

BANKRUPTCY PREDICTION MODEL FOR PRIVATE LIMITED COMPANIES OF LITHUANIA

Gediminas Šlefendorfas*

Vilnius University, Lithuania

Abstract. *The paper is mainly devoted to the bankruptcy prediction models and their ability to assess a bankruptcy probability for Lithuanian companies. The study showed that the most common type of companies in Lithuania is a private limited company, therefore, the main objective was to analyse such companies' financial information and by using these results, create a new bankruptcy prediction model, which would allow to predict the bankruptcy probability as accurately as possible. 145 companies (73 already bankrupt and 72 still operating) were chosen as a primary sample and by using multivariate discriminant analysis stepwise method a linear function Z_{GS} has been created. To achieve that, 156 different financial ratios were selected as a primary input data by using correlation calculation between bankruptcy and still operating companies and Mann – Whitney U test techniques. The results showed that 89% of companies were classified correctly, which states that the model is strong enough to predict bankruptcy probability for private limited companies operating in Lithuania in a sufficient accuracy.*

Key words: *bankruptcy prediction model; private limited companies; multivariate discriminant analysis method; Lithuania.*

1. Introduction

The bankruptcy problem is always a relevant concern – as of Statistics Lithuania, during the period of 2010–2014, the number of closed bankruptcy cases in Lithuania has been growing by 24.42%, which could mean that the question of how to stop it from happening is becoming very topical. One of the tools used to predict bankruptcy are bankruptcy prediction models and starting from 1968 other researchers have created numerous of such models. As of Lithuania, during the last decade, there were several attempts to create it, however the application of them is questionable because it covers all companies without distinguishing their nature, market segment, etc., therefore, it means that the chance to predict a bankruptcy as good as possible by using such models is not as strong as it should be.

Historically, the creation of bankruptcy prediction models has started back in the late 1960s and the first model ever created was done by E. I. Altman in 1968. After that, there were lots of attempts by other researchers who used a very similar methodology.

* *Corresponding author:*

Faculty of Economics, Vilnius University, Sauletekio al. 9 (building II), LT-10222, Vilnius, Lithuania
E-mail: gediminas.slefendorfas@gmail.com

As of Bellovary et al. (2007), during the period of 1965–2007, there were 165 bankruptcy prediction models created, but these statistics were based only on papers written in English, so there is a chance that this number is even higher. In Lithuania, the first model has been created by Grigaravičius (2003), followed by Stoškus et al. (2007). Bužinskienė, Karalevičienė (2011) compared the foreign and Lithuanian models and assessed that Lithuanian models are accurate enough in comparison with the most popular foreign bankruptcy prediction models. However, Lithuanian models have some specific deficiencies disclosed in this paper that give rise to doubt about their appropriate application to Lithuanian companies. It is noted that Lithuania needs a more concentrated model, which would allow to achieve a more accurate prediction for companies that a particular model is based on. The main **object** of this research – the financial data of 145 bankrupt and still operating private limited companies that are suitable to create a bankruptcy prediction model. By using Lithuanian and foreign scientific sources, methodology of different countries' bankruptcy prediction models and analysis of their achieved results, the main **methodology** is formed followed by the **objective** to create a bankruptcy prediction model for private limited companies operating in Lithuania. Finally, the conclusions and recommendations for further studies are given.

2. The conception of bankruptcy prediction methodology

In order to properly assess a bankruptcy probability, the analysis of the companies' internal and external factors is a must. The external factors that could possibly have an impact on the companies' performance can be the economic strategy of a particular country, a competition level in a particular market segment, even a cultural or social condition in the country. In this case, the analysis of the influence of the external factors is different for every company depending on what that company is doing. All such information sources are mostly public – in Lithuania's case, this information can be possibly found through Statistics Lithuania, especially when we want to assess the tendencies of political events that can even be found in the public media – therefore, the analysis should be objective and true enough if it is properly handled. The same situation can be achieved when the internal factors are analysed – such factors include the company executives' competence, organisational structure and activity, human resources management tools, internal control and its management experience, and etc. However, in comparison with the external factors, internal information can only be found in a company's internal sources and, in most cases, it cannot be accessed through public material.

The internal information analysis mostly consists of financial market variables and financial ratios analysis. Such technique is described in lots of scientific papers and they pick out some summarised ratios that can characterise a company's financial condition, i.e., solvency, profitability, working capital sufficiency, and other ratios. With that information provided, it could possibly be true that the assessment of a company's

financial situation shouldn't be very complicated. However, the main question is still unanswered – is the analysis objective enough from the looks of the financial information compliance perspective and does the financial data correspond to the current financial condition of the company? With that noted, it is crucial to assess if the financial data used to calculate ratios and trends of some specific balance sheet variables is true and fair enough.

In most cases, the comprehensive analysis is being employed by using the bankruptcy prediction model that would allow to raise a problematic question if the company has any financial problems that must be identified as soon as possible. As of Buškevičiūtė, Mačerinskienė (2009) and Bellovary et al. (2007), the most popular and widely used is the Altman E. I. bankruptcy prediction model, however Jakimuk, Žigienė (2011) claim that it is followed by the Springtale, Taffler and Tisshaw, Liso, Fulmer, Zavgren, Chesser and other models. Such model specifics are mostly connected with a calculation of a certain coefficient value by using some particular comparative and / or not comparative ratios that show what is a company's probability to go bankrupt. Most of those models are being used globally, but researchers are still creating new models that are being applied to companies operating in a specific country. In Lithuania, the first model has been created by Grigaravičius (2003), followed by Stoškus et al. (2007). Both models can be applied in a versatile way for any company, which creates a risk of error in a probability of bankruptcy prediction. With that noted, to assess a bankruptcy probability of a specific company, a more specific bankruptcy model is also needed, which would possibly create a much better probability rate. For example, Altman E. I. has created three bankruptcy prediction models – the first one for the publicly held manufacturers, the second one for private manufacturers and the third one for non-manufacturers and service companies. As of Lithuania, there is no such specific model, which would be based on financial data of different nature companies operating in Lithuania.

3. Historical analysis of the bankruptcy prediction models

Most of the time financial ratios are being used in order to predict bankruptcy and, as of Cheng Lim et al. (2012), financial variables and ratios have started to be analysed back in the 19th century. Before Altman's bankruptcy prediction model, researchers analysed particular ratios' influence on the bankruptcy prediction accuracy and its determination (FitzPatrick (1932), Smith, Winakor (1935), Merwin (1942), Chudson (1945), Jackendoff (1962)). By analysing these listed papers, it is obvious that unanimous opinion has not been reached and, in most cases, the conclusions were different, therefore, the resolution has been declared that the complex analysis must be performed in order to cover several specific ratios at the same time, which would help to provide a concrete bankruptcy prediction coefficient. Chudson (1945) analysed the correlation between similar but profitable and unprofitable companies' ratios and discovered some certain trends – the

similar approach has been applied in further bankruptcy prediction studies by other researchers.

The first researcher who leaned on a comparative analysis of bankrupt and still operating companies was Beaver (1966). He chose 79 companies from 38 different industries that went bankrupt during the 1954–1964 period. For all chosen bankrupt companies, a similar still operating company was selected by looking into its assets size and operating industry one by one. Despite the fact that Beaver analysed ratios as individual predictors of bankruptcy, he concluded that by consolidating the ratios into one coefficient as a whole the prediction could be more efficient and correct. It was also noted that individual financial ratios are more suitable not to predict a bankruptcy fact but to forecast some sort of future events that could possibly impact the business.

Following these Beaver’s conclusions in 1968, Altman released a paper where his first bankruptcy prediction model was described. However, this model has some negative attributes, as it was created using financial data of companies operating in the USA. Also, Walton, Aerts (2007) says that such bankruptcy prediction models can be useful for audit companies and banks, but they are still based on an old statistical and financial data of companies operating in a particular market segment, therefore, there is no warranty that after some time, other companies will reflect the same financial results and statistical data.

After Altman’s research release, a lot of other researchers tried to create similar models – Bellovary et al. (2007) analysed most of the models already published starting from Beaver’s research and concluded that the number of created bankruptcy prediction models started to grow in 1970s and it’s still in its peak. The main difference between the models is their creation technique. Altman used a multiple discriminant analysis, which is the most popular technique and is still being used nowadays (Table 1).

TABLE 1. Summary of bankruptcy prediction models’ creation techniques

	Discriminant analysis	Logit analysis	Probit analysis	Neural networks	Other
1960’s	2	0	0	0	1
1970’s	22	1	1	0	4
1980’s	28	16	3	1	7
1990’s	9	16	3	35	11
2000’s	2	3	0	4	3
Overall	63	36	7	40	26

Source: Bellovary et al. (2007).

As we can see in Table 1, it is obvious that the discriminant analysis technique is the most popular one. It should be noted that the data consolidated in this table was based on papers written in English only, so the presumption that researchers from other countries also used these techniques but did not have their papers published in English language

is quite clear, therefore, the data included in this table should not be considered as reliable. Nevertheless, it can be presumed that the main reasons the discriminant analysis technique was used to create a bankruptcy prediction model were its comparatively easy application and the fact that Altman already demonstrated its usefulness. It is also obvious that in the 1990's, the neural networks technique, which has become the most popular one these days, started to be used.

In summary, it is obvious that before Altman's first model in 1968, the company's analysis using financial ratios and their reliability in predicting the bankruptcy has been studied very widely. After Altman, a lot of similar models were created and other techniques started to be used, however the multiple discriminant analysis method is still the most popular technique as of today.

4. Analysis of bankruptcy prediction models created for specific countries

The most popular bankruptcy prediction models that are being widely applied and named as the best bankruptcy predictors were based on companies operating in the USA financial information. Including the fact that most of them were created back in the 20th century, it is doubtful whether they are still reliable.

In most cases, that is exactly why other researchers seek to create new bankruptcy prediction models for their own countries by using the best practice with already developed creation techniques. That is being pursued in order to adapt the bankruptcy prediction to the specific country's economic situation and obtain better prediction results.

Xu, Zhang (2008) analysed 76 companies operating in Japan from all industry sectors, except the financial sector, that went bankrupt in 1992–2005 period. The hazard regression technique has been used and the results of created models were compared in parallel with Altman's and Ohlson's models. It was concluded that the new model shows better results in terms of bankruptcy prediction accuracy.

Pervan et al. (2011) chose 78 Croatian companies that went bankrupt in the January 2010 – June 2010 period and were operating in manufacturing and trade industries and took the same number of still operating companies with the same attributes. The research has been performed by using multivariate discriminant analysis and logistic regression techniques. With the multivariate discriminant analysis method, 80% of accuracy has been achieved, followed by the logistic regression with 83%.

With the same approach but much wider financial data, a bankruptcy prediction model has been created for Pakistan companies by Abbas, Rashid (2011). 26 bankrupt and 26 still operating companies were selected as a primary data from the 1996–2006 time period and it was assessed that the created model can achieve 77% of accuracy. The model was created by using multivariate discriminant analysis and the whole research is absolutely identical to Altman's. The only one clear difference is that the number of

variables in the function is smaller, which consists of EBIT and current assets, sales and assets, and cash flow ratios.

To create a model for Tunisian companies, Hamdi, Mestiri (2014) used a neural networks technique in parallel with logistic regression. 528 companies were selected from the period of 1999–2006 with 26 financial ratios. It was assessed that 87% of accuracy has been achieved by using the logistic regression method and 89% by using neural networks.

In Lithuania, the bankruptcy prediction models started to be created in 2003 and the first one was done by Grigaravičius (2003). The Logit technique was used as a creation method with 52 still operating and 36 already bankrupt companies' financial data. The model's prediction accuracy level has not been included in the study, therefore, it is unknown how many companies the model was able to predict correctly from the primary data, however Bužinskienė, Karalevičienė (2011) says that this model is strong enough to predict the bankruptcy.

After Grigaravičius model, Stoškus et al. (2007) created another model using the multiple discriminant analysis method. 13 companies', of which 5 were already bankrupt and 8 still operating, financial data was taken and two functions were created as a result – one for the operating companies and another for the bankrupt ones. The model shows 70% of accuracy three years prior to bankruptcy and 84% for two years. Despite the fact that this model has a significantly good results and can predict bankruptcy more than a year before, a big weakness can be noticed that the number of assessed companies is too small, therefore, the accuracy of this model is very doubtful.

No other bankruptcy prediction models for Lithuanian companies have been released yet. It is obvious that there is a lack of such models, especially the ones that are created specifically for some sort of category of companies working in a specific industry. It should be noted that both models mentioned previously have some deficiencies – Grigaravičius' model has been created by using a very big data sample, but it is unknown what criteria were used to select the companies for primary sample, therefore, it is hard to tell what kind of companies this model fits best. Also, there is no information about the model's accuracy level. Speaking about Stoškus et al. model, the primary sample used to create the model is very small, which is a very big deficiency in terms of efficiency and potential accuracy. It should be noted that the primary sample that's being used to create a model should be as big as possible and should be tailored to particular criteria of the selected companies. Due to that, the model would be much more effective and possibly demonstrate a better prediction accuracy.

All above examples confirm the presumption that universal bankruptcy prediction models do not give a warranty that the prediction will be accurate and reliable enough. Every country should have their own prediction model which reflects its economic status and business as a whole, so the lack of such models in Lithuania is very significant and

it should be tackled. Also, it is noticeable that a model adapted to a specific country is much more effective and can provide a better accuracy results. Using such model's provided results the company can identify the roots of problems that occur much easier and make a certain decision in order to stop such problems from occurring in the future.

5. Analysis of bankruptcy prediction models creation methodology

It is obvious that both internal and external individuals analysing company's status are using financial data, from which the whole previous and current business situation can be clearly evaluated including financial status, assets and liabilities, equity, profit and loss trends and changes etc. Grigaravičius (2003) says that most researchers are linking the bankruptcy prediction evaluation with financial analysis methodology. By using financial analysis, a bankruptcy prediction can be calculated with financial ratios, which is exactly a quantitative evaluation of the company's financial status, negative trends and its bankruptcy probability (Dagilienė et al., 2010). Quantitative evaluation and its parameters is precisely the main component of the whole financial analysis because it can quickly and sufficiently show the financial status and interaction between different balance sheet items.

However, the ratios can be interpreted differently depending on what company is under evaluation, therefore, it is important to know what kind of companies the bankruptcy prediction model is focused on. With that being said, the question can be raised if globally applied models are really suitable to predict the bankruptcy for specific companies. Also, it should be noted that most of such models were created not even on different kind of companies but on the financial data which is now outdated, i. e., Altman's 1968 model was created by using financial data from the 1946–1965 period. In addition to that, different countries have different economic realities, taxes, competition and other external factors that impact companies and change differently in comparison with other countries. It means that bankruptcy prediction models created using financial data of companies operating in other countries distort the prediction accuracy. Thus, these models should be used with extra caution and interpret the results only as an abstract conclusion in terms of bankruptcy probability.

Due to the reasons listed above, the proposition can be raised that the bankruptcy prediction model should be based on carefully classified financial data. That includes the industry sector in which the company is operating, the size of the company, etc. Using carefully selected components, a company belonging to the same criteria could be assessed in the best possible way and accuracy in terms of bankruptcy prediction. It is obvious that the most popular and globally used models do not reflect today's economic status shifting, competition change, country differences and the primary input of such models is also outdated. Therefore, it means that there is a need for new analytical tools that are adapted to particular criteria from the country's perspective.

It was also mentioned that the bankruptcy prediction models are usually based on financial information data. By using quantitative parameters, the function is created from which it is possible to calculate a particular coefficient that shows a bankruptcy probability. The function variables, most of the time, are comparative ratios that show some particular interaction between the balance sheet items. It should be noted that scientists group them by characteristics. In Figure 1, we can see what kind of financial ratios grouping was used by different researchers who have already created a bankruptcy prediction model.

By consolidating the information provided in Figure 1, it can be stated that ratios grouping and their types are very similar. The main difference occurs when the ratios are

Grigaravičius (2003)
<ul style="list-style-type: none"> • solvency and liquidity ratios; • financial leverage ratios; • profitability ratios; • asset utilisation ratios.
Pervan et al. (2011)
<ul style="list-style-type: none"> • liquidity ratios; • activity ratios; • financial structure ratios; • profitability ratios; • cash flow ratios.
Abbas, Rashid (2011)
<ul style="list-style-type: none"> • financial leverage ratios; • liquidity ratios; • profitability ratios; • turnover ratios.
Altman (1968)
<ul style="list-style-type: none"> • liquidity ratios; • profitability ratios; • financial leverage ratios; • solvency ratios; • activity ratios.

FIG. 1. Comparison of ratios grouping by different researchers

Source: compiled by author according to the sources included in the figure.

assessed and selected during the model's creation process. Therefore, it is important to select as many ratios as possible in the primary selection stage in order to distinguish the best ratios whose potential to reflect the future bankruptcy probability is most notable.

Bellovary et al. (2007) have studied 165 bankruptcy prediction models that were created in the 1965–2007 period and compiled a list of the most frequently used ratios. The study showed that 674 out of 752 ratios have been used once or twice in a model and only 42 ratios have been used more than 5 times. Despite the fact that different ratios belong to the same group, it is clear that depending on different criteria, ratios forming the bankruptcy prediction model are also different. Even though there are some ratios which are being used more often, it is not true that they will show the same bankruptcy prediction accuracy under the same primary sample criteria the other bankruptcy prediction model was built on. Therefore, a new correlation analysis needs to be performed in order to check which ratios can show the best bankruptcy prediction results depending on the criteria that the primary sample is selected on.

Du Jardin have assessed 190 bankruptcy prediction models and came to a conclusion that the most popular ratios appearing in the model functions are comparative ratios and they are being used in 93% of the cases analysed (Table 2).

TABLE 2. Typology of explanatory variables commonly used by bankruptcy prediction models

Variables	Frequency (decreasing order) of use in the 190 studies
Financial ratio (ratio of two financial variables)	93%
Statistical variable (mean, standard deviation, variance, logarithm, factor analysis scores... calculated with ratios of financial variables)	28%
Variation variable (evolution over time of a ratio or a financial variable)	14%
Non – financial variable (any characteristic of a company or its environment other than those related to its financial situation)	13%
Market variable (ratio or variable related to stock price, stock return)	6%
Financial market variable (data coming a balance sheet, an income statement or any financial documents)	5%

Source: Du Jardin (2009).

NOTE: the total is greater than 100% as several types of variables may have been used at the same time.

Regardless of the popularity of the comparative ratios, it is certain that other variables are being used, too. This means that they are capable of showing any bankruptcy signs to the company. The second variable seen along by frequency of use is statistical variable, which is essentially used as a statistical or mathematical function in order to transform a financial ratio into a standardised one, which could be compared to different size companies. Such variables were applied by Fulmer in his model published in 1984 (Mackevičius et al. (2014)). As of Du Jardin (2009), one of the ratios capable of predicting bankruptcy is the total assets logarithm, which has a big discriminatory power.

An interesting fact is that the usage of variation variables is quite low – only in 14% of the studies analysed. A reason for this could be that such ratios show not the current status but the direction of a company.

Non-financial variables are variables or ratios that cannot be found in the company’s financial documents. Essentially, these variables are external factors, such as macro-economic status of the country, inflation level, unemployment rate, etc. and / or internal factors – as per Du Jardin (2009), such factors include leaders’ characteristics, long-term strategy, number of partners, relationship with banks, age of the company and others. These factors, viewed from the bankruptcy prediction perspective, has a big weakness as they cannot be assessed objectively enough. The result, most of the time, depends on someone’s opinion, therefore, it is assumed that such variables are not suitable for bankruptcy prediction models.

For other variables, it should be noted that market variables can be included in a model only if that model is oriented to companies that are publicly held. Also, ratios directly taken from a balance sheet and other financial documents cannot be compared between different-size companies, therefore, the final result of a prediction would be highly distorted.

It is noted that the most appropriate way to create a bankruptcy prediction model is by using comparative financial ratios, as they are the most capable of reflecting bankruptcy

as a fact. Also, they display a relationship between different balance sheets and other financial documents data. Nevertheless, it is also worth analysing the variation variables because they express a company's tendencies that may be able to show a positive result in terms of predicting a future fact of bankruptcy.

It is obvious that the main purpose of bankruptcy prediction models is to predict the probability of bankruptcy as accurately as possible by using the best financial ratios that have the biggest potential to evaluate a company's bankruptcy as a future fact. The model's potential is precisely the main factor which needs to be focused on. It is evident that the potential is the result of a created model because it depends on how the primary sample of financial data is being used, analysed and selected during the creation process. Also, it relies on the selected ratios and how much of potential and accuracy they can draw out of their capability to reflect a company's bankruptcy probability. Studies show that the model's accuracy and potential is calculated by taking the sampled companies financial data and checking how many companies the model's function was able to classify correctly.

Bellovary et al. (2007) assessed bankruptcy prediction models potentiality to correctly classify the companies from the primary sample (Table 3).

TABLE 3. Predictive ability by creation technique

	Lowest accuracy	Highest accuracy
Multiple discriminant analysis	32%	100%
Logit analysis	20%	98%
Probit analysis	20%	84%
Neural networks	71%	100%

Source: Bellovary et al. (2007)

It should be noted that only two techniques – the multiple discriminant analysis and neural networks – were able to provide a 100% accuracy. Due to that, Bellovary et al. (2007) claims that the best bankruptcy prediction model techniques are precisely multiple discriminant analysis and neural networks. That is confirmed by another analysis done by Bellovary et al. (2007), which summarises the models by the time period a model was created, techniques used, and their generated accuracy (Table 4).

TABLE 4. Predictive ability by decade and technique

	Lowest accuracy	Highest accuracy	Method used to obtain highest accuracy
1960's	79%	92%	Univariate discriminant analysis
1970's	56%	100%	Multiple discriminant analysis
1980's	20%	100%	Multiple discriminant analysis, neural networks
1990's	27%	100%	Neural networks
2000's	27%	100%	Multiple discriminant analysis

Source: compiled by author according to Bellovary et al. (2007).

Table 4 shows that the multiple discriminant analysis and neural networks techniques are precisely the best methods to use in order to obtain the best prediction results.

It needs to be noted that in most of the cases analysed, the accuracy is denominated in percentage value and the prediction is calculated in order to assess the bankruptcy probability one year prior to the company's default.

The one fact that needs to be excluded and that scientists do not agree on is which bankruptcy prediction model is the best and has the highest accuracy. As per Krancevičiūtė (2012), there is no such model that could confidently calculate the bankruptcy probability because every model is based on different type of companies, so the power of prediction accuracy may be estimated in a very subjective manner. From the company's perspective, in order to select the best fitting model for the company, the model's parameters and original sample needs to be analysed at first. If it fits, the model should reflect a bankruptcy probability correctly. Such analysis is challenging, as most of the time scientists do not distinguish this information very clearly, therefore, it complicates the whole selection procedure for the company and the final prediction is not as correct as it could be in result.

6. Methodology of bankruptcy prediction model creation for Lithuanian companies

In the previous section the elements of bankruptcy prediction model creation process were assessed. It was decided that the best technique to use is the multiple discriminant analysis method with financial ratios and the financial information of specifically clarified sample of companies.

In Lithuania's case, the best way to decide which companies to create a model for is by taking into account what kind of companies are dominant by legal form in the country. As per Statistics Lithuania (2015), the biggest portion of companies operating in Lithuania consists of private limited companies (Table 5).

TABLE 5. Distribution of operating entities by legal form in the beginning of 2015

Legal form	Quantity	Percentage
Private limited company (UAB)	62565	67,26%
Sole proprietorship (II)	10190	10,95%
Public institution (VšĮ)	4203	4,52%
Small partnership (MB)	2204	2,37%
Joint – stock company (AB)	317	0,34%
Other	13538	14,55%
Grand total of entities in the beginning of 2015:	93017	100,00%

Source: compiled by author according to Statistics Lithuania (2015).

As of Table 5, private limited companies form a little bit more than two thirds of the total number of entities, which is obviously a dominant legal form in the country.

Another aspect, which needs to be considered, is the size of a company. It is likely that micro-sized and big companies shouldn't be included in the primary sample of the model. Micro-sized companies' financial information is very sensitive to changes, therefore, it could distort the model's final result followed by a diminished prediction reliability. And vice-versa – big companies' financial information is not very responsive to changes and the bankruptcy risk is relatively low. All these statements lead to the conclusion that the model for private limited companies operating in Lithuania should be based on the financial data of small and medium-sized companies.

After the evaluation of Lithuanian bankruptcy prediction models, it was concluded that the lack of such studies is very clear. As a result, it was decided to create a model that would cover companies that belong to a particular functional field. It is likely that such model would be useful in order to obtain some kind of caution signals that would stimulate the companies to review their financial information and activity and as a result, lower the risk of having any severe problems or even going bankrupt.

The bankruptcy prediction model creation needs a complex methodology, which leads into a step-by-step procedure. In accordance to the previous analysis of other bankruptcy prediction models' creation techniques described in this paper, it was decided to design a methodology as described in Figure 2.

As per Figure 2, the first step is to get the primary sample of companies' financial information. To have the sample as much specified as possible, narrower criteria of companies should be determined. This procedure would clarify which companies the model is designed to and could possibly show the best prediction result. It was decided to go by the following criteria:

- the company is a private limited company (UAB);
- in the period of 2007–2013 the company had not less than 10 employees and not more than 250 (small and medium-sized companies);
- the company is operating for at least 6 years (the company was active in the 2007–2013 period);
- in at least one reporting period the company had total assets worth 1 M Lt.;
- in at least one reporting period the company was profitable;
- the company has started (or ended) a bankruptcy process in 2013 (applicable for bankrupt companies only)

The financial information was provided by Credit Bureau „CreditInfo Lithuania“. With the criteria listed above, 73 bankrupt companies have been picked out that were suitable for the primary sample.

With the same logic and criteria, 3,473 still operating companies have been selected. It was decided to search for the best equivalents to bankrupt companies in the still operating companies list one by one. The criteria used for such search were the number of employees as of 2007, the total assets as of 2007 and net profit as of 2007. After the selection, 72 companies have been sampled (one company has been selected twice) so the total primary sample concluded financial data for the 2007 – 2013 period of 145 companies.

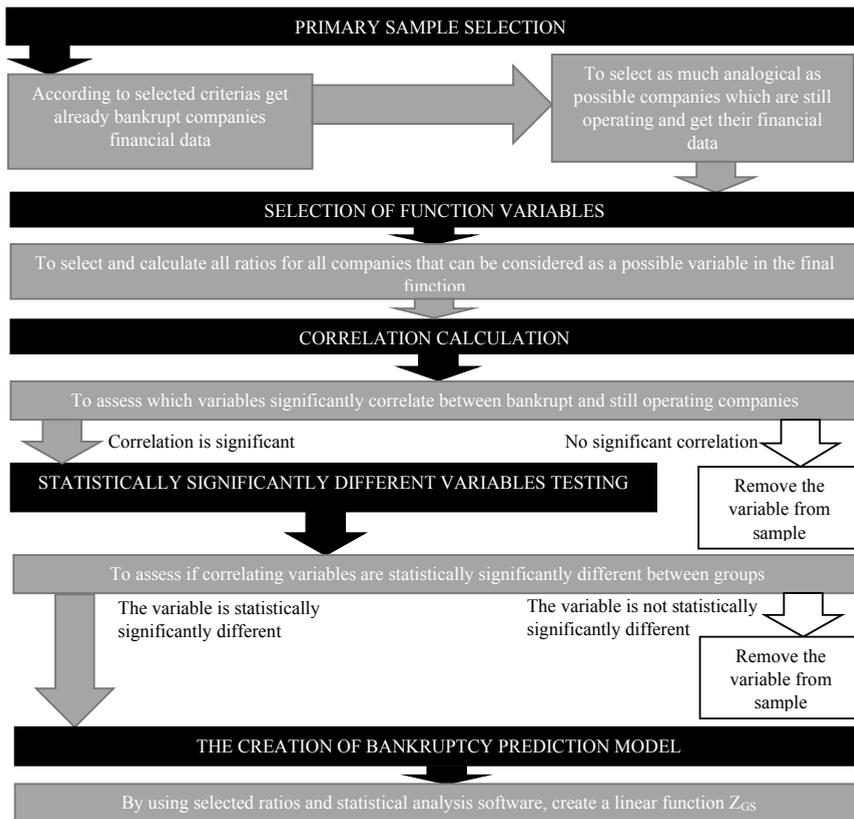


FIG. 2. The architecture of bankruptcy prediction models' methodology

Source: compiled by author.

By using financial information of all sampled companies, three types of ratios have been calculated for the period of 2007–2012 that were selected as per Du Jardin's (2009) analysis presented in Table 2:

- quantitative ratios;
- changes of balance sheet items
- changes of quantitative ratios.

After the calculation, all ratios were estimated whether they correlate between bankrupt and still operating company groups by using IBM SPSS Statistics v.21 statistical analysis software. The correlation results showed that 183 ratios correlate between groups at 95% or higher confidence level. In order to completely eliminate data that is not statistically significantly different between groups, the correlating ratios were analysed by using Mann – Whitney U test method. The results showed that 156 ratios are statistically significantly different between groups, which means that these ratios are potentially viable to be included in the final bankruptcy prediction model's function.

7. Analysis of the final bankruptcy prediction model and its results

To create a bankruptcy prediction model it was decided to use the multiple discriminant analysis stepwise method. By using IBM SPSS Statistics v.21 statistical analysis software, calculations were performed and 9 canonical discriminant function coefficients and a constant were obtained, which could be transformed into a linear function Z_{GS} presented below.

$$\begin{aligned}
 Z_{GS} = & 1,739 + 1,45 * \frac{Sales\ revenue_t - Sales\ revenue_{t-1}}{Sales\ revenue_{t-1}} + \\
 & 0,922 * \frac{Operating\ costs_{t-3} - Operating\ costs_{t-4}}{Operating\ costs_{t-4}} + 1,307 * \frac{Operating\ profit_t}{Sales\ revenue_t} - \\
 & 1,491 * \frac{Total\ liabilities_{t-4}}{Total\ assets_{t-4}} - 0,677 * \frac{Net\ profit_{t-5}}{Total\ equity_{t-5}} + \\
 & 1,257 * \frac{\frac{Total\ assets_t}{Total\ liabilities_t} - \frac{Total\ assets_{t-4}}{Total\ liabilities_{t-4}}}{\frac{Total\ assets_{t-4}}{Total\ liabilities_{t-4}}} + \\
 & 0,1 * \frac{\frac{Total\ equity_t}{Total\ liabilities_t} - \frac{Total\ equity_{t-2}}{Total\ liabilities_{t-2}}}{\frac{Total\ equity_{t-2}}{Total\ liabilities_{t-2}}} - \\
 & 0,334 * \frac{\frac{Financial\ and\ investment\ costs_{t-2}}{Sales\ revenue_{t-2}} - \frac{Financial\ and\ investment\ costs_{t-4}}{Sales\ revenue_{t-4}}}{\frac{Financial\ and\ investment\ costs_{t-4}}{Sales\ revenue_{t-4}}} - \\
 & 0,246 * \frac{\frac{Operating\ costs_{t-2}}{Sales\ revenue_{t-2}} - \frac{Operating\ costs_{t-5}}{Sales\ revenue_{t-5}}}{\frac{Operating\ costs_{t-5}}{Sales\ revenue_{t-5}}} \quad (1)
 \end{aligned}$$

where:

Z_{GS} – bankruptcy prediction coefficient for the period $t + 1$;

t – current year.

It is noted that sales revenue, total assets, total liabilities and total equity ratios have the biggest impact on the whole function.

In order to check the function's significance and accuracy, Eigenvalue and Wilks' Lambda ratios needs to be analysed (these results were included in the output of the multiple discriminant analysis calculation). For the function Z_{GS} Eigenvalue is 1,205 with a canonical correlation significance of 0,739, which shows a very strong sign of the function's ability to differentiate the groups and explain the variance of dependant variables (Table 6). Wilks' Lambda value is 0,453 with a significance less than 1%, which means that the function can explain 54,7% of total variance of discriminant scores by differences in groups (Table 7).

TABLE 6. Eigenvalue statistics of the function Z_{GS}

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
Z_{GS}	1,205	100,0	100,0	,739

TABLE 7. Wilks' Lambda statistics of the function Z_{GS}

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
Z_{GS}	,453	109,533	9	,000

Based on the primary sample of 145 selected companies, the function Z_{GS} was able to correctly classify 89% of original grouped cases (Table 8).

TABLE 8. Classification results of the function Z_{GS}

		Status	Predicted Group Membership		Total
			Still operating	Bankrupt	
Original	Count	Still operating	65	7	72
		Bankrupt	9	64	73
	%	Still operating	90,3	9,7	100,0
		Bankrupt	12,3	87,7	100,0

89,0% of original grouped cases correctly classified.

The main purpose of this classification is to use the Z_{GS} coefficient to determine whether the company is going to be bankrupt or will still be operating next year. Such conclusion can be raised after the calculation of the coefficient value and assessing if it is lower or higher than the cutting point value. The cutting point value is a function centroid's weighted average (Table 9). Therefore:

$$WA_{Z_{GS}} = \frac{(SOC \text{ centroid} * SOC \text{ volume}) + (BC \text{ centroid} * BC \text{ volume})}{Total \text{ volume}} = \frac{(1,098 * 72) + ((-1,083) * 73)}{145} = 2 * 10^{-5} \quad (2)$$

where:

WA – weighted average;

SOC – still operating companies;

BC – bankrupt companies.

According to calculations, the cutting point is $2 * 10^{-5}$, which basically is zero. Also, it should be noted that when Z_{GS} coefficient falls between centroids, the company under evaluation enters into a so-called "grey zone", which indicates that the prediction is not very reliable. However, if the Z_{GS} value is lower than zero, that means that the company will more likely be under bankruptcy than still operating the next year, and vice-versa – if the Z_{GS} value is higher than zero that means that the company will more likely be

operating than bankrupt. The farther the coefficient value is from the centroid, the better and accurate the prediction is.

TABLE 9. Functions at group centroids values

Status	Function
	Z_{GS}
Still operating	1,098
Bankrupt	-1,083

Unstandardized canonical discriminant functions evaluated at group means

From the original primary sample, 65 of 72 still operating companies had higher than cutting point Z_{GS} coefficient score, from which 26 fell into the “grey zone”. However, these companies have been classified as operating the next year (Figure 3). The rest of the companies have been incorrectly classified but all of them have fell into the “grey zone”, which could mean that these companies have some issues that will probably be handled. Nevertheless, that could also mean that these companies are going to go bankrupt in two or more years, therefore, having such a result, a deeper analysis should be performed in order to identify problems and take any actions needed to eliminate them.

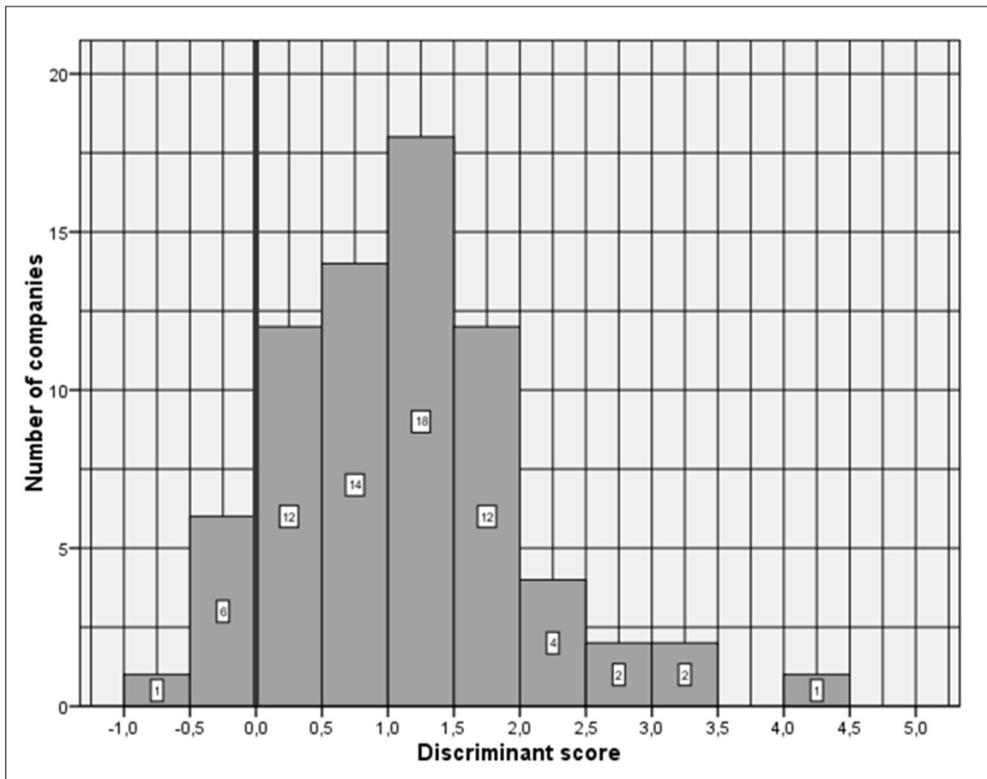


FIG. 3. Histogram of Z_{GS} scores of sampled still operating companies

When evaluating the bankrupt companies, the results were nearly the same – out of 73 companies, 64 had a lower than zero Z_{GS} coefficient score, which means that they were classified correctly (Figure 4) and 32 of 64 companies hit the “grey zone”. The rest 9 companies were misclassified and had greater than zero Z_{GS} coefficient score. 8 of them hit the “grey zone” and only one bankrupt company has been classified as a potentially operating company the next year. It is likely that the misclassified companies went bankrupt due to issues that do not reflect in the financial information or their bankruptcy was much unexpected and fast, therefore, the function was not able to read it. Nevertheless, the results are strong enough and allow to conclude that function Z_{GS} has enough power to separate companies with a potentially different future, followed by a strong prediction accuracy.

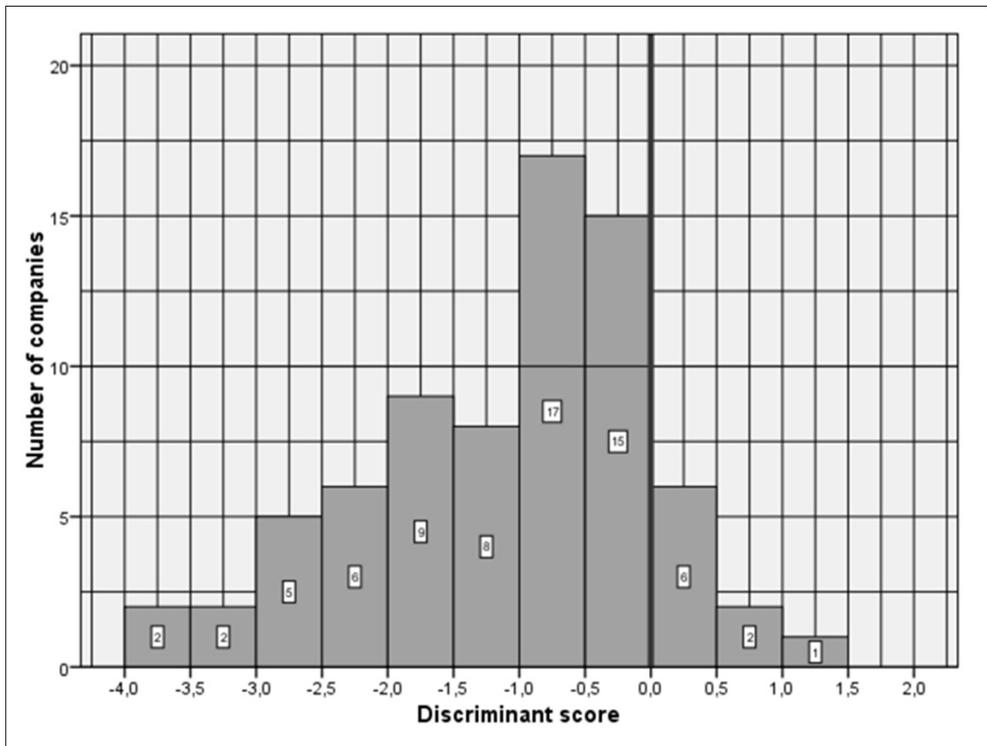


FIG. 4. Histogram of Z_{GS} scores of sampled bankrupt companies

To conclude the results, it can be stated that the function Z_{GS} is good enough to predict bankruptcy for private limited companies that are operating for at least 5 years. Both Eigenvalue and Wilks’ Lambda ratios show that the function is accurate, and the results of original sample evaluation only confirm that the function Z_{GS} can be applied in terms of bankruptcy prediction. However, it should be noted that companies were analysed by using financial data from the 2007–2012 period, which reflects the consequences of the

2008 financial crisis and due to that, the function could show rather sceptical prediction. Even though, in all cases the Z_{GS} coefficient score should be evaluated as a possible but not guaranteed future fact.

8. Conclusion

After evaluation of the Lithuanian and foreign bankruptcy prediction models and their achieved results, it was revealed that the best way is to create a model specified for a particular country – all analysed studies concluded that such new model is able to achieve much better results than the globally used popular models.

In Lithuania's case, there are only two bankruptcy prediction models created and their creation conception was applied to joint-stock companies, therefore, usage of these models to predict the bankruptcy probability for different type companies is a questionable decision.

It was assessed that the most dominant legal form of companies operating in Lithuania is a private limited company, therefore, it was decided to create a bankruptcy prediction model which would allow to predict a bankruptcy for companies operating under the mentioned legal form. 145 companies have been selected as a primary sample, followed by 156 ratios capable of showing bankruptcy indications. As a result, a linear function Z_{GS} has been created, which correctly classified 89% of the originally sampled companies. Although this result shows a strong capability, such evaluation shouldn't be estimated as a fact but more like a signal that creates a possibility to review the companies' activity and financial results, followed by the revealed issues that could be handled in a timely manner.

It is also noticeable that the bankruptcy prediction model creation studies, viewed from Lithuania's perspective, are very poorly examined. Such models could be created for different kind of companies, therefore, it is true that studies carried out from different perspectives and especially by examining different kinds of financial and non-financial ratios are really necessary.

REFERENCES

- Abbas Q, Rashid A. (2011). Predicting Bankruptcy in Pakistan. *Theoretical and Applied Economics*, volume XVIII (2011), No. 9(562), p. 103–128.
- Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, Vol. 23, no. 4, p. 589–609.
- Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research* 5, p. 71–111.
- Bellovary, J. et al. (2007). A Review of Bankruptcy Prediction Studies: 1930 – Present. *Journal of Financial Education*, Vol. 33 (Winter 2007), p. 1–42.

Buškevičiūtė, E., Mačerinskienė, I. (2009). *Finansų analizė: vadovėlis*. – Kaunas, Technologija, 379 p. – ISBN 9986-13-710-1.

Bužinskienė R., Karalevičienė J. (2011). Modernių bankroto diagnozavimo modelių taikymas įmonėje. *Vadyba: Mokslo tiriamieji darbai*, nr. 2(19), p. 113–123.

Cheng Lim, T. et al. (2012). Bankruptcy Prediction: Theoretical Framework Proposal. *International Journal of Management Sciences and Business Research*, Volume 1, Issue 9, p. 69–74.

Chudson, W. (1945). *The Pattern of Corporate Financial Structure*. New York: National Bureau of Economic Research.

Dagilienė, L. et al. (2010). Bankroto prognozavimo svarba ir metodai. *Verslas: teorija ir praktika*, 11(2), p. 143–150.

Du Jardin, P. (2009). Bankruptcy prediction models: How to choose the most relevant variables? *Bankers, Markets & Investors*, issue 98, January-February, p. 39–46.

Grigaravičius, S. (2003). *Corporate Failure Diagnosis: Reliability and Practice*. Organizacijų vadyba: sisteminiai tyrimai: 2003.28, p. 29–42.

Grigaravičius, S. Įmonių nemokumo diagnostika ir jų pertvarkymo sprendimai. – Kaunas, VDU leidykla, 126 p. – ISBN 9955-53079-0

Hamdi M., Mestiri S. (2014). Bankruptcy prediction for Tunisian firms: an application of semi – parametric logistic regression and neural networks approach. *Economics Bulletin*, Vol. 34 No. 1, p. 133–143.

Jackendoff, N. (1962). *A Study of Published Industry Financial and Operating Ratios*. Philadelphia: Temple University, Bureau of Economic and Business Research.

Jakimuk, J., Žigienė, G. (2011). Infliacijos įtaka bankroto prognozavimo modelių tikslumui. *Ekonomika ir vadyba: aktualijos ir perspektyvos*, 2011. 1 (21), p. 26–36.

Krancevičiūtė, R. (2012). Įmonių bankroto analizė ir prognozavimas. *Transporto inžinerija ir vadyba: 15-osios Lietuvos jaunųjų mokslininkų konferencijos „Mokslas – Lietuvos ateitis“ straipsnių rinkinys*. Vilnius: Technika, 412 p.

Mackevičius J. et al. (2014). Įmonių veiklos tęstinumo ir plėtros vertinimas remiantis finansinėmis ataskaitomis. Finansinės apskaitos ir analizės informacijos panaudojimas vertinant įmonių finansinį turtą // Lietuvos turto vertintojai – 20 metų veiklos patirtis nacionalinės ir Europos ekonominės erdvės kontekste. Recenzuojamas mokslo leidinys. Konferencijos, vykusios Vilniuje Vilniaus universitete 2014 m. kovo 28 d., mokslo darbai, Vilniaus universiteto leidykla, p.222-229.

Merwin, C. (1942). *Financing small corporations in five manufacturing industries, 1926-1936* New York: National Bureau of Economic Research.

Pervan, I. et al. (2011). Prediction of company bankruptcy using statistical techniques – case of Croatia. *Croatian Operational Research Review*, vol. 2, 2011, p. 158–167.

Stoškus, S. et al. (2007). Theoretical and practical decisions of bankruptcy as one of dynamic alternatives in companies performance. *Engineering Economics*, 2(52), p. 26–33.

Walton P., Aerts W. (2007). *Global Financial Accounting and Reporting: Principles and Analysis*. – London: Thompson Learning, 496 p. – ISBN 978-1-84480-265-4.

Xu M., Zhang C. (2008). Bankruptcy prediction: the case of Japanese listed companies. *Review of Accounting Studies*, volume 14, issue 4, p. 534–558.