



ORIGINAL ARTICLE

Citation: Kovacova, M., Kliestik, T., Valaskova, K., Durana, P., & Juhaszova, Z. (2019). Systematic review of variables applied in bankruptcy prediction models of Visegrad group countries. *Oeconomia Copernicana*, 10(4), 743–772. doi: 10.24136/oc.2019.034

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Received: 23.08.2019; Revised: 10.10.2019; Accepted: 3.11.2019; Published online: 25.12.2019

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Systematic review of variables applied in bankruptcy prediction models of Visegrad group countries

JEL Classification: G33; C53

Keywords: *bankruptcy; bankruptcy prediction; variables; countries of Visegrad four*

Abstract

Research background: Since the first bankruptcy prediction models were developed in the 60's of the 20th century, numerous different models have been constructed all over the world. These individual models of bankruptcy prediction have been developed in different time and space using

different methods and variables. Therefore, there is a need to analyse them in the context of various countries, while the question about their suitability arises.

Purpose of the article: The analysis of more than 100 bankruptcy prediction models developed in V4 countries confirms that enterprises in each country prefer different explanatory variables. Thus, we aim to review systematically the bankruptcy prediction models developed in the countries of Visegrad four and analyse them, with the emphasis on explanatory variables used in these models, and evaluate them using appropriate statistical methods

Methods: Cluster analysis and correspondence analysis were used to explore the mutual relationships among the selected categories, e.g. clusters of explanatory variables and countries of the Visegrad group. The use of the cluster analysis focuses on the identification of homogenous subgroups of the explanatory variables to sort the variables into clusters, so that the variables within a common cluster are as much similar as possible. The correspondence analysis is used to examine if there is any statistically significant dependence between the monitored factors — bankruptcy prediction models of Visegrad countries and explanatory variables.

Findings & Value added: Based on the statistical analysis applied, we confirmed that each country prefers different explanatory variables for developing the bankruptcy prediction model. The choice of an appropriate and specific variable in a specific country may be very helpful for enterprises, researchers and investors in the process of construction and development of bankruptcy prediction models in conditions of an individual country.

Introduction

Every enterprise may face the risk of business default. It can have a variety of forms, different course, results and consequences. The consequences, in particular, are the engine of research and development of methods and models that allow predicting failure, to know the probable development of business fundamentals over the next few years.

Therefore, mainly because of the globalization and interdependence of individual national economies, the impact of the termination and bankruptcies of enterprises is more quantitative than in the past (Balcerzak *et al.*, 2018, pp. 51–70). Individual national economies do not operate alone, but rather interact intensively with each other. Based on this, not only businesses, but also the economies of individual countries are increasingly dependent on each other, so a financial crisis of one country can be transferred to another country with a short delay and will soon become global (Ahmad *et al.*, 2018).

Business failures can be identified in the literature by different terms, such as the corporate financial health, bankruptcy, financial difficulties, default, credit risk, ex-ante financial analysis, early warning systems, etc. (Svabova *et al.*, 2018, pp. 16–29). The consequences of failure are the main platform for research and development of methods and models to predict business failure in time, as well as to detect the current financial health of enterprises. In market economies, these consequences have a direct impact not only on the owners, but on all stakeholders involved in the interaction

with the enterprise (Gandolfi *et al.*, 2018, pp. 11–36; Forgassy *et al.*, 2018, pp. 52–66). Managers and corporate analysts use a wide range of tools, algorithms and methods, while the goal of these entities is the same: to predict the future development of the corporate financial health. In case of adverse results, they would have a significant impact on them. Consequently, the bankruptcy prediction models — early warning systems allow identifying the level of the financial health of a company in terms of its past results towards the future. Individual models are based on the assumption that in the development of the company some differences can be found compared with financially sound companies some time before the bankruptcy itself (Popp *et al.*, 2018, pp. 1–15; Blanton, 2018, pp. 52–57; Salaga *et al.*, 2015, pp. 484–489).

The prediction of corporate failure or the financial health of the enterprise has been researched by different authors for decades, and their efforts to predict the future financial situation of the company have brought a large number of different prediction models using several methods and variables (Zvarikova *et al.*, 2017, pp. 145–157). The objective of the paper is to judge and compare the financial ratios used in the bankruptcy prediction models of V4 countries and, as a result, to unveil any dependencies among the prediction models considering the financial variables included in the models and a country of origin. To accomplish the given goal of the study, a scientific question was build:

Is there any dependence between explanatory variables and country of origin in models of Visegrad group countries?

The structure of the presented study is as follows: introduction part followed by a provided literature review to stress out the significance of bankruptcy prediction and models constructed in Visegrad group countries, data and methodology part describing data set of 103 analysed bankruptcy prediction models of Visegrad group countries and research methodology used, namely cluster and correspondence analysis. The following section shows the results of the provided research resulting in the discussion part, which highlights the critique of developed models and a summary of the presented study.

Literature review

Since the first and well-known studies of Fitzpatrick (1932, pp. 598–605), Altman (1968, pp. 589–609) and Beaver (1966, pp. 71–111) numerous studies dedicated to the research of bankruptcy prediction of the enterprise have been developed. There are also various research and review studies

(Ravi Kumar & Ravi, 2007, pp. 1–28; Bellovary *et al.*, 2007, pp. 1–43; Dimitras *et al.*, 1996, pp. 487–513). These models and pieces of research vary from various perspectives. Firstly, each model is developed in the specific condition of the individual country and environment. Secondly, the basic data set usually consists of companies from various economic categories. Thirdly, the main difference is the methodology used for model construction. Therefore, we can conclude that also various explanatory variables were used in these models.

Primarily, univariate analysis was used by Fitzpatrick in 1932 and Beaver in 1966. This was followed by the use of Multiple Discriminant Analysis, which is considered as one of the most popular methods applied for bankruptcy prediction. Another group of popular methods is the application of LOGIT and PROBIT for detection of the probability of default of the company (Kliestik *et al.*, 2019). These methods were followed by mathematical programming methods, such as Linear Programming (Mangasarian, 1965, pp. 444–452; Freed & Glover, 1981, pp. 44–60; Nath *et al.*, 1992, pp. 73–93), Data Envelopment Analysis (Charnes *et al.*, 1978, pp. 429–444; Banker *et al.*, 1984, pp. 1078–1092; Ouenniche & Tone, 2017, pp. 235–250), Linear Goal Programming (LPG) (Gupta *et al.*, 1990, pp. 593–598), Multi-Criteria Decision Aid Approach (MCDA) (Zopoudinis, 1987, pp. 45–67; Zopoudinis & Dimitras, 1998; Zopoudinis & Doumpos, 1999, pp. 197–218).

On the other hand, recent-year-popular methods include artificial intelligence (Sion, 2018, pp. 31–36), Fuzzy Rules-Based Classification Models (Spanos *et al.*, 1999, pp. 1–7), Survival Analysis (Lane *et al.*, 1986, pp. 511–531; Luoma & Laitinen, 1991, pp. 673–678), Decision Trees (Frydman *et al.*, 1985, pp. 269–291; Messier & Hansen, 1988, pp. 1403–1415), Rough Set Analysis (McKee, 2000, pp. 159–173; Slowinski & Zopoudinis, 1995, pp. 27–41; McKee, 2003, pp. 569–589), Genetic algorithms (Divsalar *et al.*, 2012, pp. 504–523; Gordini, 2014, pp. 6433–6445), Neural networks (Odom & Sharda, 1990, pp. 63–68; Kasgari *et al.*, 2013, pp. 927–936), Expert systems (Messier & Hansen, 1988, pp. 1403–1415) and Self-organizing maps (SOM) (Kiviluoto, 1998, pp. 191–201).

The significance of bankruptcy prediction was highlighted and a new wave of interest in this field was awoken mainly after the year 2008 when the global financial crisis appeared (Dixon, 2016, pp. 28–62).

In the Slovak Republic, the prediction of bankruptcy started to be in the spotlight of researchers after the successful transition in 1995, which initiated an institutional evolution proving remarkably robust (Schonfelder, 2003, pp. 155–180). Thereafter, a few studies dealing with the bankruptcy prediction were published (Chrastinova, 1998; Gurcik, 2002, pp. 373–378).

These models were focused on agriculture enterprises applying MDA method. Similarly, Binkert (1999) used MDA, but in this model all Slovak enterprises were included. On the other hand, Hurtosova (2009), Gulka (2016, pp. 5–9) and Delina and Packova (2013) applied LOGIT on enterprises from all sectors of the national economy. Also, Harumova and Janisova (2014, pp. 522–539) applied LOGIT, but on the dataset of Slovak small and medium-sized enterprises. Mihalovic (2016, pp. 101–118) built two national models based on a linear multi-dimensional discriminatory analysis and logit analysis using a balanced sample of bankrupt and non-bankrupt enterprises. Regression analysis for bankruptcy prediction was applied by Valaskova *et al.* (2018, pp. 105–121). Selection of one sector, in this case, Slovak logistics sector, was proposed also by Brozyna *et al.* (2016, pp. 93–114). They proposed four bankruptcy prediction models based on discriminant analysis, logit, decision trees and k-nearest neighbours' method and validated prediction power of these models in comparison with Polish logistic sector. The use of discriminant analysis can be found also in the work of Kliestik *et al.* (2018). Gavurova *et al.* (2017, pp. 370–383) applied in their study not only discriminant analysis, but also decision trees. Using decision trees, they proposed a model with prediction accuracy of almost 85 %, which can be even higher by applying the dynamic approach predictive ability of the decision tree. Logit and Probit application for the prediction of bankruptcy in Slovak companies can be found in the work of Kovacova and Kliestik (2017, pp. 775–791). Other methods were also used in the Slovak Republic, e.g. DEA analysis (Banyiova *et al.*, 2014, pp. 18–25; Rohacova & Kral, 2015), neural networks (Boda, 2009, pp. 3–6), LDA and decision trees (Uradnicek *et al.*, 2016).

In Poland, the research of bankruptcy prediction is deeper and more complex; more than sixty models have been developed, almost all of them were analysed. Firstly, these models were mainly focused on manufacturing enterprises using the multiple discriminant analysis (Maczynska, 1994, pp. 42–45; Pogodzinska & Sojak, 1995; Gajdka & Stos, 1996). Hadasik (1998) applied both MDA and LDA analysis to develop prediction models. Logistic regression is also a popular method used in Polish bankruptcy prediction models. This method was applied to enterprises from all sectors of the national economy in the research of Wrzosek and Ziemba (2009, pp. 1–19). Gruszczynski *et al.* (2005) developed eight models applying LOGIT analysis, but the basic set of enterprises varied. A similar approach was applied by Wedzki (2000, pp. 54–61). Also in the new Polish bankruptcy prediction models MDA and LOGIT were the most popular methods used (Jagiello, 2013; Pociecha *et al.*, 2014). On the other hand, artificial neural networks, genetic algorithms, classification trees or survival analysis using the Cox

model were also used in Poland (Michaluk, 2003; Korol, 2004; Pisula *et al.*, 2013, pp. 7–21; Ptak-Chmielewska, 2016, 98–111). Korol (2010, pp. 1–14) also applied the method of support vectors and fuzzy logic. This concept was also used by Pisula *et al.* (2015, pp. 7–21).

Another analysed country of the Visegrad group is Hungary. In Hungary, as in other post-Soviet countries, the problem of corporate insolvency emerged in the early 1990s. The first models of bankruptcy risk prediction for the Hungarian market were developed by Hajdu and Virag (2001, pp. 28–46) applying both LDA and LOGIT. Virag and Kristof (2005, pp. 403–425) published a paper in which, they built a model using artificial neural networks. Compared to earlier models, it was characterized by higher efficiency, which confirmed the superiority of artificial neural network techniques over linear multidimensional discriminant analysis and logistic regression in predicting the risk of insolvency of enterprises. Similar research was conducted on another sample of companies by Bozsik (2010, pp. 31–39). He built models using linear multidimensional discriminant analysis and artificial neural networks, and compared their efficiency on a validation sample. Later, Virag and Kristof (2014, pp. 419–440) formed models using the techniques of support vector machines and rough set theory. Another extensive research on the bankruptcy prediction of Hungarian small and medium-sized enterprises was conducted by Kristof and Koloszar (2014, pp. 56–73). They estimated their models using the following techniques: linear discriminant analysis, logit analysis, classification trees and artificial neural networks, and then compared the efficiencies of these models with the efficiencies of other Hungarian and foreign models. Similarly, Ekes and Koloszar (2014, pp. 56–73) applied MDA only on the set of manufacturing enterprises. Finally, Bauer and Edrész (2016) built a probit model for bankruptcy prediction of private Hungarian enterprises.

The last country from Visegrad group countries is the Czech Republic. The first attempt to develop a national bankruptcy prediction model was made by Neumaier in 1995 (so-called IN95 model). In the following years, the same authors, having a larger sample of companies, built other national models — IN99, IN01 and IN05. Korab (2001, pp. 359–368) applied a fuzzy logic technique to assess the threat of bankruptcy of the enterprise using both quantitative and qualitative measures as explanatory variables. Dvoracek and Sousedikova (2006, pp. 283–286) applied univariate discriminant analysis, which was followed by multidimensional linear discriminant analysis, logit analysis and artificial neural networks that led to the development of several models, mainly of universal nature. Jakubík and Teplý (2011, pp. 157–176) built a logit model for bankruptcy prediction based on a large sample of non-financial Czech enterprises. Also, Valecky

and Slivkova (2012, pp. 15–26) and Nemeč and Pavlík (2016, pp. 258–253) developed a LOGIT bankruptcy prediction model for Czech enterprises. Kalouda and Vanicek (2013, pp. 164–168) proposed two national bankruptcy prediction models applying linear multiple discriminant analysis. Similarly, Vavrina *et al.* (2013, pp. 1177–1182) applied DEA analysis for model development. Wide research was done also by Karas and Reznakova (2013, pp. 519–531). They built national models using linear multidimensional discriminant analysis and the boosted tree method. Machek *et al.* (2015, pp. 893–902) applied linear discriminant and logit analysis to create bankruptcy prediction models allowing to verify the risk of bankruptcy of enterprises from the cultural sector. Vochozka *et al.* (2015, pp. 109–113) developed several models for predicting the bankruptcy of Czech construction companies using artificial neural networks, having the accuracy of over 90%.

Based on the provided literature review, it can be concluded that in the countries of Visegrad four numerous studies were devoted to the issue of bankruptcy prediction models and more than one hundred models were constructed. These models were built using different methods, but also containing different financial and non-financial indicators or explanatory variables. Therefore, according to the above mentioned, the primary focus in this study is to review systematically the bankruptcy prediction models developed in the countries of Visegrad four with the emphasis on explanatory variables used in these models and analyse them. Thus, based on the cluster and correspondence analysis we can conclude the most appropriate variables, to be used in the individual country.

Research methodology

This section of the study describes the theoretical basis of applied statistical methods, data descriptions and sample design. To fulfil the given goal of the presented study, we provided a systematic review of 103 bankruptcy prediction models developed in countries of Visegrad four, namely the Slovak Republic, Hungary, Poland and the Czech Republic, with the emphasis on explanatory variables used in these models. We analysed the models developed from 1993 to 2018. The initial year of the research is crucial due to: (i) clear assignment of the model either to Slovak or Czech Republic (after the dissolution of Czechoslovakia) and (ii) changed economic conditions after the economic transformation. Applying the cluster analysis and correspondence analysis, the set of explanatory variables used

in the bankruptcy prediction models of the individual country can be determined.

Data description

Firstly, we have identified 103 models constructed in countries of Visegrad four. These models were determined by two general features, first by the number of explanatory variables and second by the method applied for the construction. Table 1 presents the number of models being formed for the bankruptcy prediction in individual countries.

Based on Table 1, it can be seen that most of the analysed models were from Poland, which is caused by two facts: it was in Poland that the largest number of studies were conducted, and it was also there that the research was the deepest. Secondly, we managed to collect all the necessary information about these models, which was a problem to gain correct and detailed information about the models. Therefore, we were forced to exclude these models from our analysis and limit them to 103 models from four all countries in total. Only six models from Hungary were included, which makes them hard to compare and provide some general conclusions. We took into account that limitation of the presented research, but we decided to include these models to accomplish the given goal.

As mentioned in the literature review, the construction of bankruptcy prediction models is done using different statistical methods. Newly constructed models and studies use advanced statistical methods and machine learning models. The research on prediction models in the countries of Visegrad four reveals that authors prefer to use the discriminant analysis, mainly the linear, multiple and quadratic discriminant analysis. This is followed by conditional probability (logit and probit models), neural networks (artificial neural networks, adaptive network-based fuzzy inference system, self-organizing map and fuzzy logic), decision trees (regression trees, REEM, CHAID), data envelopment analysis and some other. Application of these methods in individual countries is shown in Table 2. The analysis of applied methods presents a supplement to accomplish the given goal. Therefore, we do not focus on a comparison of these method respecting their advantages and disadvantages.

The national environment of a country where the bankruptcy prediction model was constructed, with its political, economic and legislative conditions, plays an important role together with the statistical method used for its development. The study aims to focus on and highlight the explanatory variables used in these models. Therefore, Table 3 summarizes the number

of explanatory variables used in the analysed bankruptcy prediction models of Visegrad group countries.

Based on the table, we can conclude that it is optimal to use three to seven variables in the final bankruptcy prediction models. Together, there are 507 financial indicators identified in the models. Some of them are used almost in every study, especially the ones from the earliest studies, some of them are unique. In the presented research, we focus on those financial ratios which appear at least 4 times in all models (30 most frequently used ratios in Visegrad group countries). These variables were used as a basis for the statistical analysis to test the relationship between these variables and countries of origin. Also, using the cluster analysis, we can compare if the designed clusters match with the basic groups of financial ratios.

Method

The provided review and analysis of the bankruptcy prediction models developed in the countries of Visegrad four with the emphasis on explanatory variables used in these models was followed by the application of the cluster and correspondence analysis to examine the relationship between these variables and countries as well as to provide suggestions of the most appropriate variables, to be used in the individual country.

Due to the heterogeneity of the variables obtained in the models, an attempt was to divide these variables into groups with similar assessments. For this purpose, one of the methods of statistical multivariate analysis, namely cluster analysis, was used. This method is one of the so-called interdependency analysis methods, which means that all variables in the analysis are treated as interdependent without their division to dependent (effects) and independent variables (reasons) (Arbolino *et al.*, 2017, pp. 115–123). Cluster analysis allows researchers to sort the objects into clusters so that the objects within a common cluster are as much similar as possible, objects in different clusters are significantly divergent (Guha *et al.*, 2000, pp. 345–366). To use the cluster analysis, the calculations have to meet a few preconditions: i) there are no outliers and no available missing data in the dataset; ii) it is appropriate to have standardized variables and (iii) the results may be negatively influenced by the existence of dependence among the variables (Kaufman & Rousseeuw, 2005). After that, the research was realized in four main stages: selection of variables and adoption of the method of determining similarities between objects (i), selection of the method of assigning given objects to a homogenous group (ii), selection of the number of identified clusters (iii) and interpretation and profiling

of acquired clusters (iv) (Granato *et al.*, 2018, pp. 83–90; Javadi *et al.*, 2017, pp. 27–37).

The choice of the proper measurement method depends on the analyst and the character of the application solved. To cluster the explanatory variables used in bankruptcy prediction models in Visegrad group countries, the authors use the heuristic-based agglomerative hierarchical method of clustering. In the hierarchical approach, we obtain a hierarchical structure of similarities between objects in the form of a tree, called a dendrogram, which illustrates the arrangement of the clusters produced by the analyses (Ward, 1963, pp. 236–244). The hierarchical method was calculated using the Ward's method, which minimizes the heterogeneity of clusters according to the minimum variance criterion. Ward's minimum variance criterion minimizes the total within-cluster variance. At each step, the pair of clusters is found that leads to a minimum increase in the total within-cluster variance after merging. This increase is a weighted squared distance between cluster centres. At the initial step, all clusters are singletons (clusters containing a single point). To apply a recursive algorithm under this objective function, the initial distance between individual objects must be (proportional to) squared Euclidean distance. The initial cluster distances in Ward's minimum variance method are therefore defined to be the squared Euclidean distance between points:

$$d_{ij} = \sqrt{\sum_{k=1}^K (x_{ik} - x_{jk})^2} \quad (1)$$

where: x_{ik} is the value of k -th variable of the i -th object and x_{jk} is the value of k -th variable of the j -th object.

To examine the relationship between variables and countries, taking into account the results of the cluster analysis, the correspondence analysis was used. Correspondence analysis is a descriptive, exploratory technique of multivariate statistical analysis, allowing researchers to define the nature and structure of the relationship between qualitative variables, measured on nominal and ordinal scales. Correspondence analysis belongs to the group of incomplete taxonomic methods (Cygler & Wyka, 2019, pp. 25–45). This technique, as well as multidimensional scaling, principal component analysis of factor analysis, which are frequently used in the validation of scales and syndromes, leads to an increase in the transparency of data and simplifies its interpretation, although at the expense of losing some of the information. The use of statistics and charts specific to that method provides the

researcher with easy, intuitive reasoning on the relationships between the analysed categories of variables (Sourial *et al.*, 2010, pp. 638–646).

Correspondence analysis is a multi-step procedure that starts from the arrangement of the data into the contingency table through the row and column profiles. The primary goal of correspondence analysis is to illustrate the most important relationships among the variables' response categories using a graphical representation (Stevens, 2002). Interpretation of the correspondence map allows the researcher to find diversity within the analysed variables profiles, as well as the co-occurrence of different categories.

The usual purpose of the use of correspondence analysis is to portray these relative frequencies in terms of the distance between individual row and column profiles and the distance to the average row and column profile, respectively, in a low-dimensional space (Hill, 1974, pp. 340–354). The distance is measured using the chi-square metric (Higgs, 1991, pp. 183–194). The chi-square distance between row i and row i' ($i \neq i'$) is given by the equation:

$$d_i = \sqrt{\sum_j \frac{(p_{ij} - p_{i+})^2}{p_{+j}}} \quad (2)$$

where p_{ij} and $p_{i'j}$ are relative frequencies for row i and i' in column j and p_{+j} is the marginal relative frequency, or “mass” as it is called in correspondence analysis, for column j . The weighted sum of the squared chi-square distance between each row profile and the average row profile is the total variance, or “Inertia” (I), of the row variable and is defined as follows:

$$I^2 = \sum_i p_{i+} d_i^2 \quad (3)$$

where p_{i+} is the marginal relative frequency (or mass) of row i and, d_i (Eq. 2) is the chi-square distance between row i 's profile and the average row profile. The closer the points in the correspondence map, the more similar the categories and the stronger their mutual correspondence (Sourial *et al.*, 2010, pp. 638–646).

Results

To test the relationship between explanatory variables detected in the bankruptcy prediction models developed in Visegrad group countries and countries of origin, firstly it was necessary to provide a cluster analysis of these variables. For the purpose of this study, it is important also to investigate these explanatory variables in the context of the frequency of their usage in the bankruptcy prediction models of Visegrad group countries. This is shown in Table 4, where these variables are arranged in the basic groups of financial ratios; ratios of activity, liquidity, profitability and debt. Also according to the cluster analysis, we can compare if the designed clusters match with the basic groups of financial ratios.

According to Table 4, we can summarize that the most important and the most frequently used is the group of profitability ratios, focusing on the assessment of a corporate ability to generate earnings. This is in the mutual correlation with the bankruptcy prediction, while in most countries the enterprise which does not generate earnings is considered as bankrupt. On the other hand, the variable with the highest frequency is the current ratio, which is a liquidity and efficiency ratio that measures a corporate ability to pay off short-term liabilities by its current assets. The fact that the enterprise is not able to pay its short term liabilities signalizes financial problems. The second most significant variable is the liabilities-to-total-assets ratio, from the group of debt ratios. This variable examines how the corporate assets are covered by liabilities. It is also a signal for the enterprise if the value of this variable is high that there are some potential solvency problems, which may result in the corporate's bankruptcy.

Based on Table 4 the cluster analysis was calculated and the dendogram was created (Figure 1).

Dendogram presents the results of clustering of 30 most frequently used explanatory variables and it can be seen that three main clusters are identified. These are presented in Table 5.

Based on the results of cluster analysis, it can be summarized that from the four basic groups of financial ratios only three groups of ratios were designed and these are grouped differently from their original classification. Therefore, these results — clustered groups of explanatory variables create the input data of the correspondence analysis.

Firstly, the contingency table of the correspondence analysis was designed, which represents the frequency of explanatory variables and their use in each country according to designed clusters (Table 6).

To test the basic precondition of the correspondence analysis, the hypothesis of the independence of selected factors (explanatory variables and

countries) has to be tested using the Pearson Chi-square test of independence (Table 7).

Based on the p-value of the test, which is approximately zero, we reject the hypothesis about the independence of the factors (asymptotic significance is lower than the significance level of 1 %). Furthermore, the dependence between the groups of factors is measured by the Cramer's V coefficient, which confirms moderate and statistically significant relation between the explanatory variables and a country, where the prediction model was developed (Table 8).

The results show that it makes sense to explore the internal structure of the contingency table (Table 6) in the correspondence analysis. To explore the mutual relationships among the selected categories, so the connection between row (clusters of explanatory variables) and column (countries of Visegrad group) categories (Table 9).

According to the results presented in Table 9, the score in dimension presents the axes of individual correspondence maps in two-dimensional space (Figure 2a and 2b). The overview of created maps is given by the total inertia, which describes the proportion of column (row) points on the total inertia. The total inertia, in both cases, equals to 1, which proves that two-dimensional correspondence maps are well created and represent the individual categories appropriately.

The results of the correspondence analysis provide factor scores for both row and column points of the contingency table. The co-ordinates of these profiles are used to visualize graphically the association between the row and column elements in the contingency table. Therefore, the result is the individual correspondent map both for row and column profiles. If we overlay both corresponding maps together, then we get the symmetric correspondence map (Figure 3).

The results of the realized cluster and correspondence analyses reveal that the prediction models developed in the Slovak Republic and the Czech Republic use the explanatory variables grouped in the cluster 2, which contains the largest number of variables (11) and consists of four debt ratios, three liquidity ratios, three profitability ratios and one activity ratio. From the mentioned, mostly current ratio, liabilities/total assets ratio, equity/total assets ratio, ROA and cash ratio are used. Prediction models developed in Hungary prefer explanatory variables from cluster 3 and Poland uses explanatory variables from cluster 1 in the process of the prediction models development.

In Hungary, ROE, total revenues/total assets ratio, total assets/liabilities ratio, EBIT/interest expense ratio and quick ratio are mostly used. However, in the case of Hungary, we have to state that only six models were ana-

lysed. Therefore, the sensitivity may be higher in the case of more models from this country.

On the other hand, revenues from sales/total assets ratio, (current assets + accrued assets)/(current liabilities + accrued of liabilities + special funds + accrued revenue) ratio, EBT from sales/operating costs ratio, interest income/(profit from economic activity + interest income) ratio and (equity — share capital)/total assets ratio are used in Polish bankruptcy prediction models. The research results confirm that there is a dependence between the explanatory variables and a country in which they are designed to predict the corporate bankruptcy.

Discussion

In spite of the provided extensive review, calculations and analyses, there are some limitations to the presented research. The primary focus of this study was on the role and use of explanatory variables in the bankruptcy prediction models of Visegrad group countries. Therefore, we limited our research only to four countries and models developed there. Thus, it could be interesting to reveal the importance and significance of explanatory variables also in other European or even American countries and compare the results mutually. It could be also useful to find the impact of the statistical method on the use of the explanatory variable in the prediction models.

On the other hand, respecting gained results, there are a lot of studies and discussions about applicability, usefulness and critique to these models. The critiques formulated in the bankruptcy prediction are focused mainly on the use of financial variables, sampling methods, the lack of non-financial variables and the use of the period. The time series used is an important factor in predicting failure. The researches did not prove that the use of time series variables is better than the one-year variables before bankruptcy. The time period should be carefully chosen because if there are economic changes, besides the financial variables, the model should contain important macroeconomic variables, too (Fejer-Kiraly, 2015).

Various studies try to use financial variables with non-financial variables. Constand and Yazdipour (2011, pp. 185–204) argue that most of the research leaves out the human factor from the variables. They propose to use cognitive psychology and neuron science. Similarly, Altman et al. (2010, pp. 1–33) studied the importance of non-financial variables in SME bankruptcy prediction besides the financial ratios. Their conclusion revealed that the non-financial variables improved prediction accuracy by up to 13%. The same results were concluded in the paper of Gupta *et al.*

(2014, pp. 1–25). They applied hazard function with financial and non-financial variables.

Another feature of bankruptcy prediction models is the sensitivity to the industry because most of the models are constructed for a specific group of companies. Sensitivity of models to industry was investigated by Grice and Dugan (2001, pp. 151–166); Platt and Platt (1990, pp. 31–51), Chava and Jarrow (2004, pp. 537–569), or most recently by Calabrese and Osmetti (2013, pp. 1172–1188) or Karas and Reznakova (2015, pp. 214–223). Results of these studies show that a prediction model designed for specific industry gained higher prediction accuracy to a model which does not include industry-relative variables. Thus, there is a question whether a model which involves companies from a wide range of industries has a significant power to detect future potential problems of individual enterprise. On the other hand, also the selection of enterprises and their proportion in the basic data sample have a substantial impact on the prediction accuracy. These can be removed by the exact proportionate sampling according to the industry or by the development of the bankruptcy prediction model focusing on the particular industry.

Furthermore, the critique also focuses on the sampling or statistical method used while constructing the bankruptcy prediction models. A careful analysis of different methods and models of corporate bankruptcy prediction can leave the impression that these models are not much different from each other. Historically, researchers first suggested the use of statistical models. Availability of computers and technological advancements, particularly since the 1980s, motivated some to invent technology-oriented models. Artificially Intelligent Expert System (AIES) models, for example, emerged as an alternative to classical statistical models, are also popular. They were the result of technological advancement used to transform human intelligence in computers. Since human intelligence was initially inspired by conventional statistical techniques, AIES models employed the characteristics of both univariate and multivariate methodologies. Therefore, the role of statistical models within the theoretic approach cannot be ignored either. The fact is that statistical techniques have their position and status within all types of corporate bankruptcy prediction models and are in use for decades now. Within this category, mainly MDA, logit and probit models based on their predictive performance.

Conclusions

The importance of bankruptcy prediction is indisputable. Each enterprise should deal with the potentiality of business default. This can be caused by various reasons. Management of the enterprise with its activities is in strong correlations with possible default together with the financial indicators and statements. Inefficient management can lead to losses and in the worst case to bankruptcy. Therefore, it is in vital importance to pay attention to this possibility.

The issue of bankruptcy prediction is widely spread worldwide. Various explanatory variables and techniques have been used in the construction of bankruptcy prediction models. In our research, we focus only on bankruptcy prediction models developed in the countries of Visegrad four, namely the Slovak Republic, the Czech Republic, Hungary and Poland. Thus, the main goal of this study was to systematically review and analyse the bankruptcy prediction models developed in these countries with the emphasis on explanatory variables used in these models.

Based on the deep literature review which was provided, we analysed 103 bankruptcy prediction models of Visegrad group countries, focusing on the research methodology and explanatory variables used. Applying cluster analysis on these explanatory variables, three clusters were created, which are used as a basis and input of the following correspondence analysis. Based on the statistical analysis applied, we confirmed that each country prefers different explanatory variables during the process of the bankruptcy prediction model development. The results of the realized cluster and correspondence analyses unveil that prediction models developed in the Slovak Republic and in the Czech Republic use mostly current ratio, liabilities/total assets ratio, equity/total assets ratio, ROA and cash ratio. In Hungary are mostly used ROE, total revenues/total assets ratio, total assets/liabilities ratio, EBIT/interest expense ratio and quick ratio. On the other hand, in Poland bankruptcy prediction models use revenues from sales/total assets ratio, $(\text{current assets} + \text{accrued assets})/(\text{current liabilities} + \text{accrued liabilities} + \text{special funds} + \text{accrued revenue})$ ratio, EBT from sales/operating costs ratio, interest income/(profit from economic activity + interest income) ratio and $(\text{equity} - \text{share capital})/\text{total assets}$ ratio.

Based on the provided calculations, it can be summarized that determined groups of explanatory variables should be used for the development of bankruptcy prediction models in countries of the Visegrad group. The choice of specific financial indicators (predictors) in a specific country may be very helpful for academicians and researchers when developing models in particular economic conditions. Representing such specific circumstanc-

es together with other specificities should lead not only to the development of a model with high prediction accuracy, but also with the long prediction ability.

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Acknowledgements

This work was supported by the science project VEGA 1/0428/17 Creation of new paradigms of financial management at the threshold of the 21st century in conditions of the Slovak republic and Slovak Research and Development Agency under Grant number APVV-14-0841: Comprehensive Prediction Model of the Financial Health of Slovak Companies.

Annex

Table 1. Number of prediction models in individual countries

Country V4	Number of studies	%
Poland	63	61 %
Czech Republic	23	22 %
Slovak Republic	11	11 %
Hungary	6	6 %
TOTAL	103	100 %

Table 2. Method used for construction of the bankruptcy prediction models

Method	Method	Number of studies	%
Discriminant analysis (MDA+LDA+QDA)	DA	51	50%
Conditional probability (Logit+Probit)	PP	36	35%
Neural network (NN+ANN+ANFIS+SOM+FUZZY)	NN	2	2%
Decision trees (Regression Trees+RE-EM+CHAID)	Trees	2	2%
DEA	DEA	2	2%
Others	Other	10	10%
TOTAL		103	100%

Table 3. Number of explanatory variables used in the bankruptcy prediction models

Number of used factors	Number of studies	%
0	2	2%
2	9	9%
3	14	14%
4	30	29%
5	14	14%
6	12	12%
7	12	12%
8	4	4%
9	2	2%
11	2	2%
12	1	1%
17	1	1%
TOTAL*	103	100%

Table 4. Explanatory variables with the frequency of their usage in the bankruptcy prediction models

Activity Ratios		Freq.	Liquidity Ratios		Freq.
Total Revenues/Total Assets		11	Current ratio		28
Total Sales/Total Assets		10	Quick ratio		19
Cash Flow/Total Assets		6	Working Capital/Total Assets		16
Revenues from Sales/Total Assets		7	Cash ratio		16
Inventory/Revenues from Sales*365		5	Working Capital/Fixed Assets (Equity - Share Capital)/Total Assets		5
Total		39	Total		89
Profitability Ratios		Freq.	Debt Ratios		Freq.
ROA		17	Liabilities/Total Assets		26
ROE		12	Equity/Total Assets		18
EBIT/Total Assets		14	Cash Flow/Liabilities		13
Operating Profit/Total Assets		14	Equity/Liabilities		6
EBT from Sales/Operating Costs		6	Total Assets/Liabilities (Current Assets + Accrued Assets)/(Current Liabilities + Accrued of Liabilities + Special Funds + Accrued Revenue)		6
ROS		6	Interest Income/(Profit from Economic Activity + Interest Income)		6
Retained Earnings/Total Assets		5	Cash Flow/Total Liabilities		4
EBIT/Interest Expense		5			
EBT/Total Assets		4			
EBT/Total Sales		4			
EAT/Inventory		4			
Total		91	Total		85

Table 5. Contingency table of the correspondence analysis

Cluster Factor * Country Cross tabulation						
		Czech Republic			Slovak Republic	
		Republic	Hungary	Poland	Republic	
Cluster Factor	Cluster1	0	0	48	0	48
	Cluster2	47	0	87	26	160
	Cluster3	25	11	52	8	96
Total		72	11	187	34	304

Table 6. Created clusters of analyzed explanatory variables

Cluster1		Cluster2		Cluster3	
f14	Revenues from Sales/Total Assets (Current Assets + Accrued Assets)/(Current Liabilities + Accrued of Liabilities + Special Funds + Accrued Revenue)	f1	Current ratio	f11	ROE
f15	EBT from Sales/Operating Costs	f2	Liabilities/Total Assets	f12	Total Revenues/Total Assets
f18	Interest Income/(Profit from Economic Activity + Interest Income)	f4	Equity/Total Assets	f17	Total Assets/Liabilities
f20	(Equity - Share Capital)/Total Assets	f5	ROA	f23	EBIT/Interest Expense
f22	Working Capital/Fixed Assets	f6	Cash ratio	f3	Quick ratio
f25	Inventory/Revenues from Sales*365	f7	Working Capital/Total Assets	f9	Operating Profit/Total Assets
f26	EAT/Inventory	f8	EBIT/Total Assets	f10	Cash Flow/Liabilities
f28	EBT/Total Sales	f13	Total Sales/Total Assets	f16	Cash Flow/Total Assets
f30		f21	Equity/Liabilities	f19	ROS
		f24	Retained Earnings/Total Assets	f29	EBT/Total Assets
		f27	Cash Flow/Total Liabilities		

Table 7. Test of independence of selected variables

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	61.078 ^a	6	0.000
N of Valid Cases	304		

a. 2 cells (16.7%) have expected count less than 5. The minimum expected count is 1.74.

Table 8. Correlation test between explanatory variables and countries

Symmetric Measures			
		Value	Approximate Significance
Nominal by Nominal	Cramer's V	0.317	0.000
	Contingency Coefficient	0.409	0.000
N of Valid Cases		304	

Table 9. Overview of row and column points

Overview Row Points^a									
Cluster Factor	Score in Dimension				Contribution				
	Mass	1	2	Inertia	Of Point to Inertia of Dimension		Of Dimension to Inertia of Point		Total
					1	2	1	2	
Cluster1	0.333	0.775	-0.135	0.065	0.621	0.046	0.988	0.012	1.000
Cluster2	0.333	-0.569	-0.363	0.041	0.335	0.331	0.857	0.143	1.000
Cluster3	0.333	-0.206	0.497	0.015	0.044	0.623	0.294	0.706	1.000
Total	1.000			0.121	1.000	1.000			
a. Symmetrical normalization									
Overview Column Points^a									
Country	Score in Dimension				Contribution				
	Mass	1	2	Inertia	Of Point to Inertia of Dimension		Of Dimension to Inertia of Point		Total
					1	2	1	2	
Czech Republic	0.250	-0.590	-0.064	0.028	0.271	0.008	0.995	0.005	1.000
Hungary	0.250	0.016	0.604	0.012	0.000	0.689	0.002	0.998	1.000
Poland	0.250	0.909	-0.184	0.068	0.642	0.064	0.983	0.017	1.000
Slovak Republic	0.250	-0.335	-0.356	0.013	0.087	0.239	0.684	0.316	1.000
Total	1.000			0.121	1.000	1.000			
a. Symmetrical normalization									

Figure 1. Dendrogram of analyzed explanatory variables

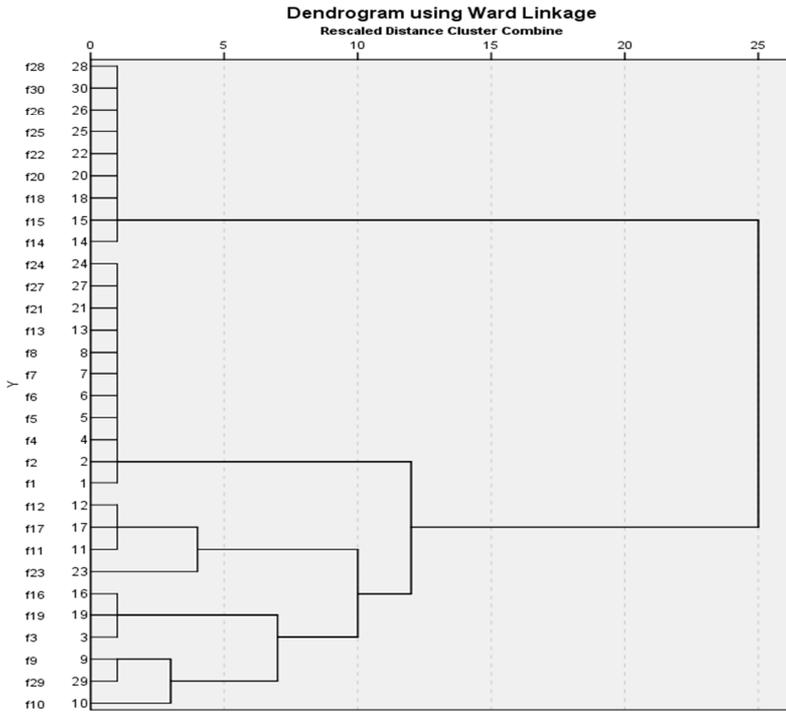


Figure 2. Individual correspondence analysis (a. Clustered explanatory variables, b. Individual countries)

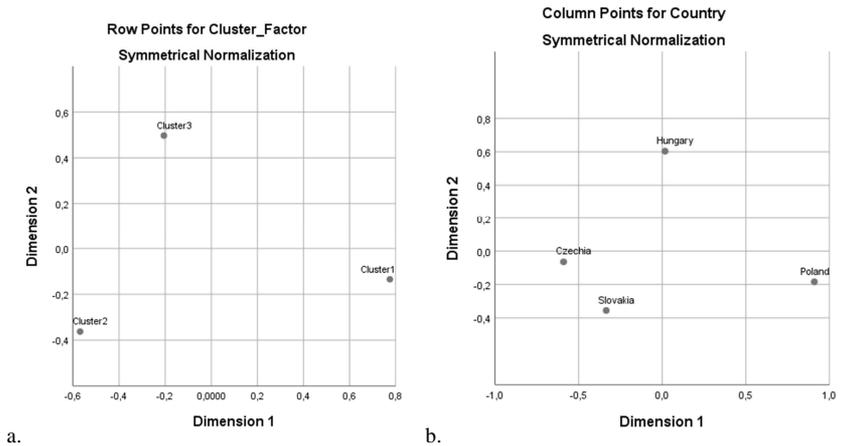


Figure 3. Symmetric correspondence map

