to rethink the model for conditions of a different environment (here the Czech Republic). This can be done at two levels.
The first involves recalculating the discriminant function, including the boundaries of the grey zone, while keeping the current variables of the model.
The second involves a change in the variables of the formula, possibly a change in the method of deriving the formula - in other words inventing a completely new formula. The latter option has already been dealt with earlier (see Karas, Režňáková, 2012, 2013). Thus in this article we must deal with the first option only.

3 Proposed modification of the model

We have modified the Altman Model into two stages. During the first stage a new derivation of the formula, including the discriminant rule, was carried out. During the second stage the error rate of the formula was analyzed and the boundaries of the grey zone were derived. Details of the newly derived model can be found in the following Table 2.

Table 2, Revised Altman Model

	Wilks lambda	**Parc. lambda**	**F to rem.**	**p-val.**	**Toler.**	**R^2**
X_1	0.8310	0.9981	3.049	0.08095	0.1290	0.8710
X_2	0.8309	0.9983	2.794	0.09481	0.1295	0.8705
X_3	0.8658	0.9580	70.209	0.00000	0.8414	0.1586
X_4	0.8393	0.9882	19.158	0.00001	0.9482	0.0518
X_5	0.8294	1.0000	0.000	0.98897	0.9705	0.0295

Source: Our own analysis of data from the Amadeus database

Using the F-test, the model as a whole is statistically significant at 1% (see overall characteristics of the model, Wilks lambda 0.82942 approx. F (5.1603) =65.934, p<0.0000).
However, only two out of five variables of the formula are statistically significant at 1% and 5%, respectively (shown in bold in Table 2). The variables here are the ratio of EBIT and Total Assets (X_3) and the ratio of Book Value of Equity and Book Value of Liabilities (X_4). Additionally, according to the values of tolerance, or R^2, it is possible to explain approx. 87% of the information represented by the variable X1, or X2, by a combination of other variables in the model. This conclusion is in accordance with Shumway's criticism (see Shumway, 2001) which considers that in some cases as many as half of the financial indicators included in the bankruptcy models to be redundant. For Shumway (2001) the only significant variables of the Altman Model are the variables X_3 and X_4, though he came to this conclusion using a different method (the Cox Model, see Cox, 1972).
The outcome of the application of the discriminant analysis involves in two classification functions, one for the group of active companies and the second for the group of companies facing the likelihood of bankruptcy. It is true that a company is evaluated as an active company or as likely to experience bankruptcy provided that the corresponding functional value of the active function is higher than the similar value of the bankruptcy function. In any other case, such a company is evaluated as a company likely to experience bankruptcy.
It is practical to define the *spread* function, which is the difference between the active and bankruptcy functions. A company is evaluated as an active company when this difference is positive. A negative difference indicates the company’s likelihood to experience bankruptcy. The coefficients of these functions, including the difference values, have been calculated in Table 3.

Table 3, Classification function of the revised model

Variable	**Active**	**Bankrupt**	**Spread**
X_1	-0.42127	-0.7549	0.33363
X_2	0.42205	0.12748	0.29457
X_3	0.41425	-2.31813	2.73238
X_4	0.26184	0.1395	0.12234
X_5	0.94408	0.94317	0.00091
Constant	-1.24692	-3.70507	2.45815

Source: Our own analysis of data from the Amadeus database

ISBN: 978-960-474-327-8

In the adjusted form, i.e. before the application of the grey zone, the model is able to correctly identify 99.92% of active companies in the sample, but only 17.39% of companies that are likely to go bankrupt. The formula wrongly evaluated 161 companies (9.94% of the total number of companies in the sample), of which 160 companies were evaluated as companies likely to experience bankruptcy (85.55% of the total number of companies facing the risk of bankruptcy) and 1 company was evaluated as active (0.07% of the total number of active companies). We therefore looked into a way to increase the accuracy of the evaluation of the companies that are likely to experience bankruptcy. This was obtained by applying the grey zone. The grey zone represents the internal "spread" values in which the highest values of error occur. The "spread" values for these companies were divided into 50 identical intervals and the corresponding relative frequencies were calculated; see the following Table 4.

Table 4, Analysis of the "spread" error rate

Interval	Relative frequency [%]
0.2<Spread<=0.4	0.62
0.4<Spread<=0.6	1.24
0.6<Spread<=0.8	0.62
…	…
2.2<Spread<=2.4	14.91
2.4<Spread<=2.6	**20.50**
2.6<Spread<=2.8	11.80
…	…
3.4<Spread<=3.6	1.24
3.6<Spread<=3.8	0.62
3.8<Spread<=4.0	0.62

Source: Our own analysis of data from the Amadeus database

The analysis of the distributed "spread" values has shown that the model reports the highest frequency when the "spread" values range from 2.4 to 2.6. Therefore, these values were selected as the boundaries of the grey zone.

The re-calculated classification accuracy of the revised formula after the application of the grey zone is shown in the following Table 5.

Table 5, Classification accuracy of the revised formula

	Active		Going bankrupt		Total	
Amount	1,432	100.0%	187	100.0%	1,619	100.0%
Grey zone	157	11.0%	33	17.6%	190	11.7%
Correctly identified	1,146	80.0%	115	61.5%	1,261	77.9%
Errors	129	9.0%	39	20.9%	168	10.4%

Source: Our own analysis of data from the Amadeus database

The total accuracy of the revised formula is 55.49% higher compared to the original formula when applied to the data.

The revised model is 13.86% more successful in identifying companies facing the risk of bankruptcy and 61.41% more successful in identifying active companies. The total number of companies evaluated as within the "grey zone" was lower by 69.35%. Type II errors were lower by 18.35%, though Type I errors were higher by 30%.

The Altman Model adjusted for the conditions of the Czech Republic (i.e. a formula which uses the same variables as the Altman Model) can be calculated as follows:

$$Z\text{-revised} = 0.33363 \cdot X_1 + 0.29457 \cdot X_2 + 2.73238 \cdot X_3 + 0.12234 \cdot X_4 + 0.00091 \cdot X_5$$

The "spread" constant (see Table 3) can be excluded from the function, or the boundaries of the grey zone can be moved by the value of this function. The new boundaries of the grey zone (after taking into account the values of the constant) and their interpretation are the following. The interpretation of the *Z-revised* "spread" value of a company is:

- Z-revised > 0.1419 is evaluated as an active company,
- Z-revised < -0.0581 is evaluated as a company at risk of bankruptcy,
- -0.0581 =< Z-revised =< 0.1419 does not provide an unambiguous evaluation (grey zone of the model).

4 Discussion

The Altman Model within the environment of Czech companies works with a significantly lower accuracy than that stated by its author. This is in accordance with the outcomes of many studies (Scott, 1981; Platt, Platt, 1990; Grice, Dugan, 2001; Wu, Guant, Gray, 2010; Niemann et al. 2008) dealing with the problematic applicability of formulas.

For the purposes of this article we have looked into the possibility of increasing the classification accuracy of the formula when applied in a different environment. The modification of the discriminant function as well as of the boundaries of the grey zone were looked into in order to find a solution to better suit the conditions of the tested environment.

ISBN: 978-960-474-327-8

The authors of this article are aware of the fact that the application of the grey zone is a compromise between the number of non-evaluated companies and the error rate of the formula. This is a way to significantly affect the accuracy of the model.

For the purposes of our research, the boundaries of the grey zone were chosen in order to achieve the highest overall accuracy of the model and, at the same time, the lowest amount of the possible "grey zone" companies. Lowering the left boundary of the grey zone (here at a value of -0.0581) leads to the reduction of accuracy with which companies likely to go bankrupt are identified, while the corresponding accuracy regarding active companies remains unchanged. Conversely, raising the right boundary of the grey zone (here 0.1419) leads to the reduction of accuracy with which active companies are identified, while the corresponding accuracy regarding companies facing bankruptcy risk remains unchanged.

Any shift of the grey zone's boundaries is reflected in a change in the amount of non-identified companies.

The formula was created on the basis of discriminant analysis representing a parametric algorithm. Testing of the significance of the parameters (ratio indicators) of the Altman Model from 2000 has shown that the formula contains only two statistically significant predictors. These predictors are the ratio of EBIT and Total Assets (X_3) and the ratio of Book Value of Equity and Book Value of Liabilities (X_4).

It is possible that the Altman Model predictors will work more effectively when combined with another, especially non-parametric, model generation algorithm. It has been proven that the method of linear discriminant analysis benefits from a normal distribution of data (see Omar, McLeay, 2000). A normal distribution is, however, a very rare phenomenon as far as financial ratio indicators are concerned. The frequent disproportionality between the numerator and denominator of the ratio indicator can be considered as a reason for this. In the case studied, proportionality means that "*the relationship between the two variables is linear and the constant is zero*" (Whittington, 1980). The problem of disturbing the normality of the data can be effectively solved by using the Box-Cox transformation of data (see Box, Cox, 1964). A model based on discriminant analysis can then be generated from the transformed indicators (see Karas, Režňáková, 2013a).

In addition, the ability of the ratio indicator to achieve extreme values is set by its construction (see e.g. Karas, Režňáková, 2013b). However, it is extreme values that affect the conclusions of parametric methods (see Zimmerman, 1994, 1995, 1998).

5 Conclusion

By testing the Altman Model generated for companies unlisted on the capital market, it has been shown that its application within the conditions of a different environment is significantly less effective than within the environment for which it was invented. The example of the data of manufacturing companies in the Czech Republic has proved that the overall accuracy of the formula can be increased by up to 55%. This was achieved by changing the significance of the model's variables (i.e. changing the discriminant function) and shifting the boundaries of the grey zone. The number of "grey zone" companies was thus reduced by up to 69%. The procedure thus described can be used to revise the formula to suit the national conditions of every economy.

References:

[1] Altman, E. I., finanční poměry, discriminant analýzy a předpovědi firemních úpadků, *deníku financí*, vol. 23, No. 4, 1968, pp. 589-609.

[2] Altman, E. I, Haldeman, R. G., Narayanan, P., ZETA Analysis. A new model to identify bankruptcy risk of corporations, *Journal of Banking and Finance*, Vol.1, 1977, pp. 22-54.

[3] Altman, E. I. *Predicting financial distress of companies: Revisiting the Z-score and Zeta® models* [online]. 2000 [cit. 2013-04-29] Available at: http://pages.stern.nyu.edu/~ealtman/PredFnclDistr.pdf

[4] Beaver, W. H., Financial Ratios as predictors of Failure, *Journal of Accounting Research, Vol.4,* 1966, pp. 71-111

[5] Box, G. E. P., Cox, D. R. An Analysis of Transformations, *Journal of the Royal Statistical Society. Series B (Methodological*), Vol. 26, No. 2, 1964, pp. 211-252.

[6] Cox, D. R. Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological),* vol. 34, no. 2, 1972, pp. 187-220.

[7] Deakin, E. B., A Discriminant Analysis of Predictors of Business Failure, *Journal of Accounting Research*, Vol.10, No.1, 1972, pp. 167-179.

[8] Grice, J. S., Dugan, M. T., The limitations of bankruptcy prediction models: Some cautions for the researchers, *Review of Quantitative Finance and Accounting*, Vol.17, 2001, pp. 151-166.

[9] Karas, M., Režňáková, M. Financial Ratios as Bankruptcy Predictors: The Czech Republic Case. In: Advances in Finance & Accounting: *Proceeding of the 1st WSEAS International Conference on Finance, Accounting and Auditing (FAA 12).* WSEAS Press. 2012, pp. 86-91.

[10] Karas, M., Režňáková, M. Bankruptcy Prediction Model of Industrial Enterprises in the Czech Republic. *International Journal of Mathematical Models and Methods in Applied Sciences*, Vol. 7, No. 5, 2013a, pp. 519-531.

[11] Karas, M.; Režňáková, M. The Distributional Properties of Financial Ratios: The Case of Czech Bankruptcy Data. *Trends of Economics and Management*, Vol. 7, No, 13, 2013b, pp. 56-67.

[12] Li, H., Sun, J., Predicting business failure using multiple case-based reasoning combined with support vector machine, *Expert Systems With Applications*, Vol.36, 2009, pp. 10085-10096

[13] Martin, D. Early warning of bank failure: A logit regression approach. *Journal of Banking & Finance*, vol. 1, no. 3, 1977, pp. 249–276.

[14] Mandru, L., Khashman, Carstea, A. C., David, N., Patrascu, L., The diagnosis of bankruptcy risk using score function. Recent advances in artificial intelligence, knowledge engineering and data bases. Proceedings of the 9th WSEAS International Conference on Artificial intelligence, knowledge engineering and data bases (AIKED '10), 2010, pp. 83-87

[15] McLeay, S., Omar, A. The sensitivity of prediction models to the non-normality of bounded and unbounded financial ratios. *British Accounting Review*, 2000, Vol. 32, pp. 213–230.

[16] Niemann, M., Schmidt, J. H., Neukirchen, M., Improving performance of corporate rating prediction models by reducing financial ratio heterogeneity, *Journal of Banking & Finance*, Vol.32, 2008, pp. 434-446.

[17] Ohlson, J. A., Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research*, Vol.18, No.1, 1980, pp. 109-131

[18] Platt, D. H., Platt, M. B. Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction. *Journal of Business Finance & Accounting*, Vol. 17, No. 1, 1990, pp. 31-51.

[19] Sánchez-Lasheras, F., De Andrés, J.,Lorca, P., De Cos Juez, F. C. A hybrid device for the solution of sampling bias problems in the forecasting of firms' bankruptcy. *Expert Systems with Applications*, vol. 39, 2012, pp. 7512–7523.

[20] Scott, J. The probability of bankruptcy: a comparison of empirical predictions and theoretical models. *Journal of Banking & Finance*, vol. 5, 1981, pp. 317-44.

[21] Shumway, T., Forecasting Bankruptcy More Accurately: A Simple Hazard Model, *Journal of Business*, Vol.74, No.1, 1999, pp. 101-24,

[22] Taffler, R. J. Forecasting company failure in the UK using discriminant analysis and financial ratio data. *Journal of the Royal Statistical Society*, vol. 145, 1982, pp. 342–358.

[23] Tam, K., Kiang, M. Managerial applications of neural networks: the case of bank failure prediction, *Management Science*, vol. 38, no. 7, 1992, pp. 926–947.

[24] Whittington, G. Some basic properties of accounting ratios. *Journal of Business Finance and Accounting*, Vol. 7, No. 2, 1980, pp. 219-232

[25] Wu, Y., Gaunt, C., Gray, S., A comparison of alternative bankruptcy prediction models, *Journal of Contemporary Accounting & Economics*, Vol.6, 2010, pp. 34-45

[26] Zimmerman, D. W. Invalidation of parametric and nonparametric statistical tests by concurrent violation of two assumptions. *Journal of experimental education*, Vol.67, No.1, 1998, pp. 55-69.

[27] Zimmerman, D. W. A note on the influence of outliers on parametric and nonparametric tests, *The journal of general psychology*, Vol. 121, No.4, 1994, pp. 391-401.

[28] Zimmerman, D. W. Increasing the power of nonparametric tests by detecting and down weighting outliers, *Journal of experimental education*. Vol.64, No.1, 1995, pp. 71-79.

[29] Zmijewski, M. E., Methodological issues related to the estimation of financial distress prediction models, *Journal of Accounting Research*, Vol.22, 1984, pp. 59-82.

[30] Zhou, Y., Elhag, T. M. S. Apply Logit analysis in Bankruptcy Prediction. In: *Proceedings of the 7th WSEAS International Conference on Simulation, Modelling and Optimization*. 2007, pp. 301-308.