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ADAPTATION OF THE ALTMAN'S CORPORATE INSOLVENCY PREDICTION MODEL – THE BULGARIAN CASE[2]

Having an adapted model for prediction of Bulgarian corporate insolvency is a useful tool for a wide range of financial statement users. In the past sixty years, plenty of papers was published in this field. However, a statistically significant insolvency prediction model hasn't been constructed based on Bulgarian financial ratios. The purpose of the study was to solve this task. Linear Discriminant Analysis was used to select variables and to quantify the coefficients of the insolvency financial indicators for Bulgarian companies. The classification tests were applied to initial and test samples. Analysis of the classification accuracy was made comparing the adapted model and the revised Altman's Z-score model in 2000. The result confirmed the need for adaptation of Altman's Z-score model.
JEL: C51; C52; C53; D22; G33

Introduction

Entering in insolvency proceedings is a significant problem all around the world. Moreover, it has generated high social direct and indirect costs (Lensberg et al., 2006). An accurate forecast is needed to make informed decisions. It is a tool which may prevent entering in insolvency proceedings.

Since the early 1930s, the studies that investigate the importance of insolvency prediction has been discussed. The Altman's study, published in 1968 (Altman, 1968), is the first that analyses the interaction between several financial ratios, constructing an insolvency prediction model based on Multiple Discriminant Analysis (MDA). He published a new methodology applying a method typically used in biology and chemistry. During the 70-es the researchers started to use other statistical methods such as logistic regression and probit analysis (e.g. Martin, 1977 and Zmijewski, 1984, respectively). Driven by the computers' development, the intelligent models became the most used one during the '90s. The most popular self-learning method in the area of insolvency prediction models was neuron networks.

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The current studies related to insolvency prediction are focused on building both scoring models (e.g. Matsanov, 2014; Stefanova, 2016) and models for prediction of 12-months or lifetime Probability of default (PD). The latter is mainly driven by the implementation of the International Financial Reporting Standard (IFRS) 9 "Financial Instruments" which came into force on the 1st of January 2018. In the lifetime PD models have to be implemented the macroeconomic scenario of the country (e. g. Jovic, 2015). One of the most affected economic sectors by the new models for assessing a significant increase in credit risk is the banking sector. The Russian and Slovakian bank sector analysis confirms the significance of liquidity, capital adequacy, and assets quality (e. g. Lanine and Vennet, 2005; Fidrmuc and Hainz, 2009). Mehmed (2014) evaluates the Bosnia's bank sector liquidity using linear regression, while Derviz and Podpiera (2008) make synchronization between the Czechs regulatory credit ratings and those of Standard and Poors using logistic regression.

The other stream of the studies in the transition economies is to apply an already built model with/ without corrections. Lace and Koleda (2008) analyse 14 popular models using four characteristics to assign a weight to any of them (Koleda and Lace, 2009). They claim that the integration and modification make the non-adapted models applicable for Latvian companies. The statement is confirmed in Sneidere and Bruna's (2011) study in which they test Altman's Z" – score (2000) for non-public companies and Fulmer's H model. It is worth mentioning that these two models are also included in Lace and Koleda's research (2009). Both models achieve better accuracy results than the Latvian adapted model.[3] Moreover, Pavlović et al. (2012) achieve the same accuracy rate applying Zmijewski's model (1984) on Serbian companies like the one achieved by Zmijewski using his initial sample. However, the accuracy results weren't satisfying using Zmijewski's model to predict the Croatian companies insolvency. Pavlović et al. (2011) apply the Argentine dataset based model of Sandin and Porporato[4] to Serbian companies. The result is not satisfying. Muminović (2013) confirms the conclusion derived in previous studies (e. g. Muminović et al. 2011; Panayotova and Dobreva, 2014) that Altman's Z-score (1968) is not applicable to predict the Serbian companies insolvency. The Borlea and Achim's (2014) study shows that Conan and Holder (1979)[5] model works better than Altman's Z-score (1968) for Romanian metallurgical companies. Bulgarian authors (e. g. Todorov, 2014; Timchev, 2011; Mladenova, 2016; Yovchev 2016; Dimitrova, 2013) use already built insolvency prediction models (Altman (1968), Taffler (1982), etc.) with acceptable accuracy. It hasn't escaped my notice that the used samples include relatively large, active, and financially sound companies (e.g. Kaolin AD, CCB Real Estate Fund REIT-Sofia, Bulgarian Real Estate Fund REIT-Sofia, Sofia Commerce-Pawn Brokerage AD-Sofia, etc.).

[3] Šorins, R., and Voronova, I. (1998). Uzņēmuma maksātnespējas novērtējums. Ekonomiskās problēmas uzņēmējdarbībā, RTU Riga, pp. 125-131. [Source: Sneidere and Bruna 2011]

[4] Sandin, A., Porporato, M. (2007). Corporate bankruptcy prediction models applied to emerging economies: Evidence from Argentina in the years 1991-1998. International Journal of Commerce and Management. 17(4), pp. 295-311. [Source: Pavlović et al. 2011]

[5] Conan, J., Holder, M. (1979). Explicatives variables of performance and management control, Doctoral Thesis, CERG, Universite Paris Dauphine. [Source: Borlea, S. and Achim, M. (2014)]

Männasoo (2007) concludes that Estonian companies' size has a significant influence on company success. Moreover, Estonian industrial companies are much more resilient than companies in other sectors. He also confirms that the companies met higher insolvency risk in their first few years. Fijorek and Grotowski (2012) apply above 1500 different models on a large sample of over 13 000 Polish companies. The most significant financial ratios for insolvency prediction are the same as the most commonly used such as Current Assets on Total Assets, Return on Sales, and EBIT on Total Assets. They stress that in one country could be built several statistical significant models with high accuracy based on financial ratios.

However, it hasn't been published an analysis of the appropriate methods for Bulgaria. The predictability of the financial ratios using Bulgarian companies' data also hasn't been analysed. The analysis's first step is to select the appropriate method. The method choice is fundamental in a building of insolvency prediction models. The appropriate method should meet several criteria. It has to be applied frequently enough in case of insolvency prediction. It is needed to ensure high accuracy with a relatively small sample. The lack of a publicly available database with Bulgarian companies' financial statement makes the model construction based on very large samples a much longer process. In addition, it should have a clear calculation algorithm which is a good basis for the following data interpretation. The method should generate a clear, unambiguous result which allows a clear and accurate interpretation of the results. The latter instil more confidence in the potential users of the constructed model. Moreover, the financial ratio's dynamic over time requires periodic revision and therefore efficient and effective revision is needed characteristic. The latter also allows being build models for specific Bulgarian economic sectors. The dependent variable should not be discrete because it should be determined intervals with different probability to enter in insolvency proceedings – high, medium and low. The selection of the most appropriate method was made based on an analysis of studies published between 1966 and 2014 using the criteria mentioned above. It was included 113 studies, with 232 models to 124 authors. The insolvency prediction models' analysis covered models build on corporate data from 19 countries on 5 continents – Australia, Asia, Europe, South, and North America. The included countries are with different economic and social development, degrees of economic freedom and economic growth. As a side note, during the analysed period there were 4 big economic recessions: the 2 major oil crises in 1973 and 1978; the bursting of the so-called "dotcom" bubble in the USA in 2000; and Global Financial Crisis in 2007. MDA was the most appropriate method for the Bulgarian conditions by virtue of the following reasons: (i) it was the most popular method; (ii) the models based on it were the most accurate; (iii) it had a clear algorithm; (iv) despite both the need to meet several assumptions and its intuitive interpretation, it was one of the models which allowed efficient and effective revision.

In addition, it was analysed insolvency prediction models using data set from European countries which passed from centrally planned to a market economy.[6] The purpose was to analyse the models constructed in transition economies like Bulgaria. The methods used in countries such as Bosnia and Herzegovina, Croatia, Czech Republic, Hungary, Poland,

[6] Studies published in English for the following countries: Bosnia and Herzegovina, Croatia, Czech Republic, Estonia, Hungary, Latvia, Poland, Romania, Russia, Slovakia, Serbia and Ukraine.

Russia, and Serbia are mainly MDA, logit regression, probit analysis, and neuron networks. Generally, the models' accuracy was lower than the reported in the analysis mentioned above. Moreover, they did not provide a test sample accuracy or Lachenbruch (1967) test. The models were built using large samples (more than 1000 companies) which allows to include more independent variables (e. g. Fedorova et al. 2013; Memić, 2015). However, the authors select the variables from a very short list of financial ratios. It is not clear how they made the selection. They didn't include significant financial ratios such as Earnings Before Interest and Taxes (EBIT) on Total Assets (e. g. Memić 2015; Pervan et al. 2011). In transition economies and emerging markets are applied mainly statistical methods to construct an insolvency prediction models despite the used large datasets. There is a hypothesis that in some countries can be applied an already built model without corrections. However, the poor accuracy results of Altman's Z-score (1968) model application provides evidence that the Altman Z-score model has to be adapted.

Despite the worldwide development of the insolvency prediction models in the last century, in Bulgaria, there are no studies that investigate a statistically significant insolvency prediction model for Bulgarian companies based on financial data[7]. In this study, it was solved this task as it is presented an insolvency prediction model using linear discriminant analysis and Bulgarian dataset.

Methodology

In this section is presented the methodology that was applied to construct an insolvency prediction model using discriminant analysis. The aim was to achieve at least 90% correctly classified companies of the initial sample and 80% of the test sample. The methodology includes five major steps as follows:

Insolvency definition

The first step was clearly to define the meaning of insolvency. The determination of the company's insolvency date affects data collection and model validation. The Bulgarian Commerce Act (Ciela, 2015) provides the following three possible definitions: (i) actual insolvency – at the time of filing the application for opening of insolvency proceedings; (ii) formal insolvency – at the time of the court judgment to open insolvency proceedings based on submitted application, and (iii) final insolvency – at the time specified in the court decision for company insolvency based on expert analysis. In the study was adopted the actual insolvency considering it 1) is the earliest data which can be determined and, 2) undeniably shows the moment when the company can't pay its obligations. The actual

[7] Georgiev and Petrova (2014) published adapted Altman (1968) Z-score insolvency prediction model for Bulgarian public companies. They use the same financial ratios but calculate the new discriminant coefficients. Their model accuracy is 70% correctly classified out of 40 companies included in the initial sample. The discriminant function quality is unsatisfying. There is a number of methodological flaws. Moreover, they don't meet the LDA method's assumptions. The latter raises doubts about the stability and accuracy of the presented model.

insolvency definition was to determine: (i) the financial statements' year of the insolvent companies included in the initial sample; (ii) the industry in which they operate.

Sampling

Usually, the authors (e.g. Altman, 1968 and Tam, 1991) use criteria such as company size (expressed by total assets amount) to select the companies' sample. However, the Bulgarian companies' structure (NSI, 2016) is different compared with other Western countries characterizing with more than 90% share of the micro-business (up to 9 employees). Thus, it was decided not to apply any criteria for company grouping.

It was used two samples to be constructed reliable and as accurate as a possible model. The model was built with an initial sample, while it was validated using a test sample.

First, the initial sample was collected using a matched pair sample.

Companies in actual insolvency (insolvent companies). It was used the APIS Law Web system where 528 companies met the definition of actual insolvency. ***Only 87 of them were published non-zero financial statements in four consecutive years before entering in insolvency proceedings.*** It was used the four-year financial statement criteria by reasons of: 1) long-term model validation and 2) to exclude the companies which are established for other reasons than to develop a profitable business.

The financial statements were mainly reported after 2007 so a longer period than four years will significantly affect on the sample size. It is worth mentioning that the companies remained only 87 from 528 due to the following reasons: (i) a lot of companies didn't publish their financial statements in four consecutive years; (ii) a lot of companies didn't publish a financial statement at all; (iii) some of the companies didn't provide their Cash Flow statements; (iv) some of the companies published zero financial statements.

The 87 insolvent companies were separated randomly into two groups – 43 in the initial sample and the remaining 44 – in the test sample. Later on, two companies were moved from the initial sample to the test sample as a result of the extreme figures. Thus, it has remained 41 and 46 companies, respectively in the initial and in the test sample.

The companies' economic sector in the year before the companies enter in actual insolvency was determined in line with the National Classification of Economic Activities (NCEA-2003).

Solvent companies. As mentioned above, the method of sample collection was matched-pair. The decision was taken based on an analysis on about 232 insolvency prediction models published between 1966 and 2014 (Tzvetanova and Kostov, 2016). MDA based models with a high accuracy rate were constructed based on matched-pair samples (e.g. Altman, 1968; Altman et al., 1977; Moyer, 1977; Tam and Kiang, 1992). Thus, for any insolvent company it was selected a solvent one which met the following criteria: (i) have the same amount of total assets (± 10%), (ii) operates in the same industry and (iii) published a financial statement in the year before the insolvent company enter in actual insolvency. The solvent companies also should have a published financial statement for at least four consecutive years. It was used consolidated financial statements in case of available consolidated and unconsolidated figures.

Second, it was collected test sample to verify the model accuracy:

Insolvent companies. The remaining 46 companies identified as actual insolvent companies but not included in the initial sample.

Solvent companies. It was exported all active companies by sector for the period between 01.01.2006 and 30.06.2016 from APIS Law Web system. The following procedure was performed: (i) for any economic sector all companies were arranged in alphabetic order; (ii) for any observation it was generated a random number; (iii) all companies were sorted from the smallest to the largest random number and (iv) it was analysed first *n* rows to collect a sample with 44 companies (8 of them didn't publish a Cash Flow statement).

The companies met the following criteria: (i) published financial statements for at least three consecutive years; (ii) the company has operational activities. In the sample was included the last published financial statement without taking into consideration the year.

In addition, 10 solvent companies were included in the test sample even if they were collected using a matched pair sample.

Multiple Discriminant Analysis

In this study, it was applied Multiple Discriminant Analysis as a construction method because: *(i) it was the most popular method; (ii) the models based on it were the most accurate; (iii) it has a clear algorithm; (iv) despite both the need to meet several assumptions and its intuitive interpretation, it was one of the models which allowed efficient and effective revision.*

Linear Discriminant Analysis (LDA) is a statistical method used to classify an observation into one of several a priori groups. After the groups' establishment and the observations' classification, the method calculates liner combination of tested characteristics which "best" discriminate between the groups and MDA determines a set of discriminant coefficients.

LDA has the advantage to reduce the analysis space dimension from the number of different independent variables to G – 1 dimension, where G equals the number of original *a priori* groups. In this study, the *a priori* groups are two – insolvent and solvent companies. The LDA function will be the following:

$$Z_i = V_0 + V_1 X_1 + V_2 X_2 + \ldots + V_j X_j,$$

where Z is the value based on which the observation *i* is classified observation where *i* = 1, 2, 3 ... n (number of companies), $V_1, V_2, \ldots, V_j$ are discriminant coefficients and, $X_1, X_2, \ldots, X_j$ are independent variables. LDA computes the discriminant coefficients V_j, while X_j are actual values where, $j = 1, 2, \ldots, n$.

It was used a standard discriminant function in statistical software SPSS. There is a significantly lower insolvency rate in Bulgaria (Stoyanova, 2013) but the *a priory* probability of insolvency was determined on 50%. Some authors criticise this approach considering it may influence on the model accuracy. However, the models based on 50% *a* *priory* probability to enter in insolvency proceedings were one of the most accurate. There is no evidence which clearly to prove the hypothesis that the models based on *a priory* probability closer to the real population are more accurate than the one with 50% a priory probability.

All independent variables were entered together instead of using a stepwise selection method. The first approach was preferred because it provides the opportunity to include variables that aren't statistically significant enough but nevertheless they complemented the model.

Acceptable was the model which can pass accuracy tests described below and met the following criteria:

- To be rejected the hypothesis for equality of the group means – insolvent and solvent.
- A high correlation between the discriminant coefficient and the groups.
- Test of the discriminative power of the constructed function to be passed with the lowest possible Wilks' Lambda value
- To be achieved at least 90% correctly classified of the initial sample and 85% of the cross-validation (each case is classified by the functions derived from all cases other than that case).

Model validation

The purpose of the study was to build a model which can predict the insolvency achieving the highest accuracy as early as possible. To be ensured the latter, the model passed the following tests:

Preliminary classification test. This test evaluates the Type I and Type II statistical errors. Type I error is when the model classifies insolvent as a solvent company. Type II error is when the model classifies the solvent as an insolvent company.

Ex post classification. This test evaluates the accuracy of the model on the test sample which covers the same period as the initial sample (Altman, 1978). It was applied only this test because it was not possible to collect a test sample from a different period than the covered from the initial sample. Ex post-classification (using new data from the same sample period) provides a crude test of the stationarity of the model and its individual component measures and parameters (Altman and Eisenbeis, 1978). In addition, ex post-classification provides an indication of the confidence one can have with respect to the observed group overlap among the variable distributions in the groups being investigated (Altman 1978, Winter). The Z_{BG}-score of all companies included in the test sample was calculated using the already received discriminant coefficients and the financial ratios of the test sample.

Long-Range Predictive Accuracy. The results from the validation tests described so far ensure enough evidence to be concluded that the initial sample is suitable to be constructed a model based on it. In order to verify the stability of long-term predictive accuracy, the model was tested on the initial sample with financial ratios for four consecutive years before entering in insolvency proceedings.

Comparative analysis. Analysis of the classification accuracy was made comparing the adapted model and the revised Altman's Z-score model in 2000 (Altman, 2000). The purpose was to prove the necessity of adaptation. The analysis covered both the initial and the test sample. Discriminant equations of the adapted model (Z_{BG}-score) and the revised Altman's Z-score (Z-score) were applied.

Empiric Results

Individual statistical analysis

It has never been published studies related to the forecasting ability analysis of the financial statement for Bulgarian companies. Moreover, Laitinen and Suvas (2013) conclude that the most used financial ratios for insolvency prediction aren't enough accurate for Bulgarian companies. The latter is due to specific country factors which have a strong influence on the forecasting ability of the model. Thus, it was needed a thoughtful and in-depth selection of the appropriate financial ratios starting from a large group of financial ratios. The analysis started with 60 financial ratios divided into five groups: Cash Flow; Profitability; Turnover; Liquidity and solvency; Leverage. The companies' financial ratios were calculated from the initial sample for both one and two years before the actual insolvency. They were selected based on the following criteria: (i) data availability; (ii) popularity in empirical research; (iii) avoiding both overlapping and interdependent financial ratios.

It is important to note some of the input data characteristics. The companies included in the initial sample have an average assets amount of BGN 7 683 thousand. The companies have a wide range of total assets amount – from BGN 115 thousand up to BGN 61 664 thousand. However, it was not applied some bounds considering it would remain a few observations. The samples cover the non-financial sectors of the Bulgarian economy. The economic sectors with more than one observation were Building Constructions, Hotels and Wholesale of milk and other household goods – sectors that were significantly affected by the Global Financial Crisis that hit in 2007. Bulgarian companies have to publish their financial statements in line with the National or International Accounting Standards. Nevertheless, most of the companies included in the sample published their financial figures filled in the National Statistical Institute Template. In addition, the Bulgarian companies can have operating activity even if they have reported negative equity in several consecutive years. There is no legislation which defines the period in which some company can have operating activity even if it has negative equity. It was included 16 companies in the sample which reported negative equity but are solvent. Another characteristic was that the Intangible Assets had an insignificant share in the Non-Current Assets' structure. Moreover, there were Intangible Assets only after reaching a certain amount of assets (above BGN 4 000 thousand). So, it wasn't needed to apply some corrections to the financial ratios which include Non-Current Assets. Furthermore, the companies made their revenues mainly from their core business (99% of their revenues on average). The remaining insignificant share was thanks to Interest Revenues. In terms of costs, the significant share of the operating expenses was taken by: (i) amortization and impairment losses, (ii) the book value of assets sold and (iii) provisions. The financial expenses are mainly interest payments – 8% from total insolvent companies' expenditures and 2% from total solvent companies' expenditures on average.

As mentioned above, it was needed a thoughtful and in-depth selection of the appropriate financial ratios to be performed. The latter ensures to be collected the appropriate variable to build an accurate and stable insolvency prediction model. The purpose of the analysis was to collect those financial ratios which: (i) are able accurately to predict the insolvency of Bulgarian companies; (ii) are relatively independent of each other.

The evaluation is based on the following criteria:

- clear difference between the two groups – insolvent and solvent companies;
- distribution which doesn't overlap significantly between the two groups;
- low correlation coefficients.

The individual statistical analysis of the 60 financial ratios was performed in two stages.

In stage 1, the sample passed through the following analysis: (i) descriptive statistics (mean, min, max, variance, standard deviation), (ii) frequency distribution histograms of the financial ratios in both groups – insolvent and solvent companies, and (iii) correlation analysis. Base on them it was derived the basic statistical characteristics of the sample. It allowed deriving a conclusion if the financial ratios are appropriate for the statistical method – was there a clear difference between the two groups, was there any extremums, which is the variables' distribution. The main findings were the following:

- *It was identified financial ratios with low standard deviation and with a clear difference between the groups' mean, which indicated that these variables had a discriminative ability.*
- *The lack of normal distribution function led to the need for the data transformation (Tzvetanova, 2018) and the exclusion of some observations from the initial sample. The use of methods such as MDA and Neuron Networks allows applying this approach because they examine the relationship between the data, not the data itself.*
- *Five financial ratios were excluded due to the high correlation with the other one. The decision was based on the results from the descriptive statistics and how close is the distribution function to the normal one.*

In stage 2, both the original and the transformed initial sample was analysed applying the following tests: (i) normality test; (ii) test of equality of the group means; (iii) Identification of the variables which follow one direction between the groups (linearity testing). The results showed those financial ratios which have characteristics to meet the assumptions of the MDA method which is obligatory to be constructed a significant discriminant function with stable results and acceptable accuracy.

At the end of the individual statistical analysis of the variables, it was identified 24 financial ratios (table 1) with appropriate characteristics to build a statistically significant insolvency prediction model. The result is similar to Altman (1968) who used 22 financial ratios. None of them was related to the cash flow statements.

Table 1

List of the financial ratios included in the variable list for the model

Group	**Financial ratio**	
Profitability	1	EBIT[8] on Total Liabilities
	2	EBIT on Total Revenues
	3	EBIT on Current Liabilities
	4	EBIT on Total Assets
	5	Operating Revenues on Operating Expenses
	6	Retained Earnings on Total Assets
	7	EBITDA[9] on Non-Current Tangible Assets
	8	Net Interest Payments[10] on Net Profit/ Loss
	9	EBIT on Net Interest Payments
Turnover	10	Total Revenues on Non-Current Tangible Assets
	11	Total Revenues on Total Liabilities
	12	Total Revenues on Current Liabilities
	13	Total Revenues on Total Assets
	14	Net Assets[11] on Total Revenues
Liquidity and solvency	15	EBITDA on Total Revenues
	16	Cash and cash equivalents on Current Liabilities
	17	Cash and cash equivalents on Total Assets
	18	Cash and cash equivalents on Total Liabilities
	19	Working Capital[12] on Total Assets
	20	Equity on Total Liabilities
	21	Equity on Total Assets
Leverage	22	Total Liabilities on Total Assets
	23	Total Financial Debt on EBIT
	24	Retained Earnings on Total Liabilities

The model

Based on the analysis and the empirical research it was built the following standardized model:

$$Z_{BG}=2.213 * X_1+0.243 * X_2 + 0.760 * X_3 + 2.821 * X_4,$$

where the financial ratios are:

X_1 – EBIT on Total Assets

[8] EBIT is equal to Net Profit plus Taxes plus Net Interest Payments.
[9] EBITDA is equal to EBIT plus Amortizations.
[10] Net Interest Payments is the difference between Interest Revenues and Interest Expenses.
[11] Net Assets is the difference between Total Assets and Total Liabilities.
[12] Working Capital is the difference between Current Assets and Current Liabilities.

X_2 – Total Revenues on Total Assets

X_3 – Equity on Total Assets

X_4 – Cash and cash equivalents on Total Assets

Z_{BG} – Overall Index

X_1 – *EBIT on Total Assets*. It shows the operating profitability of the company's assets. It measures the company's overall profitability which makes it an appropriate indicator for credit risk evaluation. Moreover, the financial ratio is very important by reason of it evaluates the current income isolated from the leverage effect. The latter determines the current profit as a key to long-term financial stability (Timchev, 2011). EBIT is equal to the sum of net profit, taxes, and net interest payments. EBIT on Total Assets was the most significant ratio in the model. Actually, it is one of the most-used components of the insolvency prediction models (e. g. Hopwood et al. 1994; Theodossiou, 1993; Kahya and Theodossiou, 1999; Zavgren, 1985).

X_2 – *Total Revenues on Total Assets*. The financial ratio which measures the company's turnover and shows: (i) the level of fulfilment of the company's obligations; (ii) and is the company uses its assets efficiently to increase its revenues. Total revenues included all revenues considering the revenues from non-core activities were an insignificant amount. Another aspect is that this ratio has a weakness to vary significantly across different sectors. Hence, this ratio is not an appropriate indicator when comparing companies which operate in different sectors. Total Revenues on Total Assets is with both the lowest correlation with the discriminant function and the lowest statistical significance.

The financial ratios mentioned above coincided with those of Altman's discriminant function (1968). However, the following two financial ratios are structure indicators based on Balance Sheet statement. They largely reflect the specific factors and practices applied in the country.

X_3 – *Equity on Total Assets*. It compares the company's equity to total assets, indicating its financial independence. It is a key financial ratio that stands on the balance sheet and shows the relative share of equity capital in the entire capital. Equity on Total Assets is an important indicator based on which it can be determined the degree of the company's financial stability. It is a statistically significant variable in many insolvency prediction models (e. g. Lee, et al., 1996; Altman and Lavallee [Source: Altman, 1984]).

X_4 – *Cash and cash equivalents on Total Assets*. The financial ratio measures the share of the assets held as cash, in bank accounts, and cash equivalents. It also evaluates the company's financial stability – higher liquidity means lower risk in the short term. Cash and cash equivalents on Total Assets is statistically significant variable according to a number of studies (e. g. Jones and Hensher, 2004; Hopwood, et al. 1989; Hopwood, et al. 1994; Tam and Kiang, 1992; Zavgren, 1985; Salchenberger, et al., 1992; Gombola, et al., 1987; Libby, 1975). It was the second most significant ratio in the model after EBIT on Total Assets. I may perhaps be forgiven for calling attention here to the fact that this financial ratio was affected by different practices for tax evasion and the accumulation of these amounts in cash.

Defining the new model's areas

It was proposed new risk criteria Z_1 and Z_2 (Tzvetanova, 2018, p. III.3.3.2., p. 100), based on the calculated discriminant function for any single original (non-transformed) observation (Z_{BG}-score). Z_{BG}-score of all original observations, which were included in the initial and in the test sample, were used to classify the companies according to the level of the risk to enter in insolvency proceedings in the following areas:

- [Z_{BG}-score $\leq Z_2$] – 95.12%, very high probability to enter in insolvency proceedings in the next year;
- [$Z_2 < Z_{BG}$-score $\leq Z_1$] – 53.66%, the company has a medium probability to enter in insolvency proceedings;
- [Z_{BG}-score $> Z_1$] – 12.2%, low probability to enter in insolvency proceedings or the company has 87.8% probability to survive.

Model validation

It was used the original data (non-transformed) to perform the model validation. The models' cut-off point were individually determined.

Preliminary classification test

Preliminary classification test evaluates the Type I and Type II statistical errors. The adapted model correctly classifies 91.5% of the initial sample companies (table 2). The model is relatively conservative because Type II error was bigger than the Type I error.

Table 2

Preliminary classification test results

Sample		**Actual state**	**Predicted state**		**Total**
			Insolvent	**Solvent**	
Initial sample	Number	Insolvent	39.00	2.00	41.00
		Solvent	5.00	36.00	41.00
	%	Insolvent	**95.12**	4.88	100.00
		Solvent	12.20	**87.80**	100.00

Ex post-classification

The ex post-classification evaluates the accuracy of the model on the test sample which covers the same period as the initial sample. The test was made on two test samples: sample with included companies with extremums; sample without the identified companies. The accuracy of the model decreased to 79 and 84%, consecutively (table 3). In addition, the results showed a better prediction of the solvent companies.

Table 3

Ex post-classification results

Sample		Actual state	Predicted state: Insolvent	Predicted state: Solvent	Total
Test sample with exceptions	Number	Insolvent	33.00	13.00	46.00
		Solvent	8.00	46.00	54.00
	%	Insolvent	**71.74**	28.26	100.00
		Solvent	14.81	**85.19**	100.00
Test sample without exceptions	Number	Insolvent	29.00	7.00	36.00
		Solvent	6.00	38.00	44.00
	%	Insolvent	**80.56**	19.44	100.00
		Solvent	13.64	**86.36**	100.00

Long-Range Predictive Accuracy

The previous results give evidence that the companies are appropriate to determine the overall effectiveness of the discriminant model for a longer period of time prior to insolvency. The long-range predictive accuracy test evaluates the initial sample for the second, third and fourth year prior to insolvency. Table 4 shows that the accuracy of the model is decreasing when the time prior to insolvency increases. The reason was an increase in wrong classified insolvent companies.

Table 4

Four-year predictive accuracy of the model

Year prior to insolvency	Total companies	Correct classified	Wrong classified	% Correct classified
First	82	75	7	91
Second	82	68	14	83
Third	82	60	22	73
Forth	82	56	26	68

Comparative analysis

Analysis of the classification accuracy was made comparing the adapted model and the revised Altman's Z-score model in 2000 (Altman, 2000). The purpose of this analysis was to prove the need for adaptation of the model.

The revised Altman's Z-score (2000) has the following discriminant function:

$$Z = 0.717 * X_1 + 0.847 * X_2 + 3.107 * X_3 + 0.420 * X_4 + 0.998 * X_5 ,$$

where the financial ratios are:

X_1 – Working capital on Total Assets

X_2 – Retained Earnings on Total Assets

X_3 – EBIT on Total Assets

X_4 – Equity on Total Liabilities

X_5 – Sales on Total Assets

The results of the comparative analysis between the adapted model accuracy (Z_{BG}-score) and the revised Atman's model accuracy (Z-score) showed that in the short term the adapted model is more accurate for the Bulgarian companies than the Altman's one (Table 5). One of the reasons is that the model was revised in 2000. Moreover, the financial ratios are selected based on American companies figures from the beginning of the 1960s. Test sample results confirmed the hypothesis that the adapted model is more accurate than the Altman's one. Furthermore, the achievement of 91.5% correctly classified companies versus 81.7% according to the Altman's model clearly showed the need for adaptation of both the financial ratios and the discriminant coefficients.

Table 5

Comparative analysis between the adapted model accuracy and the revised Atman's model accuracy

Sample		**Actual state**	**Predicted state, %**		**Total, %**
			Insolvent	**Solvent**	
Initial sample	Z_{BG} – score	Insolvent	**95.12**	4.88	100.00
		Solvent	12.20	**87.80**	100.00
	Z – score	Insolvent	**95.00**	5.00	100.00
		Solvent	32.00	**68.00**	100.00
Test sample	Z_{BG} – score	Insolvent	**71.74**	28.26	100.00
		Solvent	14.81	**85.19**	100.00
	Z – score	Insolvent	**76.00**	24.00	100.00
		Solvent	24.00	**76.00**	100.00

Conclusion

In this study was presented an insolvency prediction model for Bulgarian companies. It was selected financial ratios with appropriate characteristics from a large group of potential variables which ensures a stable and accurate model based on Linear Discriminant Analysis. The achieved accuracy is 91.5% correctly classified companies.

In the example below is shown the model's financial ratios of the three analysed companies which are multiplied by the discriminant coefficients of the presented function. Their sum shows with an accuracy of 91.5% in which of the defined risk areas the company falls.

	EBIT on Total Assets	Total Revenues on Total Assets	Equity on Total Assets	Cash and cash equivalents on Total Assets	Z-score	Insolvency risk
Coefficient	2.213	0.243	0.760	2.821		
Company A	-0.306	1.090	-0.560	0.010	-0.810	Very high probability
Company B	0.012	0.538	0.294	0.184	0.900	Medium probability
Company C	0.102	6.610	0.169	0.023	2.026	Very low probability

Company A has a very high probability to enter in insolvency proceedings due to its Z-score is significantly below 0.4. On the other hand, Company C has a very low probability to enter in insolvency proceedings reporting Z-score above 1.5. Company B falls in medium risk area being its Z-score between 0.4 and 1.5.

As a side note, the long-range predictive accuracy falls to 68% in the fourth year prior to insolvency. The latter is mainly due to the increase in wrong classified insolvent companies. Moreover, the model should be revised over a period of time.

Analysis of the classification accuracy was made comparing the adapted model and the revised Altman's Z-score model in 2000 (Altman, 2000). *The achievement of 91.5% correctly classified companies versus 81.7% according to the Altman's model clearly showed the need for adaptation of both the financial ratios and the discriminant coefficients.*

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