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SEARCHING FOR KEY FACTORS IN ENTERPRISE BANKRUPT PREDICTION: A CASE STUDY IN SLOVAK REPUBLIC

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Abstract. The issue of enterprise in bankrupt or financial health as a whole is still very actual topic not only in Slovakia but also in abroad. Works dealing with the enterprise in bankruptcy have already appeared in the 1930s of the 20th century. Bankrupt of enterprise affect all subject in relationship with this enterprise. Financial experts were looking for the ways for enterprise bankrupt prediction. This article is based on the searching for key factors that could indicate the enterprise in bankrupt in Slovak conditions. This article tries to work with financial variables from the area of financial health assessment of enterprise and works with the sample of Slovak enterprises. This sample includes 8,522 financial statements of enterprises in 2016. According to several relevant decisions rules, for example, the value of equity or equity debt ratio, enterprises are divided into two categories – bankrupt enterprises and creditworthy enterprises. Subsequently, this article tries to find statistically significant financial variables that could indicate involving enterprises in these two categories and works with several statistical methods for searching significant relationship between variables and the tightness of relations between them. As a main statistical method, Pearson´s correlation coefficient is used, which is supported by correlation matrices. In addition, it is necessary to test an existence of outliers in the sample of enterprises. Existence of outliers is tested by the Grubbs test of outliers.

Keywords: bankrupt; prediction model; financial health; financial ratios

JEL Classification: G1, G32, G33

Introduction

Nowadays, the problem with failure of business entities is very actual topic in market economy. One of the biggest business risks is credit risk, which relates to secondary insolvency of business entity. The failure of business entity has negative influence on all subjects in relationship with this business entity. Possibility of evaluating and predicting credit risk and financial situation of business entities is an advantage for creditors, investors and business owners. On the basis of the assessment and forecasts of credit risk and financial health of business entities, we are able to take necessary corrective action in time. Economists are able to evaluate and predict credit risk and financial health of business entities because of ex-ante financial analysis – through prediction models. Prediction models can predict early the probability of failure of business entity. The problem that is necessary to solve for the application of prediction models is the selection of prediction model that is able to provide the best evaluation of probability of failure of analysed business entity and, of course, model that is able to provide exact and relevant results (Siekelova, Moravcikova 2015).

The possibilities of forecasting the development of financial health of business entity and its future solvency or insolvency have taken attention of economists since past century. The issue of relevant prediction model is very actual topic not only in Slovakia but also in abroad. Prediction models are suitable for the management of business entity because they allow to correctly interpret relevant indicators of potential problems in the future. Thanks to these indicators, the negative development in entity may be identified before its results bring more serious financial and economic problems or financial crisis. In case, when business entity was not able to find any crisis solution, these financial problems can end up like its bankrupt.

The main aim of this article is to find the key factors in enterprise bankrupt prediction in Slovak condition.

Literature Review

The first studies devoted to bankruptcy prediction were based on one-dimensional analysis of the financial ratios. These studies simply analysed financial ratios and compared the results of these indicators in creditworthy enterprises and enterprises in bankrupt. In 1930, the Bureau of Business Research (BBR) presented a study that analysed the development of 24 financial ratios from 29 industrial enterprises in bankrupt (Fitzpatrick 1932, Malin 2017).

In 1935, Smith and Winakor verified the BBR study results. They analysed financial indicators of 183 enterprises in bankrupt and their results confirmed the BBR study (Bellovary et al. 2007).

Beaver was the first economist who used statistical methods for the prediction of financial health of enterprises. In his study, '*Financial Ratios of Prediction of Failure*', in 1966, he divided enterprises into the two categories, creditworthy enterprises or bankrupt enterprises, based on the certain number of financial indicators (Beaver 1966, Jones 1987).

In 1968, Altman created one of the most famous and also the first bankruptcy prediction model, which is known as 'Z-score'. This model interconnected explanatory power of several variables. This model is the basic stone of multiple discrimination analysis (Altman 1968).

Since this time, the number of bankruptcy models has risen up. In 1970s, 28 studies about prediction models were published; in 1980s 53 studies were published; and in 1990s, 70 studies were published. Other authors who have tried to improve Altman's multiple discrimination analysis are, for example, Deakin (1972), Taffler (1974), Loris (1976), Springate (1983), Fernandez (1988), Neumaier and Neumaierova (1995, 1999, 2000, 2005), Gajdka and Stos (1996), Virag and Hajdu (1996), Chrastinova (1998), Binkert (2000), Gurcik (2002), Sharita (2003) and so on (Virag, Kristof 2005, Mousavi et al. 2015, Gurcik 2002, Agarwal, Taffler, 2007, Kubickova 2015, Zavrgen 1985, Siekelova 2017, Poddig 1995, Ohlson 1990).

In 1970s, prediction models based on the logistic regression – logit and probit models – also raised. The first authors who used logistic regression for predicting the bankrupt of enterprise were Santomero and Vinso (1977) and Martin (1977). They only analysed the bankrupt of American banks. In 1980, Ohlson analysed bankrupt of enterprise using logistic regression in general. The result of his model is one value that directly determined the probability of bankrupt of enterprise. Logit analysis was also analysed in the works of Casey and Bartczak (1985), Zavgren (1985), Pantalone and Platt (1987), Jakubik and Teply (2006), Sajter (2008), Hurtosova (2009), Bredar (2014), Gulka (2016) (Zavrgen 1985, Siekelova 2017, Poddig 1995, Ohlson 1990, Hiadlovsky, Kral 2014).

A pioneer in the area of probit regression was Zmijewski (1984) with his work '*Methodological Issues Related to the Estimation of Financial Distress Prediction Models*'. Other authors followed up his results, for example, Gloubos and Gramamatikos (1988), Skogsvik (1990), Theodossiou (1991), Boritz and Kennedy (1995), Lennox (1999) (Gulka 2016, Zmijewski 1984, Skogsvik 1990, Svabova, Kral 2016, Durica, Adamko 2016).

Since the 1990s, studies focused on the development of prediction models using neural network methods have been conducted. The foundation to this method was laid by Odoma and Sharda in 1990, later followed by Coats aFant (1992), Altman aVaretto (1994), Wilson aShardy (1994), Rudorfer (1995), Alici (1996), Serrano-Cinca (1996), Kivilluoto (1998), Sung, Chang and Lee (1999), Zhang (1999) Lee (2001), Witkowska (2002) (Bellovary et al. 2007, Hiadlovsky, Kral 2014, Press, Wilson 1978).

Table 1 captures historical development of individual methods for prediction model creations. The table shows the number of prediction models that was created by individual methods in studies about prediction model creations.

Table 1. Historical development of methods for prediction model creations. (Source: author's own compilation according to Bellovary et al. (2007), Spuchlakova (2016) and Kubickova and Nulicek (2017))

Period	Methods				
	Discrimination analysis	**Logit analysis**	**Probit analysis**	**Neural networks**	**Different**
1960	2	0	0	0	1
1970	22	1	1	0	4
1980	28	16	3	1	7
1990	9	16	3	35	11
2000–2004	2	3	0	4	3
2010–2017	5	10	0	15	2
Total	68	46	7	55	28

According to the data in Table 1, the most commonly used method for the prediction model creation is discrimination analysis. Neural networks are at the second place. However, there exists a very thin border between neural networks and logit analysis – only nine studies. Logit analysis was used in 46 studies about prediction models, and neural networks were used in 55 studies about prediction models.

Methodology

The methodology of prediction models has had long history, as mentioned earlier. The main aim of this article is to find key factors in enterprise bankrupt prediction in Slovak condition. The methodology used in this article is adapted according to the main aim. Authors work with the database of Slovak enterprises. This sample includes 8,522 financial statements of Slovak enterprises in 2016. The methodology used in this article is divided into four basic steps.

In the first step, it was necessary to choose several decision rules for dividing enterprises into two categories – bankrupt enterprises and creditworthy enterprises. On the basis of the relevant literature, three basic decision rules were selected:

- *the value of equity* – according to Slovak law – 'enterprise in bankrupt' is an enterprise with the negative value of equity. If the value of enterprise equity is negative, then this enterprise was considered as an enterprise in bankrupt,
- *the value of net income* – the negative value of enterprise net income may indicate 'enterprise in crisis',
- *the value of equity to debt ratio* – this financial indicator shows the share of equity of total liabilities. According to Slovak law – 'enterprise in crisis' is an enterprise with an equity-to-debt ratio lower than 0.04. It means that the value of equity must represent 40% of total liabilities (Svabova, Kral 2016, Durica, Adamko 2016).

In the second step, it was necessary to choose the most used prediction models created in Slovak Republic. These models were calculated in database of Slovak enterprises and considered their total explanatory power in current Slovak conditions. The following models were chosen for this article: Chrastinova model, Gurcik model and Delina–Packova model. In Slovak Republic, there is a lack of relevant prediction models created in Slovak conditions. For these reasons, the article analysed the three most popular prediction models in Slovak Republic.

Chrastinova model

This model was created by Chrastinova in 1998 and is also known as 'CH-index'. Model was adapted to the specific needs of enterprises operating in the agricultural sector, which is its disadvantage. Final model prediction equation is the product of multiple discriminant analysis. Chrastinova analysed 1,123 enterprises from agricultural sector and she worked with 10 input variables.

$$CH = 0.37_{x1} + 0.25_{x2} + 0.21_{x3} - 0.1_{x4} - 0.07_{x5} \quad (1)$$

Table 2 shows five financial variables that represent individual parameters of prediction equation.

Table 2. Financial variables of CH-index. (Source: author's own compilation according to Chrastinova (1998))

Variables	Calculations
x1	EAT/total equity and liabilities
x2	EAT/total revenues
x3	Cash flow/total liabilities
x4	(Total liabilities/total revenues)*365
x5	Total liabilities/total equity and liabilities

According to the results of prediction equation given in the 'CH-index', the probability of enterprises in bankrupt was classified into three groups. Limits for classification are given in Table 3.

Table 3. Limits for CH-index. (Source: author's compilation own according to Chrastinova (1998))

Limits	Categories
$CH \geq 2.5$	Creditworthy zone
$2.5 < CH > -5$	Grey zone
$CH \leq -5$	Bankrupt zone

Gurcik model

This model was created by Gurcik in 2003 and is also known as 'G-index'. His model is based on the multiple discriminant analysis. He analysed 60 enterprises from agricultural sector in Slovak republic. The number of samples and the sector analysed are the disadvantages of the model. Finally, his final form of model includes five variables:

$$G = 3.412_{x1} + 2.226_{x2} + 3.227_{x3} + 3.419_{x4} - 2.063_{x5} \quad (2)$$

Table 4 shows five financial variables that represent individual parameters of prediction equation.

Table 4. Financial variables of G-index. (Source: author's own compilation according to Gurcik (2002))

Variables	Calculations
x1	Retained earnings/total equity and liabilities
x2	Earnings before taxes/total equity and liabilities
x3	Earnings before taxes/total revenues
x4	Cash flow/total equity and liabilities
x5	Stocks/total revenues

According to the results of prediction equation given by the 'G-index', the probability of enterprises in bankrupt was classified into three groups. Limits for classification are given in Table 5.

Table 5. Limits for G-index. (Source: author's own compilation according to Gurcik (2002))

Limits	Categories
$G \geq 1.8$	Creditworthy zone
$-0.6 < G > 1.8$	Grey zone
$G \leq -0.6$	Bankrupt zone

Delina–Packova model

This model was created in Slovak Republic in 2013 by Delina and Packova (P-model). They analysed financial statements of 1,560 Slovak enterprises. They created the model using logistic regression. Authors worked with all sectors and big sample, which are the advantages of this model. Finally, their prediction equation included six financial variables:

$$P = 2.86 - 0.0001278_{x1} + 0.04851_{x2} + 0.2136_{x3} - 0.000071_{x4} + 0.0001068_{x5} - 0.0006116_{x6} \quad (3)$$

Table 6 shows six financial variables that represent individual parameters of prediction equation.

Table 6. Financial variables of P-model. (Source: author´s compilation according to Delina, Packova (2013))

Variables	Calculations
x1	(Financial assets – current liabilities)/(operating costs – depreciation)
x2	Retained earnings/ total equity and liabilities
x3	Basic capital/total equity and liabilities
x4	Cash flow/total liabilities
x5	Earnings before taxes/total revenues

According to the results of prediction equation given by the ‘P-model’, the probability of enterprises in bankrupt was classified into two groups. Limits for classification are given in Table 7.

Table 7. Limits for P model. (Source: author’s own compilation according to Delina, Packova (2013))

Limits	Categories
$P > 0$	creditworthy zone
$P < 0$	bankrupt zone

In the third step, it was necessary to choose several relevant financial indicators that may have significant relationship with the probability of enterprise in bankrupt. According to the analysis of relevant literature, the most used financial ratios in prediction models in studies from all over the world were found. Table 8 shows the most used financial ratios studies about prediction models.

Table 8. The most used financial ratio in studies about prediction models. (Source: author’s own compilation according to Bellovary et al. (2007), Pawelek et al. (2016), Bressan et al. (2017), Plihal et al. (2017))

Code	Financial indicator	Number of studies	Code	Financial indicators	Number of studies
ratio1	Earnings after taxes (EAT)/total assets	54	ratio6	Sales/total assets	32
ratio2	Current assets/short-term debts	51	ratio7	(Current assets – inventory)/ short-term debts	30
ratio3	Net working capital/total assets	45	ratio8	Total debts/total assets	27
ratio4	Retained earnings/total assets	42	ratio9	EBIT/interest expense	10
ratio5	Earnings before interest and taxes (EBIT) /total assets	35			

Significant relationship between variables was tested using Pearson’s correlation coefficient, which is supported by correlation matrices. This article tested the significant relationship between the equity-to-debt ratio, which represents basic decision rule about enterprise in crisis, and several chosen financial ratios/indicators. These ratios were chosen based on the analysis of Slovak and foreign literature. This includes the following steps:

- calculation of financial indicators in database of 8,522 Slovak enterprises,
- identification of outliers in the results of calculations,
- creation of correlation matrices between equity-to-debt ratio and other financial indicators.

In the last step, it was necessary to compare the results of total explanatory power of Slovak prediction models in database of Slovak enterprises with the results of literature articles on the significant relationship between equity-to-debt ratio and other financial indicators. Thanks to this comparison, an existence of significant financial ratio in current Slovak prediction models was identified.

Results

The results were obtained by following the four basic steps, which were described in previous section – methodology.

In the first step, 8,522 enterprises from database were divided into two categories – enterprise in bankrupt and creditworthy enterprise. This distribution was created according to decision rules, which were described in methodology. Three decision rules created the group of enterprises in bankrupt with 2,556 enterprises and the group of creditworthy enterprises with 5,966 enterprises.

The second step includes the results of Slovak prediction models (Chrastinova model, Gurcik model and Delina–Packova model) in the database of 8,522 Slovak enterprises. The results of Slovak prediction models and the results based on the decision rules are compared in Table 9.

Table 9. Explanatory power of Slovak prediction models. (Source: author's own compilation)

Decision rules	**CH-index**		**Total**
	Creditworthy	**Bankrupt**	
Creditworthy	521	5,445	5,966
Bankrupt	113	2,443	2,556
			8,522
Decision rules	**G-index**		**Total**
	Creditworthy	**Bankrupt**	
Creditworthy	3,269	2,697	5,966
Bankrupt	1,514	1,042	2,556
			8,522
Decision rules	**P-model**		**Total**
	Creditworthy	**Bankrupt**	
Creditworthy	1,888	4,078	5,966
Bankrupt	256	2,300	2,556
			8,522

According to data in the table, CH-index was right in 2,964 cases – it determined 521 enterprises as creditworthy and these enterprises were really creditworthy according to the decision rules. In addition, the model determined 2,443 enterprises as bankrupt and these enterprises were really bankrupt according to the decision rules. The CH-index was wrong in 5,558 cases. The total explanatory power of CH-index was 34.78%.

G-index achieved the following results: the model was right in 4,311 cases – it determined 3,269 enterprises as creditworthy and these enterprises were really creditworthy according to the decision rules. In addition, the model determined 1,042 enterprises as bankrupt and these enterprises were really bankrupt according to the decision rules. The G-index was wrong in 4,211 cases. The total explanatory power of G-index was 50.59%.

P-model achieved the following results: the model was right in 4,188 cases – it determined 1,888 enterprises as creditworthy and these enterprises were really creditworthy according to the decision rules. In addition, the model determined 1,042 enterprises as bankrupt and these enterprises were really bankrupt according to the decision rules. The P-model was wrong in 4,334 cases. The total explanatory power of the P-model was 49.14%.

In the third step, nine financial ratios/indicators in database of 8,522 Slovak enterprises were calculated. Subsequently, outliers in these data were identified (Figure 1). For outliers, the values with variance significant from other values were considered. Outliers could influence the final results. For testing of outliers, interquartile range was used. Interquartile range for all variables was the basic stone for removing outliers. Next step was identifying the limits that indicate outliers. Limits were set as triple of upper and lower quartile, which means triple of interquartile range. Values between these limits were not considered as outliers.

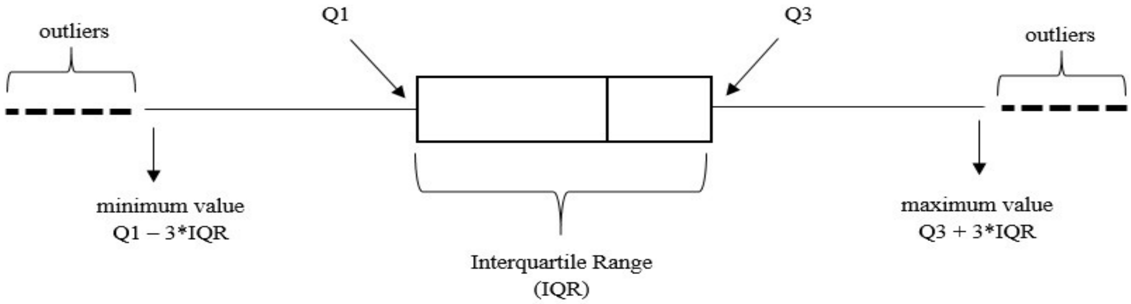

Fig. 1. Searching for outliers using interquartile range. (Source: author's own compilation)

In total, the data included 511 outliers. Table 10 presents the number of outliers in all financial ratios.

Table 10. Outliers in data. Source: author's own compilation.

Code for ratio	Financial ratio	Number of outliers
debt-equity ratio	Equity/total debts	28
ratio1	EAT/total assets	4
ratio2	Current assets/short-term debts	37
ratio3	Net working capital/total assets	28
ratio4	Retained earnings/total assets	35
ratio5	EBIT/total assets	52
ratio6	Sales/total assets	3
ratio7	(Current assets – inventory)/short-term debts	270
ratio8	Total debts/total assets	48
ratio9	EBIT/interest expense	11
Total		511 outliers
Database		8,005 enterprises

Outliers were excluded from database; subsequently, the database consisted of 8,005 Slovak enterprises. Then correlation matrices between equity-to-debt ratio and all financial ratios were created. Correlation matrices were created using Pearson's correlation coefficient (Cipra 2008).

On the basis of the results of Pearson's correlation coefficient, obtained from correlation matrices, determined the strength of dependence between variables (Rimarcik 2007).

Figure 2 shows correlation matrices between equity-to-debt ratio and all financial ratios.

Variables	debt-equity ratio	ratio1
debt-equity ratio	1	0.354
ratio1	0.354	1

Variables	debt-equity ratio	ratio2
debt-equity ratio	1	0.368
ratio2	0.368	1

Variables	debt-equity ratio	ratio3
debt-equity ratio	1	0.062
ratio3	0.062	1

Variables	debt-equity ratio	ratio4
debt-equity ratio	1	0.077
ratio4	0.077	1

Variables	debt-equity ratio	ratio5
debt-equity ratio	1	0.057
ratio5	0.057	1

Variables	debt-equity ratio	ratio6
debt-equity ratio	1	-0.077
ratio6	-0.077	1

Variables	debt-equity ratio	ratio7
debt-equity ratio	1	0.393
ratio7	0.393	1

Variables	debt-equity ratio	ratio8
debt-equity ratio	1	-0.151
ratio8	-0.151	1

Variables	debt-equity ratio	ratio9
debt-equity ratio	1	0.273
ratio9	0.273	1

Fig. 2. Correlation matrixes between variables. (Source: author´s compilation)

On the basis of the results obtained from Figure 2, three variables (financial ratios) that have medium dependence with equity-to-debt ratio were identified. These ratios are ratio1, EAT/total assets; ratio2, current assets/short-term debts; and ratio7, (current assets – inventory)/short-term debts. In addition, interesting results were achieved by ratio8, total debts/total assets, and ratio9, EBIT/interest expense. Other variables have weak dependence.

The results of the article showed that financial ratios may be used in prediction model creation in future. These variables may be decisive in the process of identification of the probability of enterprise in bankrupt. Subsequently, they may have an influence on the total explanatory power of prediction model as a whole. Despite the fact that the most used financial ratios in the prediction models were chosen from all over the world, according to the relevant literature, in Slovak conditions, only three of them had relationship to decision rule about the probability of enterprise in bankrupt.

The last step includes comparison of the results of total explanatory power of Slovak prediction models in the database of Slovak enterprises with the results of testing of significant relationship between equity-to-debt ratio and other financial indicators. The CH-index achieved the worst total explanatory power in the database of Slovak enterprises – only 34.78%; the second one was the P-model, with total explanatory power of 49.14%; and the best total explanatory power was achieved by the G-index, 50.59%. From these results, the total explanatory power of Slovak prediction models is relatively low. Interesting is that none of them contain ratio2, ratio7, ratio8 or ratio9, which could be potentially decisive ratios in the process of identification of the probability of enterprise in bankrupt. It could be the reason for their low value of total explanatory power. Only the CH-index contains ratio1, which could be potentially decisive ratio in the process of identification of the probability of enterprise in bankrupt. Despite this fact, the CH-index had low total explanatory power.

Conclusions

The main aim of this article was to identify the key factors in enterprise bankrupt prediction – a case study conducted in Slovak Republic. The article worked with the database of 8,522 Slovak enterprises. Three basic decision rules were determined for identifying the enterprise in bankrupt. Subsequently, three prediction models, created in Slovak Republic, were chosen and their total explanatory power in Slovak enterprises was provided. In addition, the relevant Slovak and foreign literature were analysed and the most used financial ratio in prediction models from all over the world were found. Subsequently, significance of the relationship between these ratios and equity-to-debt ratio were calculated, which was stated as key identifier in the process of quantification of the probability of enterprise in bankrupt. This study also found the three variables with medium dependence on the equity-to-debt ratio –EAT/total assets, current assets/short-term debts and (current assets – inventory)/short-term debts. These financial ratios may be used in the prediction model creation, in the future. These variables may be decisive in the process of identification of the probability of enterprise in bankrupt. In addition, interesting results were achieved by ratio8, total debts/total assets, and ratio9, EBIT/interest expense. Other variables have weak dependence. In addition, it was found that the total explanatory power of Slovak prediction models is relatively low. Interesting is that none of them contain financial ratios (ratio2, ratio7, ratio8 or ratio9) that could be potentially decisive in the process of identification of the probability of enterprise in bankrupt, according to the correlation matrices. It could be the reason of their low value of total explanatory power. Only CH-index contains ratio1, which could be potentially decisive ratio in the process of identification of the probability of enterprise in bankrupt. Despite this fact, the CH-index had low total explanatory power.

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