Received: 31 July 2018
DOI: https://doi.org/10.32025/RIS18004

Validation of insolvency models: The case of Latvian enterprises

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ABSTRACT

Purpose: The research is related to solvency forecasting methods and their models, their possible application and determination of precision. The objectives of the study are to examine the ten most commonly used models of insolvency, their application in Latvian companies, and to enable manufacturing companies to continue their business activities with a certain degree of reliability. It is necessary to predict probable insolvency in a timely manner and evaluate it in order to comply with the principle of continuation of business.
Design/methodology/approach: The study is conducted on the basis of Latvian manufacturing companies with an annual turnover of 1 million EUR to 3 million EUR over the period of 2011 to 2016. The research methods are as follows: monographic, graphical, analysis of statistical data, correlation and comparative analysis.
Findings: According to the results, the lowest Type I error of only 7% was shown by the Skiltere and Zuka model and the Type II error for the model was 29%. The highest classification abilities were shown by the Zmijewski, Altman Z" and Lis models, while the Type I errors were from 11% to 22%, and the Type II errors were higher, from 33% to 55%. The authors of this paper suggest using other cut-off points than the model proposed by the above authors, thus significantly increasing model accuracy.
Research limitations/implications: The paper examines discriminant analysis-based models and the validation is performed by estimating two types of errors and using ROC curves. A Type I error occurs when a model does not predict bankruptcy. A Type II error means that the model has predicted a solvent company as bankrupt.
Practical implications: The results of the study comprise the authors' considerations of the models as recommended, possible and not recommended for predicting insolvency of Latvian manufacturing enterprises.

Originality/value: The authors of the paper not only focus on the results of validation using a two-error method but also analyse the classification abilities of insolvency prediction models determined by area under the ROC curve. The study is also innovative because the authors suggest changing the cut-off points for some models to increase the accuracy of the prediction.
Keywords: solvency, bankruptcy, solvency models, solvency forecasting, validation, Latvian companies
Paper type: Research paper

INTRODUCTION

Today's economy is booming, but most recently a major crisis has touched states and their companies near and far and has had an especially significant impact on the Latvian economy. Every year, a significant number of companies become insolvent, including those that have worked very steadily and convincingly, so that the company's solvency and its assessment are very important. On average, 2.5% of businesses become insolvent each year (Genriha et al., 2011). According to the Register of Latvian Companies, more than 11,088 insolvency cases were proposed for commercial companies between 2008 and 2016, averaging 1,232 a year or 103 a month. During this period, most insolvency applications were made between 2008 and 2010, while insolvency was significantly lower from 2011 to 2016.

Forecasts should be carried out with a view to the near future, and current solvency can be assessed with a simpler calculation, but it is particularly important to make future predictions by comparing them with previously obtained calculations and evaluations. In order to assess whether the company itself or its cooperation partner is secure and financially sound, and whether there will be problems in the near future, it is necessary to assess its financial soundness. It is necessary to assess the firm's solvency as it is and, in particular, how it will be in the future. Different methods and models have been developed, supplemented and modified by both foreign and local researchers. The complexity and flexibility of statistical methods and modern computing technologies have allowed solvency assessment to be carried out using different methods. These models can be divided into parametric and nonparametric models. The most popular parametric models are linear discriminant analysis and logit regression. Linear discriminant analysis was proposed as the first solution. The nonparametric methods used for credit acquisition include neural networks, genetic programs and expert systems, support vector machines, the nearest neighbour approach and decision trees (Genriha and Voronova, 2012).

The study focuses on insolvency prediction models based on a linear discriminant analysis. The goal of the study is to obtain solvency prediction methods, their use for Latvian companies, by laying down a more suitable method for processing industrial companies with an annual turnover of 1 million EUR to 3 million EUR. The objectives of the research are as follows:

To carry out an overview of the results of previous research by Latvian authors on insolvency prediction models;

To evaluate the performance of insolvency prediction models using a two-error method and ROC curves;

To make conclusions on the performance of insolvency prediction models and work out recommendations on their application.

The paper examines the performance of ten commonly applied insolvency prediction models, including two models by Latvian authors: Altman Z’, Altman Z”, Fulmer, Springate, Zmijewski, Sorins/Voronova, Lis, Taffler/Tisshaw, Tisshaw, and Skiltere/Zuka.

The analysis is conducted on a sample of 300 Latvian processing industry companies over the period of 2011 to 2016. In the research paper, the following qualitative and quantitative methods are applied: the monographic method, the graphical method, analysis of statistical data, correlation analysis, and comparative analysis. The research is based on published papers on insolvency prediction models as well as on information provided by Lursoft.

LITERATURE REVIEW

The practical application of foreign and domestic prediction models is impossible without an analysis of their adequacy with regard to insolvency assessment. The reasons for distortions of the estimates may be as follows: a different procedure for calculating some indicators; the disparity of the data used to construct models and the macroeconomic situation; the industry specificity of companies’ activities is not taken into account, etc. Particular attention has been devoted to fine adjustment of the logical and technical system of models, proof of efficiency in terms of overall accuracy and proportional impact of errors made in accordance with the type. One of the aspects that affects the usability of these tools in practical applications was explored by Cestari et al. (2013). A study of the adequacy of insolvency models was carried out by Pavlovic et al. (2012) using the Zmijewski model on Serbian companies. According to Guerard and Schwartz (2007), the Altman Z-score model predicts bankruptcy for an industrial company with 97% accuracy a year before actual bankruptcy.

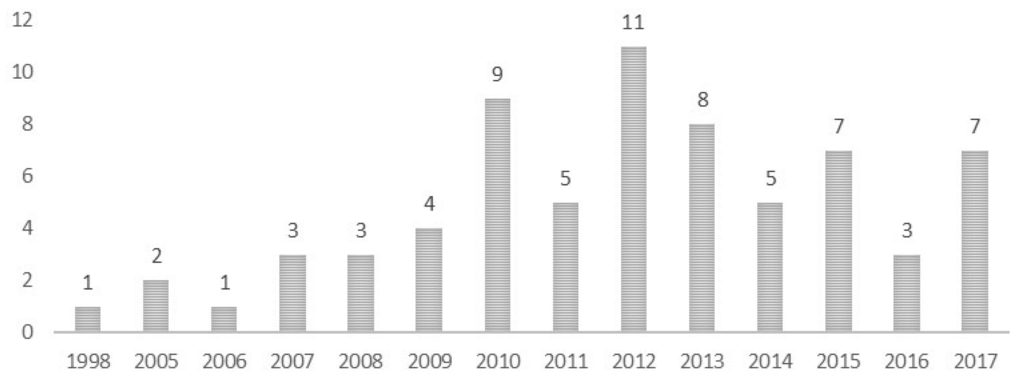

Figure 1. Number of solvency-related documents according to year from 1998 to 2017
(Source: Created by the authors)

The authors of the study have compiled information from 69 different articles related to solvency issues, with the exception of legal aspects, written by authors in Latvia. Articles published as of 1998 have been included, although there is only one article from 1998, and the next article was published only in 2005. Figure 1 shows the number of articles according to year.

The largest activity was observed in the period of 2010 to 2012, which is clearly related to a significant increase in the number of insolvent companies as a result of the crisis. During this period, solvency assessment, its causes and risk prevention, were topical issues. However, the topicality of solvency determination has not diminished much in recent years, and research on the related issues is still being carried out. In comparing the number of publications with the number of insolvent companies for the period of 2008 to 2016, there is no correlation since the correlation coefficient is close to zero.

Validation of insolvency models is examined in eleven studies, but validation of the ten models reviewed in the present study has been analysed in eight articles and summarised in Table 1. Recent studies (Berzkalne and Zelgalve, 2013; Meziels and Voronova, 2013) are based on data up to 2011 and thus on data from the crisis period, so that validation results may not be in line with the current situation. In seven studies, the Zmijewski model has been validated, while the Altman Z’ and Z”, Fulmer, and Springate models are also popular; their validation is included in six out of the eight studies. The most popular model in Latvia is the one created by Sorins/Voronova, while the Skiltere/Zuka model has only been validated in one study.

Table 1

Insolvency prediction models validated by Latvian authors

	Insolvency prediction models									
Authors	Altman Z’	Altman Z”	Fulmer	Springate	Zmijewski	Sorins/Voronova	Lis	Taffler/Tisshaw	Tisshaw	Skiltere/Zuka
Berzkalne and Zelgalve, (2013)	√	√	√	√	√	√	-	-	-	-
Meziels and Voronova, (2013)	-	-	-	-	√	-	-	-	-	-
Golubova et al., (2013)	√	-	√	-	√	√	-	-	-	√
Sneidere and Bruna, (2011)	√	√	√	√	√	√	-	√	√	-
Genriha et al., (2011)	√	√	-	√	√	√	√	√	-	-
Mackevicius and Sneidere, (2010)	√	√	√	√	√	√	-	√	√	-
Sneidere, (2007)	√	√	√	√	√	√	-	√	√	-
Skiltere and Zuka, (2006)	-	√	√	√	-	-	-	√	-	-
Total	6	6	6	6	7	6	1	5	3	1

(Source: Created by the authors)

Researchers in Latvia have used various types of companies in their studies. Berzkalne and Zelgalve (2013) used listed companies; Meziels and Voronova (2013) and Golubova et al. (2013) used small and medium-sized enterprises; Sneidere and Bruna (2011), Mackevicius and Sneidere (2010) and

Sneidere (2007) used construction, service, processing and trading companies; and Skiltere and Zuka (2006) used small enterprises with up to 50 employees and a balance sheet total of up to 0.57 mil. EUR. None of these studies used the manufacturing industry, chosen by the authors of the present study; therefore, the comparison with the results of other studies should be evaluated with caution.

E. Altman was the first researcher who, using the statistical method, the analysis method of a compound discriminant, developed a bankruptcy prediction model – the Z-function. Later Altman also developed two models for non-listed companies. The Z' model is intended for large manufacturing companies, while the Z" model is aimed at small enterprises operating in various industries (Sneidere, 2009). Subsequently, many other researchers have used this method to create their own models, for example, Sorins and Voronova (1998) and Skiltere and Zuka (2010); the latter is based on classification principles. In general, the study involves ten solvency prediction models, the creation of which is based on a linear discriminant method. In order to remain consistent with previous research on Latvian companies, the authors have selected insolvency prediction models that have been validated in other studies. Table 2 summarises the insolvency prediction models examined in the present study.

Table 2

Bankruptcy prediction models examined in the paper

Model	Description	Criterion
Altman Z' (2000)	Z' = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5 X1 – Working capital/Total assets; X2 – Retained earnings/Total assets; X3 – Earnings before interest and taxes/Total assets; X4 – Book value of equity/Book value of total debt; X5 – Sales/Total assets.	Z' > 2.9 "Safe" zone 1.23 < Z' < 2.9 "Grey" zone Z' < 1.23 "Distress" zone
Altman Z'' (2002)	Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 X1 – Working capital/Total assets; X2 – Retained earnings/Total assets; X3 – Earnings before interest and taxes/Total assets; X4 – Book value of equity/Total liabilities.	Z'' > 2.6 "Safe" zone 1.1 < Z'' < 2.6 "Grey" zone Z'' < 1.1 "Distress" zone
Springate (1978)	Z = 1.03V2 + 3.07V8 +0.66V9 +0.40V18 V2 – Working capital/Total assets; V8 – Net profit before interest and taxes/Total assets; V9 – Net profit before taxes/Current liabilities; V18 – Sales/Total assets.	Z < 0.862 "Distress" zone Z > 0.862 "Safe" zone
Fulmer (1984)	H = 5.528V1 + 0.212V2 + 0.073V3 + 1.27V4 – 0.120V5 +2.335V6 + 0.575V7 + 1.08V8 + 0.894V9 – 6.075 V1 – Retained earnings/Total assets; V2 – Sales/Total assets V3 – Net profit before taxes/Book value of equity; V4 – Cash flow/Total liabilities; V5 – Total liabilities/Total assets;	H < 0 "Distress" zone H > 0 "Safe" zone

	V6 – Current liabilities/Total assets; V7 – Fixed assets/Total assets; V8 – Working capital/Total liabilities; V9 – Earnings before interest and taxes/Interest expenses.	
Zmijewski (1984)	X = - 4.3 – 4.5X1 +5.7X2 – 0.004X3 X1 – Net profit/Total assets; X2 – Total liabilities/Total assets; X3 – Current assets/Current liabilities.	X > 0 "Distress" zone X < 0 "Safe" zone
Lis, (Taffler, 1984)	Z = 0.063 X1 + 0.092 X2 + 0.057 X3 + 0.0014 X4 X1 – Working capital/Total assets; X2 – Earnings before interest and tax/Total assets; X3 – Retained earnings (adjusted for scrip issues)/Total assets; X4 – Net worth/Total debt.	Z < 0.037 "Distress" zone Z > 0.037 "Safe" zone
Tisshaw, (Sneidere, 2007)	Z = 0.298X1 + 0.222X2 + 0.168X3 + 0.164X4 + 0.148X5 X1 – Earnings before interest and tax/liabilities; X2 – Profit before tax/net turnover; X3 – Current Assets/(Liabilities – Taxes); X4 – (Funds + Short-term securities)/Current assets; X5 – Quick ratio.	Z < 0.11 "Distress" zone Z > 0.11 "Safe" zone
Taffler/Tisshaw (Sneidere, 2007)	Z = 0.53X1 + 0.13X2 + 0.18X3 + 0.16X4 X1 – Earnings before interest and tax/Current liabilities; X2 – Current Assets/Total/Liabilities; X3 – Total current liabilities/Assets; X4 – Net turnover/Total assets.	Z > 0.3 "Safe" zone 0.2 < Z < 0.3 "Grey" zone Z < 0.2 "Distress" zone
Sorins/Voronova (1998)	Z = - 2.4 + 2.5X1 + 3.5X2 + 4.4X3 + 0.45X4 +0.7X5 X1 – Working capital/Total assets; X2 – Retained earnings/Total assets X3 – Net profit before taxes/Total assets; X4 – Book value of equity/Total liabilities; X5 – Sales/Total assets.	Z < 0 "Distress" zone Z > 0 "Safe" zone
Skiltere un Zuka, (2010)	fk1(X)= -108.714+40.749*X1+0.795*X2+4.816*X4+116.754*X5 +126.262*X6 +34.814*X7 +6.395*X8 fk2(X)= -56.381+74.753*X1+2.856*X2+2.243*X4+72.802*X5 +68.665*X6+ +47.620*X7+5.865*X8 fk3(X)= -62.565+97.143*X1+4.276*X2+2.489*X4+61.295*X5 +66.883*X6+ +44.484*X7+6.387*X8 X1 – Retained Earnings/Total assets; X2 – Net turnover/total assets; X4 – Cash (total)/Creditors (total); X5 – Creditors (total)/Total assets; X6 – Short-term debts /Total assets; X7 – Fixed Assets total/Total assets	The highest fk result points out the group fk3 – "Safe" zone fk2 – "Grey" zone fk1 – "Distress" zone

	X8 – (Current assets (total)-short-term debt total)/short-term debt total.

"Safe" zone – a model does not predict bankruptcy.
"Distress" zone – a model predicts bankruptcy.
"Grey" zone – cannot make significant conclusions (company may or may not be insolvent).

(Source: Summarised by the authors)

RESEARCH METHODOLOGY

According to the Register of Latvian Companies, more than 11,088 insolvency cases were proposed for commercial companies between 2008 and 2016, averaging 1,232 a year or 103 a month. During this period, the most insolvency applications were in 2010 – 2,574 – and 2011 was marked by a sharp decline of 66%, i.e., only 880 insolvency claims – there was some stability over the years ahead and no major fluctuations were observed. Following the breakdown by month, it can be concluded that the number of insolvency applications does not vary significantly within the months; however, a slight increase is observed right in the last months of the year.

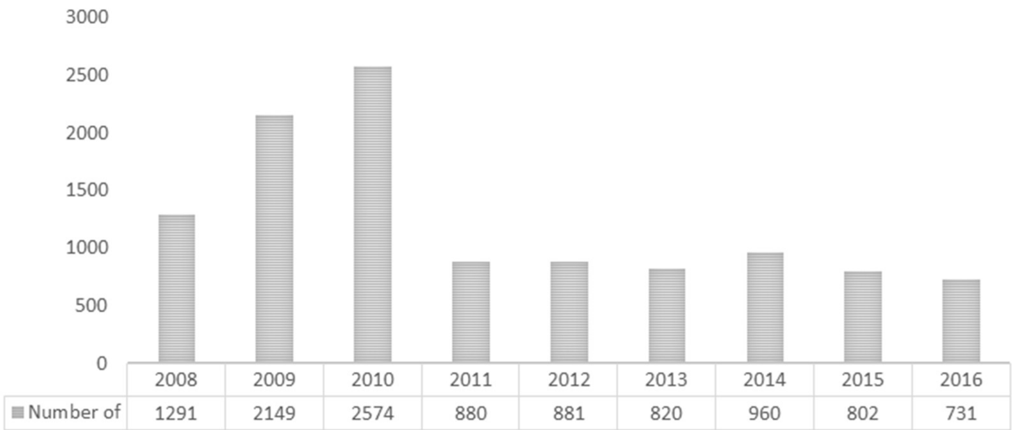

Figure 2. The number of insolvency cases proposed in Latvia from 2008 to 2016

(Source: Created by the authors based on Lursoft, 2017)

To conduct the research, companies were selected whose turnover in the period of 2011 to 2016 was, in at least one year, in the range of 1 million EUR to 3 million EUR. According to the selection criteria, this group of companies had 1,111 companies of which, in 2016, 26 companies had become insolvent. In order to determine the sample size required, an estimate of its size at a confidence interval of 95% was made. The American company Raosoft's random selection algorithm was used to determine the sample set. The calculation was carried out using the following parameters: a permissible error limit of 5%; a confidence interval of 95%; the number of enterprises from which the sample is created – 1,111; breakdown – 50% (Raosoft, 2017). The calculated required sample size is 286 companies. It was therefore decided to randomly select 300 companies. The financial information was obtained from 1334 balance sheets, 1289 profit and loss accounts and 1041 cash flow statements, data of 5 years from 2011 to 2015 and information on the insolvency status in 2016 was used. The study analysed the adequacy of the solvency prediction models for a period of five years to one year prior to its accession. Therefore, companies whose solvency was before 2016 were excluded from the sample. Only companies that had been solvent during the period of 2011 to 2015 were analysed. In addition, companies whose accounts indicated characteristics of fraud were excluded. As a result, 23 out of 276 companies were insolvent.

Many companies operate in the woodworking industry, accounting for 25%; the second largest group (15%) is comprised of companies dealing with the production of food products, while the third largest group (9%) is represented by companies operating in the sphere of metalwork production. The breakdown of companies by sector is shown in Figure 3.

The accuracy of each model was estimated in two ways. First, the two-error method described by Altman (1968) was used. The results are presented in a matrix in Table 3. The H's stand for correct classifications and the M's stand for misclassifications. M_1 represents a Type I error and M_2 represents a Type II error. A Type I error occurs when a model does not predict bankruptcy and a Type II error means that the model mis predicted a solvent company as bankrupt. The sum of diagonal H's equals the total correct "hits" and, when divided by the total number of tests made, shows the percentage of correct classifications. This percentage is equivalent to the coefficient of determination (R^2) in regression analysis, which measures the percentage of variation of the dependent variable explained by the independent variables (Altman, 1968).

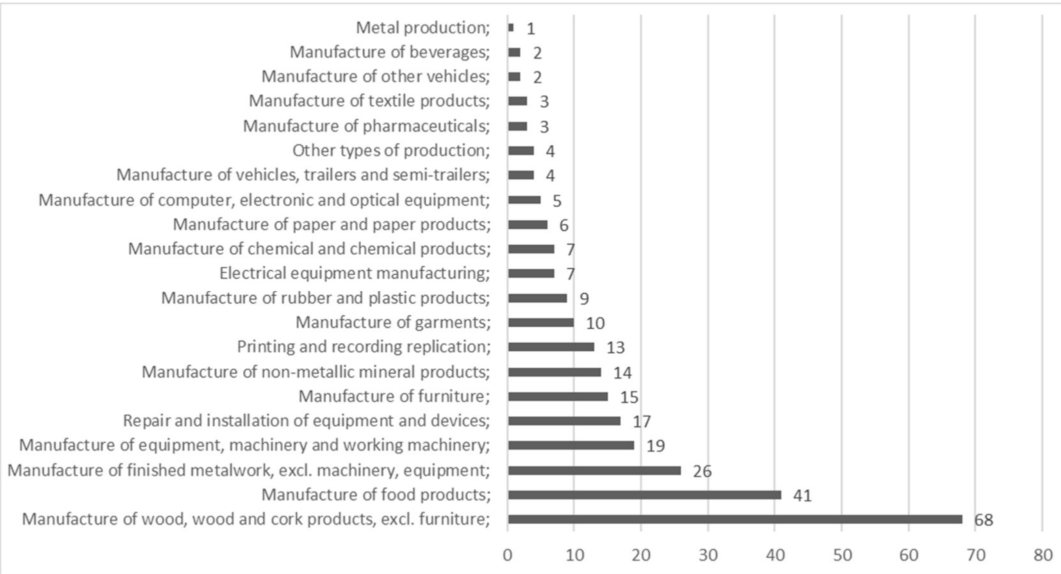

Figure 3. Distribution of validated companies by sector

(Source: Created by the authors)

Table 3

Accuracy Matrix

	Predicted Group Membership	
Actual group membership	Bankrupt	Non-Bankrupt
Bankrupt	H	M_1
Non-Bankrupt	M_2	H

(Source: Altman, 1968)

Model validation using the two-error method was performed according to the following steps:

1. Selection of the required balance sheet, Profit or Loss Statement, Cash Flow Statement items.
2. Validation check whether the necessary data are available.
3. Calculation of financial ratios.
4. Model Index value calculation.
5. Comparison of results with a scale-determination of the estimated solvency status.
6. Comparison of the forecast with the solvency, identification of incorrectly classified Companies.

Secondly, for each model for the last year, 2015, using the IBM SPSS, the ROC (receiver operating characteristic) curve and the size of a specific area under its AUROC (area under ROC) are calculated. The ROC curve indicates how well the classifier, within the framework of the present study, can classify the results obtained by separating solvent companies from insolvent companies.

ANALYSIS OF RESEARCH RESULTS

First, the authors of this study calculated and analysed the results by a two-error method. Second, the ROC curve was constructed for all the models, and the area under the ROC curve (AUROC) was calculated. In cases where the authors of the model identified a number of possible cut-off points, the authors of the present study validated the model at multiple points. The results are summarized in Table 4. Models that have been validated after several points in the rollup are included in the best results as well as the resulting cut-off points.

Table 4

Validation results

No.	Model	M_1	M_2	H	AUROC	Possibility of use
1	Altman Z' Z<1.23	63%	18%	79%	0.556	unrecommended
2	Altman Z" Z<1.1	22%	35%	66%	0.833	possible
3	Springate Z<0.862	47%	33%	67%	0.633	unrecommended
4	Fulmer H<0	33%	40%	61%	0.711	unrecommended
5	Zmijewski X>0	18%	33%	68%	0.862	possible
6	Lis Z<0.037	11%	55%	48%	0.830	unrecommended

7	Taffler and Tisshaw Z<0.2	80%	9%	86%	0.553	unrecommended
8	Tisshaw Z<0.11	67%	10%	87%	0.722	unrecommended
9	Sorins and Voronova Z<0	31%	38%	63%	0.755	possible
10	Skiltere and Zuka (1 class)	7%	29%	73%	0.809	recommended

(Source: Created by the authors)

Altman Z'. The model was assessed at two cut-off points, since a very large bankruptcy risk exists at a value lower than 1.23, while in the range of 1.23 to 2.9 bankruptcy is possible. Therefore, the cut-off point A is 1.23, and option B was chosen as the mean value of the interval 2.065; thus, it is broken down into two parts, of which the first one was added to the solvent the other to the insolvent group. Option A better classifies enterprises as a whole because their overall error is lower; however, insolvency is only correctly classified in 38% of cases. Generally, the use of the model is not convincing. At the ROC curve and the area below, it can be concluded that the model classifies results rather poorly, as the field value is close to 0.5.

Altman Z", similar to the previous model, was assessed in two versions. A very high risk of bankruptcy exists at a value lower than 1.1, while within the range of 1.1 to 2.6 bankruptcy is possible. Therefore, the cut-off point (A) is 1.23, and variant B was chosen as the mean value of the interval – 1.85; thus, it is divided into two parts which are added to the solvent or the insolvent group. Compared to the Z' model, this model has higher accuracy in forecasting insolvency; in the last year it was 78%, but nearly 2 times higher the error was for solvency predictions. It is unambiguous to determine which of the two Altmaņ models is better to apply. But if it is more important to determine insolvency, at the same time risking that they will be added to the solvent group, then it is better to select the Z' model. If overall accuracy is more important, then it is better to choose Z". The Z" model shows better accuracy in the last year before insolvency. The increase in accuracy in all positions is small, a few percentage points per year, but uniform. In comparing options A and B, higher accuracy is shown by option A. According to the area under ROC curve, which comprises 0.833, the Altman Z" model is much better at classifying the results than the Altman Z' model. At the cut-off point of2.59, which can be determined using the curve coordinate table, the M_1 error would be 28%, while the M_2 error would be only 9%.

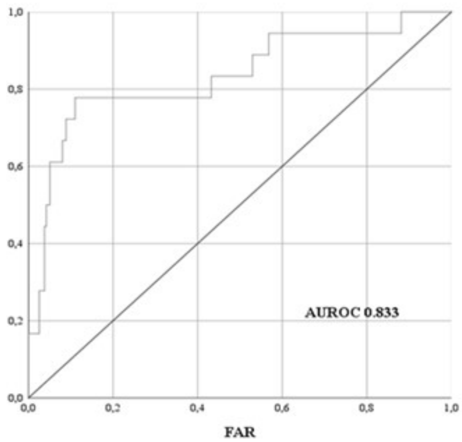

Figure 4. Altman Z'' model ROC curve
(Source: Created by the authors)

Compared to the values used for the test, inaccuracy would increase by 1 company, or 6%, while the insolvency accuracy of 65% in version A would rise to 91%. In general, the Altman Z" test shows a good grading capacity, but the cut-off point is 1.1, which is specified by the author of the model as too high in this situation; a decrease to -2.59 can greatly increase accuracy. It is also possible to see this point graphically (Figure 4), where the value of HR (the relative value of properly classified insolvents) is close to 0.8 and the FAR value (the relative value of incorrectly classified solvents) is increasing rapidly.

It should be noted that the determination of the cut-off point is ambiguous; there are no best or worst points. They must be chosen in an empirical way according to the needs, whether greater accuracy is required for insolvency or solvency, or overall accuracy is most important.

The **Springate** model. The risk of bankruptcy is determined to be high if the index Z is less than 0.862. The total accuracy over the years is very minimal, but it is very volatile for insolvent companies. They fluctuate quite considerably over the years, growing and declining. Overall, the results are not very convincing; from this model you can expect a precision of around 65% or an error of about ⅓. According to the ROC curve and area of 0.633, it can be concluded that the model does not classify results particularly well.

The **Fulmer** model is one of the models which includes the most financial coefficients, a total of nine. The risk of bankruptcy is high below a critical value of 0. There are few company data used in this model test because of the need for data from a cash flow, which are not available to many enterprises because they may not be subject to legislation. The best accuracy the model has shown 2 years before insolvency onset, with an error of only 17%, which is a good result as accuracy is more than 80%. In the last year, accuracy fell to 67%, which was not positive. Overall, in the last year the accuracy of both solvent and insolvent companies is above 60%. Accuracy in determining insolvent companies increased in the last two years, while for solvent companies accuracy was quite similar in all years within a range of 55% to 60%. According to the ROC curve (Figure 5) and the area below it of 0.711, it can be concluded that the model classifies companies in a quite acceptable manner. The curve can observe 2 fracture points at HR ≈ 0.5 (a relative value of correctly classified insolvent companies) and HR ≈ 0.9. At the upper breaking point, if a cut-off point of 1.15 is selected, then M_1 is 22% while M_2 is 47% by increasing M_1 by 11% and decreasing M_2 by 7%. At the other point of the fracture, by selecting a cut-off point below -7.2, M_2 is 16% while M_1 is 44.6%. In the second option, the M_1 error is too big, while the first option is acceptable.

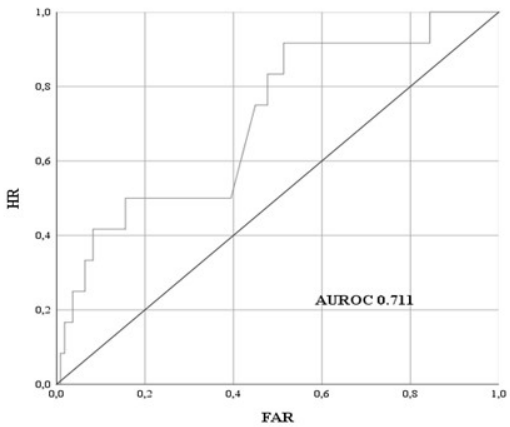

Figure 5. Fulmer model ROC curve
(Source: Created by the authors)

The **Zmijewski** model states that when the index X value is greater than 0, there is a significant risk of bankruptcy. The model successfully predicts insolvent companies, practically in all years excluding 2013. Accuracy is greater than

70%, and the accuracy of the last year exceeds 80%. Overall and solvency accuracy gradually increases over the years and the accuracy of the last year exceeds 65%.

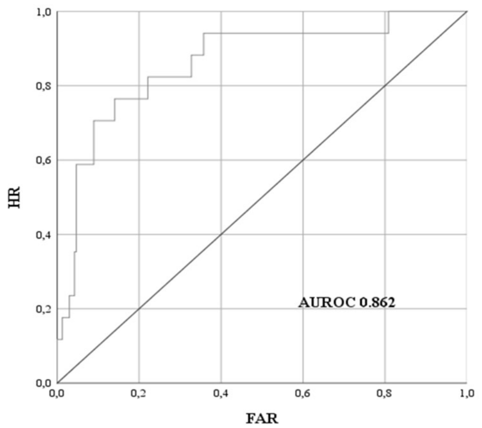

Figure 6. ROC curve of the Zmijewski model
(Source: Created by the authors)

After this test, it can be concluded that the model works quite well. At the ROC curve and AUROC of 0.862, (Figure 6), the model shows very good results. Visually, it can be observed that the curve is approaching the upper left corner. Consequently, the model classifies solvent and insolvent companies well. If the cut-off point is reduced to -1, M_1 is 6% and M_2 is 47%, and only one of the insolvent companies is incorrectly classified, while the total accuracy is 54%. At a cut-off point of -0.5, M_1 is 6% and M_2 is 42%, and the total accuracy is 61.5%. At a cut-off point of 0.6, the overall accuracy is 78.5% and M_1 is 18%, even at a cut-off point of 0, while M_2 decreases from 22% to 11%. The authors believe that in this case, it is possible to change the cut-off point to 0.6, in this way improving accuracy slightly, but one would have to stick to the 0 values specified by the model's author.

The **Taffler and Tisshaw** results are generally not satisfactory, as there is a lack of accuracy regarding insolvent companies in the last year (only 20%), which means that only one in five cases is predicted. At such low precision for insolvent companies, there is logically high accuracy for solvent companies (over 90%). However, the classification capacity of the model should also be considered. AUROC is low, so changing the cut-off points will not produce better results, practically increasing one mistake of a similar size to increase the other. This model is not applicable to the solvency prediction of the group of enterprises established in the framework.

The **Tisshaw** model. The accuracy of this solvency prediction model increases with the number of years to the reference point 2016, which the solvency status is being compared to. The M_2 error indicators are very good, for the last year only 10%, but M_1 was too high in 2015 (67%). According to these results, it can be concluded that the model, at the cut-off point identified by its author, does not work with sufficient accuracy. According to the ROC curves and AUROC, it can be concluded that the model classifies data quite successfully. By increasing the boundary from 0.11, by the author oft he model, to 0.2 thus adding additional companies to the specified insolvent group can smooth out the errors and in some way improve the results obtained.. In this case, M_2 increases from 10% to 23% and M_1 falls from 67% to 33%.

The **Lis** model results. According to the results, we can see that, over the years, the M_1 and M_2 errors decrease, so the closer the possible insolvency status is, the more accurate it becomes as it should be.Overall, the accuracy of bankruptcy determinations is high – 89% in the last year – while solvency accuracy is not acceptable at 45%, which means that more than half of solvent companies are classified as insolvent. To draw a conclusion, the ROC curve should be observed (Figure 7). The area under the curve is 0.83, which indicates a good classification capacity. To increase accuracy, it is possible to change the cut-off point to -0.023; in this case, the insolvency accuracy decreased slightly, M_1 increased from 11% to 22%, while M_2 decreased from 55% to 13%. Overall, the accuracy would be 74%, which would be a pretty good result.

The first validated model created in Latvia is by **Sorins and Voronova**. The authors of the model have determined that if the index Z value is negative, there is a very high risk of insolvency.

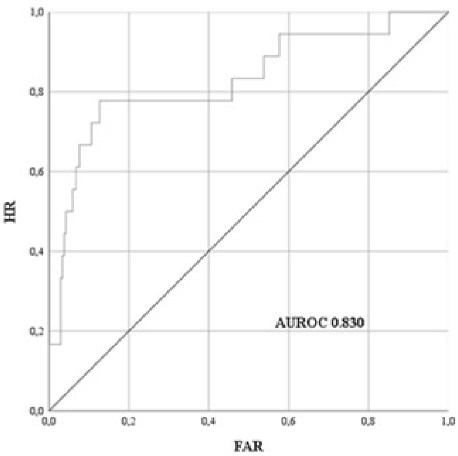

Figure 7. ROC curve of the Lis model
(Source: Created by the authors)

The accuracy of the model is over 60% at all cut-off points, and the model is almost equally well able to predict insolvency for 5 years and one year before its occurrence. The overall level of precision is not high; it is realistic to count on the fact that a third of the companies' projections will be inaccurate. According to the results of the ROC curve, the area under the curve of 0.755, the model classifies companies pretty well. When the cut-off point is changed in one direction or another, proportionally increasing the accuracy of insolvent companies, the accuracy of solvent companies will decrease.

The second model in Latvia, developed by **Skiltere and Zuka**, differs from the type-validated models in the fact that it is based on the principle of classification. Three indices are calculated, and the largest value indicates the affiliation of the company to one of the groups. The model is tested in two variants, A and B. A represents the case of insolvent companies, while enterprises classified as bankrupt are handled in option B; they are also added to the companies classified as non-fixed.

Compared to the aggregated results, it can clearly be seen that it is better to use option A, as in the last year the M_1 errors were identical. They were lower in the previous years in option B, but the M_2 error in option A was at 37% in 2011, with a further fall to the range of 29% in 2015. In option B, the M_2 error in all years exceeded 70%, which was completely unacceptable. Variant A in 2015 presented an acceptable total accuracy of 28%, while the accuracy for solvent companies was 71.4% and the accuracy for insolvent companies was 93%. Only one insolvent company is not classified correctly. The results of earlier years also classify companies fairly well and already point out the challenges ahead. The test results are summarised in Table 5.

Table 5

Validation Results of the Skiltere and Zuka Model

	Option A					Option B				
	2011	2012	2013	2014	2015	2011	2012	2013	2014	2015
M_2	37%	33%	30%	29%	29%	78%	77%	75%	76%	71%
M_1	36%	38%	35%	23%	7%	18%	5%	10%	14%	7%
H	63%	67%	69%	72%	73%	28%	29%	31%	29%	33%

(Source: Created by the authors)

Compared to other studies conducted in Latvia, the results of validation are very volatile. As mentioned above, not all models have the same number of validated versions, and the data used are very diverse in terms of scope and industry. The results are summarised in Table 6. In this study, convincing results were demonstrated by the Skiltere and Zuka model, but it did not show such good results in the study by Golubova et al. (2013). The relatively most uniform results are with the study by Genriha et al. (2011). When comparing the results with other studies carried out by Latvian researchers, definite conclusions cannot be reached.

Table 6

Comparison of Validation Results

No.	Model	This study		Other Latvian studies	
		M_1	**M_2**	**M_1**	**M_2**
1	Altman Z’	63%	18%	6% – 56%	6% – 37%
2	Altman Z”	22%	35%	0% – 52%	6% – 28%
3	Springate	47%	33%	35% – 47%	25% – 53%
4	Fulmer	33%	40%	14% – 45%	5% – 78%
5	Zmijewski	18%	33%	23% – 30%	7% – 50%
6	Lis	11%	55%	50%	26%
7	Taffler and Tisshaw	80%	9%	59% – 77%	13% – 14%
8	Tisshaw	67%	10%	57% – 68%	Not tested
9	Sorins and Voronova	31%	38%	11% – 58%	3% – 68%
10	Skiltere and Zuka (1 class)	7%	29%	41%	21%

(Source: Created by the authors)

CONCLUSIONS

The assessment of companies' solvency models is necessary not only for business owners and their partners as a part of prevention, but also for experts in criminal procedure in cases of fraudulent bankruptcy. When choosing a solvency prediction model, it is necessary to assess its suitability for a particular sector, the size of the company, and the requirements of the user regarding its accuracy. There are no definitively best or worst solvency prediction models since each user has his/her own criteria, but it is possible to determine the ones that can probably provide higher accuracy. Some users would like to choose models with higher accuracy within Type I errors while others would prefer models with lower Type II errors, since some users consider it worse to regard an insolvent company as solvent while for others the opposite is true. In any case, users should pay attention to the results of insolvency prediction model validation and should not choose models with insufficient results.

It is possible to increase a model's accuracy by changing the cut-off points. To determine the cut-off points, the ROC curve and AUROC values should be investigated and the cut-off points must be chosen in an empirical way according to the needs at hand, whether greater accuracy is required for insolvency, solvency, or overall. If the cut-off point for the Altman Z'' model is changed from 1.1 to -2.59, there is a significant increase in accuracy. The same is true for the Lis model if the cut-off point is changed from 0.037 to -0.023.

For Latvian manufacturing enterprises with a turnover of 1 million EUR to 3 million EUR, the following insolvency prediction models are:

Unrecommended – Altman Z', Taffler and Tisshaw, Tisshaw;

Possible to use – Altman Z", Zmijewski;

Recommended – Skiltere and Zuka, Lis at the adjusted cut-off point of Z<-0.023.

According to the validation results, the estimated accuracy of the Skiltere and Zuka model would be 7% for Type I errors and 29% for Type II errors, and the percentage of correct classifications would be 73%, where a Type I error occurs when a model does not predict bankruptcy and a Type II error means that the model mis predicted a solvent company as bankrupt. The estimated accuracy of the Lis model at the adjusted cut-off point of Z<-0.023 would be 22% for Type I errors, 13% for Type II errors and overall accuracy of 74%.

The paper examines discriminant analysis-based models, but there are other types of insolvency prediction models, such as logit-probit or simple classification. In further research the forecasting capability of different types of models could be compared. Furthermore, an analysis of models in the Baltics could be carried out and other specialized insolvency prediction models for the manufacturing sector could be compared.

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