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Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis

JEL Classification: *G17; G33*

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Abstract
Research background: The problem of bankruptcy prediction models has been a current issue for decades, especially in the era of strong competition in markets and a constantly growing number of crises. If a company wants to prosper and compete successfully in a market environment, it should carry out a regular financial analysis of its activities, evaluate successes and failures, and use the results to make strategic decisions about the future development of the business.
Purpose of the article: The main aim of the paper is to develop a model to reveal the unhealthy development of the enterprises in V4 countries, which is done by the multiple discriminant analysis.

Methods: To conduct the research, we use the Amadeus database providing necessary financial and statistical data of almost 450,000 enterprises, covering the year 2015 and 2016, operating in the countries of the Visegrad group. Realizing the multiple discriminant analysis, the most significant predictor and the best discriminants of the corporate prosperity are identified, as well as the prediction models for both individual V4 countries and complex Visegrad model.
Findings & Value added: The results of the research reveal that the prediction models use the combination of same financial ratios to predict the future financial development of a company. However, the most significant predictors are current assets to current liabilities ratio, net income to total assets ratio, ratio of non-current liabilities and current liabilities to total assets, cash and cash equivalents to total assets ratio and return of equity. All developed models have more than 80% classification ability, which indicates that models are formed in accordance with the economic and financial situation of the V4 countries. The research results are important for companies themselves, but also for their business partners, suppliers and creditors to eliminate financial and other corporate risks related to the unhealthy or unfavorable financial situation of the company.

Introduction

The development of a corporate financial situation is an issue of a financial analysis, but it also helps to identify the causes of the corporate development by searching the detail relationship between financial indicators and information. It does not satisfy only with quantifiable information, but also searches non-quantifiable (non-financial) information. A comprehensive view requires to consider a company as an integral part of the economic environment, in which the company is located; for instance, business sector, market position, raw material base, energy demand, supply position (Sedlacek, 2011). It is important, however, to monitor and evaluate not only the current financial situation of the company, but also the future development (see Meluzin *et al*, 2018a, pp. 148–169; Meluzin *et al*, 2018b, pp. 63–79; Meluzin *et al*., 2017, pp. 171–187). The basis of predicting is the knowledge of the current state of the corporate financial health and the development of key indicators, which is forwarded to the next period using predictive models.

Efforts to recognize the causes of instability in the organization at an early stage and to avoid their acute stage led to the formation of specific methods of predictive financial analysis, which are called early warning systems. The role of early warning systems should be to respond to financial distress, which represents the state of the company that is opposed to extreme financial health. Financial distress is usually defined as the state of an enterprise when it has serious payment problems, which must be addressed either by a radical change in its structure or by a change in business activities. An objective criterion of financial stress is often referred to as bankruptcy (Grunwald & Holeckova, 2007, pp. 6).

Methods of the financial situation prediction distinguish, with a reasonable reliability, between the companies that are prosperous and those that do not prosper. However, this activity requires the total financial and economic performance of a company be expressed in a current, concise and, if possible, one-digit expression. To get this discriminator, it is necessary to assume the choice of well-differentiated indicators and methods enabling them to be summarized (Zalai, 2000, pp. 12–14). The paper is focused on the use of the method of multiple discriminant analysis, which in the practical part of the paper used to form the prediction models in conditions of V4 economies. The main aim of the paper is to develop a model to reveal the unhealthy development of the enterprises in V4 countries, which is done by the multiple discriminant analysis.

The originality of the research lies in the formation of the complex model of Visegrad countries, identifying the crucial predictor and determinants than can best discriminate the groups of prosperous and non-prosperous companies. The formation of both individual V4 models and the complex V4 model would be beneficial for all market subject, as it closely reflects the current political, economic and financial situation in the reached countries.

The purpose of the paper is the formation of an econometric model of the corporate financial health, considering national conditions, using the results of the multiple discriminant analysis. We consider the formation of the complex V4 model and subsequent identification of mutual significant predictors and discriminants to be the main contribution of the paper.

The paper is divided into four main parts. Literature review depicts the most important pieces of research being done in the field of prediction models, using the multiple analysis, focused on the Visegrad group (V4). The primary aim and the methodology of the multiple discriminant analysis are determined in Research methodology. Description of the models developed in condition of individual V4 countries and the complex V4 model, as well as their validation by ROC curve are portrayed in chapter Results. Discussion compares and analyzes the studies and research of other authors in the field of prediction models used a developed in V4 countries.

Literature review

The first findings in the field of future financial distress, i.e. future corporate financial development, appeared in the thirties of the 20th century. The first to address the issue was Fitz Patrick when he published a study in 1931, comparing the development of indicators in insolvent and solvent companies. He pointed out that the development of selected corporate indicators differed in both groups of companies long time before the financial distress itself. Merwin (1942) also dealt with the issue when he published research in 1942, which aimed to compare the arithmetic means of selected corporate indicators in successful and unsuccessful companies (Zalai, 2000, pp. 12–14). A little later H. I. Ansoff (Grunwald & Holeckova, 2004, pp. 32) formulated assumptions that strategic failures are indicated by weak signals. The more information we have, the lesser the ignorance, the threat can be identified and the effects localized.

This type of financial analysis, known as an ex-ante analysis, was later developed by Tamari (1966, pp. 15–21) and Beaver (1966, pp. 111–115) and in two years by Altman (1968, pp. 609–611). These authors are also considered the founders of the scientific prediction of the financial health and enterprise future development. The formation of a prediction is an effort to predict the financial development in individual enterprises and to prevent them from financial collapses. The mentioned authors have verified dozens of indicators that they think can be used to predict the insolvency. It is characteristic for the indicators that their level in prosperous or non-prosperous companies is different. Another feature is a divergent development of indicators long before the financial distress.

Altman´s model using multiple discriminant analysis is still considered to be extremely relevant, as evidenced by several of its significant modifications (Altman 1977, 2000, 2002, 2014). The popularity of the model was summed up by Mandru *et al*. (2010, pp. 83–87), based on which the Altman's model is still solid and durable, despite being formed more than 30 years ago. This view was confirmed by other studies (Li & Ragozar, 2012, pp. 19; Satish & Janakiram, 2011, pp. 206; El Khoury & Al Beaino, 2014, pp. 18; Al Khatib & Al Bzour, 2011, pp. 215–217). On the other hand, for instance, Wu *et al.* (2010, pp. 34–45), Grice & Dugan (2001, pp. 151–166) or Pitrova (2011, pp. 76) came to the opposite conclusion. The results of these studies show that the accuracy of the prediction models is significantly reduced when the model is used in another industry, at another time or in a different trading environment than the data used to derive the model. Therefore, it is essential to develop a model for each country, accepting its economic, political and entrepreneurial uniqueness.

Authors and researchers in the field of predictions models have verified dozens indicators, which they think can help to predict the insolvency. For these indicators, it is characteristic that their level in prosperous or non-prosperous enterprises is different as well as the divergent development of indicators long time before the crisis itself. Methods of forecasting a financial situation require the overall financial and economic performance of a firm to be expressed by a current and unambiguous expression. Thus, it is necessary to assume the choice of well-differentiated indicators and method summarizing them (Zalai, 2000, pp. 12–14). Another important thing is to consider the conditions of the national economy, its legislation, operation of financial instruments, but also the external factors, prediction models can indicate the risks, weak and strong points of the financial health of the company.

As the paper is devoted to the use of the method of multiple discriminant analysis to form the prediction models in the conditions of V4 economies, the research interest is aimed at the models formed I the Visegrad group: Chrastinova (1998), Gurcik (2002), Zalai (2000), Gajdka and Stos (1996, pp. 59–63), Prusak (2005), Maczynska (2004, pp. 42–45), Hamrol *et al.* (2004, pp. 34–38), Holda (2001), Virag and Hajdu (1996, pp. 42–53), Doucha (1995) and Neumaierova and Neumaier (1995, pp. 7–10; 1999, pp. 32–75; 2001, pp. 23–39; 2005). Specific conditions in Slovak and Czech environment were searched also by Rybarova *et al.* (2016, pp. 298–306), Karas and Reznakova (2014, pp. 214–223) or Reznakova *et al.* (2013, pp. 203–208) who focus on specific economic areas. The complex review of research into corporate bankruptcy prediction in Visegrad group countries is presented in the study of Prusak (2018); Karas and Reznakova (2018); Kliestikova *et al.* (2017); Zvarikova *et al.* (2017) and Boratynska (2016).

Review of bankruptcy prediction in V4 countries

In the Slovak business environment, there are also some representatives of prediction models. Chrastinová (1998) and Gurcik (2002) were the first authors who applied the methodology of financial health predictions to companies in the agricultural sector, and Binkert (1999) and Zalai (2000) in commercial enterprises, using multiple discriminant analysis. Kamenikova (2005) solved the limitations in the use of foreign models predicting the financial development of enterprises in the conditions of the Slovak Republic. Gundova (2015) depicted the main reasons for not using foreign methods of predicting the financial situation in Slovak companies and emphasized the importance of the formation of the national prediction model. A method for logistic regression to assess the future corporate prosperity was in our national conditions firstly applied by Hurtosova (2009). Later, Delina and Pacikova (2013, pp. 101–112) developed a new modified model in the Slovak business environment while using regression analysis to get higher predictive performance of the model. Mihalovic (2016, pp. 101–

118) formed two models based on multiple discriminant analysis and logit analysis, recommending the use of the latest. Kovacova and Kliestik (2017, pp. 775–791) introduced a bankruptcy prediction model in the Slovak Republic, using logistic regression and they proved significant classification accuracy of this model, Adamko and Svabova (2016, pp. 15–20) tested the Altman´s model on the data of Slovak entities; the prediction ability of the model depends on the model used and year of the quantification. Reznakova and Karas (2015, pp. 397–403) presented the results of their research aimed at the classification ability of prediction models in different environment of Visegrad group countries using the Altman´s model.

In the Czech Republic, the pioneers in the prediction models formation are the Neumaiers, who have developed several models. IN95 (Neumaier & Neumaierova, 1995, pp. 7–10) was the first model achieving more than 70% accuracy in predictions of corporate financial situation. IN99, IN01 and IN05 were further modifications reflecting the national changes. Jakubik and Teply (2011, pp. 157–176) built a logit model to predict the unfavourable financial situation and they formed a new indicator JT index evaluating the economy’s financial stability, which is based on a financial scoring model estimated on Czech corporate accounting data. Hampel *et al.* (2012, pp. 243–248) proposed a model based on a function of production, comparing the results with the Altman´s model. Artificial neural networks are used to form the bankruptcy prediction model by Vochozka *et al.* (2015, pp. 109–113; 2016, pp. 5–18). Kubickova and Nulicek (2017, pp. 494–505) applied regression and try to classify the companies into groups of healthy and after bankruptcy setting the specific national criteria.

Research in the field of bankruptcy prediction in Poland was focused on the use of Altman´s model. The first notable outcomes were presented in the research of Maczynska (1994, pp. 42–45) and Gajdka and Stos (1996, pp. 59–63). The model of Hamrol *et al.* (2004, pp. 34–38), known as Poznanski model is famous for its very good classification and prediction ability of almost 93%. Prusak (2005) suggested two discriminant function, one to predict the bankruptcy one year in advance, the other one forecasts the corporate non-prosperity two years in advance. The discriminant analysis is also used in the model of Holda (2001), Maczynska (2004, pp. 4–9), Korol (2004, pp. 1–14) or Juszczyk and Balina (2014, pp. 67–94). However, not only the discriminant analyses are used to develop the Polish prediction models, some authors use logistic regression, e.g. Pisula *et al.* (2013, pp. 113–133) or Karbownik (2017) or neural networks (Michaluk, 2003).

The Hungarian prediction models do not have a long tradition. The first authors are Hajdu and Virag (2001, pp. 42–53) who developed the model based on the discriminant analysis and logistic regression, using the data of the Hungarian companies from 1990 and 1991. The latest research on the bankruptcy prediction in the Hungarian economic condition was conducted by Andrea and Dorisz (2015, pp. 426–447), Dorgai *et al*. (2016, pp. 341–349) and Bauer and Edrész (2016).

Research methodology

Prediction methods are aimed at comparing financial ratios between prosperous and non-prosperous companies. They are used to predict the difficulties of business entities. In order to provide the most accurate information, they have gone through several modifications. In practice, it was found that not all of the indicators have the same reporting ability, and the use of selected simple ratios provided insufficient and distorted views on the future business development. For this reason, other ratios and indicators were used to achieve higher prediction ability. This introduced prediction models based on more complex, multidimensional statistical methods — multiple discriminant analysis. Therefore, the aim of the contribution is to form a prediction model using multiple discriminant analysis and to verify its classification ability in conditions of business environment of V4 countries.

In multiple discriminant analysis, the objective is to model one quantitative variable as a linear combination of others variables. The purpose of discriminant analysis is to obtain a model to predict a single qualitative dependent variable from one or more independent variable(s). In most cases, the dependent variable consists of two groups or classifications, and we consider the group of defaulting (non-prosperous) companies and non-defaulting (prosperous, healthy) companies. Discriminant analysis derives an equation as linear combination of the independent variables that will discriminate best between the groups in the dependent variable. This linear combination is the discriminant function (Kral & Kanderova, 2009). The objective of the discriminant analysis is to test if the classifications of groups in the dependent variable (Y) depends on at least one of the independent variables (X). In terms of hypothesis, it can be written as:

H0: *Y does not depend on any of the Xi's.*

H1: *Y depends on at least one of the Xi's*.

Business failure can take various forms, different changes and consequences. In particular, the consequences are the engine of the research and development of methods and models to anticipate failure with certain ahead of time. To be able to form a model for V4 countries, it was necessary to have appropriate data base; we used the financial and statistical indicators from the Amadeus database from 2015 (for all independent variables, i.e. for all financial variables) and 2016 (for the dependent variable, i.e. corporate prosperity).

To develop a prediction model in Visegrad countries we work with the following data:

– financial data of following countries: the Slovak Republic, the Czech Republic, Poland, Hungary, Romania, Bulgaria, Lithuania, Latvia, Estonia, Slovenia, Croatia, Serbia, Russia, Ukraine, Belarus, Montenegro and Macedonia.
– a statistical Nomenclature of Economic Activities in the European Community (NACE classification) including the following economic categories: A — agriculture, forestry and fishing; B — mining and quarrying; C — manufacturing; D — electricity, gas, steam and air conditioning supply; F — construction; G — wholesale and retail trade; H — transporting and storage; I — accommodation and food service activities; J — information and communication; N — administrative and support service activities; P — education; Q — human health and social work activities..
– the conditions set out in the Amadeus database were used to determine the size criteria; a large enterprise is considered to be an enterprise that meets at least one of the following conditions: operating revenue ≥ 10 million EUR, total assets ≥ 20 million EUR and employees ≥ 150. A medium-sized enterprise is an enterprise fulfilling at least one of the conditions: operating revenues ≥ EUR 1 million, total assets ≥ EUR 2 million and employees ≥ 15. If the enterprise is not included in any of the previous categories, it is a small enterprise.
– to determine the independent variables used to develop a prediction model, we focused on indicators determined by outstanding authors as the key predictors of financial health. We analyzed the studies and research of Sharifabadi *et al.* (2017, pp. 164–173), Tian *et al*. (2015, pp. 89–100), Bellovary *et al*. (2007, pp. 1–43), Ravi Kumar and Ravi (2007, pp.1–28), Dimitras *et al*. (1996, pp. 487–513) and Kliestik *et al.* (2016, pp. 89–96; 2018, pp. 791–803). Based on the analysis, we selected the following indicators, Table 1.

The listed parameters for all countries and for the relevant time period (2015 and 2016) were obtained from the Amadeus database. Given the lack of required data in individual country variables, some variables had to be excluded from further investigation — financial indicators X03, X05, X06, X13, X14, X17, X19, X23, X28, X29, X31, X32, X33, X34. Subsequently, we deleted the enterprises which did not state the value of the dependent variable, i.e. it was not possible to determine whether an enterprise is prosperous or non-prosperous.

The multiple discriminant analysis consists of the following methodological steps:

1. Choosing a sufficiently large sample that accept some of the rules for determining the appropriate sample size to perform the discriminant analysis. The general agreement is that there should be at least 5 cases for each independent variable, bet at least 20 cases. As we work with more than 2.7 million cases, the condition is met.
2. The tests of equality of group means measure each independent variable' s potential before the model is created. Each test displays the results of a one-way ANOVA for the independent variable using the grouping variable as the factor. If the significance value is greater than the given level of significance (we consider 0.05), the variable probably does not contribute to the model.
3. We identify the value of Box´s M which tests the assumption of equality of variance-covariance matrices in the groups. A high value of Box´s M with a small p-value indicates violation of this assumption.
4. Canonical correlation of discriminant function and test of its statistical significance, which is used to assess the quality of the model and it measures the association between the groups in the dependent variable and the discriminant function. It works with two measures Eigenvalue and Wilk´s lambda. Eigenvalue is a ratio between the explained and unexplained variation in a model. The bigger the eigenvalue, the stronger is the discriminating power of the function. In discriminant analysis, the Wilk's Lambda is used to test the significance of the discriminant functions. Mathematically, it is one minus the explained variation and the value ranges from 0 to 1.s
5. Assessment of the values of the standardized canonical discriminant function coefficients and of correlation coefficients that help identify the best discriminants. The standardized canonical discriminant function coefficients provide information about the discrimination ability of individual indicator; the closer the coefficient to zero, the smaller the impact on the discriminant process. Otherwise, correlation coefficients calculate the strength of the relationship between dependent and independent variables, thus the higher the value the better the discrimination ability of the indicator.

7. Group centroids are the means of the discriminant function scores for each participant group. They show the typical location of an enterprise from a participant group on a discriminant function. The centroids are in a unidimensional space, one centre for each group. SPSS for centroid

calculation uses the model constant to make an intentional correction so that the weighted average of the centroid (weighted by the number of enterprises in the individual groups) is 0. The result is that it is enough to compare the Z-score value to zero — the positive value then means a non-prosperous enterprise, while the negative value determines a prosperous enterprise.

8. The discriminant function is written using the calculated unstandardized canonical discriminant analysis coefficients.
9. The classification and discrimination ability of the model and its validation are verified.
10. The construction of ROC curves to test the classification ability of the model using the area under curve.

We used the IBM SPSS Statistics software, v. 24, to develop the models.

Results

To develop the prediction models, we firstly focus on the models for particular Visegrad countries, then on the formation of the general V4 prediction model.

The data was obtained from the Amadeus database, which provides financial and statistical information about:

- 105,708 Slovak enterprises. Considering the dependent variable, there are two possible future development strategies, prosperity (marked by 0) and non-prosperity (marked by 1). The database of Slovak enterprises is determined by 81,292 prosperous enterprises and 24,416 non-prosperous ones.
- 62,794 Czech companies divided into the group of prosperous companies 50,058 and 12,736 non-prosperous companies;
- 28,908 Polish companies with the majority of prosperous companies 26,210 and 2,698 non-prosperous companies;
- 252,371 Hungarian companies providing the information about 205,448 prosperous companies and 46,923 non-prosperous companies.

The first step to develop the model is to assess the results of the tests of equality of group means, Table 2.

P-values in the Sig. column are compared with the given significance level ($\alpha = 0.05$), if the p-value is below the significance level, there are statistically significant differences between prosperous and non-prosperous enterprises in the mean values of the considered statistical indicators. It means that all variables can be used as the appropriate discriminator, except for:

- X16, X18, X20, X24 and X37 in Slovakia,
- X16, X18, X20 and X24 in the Czech Republic,
- X1, X11, X16, X18, X24, X30 and X37in Poland,
- X11, X12, X16, X18, X20, X24, X30, X36 and X37 in Hungary.

The results indicate, that the conditions in these countries are really similar, as they consider the same discriminators of the prosperity.

The results of the Box test (Table 3) show that the covariance matrices cannot be considered as identical, so we use the assumption of different covariance matrices in SPSS calculation. The log determinants of the variance-covariance matrices of each group are distant.

The following part of the outputs contains a canonical correlation of the discriminant function and a test of its statistical significance (Table 4). They assess the overall quality of the model, whether the canonical discriminatory functions sufficiently differentiate individual groups.

The canonical correlation between the discriminant function and explanatory variables is statistically significant (Sig. $< \alpha$), however, the value of the canonical correlation is relatively low in all four cases.

The results of the absolute values of standardized coefficients of canonical discriminatory function (Table 5) give the information about the discrimination ability of individual indicators to distinguish prosperous and non-prosperous companies. The value of coefficients, which are close to zero, have only very small impact on the discriminant process. Negative values of coefficient contribute to an alternative membership in the group. The results show that the best discriminants are slightly different in individual V4 countries, but the same indicators are repeating. We can summarize that indices X10, X27, X2 and X4 are the ones with the best discrimination ability . The reason is that net income, profit or the level of liabilities in an enterprise are used to calculate these ratios, which, if negative (profit) or exceeding the value of assets (liabilities), indicate an unfavourable situation of the enterprise, which may lead to its future non-prosperity or bankruptcy.

Considering the correlation coefficients between the discriminatory function and the individual explanatory variables, the best discrimination ability seems to have X7, X27 and X10 in Slovakia and Bohemia; X10, X28 in Hungary and Poland. High correlation coefficient value has also X15, which was not used in the final function, as the result of the step method shows, that its contribution after the inclusion of other variables is not sufficient.

For each enterprise, it is possible to calculate the Z-score using non-standardized canonical discriminant coefficients and, comparing its value with the group centroid to decide if the enterprise belongs to a group of prosperous or non-prosperous enterprises. SPSS uses the constant of the model to make a targeted correction when calculating centroids, so that the weighted average of centroids (weighted by the number of enterprises in the individual groups) is zero. Consequently, it is enough to compare the Z-score value to zero, the positive value then determines a non-prosperous enterprise, the negative indicates the prosperous enterprise.

Using the non-standardized coefficients of the canonical discriminant function, the discriminant equations of the predictive model for V4 countries can be written.

The prediction model of Slovakia

$$y_{SK} = -1.565 + 0.025X_2 - 0.408X_4 - 7.663X_7 + 2.268X_{10} - 0.419X_{11} + 0{,}35X_{12} + 0.926X_{15} + 6.082X_{27} + 0.107X_{28} \quad (1)$$

The prediction model of the Czech Republic

$$y_{CZ} = -1.016 + 0.007X_2 - 0.884X_4 + 2.168X_7 - 0.343X_8 + 2.526X_{10} + 0{,}416X_{12} - 0.592X_{21} - 2.561X_{27} + 0.352X_{28} - 1.075X_{35} \quad (2)$$

The prediction model of Poland

$$y_{PL} = -1.563 + 0.075X_2 - 1.388X_4 + 0.658X_7 + 3.001X_{10} - 0.676X_{11} + 1.067X_{12} + 1.043X_{15} - 0.048X_{26} + 0.458X_{28} - 1.213X_{35} \quad (3)$$

The prediction model of Hungary

$$y_H = -1.516 + 0.057X_2 - 1.380X_9 + 3.967X_{10} - 0.681X_{11} + 1.561X_{12} - 1.607X_{21} - 0.051X_{22} - 0.647X_{28} \quad (4)$$

To conclude, the models of individual V4 countries are build using the same variables, financial ratios, but different coefficients. However, some ratios are used in all models (X2, X10, X12 and X28), which indicates the similarities of economic and financial environment of the countries. We find it important to form the unique model used for all Visegrad countries, which has the following discriminant function:

$$y_{V4} = -1.470 + 0.024X_2 - 0.589X_4 - 1.158X_7 + 1.870X_{10} - 0.452X_{11} + 0.613X_{12} + 1.030X_{15} - 0.012X_{22} + 0.731X_{27} + 0.173X_{28} - 0.475X_{35} + 0.244CZ + 0.522SK \quad (5)$$

Variables CZ and SK are dummy variables, which acquire two numerical values to define a certain change or a qualitative variable category. Zero is used when the given variation or category does not occur and one denotes the opposite situation, i.e. the occurrence of a given variation or category (or the presence of a particular observed attribute) (Hebak, 2005). In the case of V4 prediction model, one is used when calculating the Z score of Slovak and Czech enterprises, otherwise zero.

However, for the practical use of the model it is necessary to have sufficient discrimination ability. Based on the classification table (Table 6), it is obvious that the developed models have relatively high total discrimination ability, more than 80%. The best is the discrimination ability of the Polish model, however, the complex V4 model is also highly ranked.

Discussion

Prediction models have become an important and inseparable part of corporate financial analysis. It is important to detect early signs of unpleasant financial situation and to use effective methods to assess the financial state of the companies. The practice in the long-term horizon shows that the use of the models in different time, economic, political and financial environment is disputatious. Thus, the Visegrad countries have tried to develop the models, which could be used in their specific conditions.

As the models were developed to be able to predict the future financial development and prosperity and thus the classification ability to reveal non-prosperous entities is crucial, it is necessary to achieve high level of classification ability in this sphere. The best ability to classify the non-prosperous companies characterizes the Hungarian model (93%), the Slovak model (87.7%), the Czech model (87.3%), V4 model (85.9%) and finally the Polish model (79.1%).

In order to assess the overall performance of the models, the validation of the models was assessed by the ROC curve that evaluates the classification accuracy of the models by the area under curve (AUC). The ROC curves of the prediction models are portrayed in Figure 1. As evident in the figure, the area under the curve is large enough, the AUC value is 0.90 for Slovakia, 0.916 for the Czech Republic, 0.93 for Hungary, 0.894 for Poland and 0.908 for V4 model, indicating a good classification ability off all models, confirming the results in the classification table.

Analysing the results, the classification ability of the model is higher when considering individual national environment. It was proved by Reznakova and Karas (2015, pp. 617–633) performing the test of the discrimination ability of the Altman bankruptcy model using a group of 5,977 companies operating in one of the V4 countries. They found that the discrimination accuracy of a model falls significantly when it is used in a different environment. Considering the national environment and the specificity of individual economy is also highlighted by Szetela *et. al.* (2016, pp. 839–856) as well as Antonowicz (2014, pp. 35–45). On the other hand, the lower discrimination ability can be a results of the method used to derive the model (Karas & Reznakova, 2014). The proof is the research of Mihalovic (2016, pp. 101–118), which reveals that the accuracy of logit and probit models overdo prediction ability of multiple discriminant analysis and logistic regression.

The results indicate that the models should be formed in accordance with the economic and financial conditions and environment of the countries to have the significant classification ability, considering appropriate combination of statistical methods and model variables.

Conclusions

Financial analysis has become an integral part of comprehensive financial management and planning in each business entity. Timely quantification of determinants causing negative financial development is realized by ex-ante financial analysis. The common characteristic is the calculation of selected indicators, which can indicate potential negative development. These indicators are signs of early warning of the future unfavourable financial development of the company. A prerequisite of forecasting is the knowledge of the level and state of relevant indicators that determine the current financial state of the company. Based on this background information and by the application of appropriate prediction models, financial developments and future prosperity can be predicted. A prediction that helps determine the future prosperity or non-prosperity of the company should therefore be accurate, timely and interpret correctly the observed financial facts.

In order to be a successful company in the present dynamic changing economic environment, it is necessary not only to maintain a good corporate financial condition, but also to take care of its financial development in the future. However, the use of retrospective financial methods seems to be ineffective and insufficient. The development of the prediction models accepting the specificities of individual countries is thus of vital importance.

In the present paper, we used the method of multiple discriminant analysis to evaluate the future development enterprises in V4 countries. Using the sample of 449,781 enterprises we formed prediction model for each V4 country and a complex V4 model based on eight to ten predictors (financial indicators). The models are formed using the same combinations of predictor, but different coefficient. However, few of them are included in each model: X2 (current assets to current liabilities ratio), X7 (net income to total assets ratio), X10 (ratio of non-current liabilities and current liabilities to total assets), X12 (cash and cash equivalents to total assets ratio) and X28 (return of equity). The same predictors were determined as the best financial ratios in providing the information about the discrimination ability of individual indicators to distinguish prosperous and non-prosperous companies considering the absolute values of standardized coefficients of canonical discriminatory function. All developed models have more than 80 % classification ability; their validation was proved by ROC curve achieving the level of more than 90% in almost all cases, indicating perfect classification ability of all models. However, the research has some limitation, as the results of the multiple discriminant analysis may not be perceived sufficient, as not compared to other methods (e.g. logistic regression, classification and regression trees), which is the issue for further research, to reveal which method is the most appropriate to predict the financial health of the company.

The main purpose of the paper was the formation of the complex model of Visegrad countries, complex and individual, identifying the crucial predictor and determinants than can best discriminate the groups of prosperous and non-prosperous companies. The formation of both individual V4 models and the complex V4 model would be beneficial for all market subject, as it closely reflects the current political, economic and financial situation in the searched countries.

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Annex

Table 1. Selected financial ratios

Financial Ratios			
X1	Sales/Total assets	X20	Net income/Sales
X2	Current assets/Current liabilities	X21	Non-current liabilities/Total Assets
X3	Gross profit/Total assets	X22	Cash and cash equivalents/Current liabilities
X4	Net income/Shareholders equity	X23	Cash flow/Current liabilities
X5	EBITDA/sales	X24	Working capital/Sales
X6	(Non-current + current liabilities)/EBITDA	X25	Current ratio
X7	Net income/ Total assets	X26	Liquidity ratio
X8	Working capital/Total assets	X27	Return on assets
X9	Operating profit/Total assets	X28	Return on equity
X10	(Non-current + current liabilities)/total assets	X29	Shareholder liquidity ratio
X11	Current assets/Total assets	X30	Solvency ratio (liability-based)
X12	Cash & cash equivalents/Total assets	X31	Cash flow/Operating revenue
X13	Cash flow/Total assets	X32	Net assets turnover
X14	Cash flow/(Non-current + current liabilities)	X33	Interest paid
X15	Current liabilities/Total assets	X34	Gross margin
X16	Current assets/Sales	X35	Profit margin
X17	Operating profit/interest paid	X36	Net current assets
X18	Stock/Sales	X37	Working capital
X19	Cash flow/Sales		

Table 4. Summary of Canonical Discriminant functions

Eigenvalues					
	Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
SK	1	0.074	100.0	100.0	0.263
CZ	1	0.045	100.0	100.0	0.208
PL	1	0.066	100.0	100.0	0.249
H	1	0.051	100.0	100.0	0.220

Wilks' Lambda					
	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
SK	1	0.931	5,030.925	9	0.000
CZ	1	0.957	1,844.708	11	0.000
PL	1	0.938	1,346.199	10	0.000
H	1	0.952	531.344	8	0.000

Table 2. Test of equality of group means for V4 countries

	Slovakia		Czech republic		Poland		Hungary	
Ratio	**Wilks' Lambda**	**Sig.**	**Wilks' Lambda**	**Sig.**	**Wilks' Lambda**	**Sig.**	**Wilks' Lambda**	**Sig.**
X01_2015	1.000	0.000	1.000	0.022	1.000	0.598	0.999	0.005
X02_2015	0.993	0.000	0.998	0.000	0.999	0.000	0.999	0.009
X04_2015	0.982	0.000	0.991	0.000	0.984	0.000	0.990	0.000
X07_2015	0.978	0.000	0.990	0.000	0.987	0.000	0.989	0.000
X08_2015	0.999	0.000	1.000	0.000	0.997	0.000	0.999	0.007
X09_2015	0.983	0.000	0.995	0.000	0.989	0.000	0.988	0.000
X10_2015	0.953	0.000	0.971	0.000	0.964	0.000	0.977	0.000
X11_2015	0.997	0.000	1.000	0.003	1.000	0.978	1.000	0.247
X12_2015	0.995	0.000	0.999	0.000	0.999	0.000	1.000	0.320
X15_2015	0.959	0.000	0.978	0.000	0.975	0.000	0.982	0.000
X16_2015	1.000	0.769	1.000	0.759	1.000	0.819	1.000	0.846
X18_2015	1.000	0.805	1.000	0.939	1.000	0.637	1.000	0.913
X20_2015	1.000	0.867	1.000	0.837	1.000	0.005	1.000	0.956
X21_2015	0.998	0.000	0.997	0.000	0.995	0.000	0.998	0.000
X22_2015	0.995	0.000	0.999	0.000	0.999	0.000	0.999	0.012
X24_2015	1.000	0.765	1.000	0.905	1.000	0.822	1.000	0.913
X25_2015	0.993	0.000	0.998	0.000	0.999	0.000	0.999	0.009
X26_2015	0.993	0.000	0.998	0.000	0.998	0.000	0.999	0.013
X27_2015	0.981	0.000	0.989	0.000	0.987	0.000	0.987	0.000
X28_2015	0.991	0.000	0.992	0.000	0.986	0.000	0.988	0.000
X30_2015	0.999	0.000	0.999	0.000	1.000	0.072	1.000	0.394
X35_2015	0.988	0.000	0.991	0.000	0.988	0.000	0.991	0.000
X36_2015	1.000	0.042	1.000	0.011	1.000	0.005	1.000	0.091
X37_2015	1.000	0.175	1.000	0.006	1.000	0.130	1.000	0.648

Table 3. Box´s test of equality of covariance matrices

	Test Results			
SK	Box's M			73,577.642
	F	Approx.		1,633.675
		df1		45
		df2		135,265,736.122
		Sig.		0.000
CZ	Box's M			31,570.421
	F	Approx.		477.001
		df1		66
		df2		17,657,936.188
		Sig.		0.000
PL	Box's M			9,814.819
	F	Approx.		176.938
		df1		55
		df2		1,617,679.625
		Sig.		0.000
H	Box´s M			1,679.811
		Approx.		46.014
		df1		36
		df2		4,076,602.240
		Sig.		0.000

Table 3. Continued

Log Determinants			
	Y_2016	Rank	Log Determinant
SK	0	9	-21.349
	1	9	-14.572
	Pooled within-groups	9	-19.941
CZ	0	11	-7.162
	1	11	-5.309
	Pooled within-groups	11	-6.347
PL	0	10	-22.728
	1	10	-17.901
	Pooled within-groups	10	-22.165
H	0	8	-11.763
	1	8	-10.733
	Pooled within-groups	8	-11.587

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Table 5. Standardized canonical discriminant function coefficients and correlation coefficients

		St. can. coef.	**Corr. coef**			**St. can. coef.**	**Corr. coef**
SK	**X02_2015**	0.191	-0.302	**H**	**X02_2015**	0.423	-0.112
	X04_2015	-0.425	-0.491		**X09_2015**	-0.213	-0.483
	X07_2015	-1.359	-0.545		**X10_2015**	1.045	0,682
	X10_2015	0.691	0.810		**X11_2015**	-0.187	0.050
	X11_2015	-0.117	-0.199		**X12_2015**	0.335	-0.043
	X12_2015	0.116	-0.267		**X21_2015**	-0.238	0.175
	X15_2015	0.274	0.760		**X22_2015**	-0.248	-0.108
	X27_2015	1.208	-0.512		**X28_2015**	-0.563	-0.481
	X28_2015	0.096	-0.349	**CZ**	**X02_2015**	0.068	-0.206
PL	**X02_2015**	0.498	-0.139		**X04_2015**	-0.661	-0.451
	X04_2015	-0.891	-0,502		**X07_2015**	0.363	-0.467
	X07_2015	0.096	-0.450		**X08_2015**	-0.078	-0.083
	X10_2015	0.760	0.752		**X10_2015**	0.902	0.814
	X11_2015	-0.188	0.001		**X12_2015**	0.117	-0.154
	X12_2015	0.200	-0.114		**X22_2015**	-0.141	-0.162
	X15_2015	0.249	0.616		**X27_2015**	-0.453	-0.504
	X26_2015	-0.264	-0.156		**X28_2015**	0.261	-0.435
	X28_2015	0.311	-0.455		**X35_2015**	-0.174	-0.457
	X35_2015	-0.144	-0.433		**X37_2015**	-0.053	-0.063

Table 6. Classification ability of V4 prediction models

Classification Results						
				Predicted Group Membership		Total
			Y_2016	0	1	
SK	Original	Count	0	65,988	15,304	81,292
			1	2,291	21,425	24,416
		%	0	81.2	18.8	100.0
			1	12.3	87.7	100.0
CZ	Original	Count	0	42,131	7,927	50,058
			1	1,617	11,119	12,736
		%	0	84.2	15.8	100.0
			1	12.7	87.3	100.0
PL	Original	Count	0	23,422	2,788	26,210
			1	565	2,133	2,698
		%	0	89.4	10.6	100.0
			1	20.9	79.1	100.0
H	Original	Count	0	162,305	43,143	205,448
			1	3,290	43,633	46,923
		%	0	79.0	21.0	100.0
			1	7.0	93.0	100.0
V4	Original	Count	0	310,999	52,009	363,008
			1	12,197	74,576	86,773
		%	0	85.7	14.3	100.0
			1	14.1	85.9	100.0

For SK, 82.7 % of original grouped cases correctly classified.
For CZ, 84.8 % of original grouped cases correctly classified.
For PL, 88.4 % of original grouped cases correctly classified.
For H, 81.6% of original grouped cases correctly classified.
For V4, 85.7 % of original grouped cases correctly classified.

Figure 1. ROC curves of the prediction models