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General bankruptcy prediction models for the Visegrád Group. The stability over time

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Abstract

Managers of enterprises must constantly face the continual changes on the market and fight for survival in a world of high competition. Therefore, it is important to systematically monitor the company's financial condition. This will help to identify problems and give specific time to take corrective action. Bankruptcy prediction models are usually constructed for local goals. The purpose of the article is to build not only regional but also general discriminant and logit models for the SMEs operating in the construction industry in Visegrád Group countries. A total of 32 unique models were built and verified along with the Altman model for emerging markets. The paper also contributes to the literature by assessing the stability of the constructed models over time, which the models' authors do not usually measure. The results showed that regional models are characterized by higher accuracy than general ones. However, general models can be adapted to the analyzed Visegrád Group with an accuracy of approximately 90%. The G1 LR model can be considered the best model, as it has relatively high accuracy and over-time stability.

Keywords: *SMEs, discriminant analysis, logit analysis, construction sector, stability of models*

1. Introduction

In rapidly developing economies and ever-changing business environments, managers constantly have to deal with the challenges they face and make decisions, so that to the best possible extent, to adapt to any market requirements and above all maintain its core business at a profitable level. To maintain the basic activity at a satisfactory level, the managers of the company, first of all, must maintain its good financial condition, which will allow for maintaining liquidity and further development on the market [24]. One of the main reasons for the bankruptcy of enterprises is entering into a state of insolvency, which is characterized by the fact that the company is unable to pay its liabilities on time, losing more and more confidence and deepening the state of insolvency, ultimately leading to bankruptcy [18].

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According to the Creditreform, the number of insolvent enterprises in the Visegrád Group (Czech Republic, Hungary, Poland, and Slovakia) was almost 13,000 in 2019. Nearly 86% of them are located in Hungary. This number has tripled compared to that in 2018 and almost doubled compared to that in 2017. In turn, the insolvency rate is the share of insolvent companies in the total number of active companies – the highest is in Hungary (2.78% in 2019) and the lowest is in Poland (0.05% in 2019).

Many models have been published such as discriminant models (DA), logit models (LR), or decision trees (DT) created to ensure the possibility of easy and quick analysis of the company's situation [16]. The research carried out by Slovak authors shows that statistical methods are most often used to build bankruptcy prediction models in the Visegrád countries (Table 1). This is due to their simplicity of application and the possibility of their verification by other researchers.

Table 1. Method used for construction of the bankruptcy prediction models in Visegrád countries [15]

Method	Number of studies	Per cent
Discriminant analysis (MDA + LDA + QDA)	51	50
Conditional probability (Logit + Probit)	36	35
Neural network (NN + ANN + ANFIS + SOM + FUZZY)	2	2
Decision trees (Regression trees + RE-EM + CHAID)	12	12
Total	103	100

Models are usually built for local purposes. There are some general models constructed for a certain group of countries such as the Visegrád Group (V4), (cf. [4, 11, 20]. The first two authors built statistical models, the first one presents discriminant models, and the second one shows the logit model. The third one presents a more sophisticated model: a hybrid one mixed by some methods, namely RobustBoost, CART, and k-NN with an optimized structure.

The paper is organized as follows. Section 2 discusses the literature, Section 3 outlines the methodology, Section 4 shows the results, Section 5 discusses the findings, and Section 6 concludes the paper.

2. Literature review

The usefulness of bankruptcy prediction models has been verified by other researchers from all over the world along with their creation. They verified the accuracy of existing models, mainly statistical models for the reasons mentioned above. Altman's models are the most frequently assessed and validated bankruptcy prediction models because he has designed models for many economies, including emerging markets. Table 2 presents the literature review of the verification of statistical models concerning the Visegrád countries.

The authors presented various conclusions. Balina and Bąk [3] stated that the selected models, both Polish and foreign, had different levels of overall accuracy. The large number or lack of bankruptcy prediction models can lead to confusion, as different results can be obtained depending on which model is used. In turn, Altman et al. [2] indicated that the Z$''$-score model works well in an international context. Kisielińska [10] pointed out that the assessment of a company's financial condition cannot be based solely on the values of bankruptcy prediction models. Furthermore, Tomczak and Radosiński [28] stated that only 5 DA models were characterized by sufficient predictive power in the five years ahead of the bankruptcy of companies. Karas and Srbová [9] concluded that the accuracy of a model can be boosted by creating a branch-specific model. Similarly, Iwanowicz [7] stated that the construction of DA models should take into account the industry, the size of the company, and the conditions of its operations. Moreover, Ékes and Koloszár [5] claim that models misclassified companies to the bankruptcy group. Kovacova et al. [14] stated that the accuracy of analyzed logit and probit models outpointed the prediction power of multiple discriminant analysis. Pražák and Gongol [22] recommended the Altman and IN05 models for practical use in all V4 countries.

Table 2. The verification of statistical models. Literature review

Authors	Data	Period	Sector	Method used	Accuracy
Balina and Bąk [3]	120 PL	2009	CO, WT, GRT	28 DA models; 4 LR	76.70%
Altman et al. [2]	209,002 V4	2007–2010	general	Altman models	84%
Kisielińska [10]	110 PL	2009–2012	general	7 DA models, 4 LR	82.70%
Tomczak and Radosiński [28]	10,700 PL	2000–2012	MA	33 DA models	75.70%
Karas and Srbová [9]	4420 CZ	2006–2015	CO	5 DA models	0.839 AUC
Pražák and Gongol [22]	10,229 V4	2005–2016	general	4 DA models	45%
Kovacova et al. [14]	27,029 SK	2016	general	MRA,DA,LR,PR	79.35%
Ékes and Koloszár [5]	60 HU	not specified	SME	6 DA models, 1 LR	81.70%
Iwanowicz [7]	139 PL	not specified	MA; SE, CO	13 DA models	93.80%

CO – construction, WT – wholesale trade; GRT – goods road transport, MA – manufacturing, MRA – multiple regression analysis, SME – small and medium enterprises, PR – probit model.

The performance of the models varies significantly between studies. One of the reasons may be the size of the sample based on which the models were verified, the research period, and the re-estimation of model parameters. It is worth noting that the efficiency of the models is different from those given by the author of the model and significantly higher than the statistical error. It should be pointed out that the authors of the models do not address the issue of the stability of the models over time, except for a few exceptions, such as Altman. Based on that so far, no single optimal bankruptcy prediction model has been created, for which very high efficiency and stability can be assured.

Therefore, the paper aims to construct discriminant and logit models for SMEs operating in Poland, Czech Republic, Hungary, and Slovakia and general models for V4 for the construction sector and assess their overtime stability. The models was verified along with the Altman model for emerging markets. The research objective formulated in this way will allow us to address the following research questions:

1. Do the constructed models assess enterprises at the level of 95% of the correct classification (5% statistical error)?
2. Are general models characterized by higher efficiency of correct classification of enterprises than local models?
3. Are the models stable over time?
4. Have the models been constructed with the same financial ratios?
5. Does the Altman model evaluate enterprises more accurately than structured ones?
6. Do LR models evaluate enterprises with higher efficiency than DA models?

3. Methodology

The bankrupt companies in the learning and test sample went bankrupt and/or were in liquidation from the construction sector during the years 2012 and 2019. The sample consists of only small- and medium-

-sized limited liability and joint-stock companies with the value of assets ranging between 2 and 50 million EUR in at least one of the analyzed periods. The accuracy of the models was tested based on data covering three years ahead of the bankruptcy of enterprises. The research period was chosen due to the availability of data.

Table 3. The ratios considered in the analysis

Number	Formula	Number	Formula
X1	NP/TA	X36	TS/TA
X2	TL/TA	X37	(CA-I)/LL
X3	WC/TA	X38	CC/TA
X4	CA/SL	X39	PS/S
X5	[(C + SS + R – SL)/(OE – D)] × 365	X40	(CA – I – R)/SL
X6	RE/TA	X41	TL/((EBITDA) × (12/365))
X7	EBIT/TA	X42	EBIT/S
X8	E/TL	X43	RR + IT
X9	S/TA	X44	(R × 365)/S
X10	E/TA	X45	NP/I
X11	(GP + EI + FE)/TA	X46	(CA - I)/SL
X12	GP/SL	X47	(I × 365)/CPS
X13	(GP + D)/S	X48	EBITDA/TA
X14	EBIT/TC	X49	EBITDA/S
X15	(TL × 365)/(GP + D)	X50	CA/TL
X16	(GP + D)/TL	X51	SL/TA
X17	TA/TL	X52	(SL × 365)/CPS)
X18	EBIT /TL	X53	E/FA
X19	GP/S	X54	CC/FA
X20	(I × 365)/S	X55	WC
X21	S(n)/S ($n-1$)	X56	(S – CPS)/S
X22	EBIT/TA	X57	NP/E
X23	NP/S	X58	TC /TS
X24	GP (in 3 years)/TA	X59	LL/E
X25	(E – SC)/TA	X60	S/I
X26	(NP + D)/TL	X61	S/R
X27	EBIT/FE	X62	(SL ×365)/S
X28	WC/FA	X63	S/SL
X29	lgTA	X64	S/FA
X30	(TL – C)/S	X65	lgS
X31	EBIT/E	X66	E(n)/E($n-1$)
X32	(CL × 365)/CPS	X67	C(n)/C($n-1$)
X33	OE/SL	X68	(CA – I –SL)/(S – GP – D)
X34	OE/TL	X69	CCC
X35	PSs/TA		

NP – net profit, TA – total assets, TS – total sales, TL – total liabilities, CA – current assets, I – inventories, LL long-term liabilities, WC – working capital, CC – constant capital, SL – short-term liabilities, PS – profit on sales, S – net sales, C – cash, SS – short-term securities, R – receivables, OE – operating expenses, D – depreciation, RE – retained earnings, E – equity, RR – rotation receivables, IR – inventory turnover in days, GP – gross profit, FE – financial expenses, CPS – cost of products sold, TC – total cost, FA – fixed assets, SC – share capital, CCC – cash conversion cycle.

The model-building process consists of several stages. The first stage concerned the acquisition of a training sample based on which models could be built. The training sample comprised a total of 780 enterprises, which included 222 enterprises from Poland, 148 enterprises from the Czech Republic, 230 enterprises from Slovakia, and 180 enterprises from Hungary. Half of the businesses in the learning sample were companies that had gone bankrupt and/or were in liquidation. The other half were companies characterized by a relatively good financial condition (based on ratio analysis). The enterprises for the training sample were obtained from the EMIS database (Emerging Markets Information Service) using the pairing method, which means that for each financial statement from the bankrupt enterprise, the financial statements of the still-operating enterprise were selected for the same year. The years from which the financial statements were derived were 2009–2018 for Poland, the Czech Republic, and Slovakia, and 2010–2018 for Hungary. The criterion for selecting the enterprises was that they belong to the SMEs. The second stage considered the selection of financial indicators. The ratios most often used in discriminant models and financial analysis were taken into consideration. A total of 69 financial ratios used in bankruptcy prediction models and financial analysis were analyzed (Table 3). Indicators based on cash flows were not analyzed due to the lack of access to data for SMEs.

To analyze the model's stability and to find repeated financial ratios in the model over time, the period for each country was divided based on the availability of data. The main assumption was to include a minimum of 50 companies in the learning sample. Based on that the periods for individual countries and the Visegrád Group are presented in Table 4. Models were constructed based on two methods: discriminant and logit analysis.

Table 4. The models for individual countries and Visegrád Group by the DA, LR method

Model	Size of the learning sample	Years
PL1	68	2011–2014
PL2	78	2015–2016
PL3	76	2017
CZ1	50	2011–2016
CZ2	98	2017
HU1	64	2012–2014
HU2	62	2015
HU3	54	2016
SK1	66	2011–2015
SK2	74	2016
SK3	90	2017
G1	64	2011–2012
G2	50	2013–2014
G3	120	2015
G4	112	2016
G5	150	2017

Then, the initial list of ratios was selected separately for enterprises from each of the analyzed countries based on normal distribution, discriminant and predictive power, and correlation matrix. First, all outliers from the values of selected indicators were removed to obtain their normal distribution (Grubbs Statistic). The normal distribution of the values of selected ratios was tested using a normality Kolmogorov–Smirnov test. Later, the predictive and discriminant power of indicators were investigated. If the values of indicators decrease or increase in a minimum of three consecutive years before bankruptcy it means that the ratio is characterized by a predictive power. Together with predictive power, indicators should be characterized by discriminant power, having large differences in the values of ratios between companies in poor and good financial standing. This was verified by using a Student's t-test for independent samples. At the end of the selection, the indicators that were highly correlated with each other were excluded from the analysis. A detailed description of the way of selection of financial ratios can be found in [26]. After the selection of indicators for enterprises from individual countries, the model function was built using the Statistica 13.3 program. The functions of two kinds of models: discriminant (DA) and logit (LR) models were built. Fundamentals of discriminant models were used according to [1].

Definition 1. The discriminant functions have the same analytical form but differ only in coefficients and the constant. Usually, the linear form of the function is:

$$Z = b_0 + b_1 x_1 + \cdots + b_k x_k \tag{1}$$

where Z – dependent variable (explained), b_0 — constant parameter, $b_1, b_2, ..., b_k$ – coefficients (weights) of variables, $x_1, x_2, ..., x_k$– independent (explanatory) variables.

For each function, a threshold is set individually according to the average value obtained for operating and bankrupt enterprises in the training sample, above which the enterprise is considered to be prospering, and vice versa. In turn, fundamentals of logistic regression were used according to [6]. In this study, the dependent variable for failed companies was denoted by 1, and for healthy companies was denoted by 0.

Definition 2. The logistic regression is used to determine the conditional probability of bankruptcy as follows:

$$p(Y = 1|X) = \frac{1}{1 + \mathrm{e}^{-L}} = \frac{1}{1 + \mathrm{e}^{-(b_0 + b_1 x_1 + \cdots + b_k x_k)}} \tag{2}$$

where $b_1, b_2, ..., b_k$ are the coefficients estimated from the dataset of businesses by maximizing the log-likelihood function, $x_1, x_2, ..., x_k$ are the selected variables for the model.

Then, the constructed models were verified on the test sample which consists of a different group of companies than the one included in the training sample. The test sample consisted of 1300 enterprises, including 254 enterprises from the Czech Republic, 294 enterprises from Poland, 306 enterprises from Slovakia, and 446 enterprises from Hungary with an identical structure of non-bankrupt and bankrupt enterprises as in the learning sample. The constructed discriminant and logit models were compared to Altman's model for emerging markets. Finally, the stability of the constructed models over time was examined (in the period of 2013–2018).

4. Results

Based on the assumptions such as assessment of the stability of models, financial ratios included in models, and comparison of two kinds of models, a total number of 32 models were created -– 16 discriminant models (DA) and 16 logit models (LR) for SMEs operating in the construction sector using formula 1 and 2. Six of them were discriminant and logit models for the Polish, Hungarian, and Slovak economies, and four of them were models for the Czech economy, as well as the rest ten discriminant and logit models for general models, allowing the identification of the situation of enterprises in each of the surveyed countries. The results were compared with the Altman model in the period of 2013–2018. A confusion matrix was used to verify the models.

4.1. Model functions

The function form of the models together with their cut-off values and their accuracy are presented in Tables 5–9. The cut-off value for discriminant models means that the higher the values of the model the better for the company, and the lower the possibility of going bankrupt. On the other hand, the cut-off value for logit models means that the lower the values of the model, the better for the company and the lower the possibility of going bankrupt. The function for logit models should be substituted into equation 2. The accuracy of models means the correct classification of companies in the training sample.

Models for the Polish economy

Table 5 presents six models for the Polish economy: 3 discriminant models and 3 logit ones. The models were built based on three different periods: 2011–2014 (PL1 DA, PL1 LR), 2015–2016 (PL2 DA, PL2 LR), and 2017 (PL3 DA, LR). This choice was due to the availability of data and entailed the possibility of evaluating the models over time. The models are constructed based on 4, 6, and 7 indicators. The first two models are characterized by the highest correct classification of enterprises in the training sample, with almost 99% effectiveness.

Table 5. Models for the Polish economy

Model	Equation	Cutoff value	Accuracy
PL1 DA	$0.45\,X4 + 0.97\,X14 - 0.33\,X26 + 0.14\,X45 + 0.03\,X63 + 0.13\,X66 - 0.50$	0.52	**98.44%**
PL1 LR	$-73.65\,X10 - 35.75\,X19 - 13.73\,X45 - 2.1 \times 10^{-4}\,X55$ $-1.64\,X63 - 0.53\,X66 + 44.61$	0.5	**98.46%**
PL2 DA	$0.08\,X4 + 0.30\,X16 + 0.29\,X21 + 0.18\,X40 + 0.05\,X53 + 0.44\,X66 - 0.53$	0.65	82.05%
PL2 LR	$-0.32\,X4 - 2.92\,X16 - 0.09\,X53 - 0.09\,X66 + 0.91$	0.5	83.82%
PL3 DA	$1.45 \times 10^{-3}\,X4 - 0.16\,X30 + 4.44 \times 10^{-3}\,X53 + 0.39\,X65 - 0.97$	0.46	86.84%
PL3 LR	$0.36\,X4 + 0.06\,X28 + 8.34\,X30 + 2.74\,X46$ $-2.17\,X53 - 10.72\,X65 + 3.34 \times 10^{-4}\,X69 + 41.39$	0.5	82.86%

Models for the Czech economy

Table 6 presents 4 models for the Czech economy: 2 discriminant models and 2 logit models. In this case, the models were constructed based on two different periods 2011–2016 (CZ1 DA, CZ1 LR) and 2017 (CZ2 DA, CZ2 LR). This was due to the availability of data. The models presented are built based on 2 and 4 ratios. The second two models are characterized by the highest correct classification of enterprises in the learning sample with 100% CZ2 DA and almost 99% CZ2 LR effectiveness.

Table 6. Models for the Czech economy

Model	Equation	Cutoff value	Accuracy
CZ1 DA	$0.51\,X6 - 1.07 \times 10^{-5}\,X37 + 0.02\,X53 + 0.54\,X59 + 0.57$	0.42	85.71%
CZ1 LR	$-6.01\,X6 + 7.09 \times 10^{-3}\,X37 - 0.06\,X53 - 3.67\,X59 + 0.19$	0.5	83.67%
CZ2 DA	$-0.94\,X2 + 2.3 \times 10^{-5}\,X20 + 9.64 \times 10^{-3}\,X21 - 0.11\,X29 + 1.80$	0.55	**100%**
CZ2 LR	$35.67\,X2 + 7.00\,X29 - 59.64$	0.5	**98.98%**

Models for the Hungarian economy

Table 7 presents six models for the Hungarian economy: 3 discriminant models and 3 logit models.The models were built based on three different periods 2012-2014 (HU1 DA, HU1 LR), 2015 (HU2 DA, HU2 LR) and 2016 (HU3 DA, HU3 LR). This choice was due to the availability of data and entailed the possibility of evaluating the models over time. The models are constructed based on 4, 5 indicators. The first model HU1 is characterized by the highest correct classification of companies in the training sample, with almost 94% effectiveness.

Table 7. Models for the Hungarian economy

Model	Equation	Cutoff value	Accuracy
HU1 DA	$-0.39\,X2 + 0.31\,X29 - 1.6 \times 10^{-3}\,X30 + 0.12\,X46 - 0.23$	0.59	**93.8%**
HU1 LR	$\mathbf{5}.84\,X2 - 3.54\,X29 + 0.11\,X30 - 0.67\,X46 + 7.26$	0.5	85.9%
HU2 DA	$-0.72\,X2 - 6.83 \times 10^{-4}\,X27 + 0.14\,X29 - 0.04\,X58 + 0.67$	0.63	90.3%
HU2 LR	$\mathbf{3}.78\,X2 + 3.67 \times 10^{-3}\,X27 - 0.71\,X29 + 0.20\,X58 - 0.91$	0.5	82.0%
HU3 DA	$\mathbf{0}.18\,X24 + 6 \times 10^{-4}\,X28 + 0.36\,X29 - 0.08\,X30 + 7 \times 10^{-4}\,X69 - 0.43$	0.50	92.2%
HU3 LR	$\mathbf{2}.33\,X24 - 0.04\,X28 - 5.53\,X29 + 4.10 \times 10^{-3}\,X30 - 0.01\,X69 + 15.7$	0.5	92.2%

Models for the Slovak economy

Table 8 presents six models for the Slovak economy: 3 discriminant models and 3 logit models. The models were constructed based on three different periods 2011–2015 (SK1 DA, SK1 LR), 2016 (SK2 DA, SK2 LR), and 2017 (SK3 DA, SK3 LR). This choice was due to the availability of data and entailed the possibility of evaluating the models over time. The models consist of only 4 ratios. The SK3 DA model was characterized by the highest correct classification of enterprises in the training sample, with 92% effectiveness.

Table 8. Models for the Slovak economy

Model	Equation	Cutoff value	Accuracy
SK1 DA	$-0.37\,X2 + 0.78\,X41 - 0.62\,X56 + 0.19\,X59 + 1.45$	0.64	80.30%
SK1 LR	$\mathbf{1}.89\,X2 - 3.49\,X41 + 9.39\,X56 - 1.26\,X59 - 10.75$	0.5	80.00%
SK2 DA	$\mathbf{1}.58\,X49 - 0.64\,X52 + 0.71\,X59 + 2.04 \times 10^{-3}\,X61 + 0.71$	0.36	82.43%
SK2 LR	$\mathbf{0}.02\,X21 - 30.18\,X49 + 6.33\,X52 - 6.25\,X59 - 0.44$	0.5	86.11%
SK3 DA	$\mathbf{1}.60 \times 10^{-3}\,X23 + 0.62\,X25 - 8.65 \times 10^{-4}\,X27 + 0.03\,X53 + 0.39$	0.57	**92.22%**
SK3 LR	$-0.15\,X23 - 2.96\,X25 + 3.05 \times 10^{-3}\,X27 - 0.14\,X53 + 0.55$	0.5	89.53%

Models for the Visegrád countries

Table 9 presents ten models for the Visegrád countries: 5 discriminant models and 5 logit models. The data availability from all 4 countries enables to building 10 models based on five different periods 2011-2012 (G1 DA, G1 LR), 2013-2014 (G2 DA, G2 LR), 2015 (G3 DA, G3 LR), 2016 (G4 DA, G4 LR) and 2017 (G5 DA, G5 LR). Thus you will be able to assess the stability of the models during the six years after the creation of the G1 DA and G1 LR. The general model mainly consists of 6 indicators. The first four models were constructed based on 50–60 companies and the remaining ones – over a hundred. The

G3 LR model was characterized by the highest correct classification of businesses in the learning sample, with almost 92% effectiveness.

Table 9. General models for the Visegrád countries

Model	Equation	Cutoff value	Accuracy
G1 DA	$0.37\,X4 + 1.43 \times 10^{-4}\,X5 + 1.74\,X19 + 0.06\,X40 + 0.28\,X45 - 0.18$	0.64	83.87%
G1 LR	$-7.42\,X4 - 0.02\,X5 - 41.12\,X19 + 5.60\,X40 - 10.97\,X45 + 11.94$	0.5	88.14%
G2 DA	$-0.79\,X2 + 0.11\,X21 + 0.30\,X22 - 4.89 \times 10^{-3}\,X65 + 0.99$	0.61	88.00%
G2 LR	$44.39\,X2 - 23.70\,X22 + 0.09\,X37 - 28.63$	0.5	88.00%
G3 DA	$-0.77\,X2 + 0.04\,X4 - 4 \times 10^{-3}\,X27 - 0.21\,X30 - 0.01\,X40 - 0.03\,X53 + 1.14$	0.62	83.33%
G3 LR	$10.2\,X2 + 0.12\,X27 + 4.13\,X30 + 2.68\,X40 + 0.45\,X53 - 0.37\,X58 - 9.4$	0.5	**91.82%**
G4 DA	$-0.19\,X3 + 0.22\,X29 + 3 \times 10^{-4}\,X43 + 0.02\,X45$ $+6 \times 10^{-3}\,X51 + 0.14\,X66 - 0.11$	0.82	69.05%
G4 LR	$0.97\,X3 - 5.03\,X29 - 5.77\,X41 - 0.01\,X45$ $-0.03\,X53 - 2.79\,X66 + 19.06$	0.5	75.53%
G5 DA	$-5.68 \times 10^{-3}\,X27 - 0.03\,X33 + 0.40\,X49 + 0.06\,X53$ $-5.32 \times 10^{-4}\,X63 + 0.36\,X68 + 0.49$	0.56	86.00%
G5 LR	$0.03\,X27 + 0.20\,X33 - 2.23\,X49 - 0.35\,X53 + 1.03 \times 10^{-3}\,X63 - 1.74\,X68 + 0.16$	0.5	87.97%

4.2. Verification of models on a test sample

In this part of the article, all constructed bankruptcy prediction models were verified on a test sample (1300 companies). First, the verification was performed for each country – each local model was compared to the general one and the Altman model for emerging markets. In the end, general models also were assessed. The values presented in Tables 10–15 are demonstrated for a year before bankruptcy (referred to as the 1 year) and an average of 3 years ahead of the bankruptcy (referred to as the 3 years).

Verification of models for the Polish economy

The models allowing the prediction of bankruptcy in the Polish economy with the highest accuracy are shown in Table 10. The models were verified on an independent test sample. The test sample for each model was different. For PL1 models, it was 294 enterprises, for PL2 models, it was 204 enterprises, for PL3 models 114 enterprises. The sample is balanced which means that half of the sample are bankrupt companies, and the other half are operating companies. The differences in sample sizes are related to the availability of data. For example, the PL1 models were verified on the 2015-2018 data, while the PL3 models could only be verified on the 2018 data.

Table 10. Results for models for the Polish economy tested 3 years before bankruptcy [%]

Model	1 year	3 years
G5 LR	**90.48**	82.25
G1 LR	88.21	83.54
PL1 LR	86.73	84.06
PL2 LR	82.47	78.70
Altman G	81.75	77.32
Altman PL	74.20	70.84

The highest efficiency of the correct classification of enterprises is characterized by a general model G5 LR. The accuracy of this model is almost 91% in the year before bankruptcy and the average of 3 years before the bankruptcy is 82%. The second-ranked model is also general one G1 LR with an accuracy is 88%. The third-ranked is model PL LR 1. This model was contracted only for the Polish economy. The accuracy of the PL LR 1 model is almost 87% which can be considered a good result. The lowest ranked models are the Altman models calculated for Poland and the Visegrád countries. The accuracy oscillates between 74 and 81% in the year before bankruptcy. It is worth adding that the highest-ranked models are logistic regression ones.

Verification of models for the Czech economy

The models allowing the prediction of bankruptcy in the Czech economy with the highest accuracy are shown in Table 11. Both CZ2 DA and CZ2 LR models are characterized by the highest efficiency of the correct classification of companies. The models were contracted only for the Czech economy. The accuracy of CZ1 DA model is almost 100% in the year before bankruptcy and the average of 3 years before the bankruptcy is 96%. The third ranked model is Altman CZ whose accuracy is 91%. The fourth and the fifth-ranked models are general ones G5 DA and G5 LR. The accuracy of the G5 DA and G5 LR models is 90% which can be considered a very good result. The lowest ranked models are the Altman models calculated for the Visegrád countries. The accuracy of this model is almost 82% in the year before bankruptcy. It is worth noting that the highest-ranked models are both discriminant and logistic regression ones.

Table 11. Results for models for the Czech economy tested 3 years before bankruptcy [%]

Model	1 year	3 years
CZ2 DA	**99.29**	**95.59**
CZ2 LR	96.93	92.01
Altman CZ	91.47	89.19
G5 DA	90.35	81.70
G5 LR	90.48	82.25
Altman G	81.75	77.32

Verification of models for the Slovak economy

The models allowing the prediction of bankruptcy in the Slovak economy with the highest accuracy are shown in Table 12.

Table 12. Results for models for the Slovak economy tested 3 years before bankruptcy [%]

Model	1 year	3 years
SK3 LR	**93.51**	87.28
SK3 DA	**93.51**	85.44
G5 LR	90.48	82.25
G5 DA	90.35	81.70
Altman SK	87.04	83.12
Altman G	81.75	77.32

Similarly to the models constructed for the Czech economy, in this case, the models dedicated to the Slovak economy (SK3 DA and SK LR) are characterized by the highest effectiveness of correct classification of enterprises. The accuracy of the models equals 93.51% in the year before bankruptcy and the average of 3 years before the bankruptcy oscillates between 85-87%. The third and fourth-ranked models are general ones – G5 LR whose accuracy is 90.58% and G5 DA whose accuracy is 90.35%. The lowest ranked models are the Altman models calculated for Slovakia and for the Visegrád countries. This situation is identical to the Polish economy. The accuracy oscillates between 81–87% in the year before bankruptcy. Both discriminant and logistic regression models are characterized by similar accuracy.

Verification of models for the Hungarian economy

The models allowing the prediction of bankruptcy in the Hungarian economy with the highest accuracy are shown in Table 13. imilar to the Czech and Slovak economies, the highest efficiency of the correct classification of enterprises is characterized by dedicated model HU2 DA to the Hungarian economy. The accuracy of this model is almost 92% in the year before bankruptcy and the average of 3 years before the bankruptcy is 84%.

Table 13. Results for models for the Hungarian economy tested 3 years before bankruptcy [%]

Model	1 year	3 years
HU2 DA	**91.51**	84.22
G5 LR	90.48	82.25
G5 DA	90.35	81.70
HU2 LR	87.98	80.99
Altman G	81.75	77.32
Altman HU	79.40	75.17

General models (G5 DA, G5 LR), which are classified in second and third place, are slightly less effective. Their accuracy oscillates around 90%. The lowest ranked models are also the Altman models calculated for Hungary and for the Visegrád countries. The accuracy oscillates between 79–81% in the year before bankruptcy. In this case, both discriminant and logistic regression models are characterized by similar accuracy.

Verification of models for the Visegrád Group

The models allowing the prediction of bankruptcy in the Visegrád economy with the highest accuracy are shown in Table 14. The highest accuracy of the correct recognition of businesses is characterized by the general model G5 LR. The effectiveness of this model is 90.48% in the year before bankruptcy. This model took first place in the Polish economy. The second ranked model is G5 DA whose accuracy is 90.35%. The efficiency of these two models in three years before bankruptcy decreased from 9% to 82.25% for G5 LR and to 81.70% for G5 DA. The third-ranked is model G1 LR. The accuracy of this model equals 88.21%. The G1 LR was only 2% behind the first two ranked models G5 LR and G5 DA. Nevertheless, G1 LR was built on the data from 2011–2012 and verified based on 1300 companies. It should also be pointed out that from 6 to 10 models are marked by higher efficiency than it was demonstrated in the learning sample (Table 9). Verification of models on the test sample answers to the first, second, and fifth research questions. For these questions, the answer is no with some exceptions. For the first question, there is an exception for CZ2 models for the Czech economy, and for the second question, there is an exception for the Polish economy.

Table 14. Results for models for the Visegrád economy tested 3 years before bankruptcy [%]

Model	1 year	3 years
G5 LR	**90.48**	82.25
G5 DA	90.35	81.70
G1 LR	88.21	83.54
G1 DA	86.21	81.03
G3 LR	85.34	81.02
G4 LR	84.10	80.82

4.3. Research on the stability of models over time

Table 15 shows the results of the analysis of the accuracy of the models over time. Only models whose accuracy can be verified in a minimum of three years are shown in the table with one exception for the Czech economy.

Table 15. The verification of selected models over time [in %]

Model	LS	TS	2013	2014	2015	2016	2017	2018	V
PL1 DA	**98**	83	–	–	94.10	75.00	77.60	83.30	25
PL1 LR	**98**	87	–	–	94.40	85.40	84.10	85.70	12
CZ1 DA	86	**93**	–	–	–	–	90.90	94.40	**4**
CZ1 LR	84	91	–	–	–	–	89.60	93.30	**4**
SK1 DA	80	82	–	–	–	82.67	84.34	78.57	**7**
SK1 LR	80	80	–	–	–	81.30	81.90	77.40	**6**
HU1 DA	94	85	–	–	85.30	81.80	86.20	86.20	**5**
HU1 LR	86	87	–	–	84.50	85.70	89.70	89.70	**5**
G1 DA	83	86	84.90	86.50	87.00	79.80	87.60	90.50	13
G1 LR	88	**88**	87.90	87.90	87.40	84.90	90.80	88.40	**7**
G2 DA	88	84	–	–	77.92	80.95	85.94	90.50	16
G2 LR	88	82	–	–	78.57	78.44	82.49	89.30	14
G3 DA	83	82	–	–	–	78.57	82.70	84.17	**5**
G3 LR	92	85	–	–	–	82.99	85.35	87.15	**5**
Altman G	–	81	86.80	74.20	77.00	80.50	85.20	82.60	17

LS – learning sample, TS –test sample, V – volatility, the difference between the highest value and the lowest value in a given period.

None of the constructed models is characterized by the same effectiveness in 2013–2018. The Polish models (12% and 25%), the general models G2 DA (16%), G2 LR (14%), G1 DA (13%), and the Altman G model (17%) are characterized by the greatest variability over time. On the other hand, the lowest variability was found in the remaining models (4–7%). The general model G1 LR is the only model for which the overall accuracy of 88% is the same for both the training and test samples at such a high level and its variability is 7%. A significant difference in the efficiency of the model occurs only in 2016, where it is the lowest, and in 2017, where it is the highest. This part answers the third research question. Besides the Polish models, local models are characterized by lower volatility, but their stability is evaluated only in three years.

4.4. Analysis of ratios in the models

Table 16 presents only those ratios that were selected in half of the models from each country. There is one assumption about the general models, as in half of them none of the indicators were replicated. For this reason, a 40% share of indicators repeated in the models is assumed.

Table 16. The most repeated ratios in the models

Ratio	CZ (4)	HU (6)	PL (6)	SK (6)	V4 (10)	Total
X2	2	4			4	10
X4			5			5
X6	2					2
X27					4	4
X29	2	6				8
X30		4				4
X37	2					2
X40					4	4
X45					4	4
X53	2		4		4	10
X59	2			4		6
X66			4			4

Cz – Czech, HU – Hungarian, PL – Polish, SK – Slovak, V4 – Visegrád countries. In parentheses, the number of models considered are given.

None of the models built on different datasets was constructed based on the same indicators. The exception concerns the indicator X29 constructed for the Hungarian economy (the log of total assets used to measure firm size). The ratios indicated in Table 16 cover all four basic groups of financial indicators for liquidity, profitability, debt, and turnover. The two most common indicators in the models are X2 (debt ratio) and X53 (equity to fixed assets ratio). They appeared in 10 models in three different countries. The indicator used to measure the company's size is in third place. It appears in 8 models in two different countries. This statement answers the fourth research question.

4.5. Comparison of constructed models

In addition to the key analysis of the models' stability over time, the constructed discriminant and logistic regression models were compared. The results are presented in Table 17. Most logistic regression models are characterized by a slightly higher accuracy of correct classification of enterprises than discriminant models (these are differences of up to 7). Both in the year before bankruptcy and the average for the three years before bankruptcy, nine logistic regression models showed higher overall efficiency than discriminant models which include all models constructed for the Polish economy, most for Slovakia, and for V4 countries (general models). However, the differences observed in the percentage of accuracy of models are statistically insignificant. The statistical significance of the differences in the samples was tested using the T-test. This means that the method of constructing models is not statistically relevant in the case of discriminant and logistic regression models. It is worth noting that this result may be strongly influenced by the low number of models, which is important in such tests. This statement answers the last research question.

The following answers to earlier posed questions were obtained in the study:

Table 17. The results for the discriminant and logistic regression models [%]

Model	Discrimant model (1 year)	Logit model (1 year)	Discrimant model (3 years)	Logit model (3 years)
PL1	81.87	**86.73**	80.22	**84.06**
PL2	79.38	**82.47**	75.33	**78.70**
PL3	80.77	**81.08**	**76.01**	69.20
CZ1	**92.81**	91.62	**89.57**	86.54
CZ2	**99.29**	96.93	**95.59**	92.01
SK1	**81.82**	80.17	**77.33**	75.31
SK2	78.79	**85.13**	74.53	**81.94**
SK3	**93.51**	**93.51**	85.44	**87.28**
HU1	84.72	**86.91**	77.61	**81.83**
HU2	**91.51**	87.98	**84.22**	80.99
HU3	**78.57**	70.16	**78.78**	73.02
G1	86.21	**88.21**	81.03	**83.54**
G2	**84.00**	82.77	**78.50**	76.13
G3	82.15	**85.34**	79.67	**81.02**
G4	80.05	**84.10**	76.99	**80.82**
G5	90.35	**90.48**	81.70	**82.25**
SD	No	No	No	No

SD – statistical difference was tested by T-test, 1 year means a year before the bankruptcy, and 3 years means an average of 3 years before the bankruptcy.

1. The constructed models are characterized by much lower accuracy than the permissible 95% with one exception for two models for the Czech economy with the accuracy of 96% and 99%.

2. Except for the Polish economy, the local models are characterized by a higher efficiency of models than the general model which oscillates between 91 and 99%.

3. Local models are characterized by lower volatility (except for the Polish economy) but their stability is assessed only in three years. Moreover, half of the analyzed general models are unstable and another half is stable on the level of local models. A general model G1 LR turned out to be the most stable model taking into account the total accuracy in the training and test sample as well as stability measured in 2013-2018. The accuracy of the model for both the training and the test sample is 88% and its variability is 7%. Therefore, The G1 LR model can be considered as the best model.

4. The same indicators do not appear in any of the models based on different periods of data. The exception only concerns one ratio in the models constructed for the Hungarian economy (X29 — the log of total assets is used to measure firm size).

5. The constructed discriminant and logit models compared to the Altman model performed very well. The accuracy for the Altman model for local countries and in general is much lower than that of the constructed models and is characterized by volatility at the level of 17%.

6. In most cases, logistic regression models have a slightly higher accuracy of the correct classification of SME than the discriminant models. However, the differences observed in the percentage of accuracy between DA and LR models over time are statistically insignificant.

5. Discussion

The financial condition of companies can be checked out by many models. But only those models are useful that foresee bankruptcy relatively far in advance and their total accuracy is stable over time. The study focused on post-communist countries such as the Czech Republic, Hungary, Poland, and Slovakia, and presents 32 bankruptcy prediction models, including 10 general models for SMEs operating in the Visegrád Group of countries for the construction sector (the highest accuracy for each country and V4 oscillates between 86-99%). The models were verified over time from 2013 to 2018. Based on this analysis, the general model G1 LR had the overall accuracy at such a high level which is 88% (average), and its variability is 7%.

Compared to other studies concerning V4 models, there is a limited number of studies concerning the construction of bankruptcy models for the Visegrád Group because models are usually built for one selected country (local purpose). The Altman models are the exception [29]. Kliestik et al. [11] focused on constructing 5 discriminant models (one general model) on data from 2015 to 2016. Their models consist of 8–11 financial ratios (from the original 37 ratios) and achieve the highest accuracy for the Polish economy (88,4%) and for the Visegrád economy (85,7%). The models presented in this study outperform these results. In turn, the research of Durica et al. [4] concerns the construction of the logistic regression model for V4. They focused on data from 2016–2017. Their model consists of 12 out of all 37 financial ratios and the accuracy of the model is equal to 88.1%. They did not check the stability of the model. Therefore, the models presented in this study again outperform these results. The general model G5 LR is characterized by 90,48%. This model cannot be tested over time because it was built on data from 2017 and verified on data from 2018 (the last data available). Furthermore, Altman et al. [2] tested only his models with various modifications on a huge dataset from 31 European and three non-European countries. The accuracy of Altman models was measured by AUC and oscillated around 90% for Poland, 81–84% for the Czech Republic, 74–82% for Hungary, and 77–81% for Slovakia. They do not build the Altman model for the Visegrád Group.

Moreover, it should be pointed out that there is a quite number of studies on local models constructed for a single V4 country. Our results were compared with several recent studies. First, for the Czech Republic, Karas and Srbová [9] created a discriminant model with an accuracy of 77.28% for not-bankrupt and 85.71% for bankrupt enterprises for the construction sector. The dataset was imbalanced with 4,420 SMEs (4,243 non-bankrupt, 177 bankrupt). On the other hand, Karas and Reznakova [8] built two CART models. The models were tested also on an imbalanced sample (570 companies: 511 not-bankrupt and 59 bankrupts). The efficiency of models was 62.62% for not-bankrupt and 91.53% for bankrupt companies. They did not assess the stability of the model and the accuracy of models is lower than in this study (CZ2 DA 99.29%). Second, for Hungary, Tamás [17] assessed Hungarian 1,828 micro-enterprises. The best classification technique in his research was neural network (85% accuracy) and the second best was logistic regression (78%). Furthermore, Nyitrai [19] constructed four models on a sample of 3,370 companies. The discriminant and logit models had the highest accuracy of about 82%. Their research also did not take into account the analysis of model stability and the efficiency of models is lower than in this research (HU2 DA 91.51%). Third, for Poland, Pisula [21] created thirteen models and their validation covered 522 companies (273—bankrupt and 249 not-bankrupt). Ensemble classifiers were characterized by the highest accuracy at the level of 98-99%. The accuracy of logit model also was very high 96.5%. Next, Ptak-Chmielewska [23] built two models the best of which was the support vector machines model with an accuracy of 72.1%. Then, Korol [12] implemented a fuzzy logic in forecasting financial ratios with an accuracy of 90%. The test sample consists of 60 companies. They did not evaluate the stability of the model but the accuracy of the Ptak-Chmielewska [23] and Korol [12] models is higher than that presented in this research (PL1 LR 86.73%). Finally, for Slovakia, Svabova et. al. [25] constructed a discriminant model and they tested its accuracy on a random sample of 1% of the companies from the dataset for 2015 and 2014 (306 companies). The dataset was imbalanced. For prosperous firms, it was 92.43% and 7.57% for other ones. The accuracy of the model was 83.3% in 2015, and 81.3% in 2014. In turn, Kovacova et al. [14] built four models. The models were verified based on 1000 bankrupt and 1000 non-bankrupt companies. The best accuracy was for the probit and logit models, approximately 80% each one. Elsewhere, Kovacova and Kliestik [13] showed that the logit model had 86.7% accuracy. The test data was on 1000 companies. The analysis of model stability was not included in the research, except for the two-year evaluation of the models presented in the work of Svabova et al. [25] and the efficiency of the models was lower than in this study (SK3 LR 93.51%).

However, even though the G1 LR model can be treated as the best one, its efficiency is at 88% which is much lower than the acceptable 95%. Of course in the study, there are two models for the Czech economy with higher accuracy (CZ2 LR 96% and CZ2 DA 99%) but their accuracy has not been verified over time (verified only on data from 2018). When using models, it is important to use them to assess enterprises as accurately as possible, but it is also important that their efficiency is constant over time. On this basis, finding the best model for assessing the financial condition of enterprises still needs to be continued.

6. Conclusions

The paper presents a total of 32 unique models and the verification of their accuracy along with the validation of the Altman model for emerging markets. This paper contributes to the literature on bankruptcy prediction models in two ways. First, the construction of thirty-two bankruptcy prediction models for SMEs operating in the construction industry in Poland (6 models), Czech Republic (4 models), Hungary (6 models), Slovak economies (6 models), and general models for the Visegrád Group (10 models). Half of them were general discriminant models (DA) and the other half were logistic regression models (LR). These models are easy to use, assess, and compare with each other. Therefore, managers can easily include them in monitoring the company's bankruptcy prediction. This can reduce the risk of doing business, and reduce cooperation, with business partners who are characterized by low financial conditions and may have future financial problems. The second contribution of the paper is the analysis of the stability of models over time. The verification of the models was carried out multiple times, as it was performed for each year in the 2013–2018 period. Based on this analysis, the G1 LR model can be considered as the best model. The G1 LR is characterized by relatively high accuracy and stability.

Future research will focus on more sophisticated methods and bigger test samples considering the analyses of the overtime stability of models approximately 10 years, including the COVID period.

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