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Bankruptcy prediction in the post-pandemic period: A case study of Visegrad Group countries

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Keywords: *bankruptcy; prediction model; multiple discriminant analysis; Visegrad group countries*

Abstract

Research background: Effective monitoring of financial health is essential in the financial management of enterprises. Early studies to predict corporate bankruptcy were published at the beginning of the last century. The prediction models were developed with a significant delay even among the Visegrad group countries.

Purpose of the article: The primary aim of this study is to create a model for predicting bankruptcy based on the financial information of 20,693 enterprises of all sectors that operated in the Visegrad group countries during the post-pandemic period (2020–2021) and identify significant predictors of bankruptcy. To reduce potential losses to shareholders, investors, and business partners brought on by the financial distress of enterprises, it is possible to use multiple discriminant analysis to build individual prediction models for each Visegrad group country and a complex model for the entire Visegrad group.
Methods: A bankruptcy prediction model is developed using multiple discriminant analysis. Based on this model, prosperity is assessed using selected corporate financial indicators, which are assigned weights such that the difference between the average value calculated in the group of prosperous and non-prosperous enterprises is as large as possible.
Findings & value added: The created models based on 6–14 financial indicators were developed using different predictor combinations and coefficients. For all Visegrad group countries, the best variable with the best discriminating power was the total indebtedness ratio, which was included in each developed model. These findings can be used also in other Central European countries where the economic development is similar to the analyzed countries. However, sufficient discriminant ability is required for the model to be used in practice, especially in the post-pandemic period, when the financial health and stability of enterprises is threatened by macroeconomic development and the performance and prediction ability of current bankruptcy prediction models may have decreased. Based on the results, the developed models have an overall discriminant ability greater than 88%, which may be relevant for academicians to conduct further empirical studies in this field.

Introduction

Several prediction models have influenced failures of business entities, denoted by multiple terms, such as prediction of failure (Pervan *et al*., 2018, pp. 269–279), bankruptcy (Kubenka *et al*., 2021, pp. 167–185), financial difficulties (Svabova *et al*., 2020), default (Rybarova *et al*., 2021), credit risk assessment (Oreski & Oreski, 2018, pp. 59–73), and early warning systems (Valaskova *et al*., 2020). The first model developed in this field is the model by Fitzpatrik (1932) who compared 13 ratios of prosperous and non-prosperous enterprises to predict their future financial health. However, the main task of each concept is to predict a crisis, which will ultimately manifest itself in the insolvency of business entities (Balina *et al*., 2021), which can sometimes lead to bankruptcy (Voda *et al*., 2021, pp. 1039–1056).

Saving money and generating funds, enables businesses to deal with financial issues and thus avoid bankruptcy (Durana *et al*., 2022; Kovacova *et al*., 2022, pp. 41–59), which must be predicted carefully (Durana *et al*., 2021, pp. 425-461). Grice and Dugan (2001, pp. 151–166) point out that researchers using models to identify corporate bankruptcy should be cautious because most non-prosperous enterprises do not declare bankruptcy. They may be in financial distress, but not all declare bankruptcy (Nicolescu & Tudorache, 2016, pp. 591–621). Further, Altman and Narayanan (1997, pp. 1–57) claim that the definition of a failed enterprise or business in financial distress may vary depending on the researcher and local conditions. Failure can mean the aforementioned bankruptcy (Stefko *et al*., 2021) as well as non-payment of bonds and loans (Valaskova *et al*., 2021, pp. 167–184), among others.

Svabova and Durica (2019, pp. 359–375) state that prediction models enable, with reasonable reliability, the classification of a business unit into prosperous or non-prosperous enterprises, which requires that the overall financial performance is expressed best in a single number expression. The construction of such a discriminator presupposes the selection of well-differentiating indicators and knowledge of methods that enable their summary (Delina & Packova, 2013, pp. 101–112). However, prior to this, it is necessary to identify the sources of crucial information. According to Erdogan (2013, pp. 1543–1555), most approaches are based on information gathered from business financial accounts, which show the entire reproductive process. Generally, some approaches employ regular financial statements for information, whereas others use financial statements for numerous consecutive accounting periods (Bauer & Agarwal, 2014, pp. 432–442). This procedure ensures the credibility of conclusions and forecasts for further development.

Predictive financial analysis originated in the 1970s (Malhotra, 2021, pp. 549–581). As stated by Kaczmarek *et al*. (2021, pp. 463–498), its creation is determined by an effort to predict financial development in enterprises and prevent possible bankruptcy. According to Jang *et al*. (2021, pp. 3282–3298), individual prediction models focus on comparing financial indicators between financially healthy and unhealthy enterprises. Prediction models, however, have undergone several modifications to provide the most accurate information. In practice, not all the indicators have the same explanatory ability, and using basic ratio indicators results in insufficient and highly biased predictions of the future of the enterprise (Bragoli *et al*., 2022, pp. 156–177). Therefore, prediction models were created and supplemented with indicators with higher predictive abilities (Jandaghi *et al*., 2021, pp. 817–834). Subsequently, prediction models based on multivariate statistical approaches, known as multivariate discriminant analyses, were established to identify characteristics that separate prosperous enterprises from those that are not (Romero *et al*., 2021, pp. 255–288). According to Hiong *et al*.

(2021, pp. 1–12), prediction models are used to forecast the probability of future business failures. In business practice, several prediction models may be used to predict potential financial difficulties in an enterprise if the source of these occurrences is not eliminated.

This study primarily intends to form a bankruptcy prediction model using the financial data of 20,693 enterprises of all sectors located in the Visegrad Group countries and identify significant predictors of corporate bankruptcy. Using multiple discriminant analysis, it is possible to construct a prediction model for each Visegrad Group country and a complex model for the Visegrad Group, considering appropriate financial indicators as predictors. The use of the latest available data, which may help predict the financial stability of enterprises more accurately in the current tough period, is the largest contribution of this study. The creation of the model may bring many helpful insights into how various crises affect these prediction models, which might be obtained by comparing the COVID-19 crisis models with earlier models formed in this environment (in the context of the predictors and their coefficients). Moreover, this is a pioneering research study in the Visegrad region, modeling the financial health of enterprises in the post-pandemic period, and filling the research gap in the development of bankruptcy prediction models and the use of appropriate financial ratios in unstable economic environments. As business insolvencies have risen above pre-pandemic levels (Subran *et al.*, 2022), the value added in this study is the formation of bankruptcy prediction models reflecting the financial performance of enterprises in the crisis period. It is important to investigate the anomalies that arise in businesses that are losing their financial stability, especially as it was observed that bankruptcy risks change over time (Shumway, 2001). It has been proposed that some anomalies in the form of extreme values may diverge from the model's overall end value to the point where they cause the bankruptcy model to evaluate the firm incorrectly. As a result, busi-nesses in bankruptcy may be mistakenly determined as financially stable, or vice versa, businesses with certain extreme values that are otherwise financially solid may be misclassified as businesses in bankruptcy. Nonetheless, the existing bankruptcy prediction models are not satisfactory and should be revalidated under these new conditions, especially in the Visegrad region. As declared by Subran *et al.* (2022), in Central and Eastern European countries, enterprises' double-digit increase in business insolvency during the first part of 2022 underlines the importance of research outputs for the academic community and financial institutions and stakeholders.

The remainder of this study is organized as follows. Given the high level of interest in previously published studies, the next section is the literature review, which is centered on literary research and presents the main conceptual approach to bankruptcy prediction model development. Financial data, which are the main starting point in developing a prediction model with a description of the methodological steps of multiple discriminant analysis, are summarized in the research methodology. The section after it describes the results of the developed model based on different financial ratios, which were employed as input variables in the analysis. In the discussion, the primary findings are described and compared with those of other relevant studies. In addition to the most crucial findings, limitations and scope for future research on this topic are described at the end of this paper.

Literature review

Development of prediction models

Theoretical and empirical studies on corporate bankruptcy developed in the early twenty-first century. Among the many ratio indicators used in ratio analysis, they aimed to choose those that effectively distinguish non-prosperous enterprises from prosperous ones (Dimitras *et al*., 1996, pp. 487–513). Beaver (1966, pp. 71–111), regarded as one of the pioneers of prediction model development, observed the evolution of ratio indicators over time using a one-dimensional discriminant analysis model. When creating a dataset, each non-prosperous enterprise was paired with a prosperous enterprise of about the same size and from the same sector, resulting in pairwise selection. Beaver referred to this method as profile analysis, which, according to the author, is not a prediction model but a practical way to outline the general relationships between prosperous and non-prosperous enterprises.

Altman (1968, pp. 589–609) criticized traditional ratio analysis as being prone to misunderstanding and possibly misleading. In the same study, he presented a breakthrough prediction model that could predict corporate bankruptcy within a specific time. The model, known as the Z-score, was based on multivariate discriminant analysis. In the case of multidimensional discriminant analysis, enterprises are classified based on several indicators (Li *et al.*, 2019, pp. 25–42). It seeks to combine variables in a linear manner that best differentiates prosperous and non-prosperous enterprises (Boratynska & Grzegorzewska, 2018, pp. 175–181). In the past, numerous financial professionals changed their initial concepts with those of Altman (1983). Many later studies focused on the validation of the original and modified Altman models (Kim-Soon *et al.*, 2013, pp. 350–357; Sulub, 2014, pp. 174–184; Meeampol *et al.*, 2014, pp. 1227–1237; Lifschutz & Jacobi, 2010, pp. 130–141) as well as on revising the weights of the indicators to improve the capacity of prosperity forecasts (Grice & Ingram, 2001, pp. 53–61). Based on multivariate discriminant analysis, Daniel (1968), Deakin (1972, pp. 167–179), Blum (1974, pp. 1–25), Bilderbeek (1979, pp. 388–407), Laitinen (1994, pp. 649–673), Lussier *et al*. (1996, pp. 21–36), and many others developed models applicable across enterprise. However, because the distinctiveness of various economic sectors makes it nearly difficult to establish a universal model, several authors focused on developing models primarily applicable to specific areas, for example, a prediction model aimed exclusively at banks was created by Sinkey (1975, pp. 21–36); for manufacturing and distribution enterprises of Great Britain, a model was developed by Earl and Marais (1982), Taffler and Tishaw (1977, pp. 50–54), and Taffler (1983, pp. 295–308). Although multiple discriminant analysis has become the most commonly used method for predicting bankruptcy (Chijoriga, 2011, pp. 132–147), it has many disadvantages in terms of statistical assumptions (Amendola *et al.*, 2017, pp. 355–368), such as linearity (Delina & Packova, 2013, pp. 101–112), normality (Jones & Hensher, 2004, pp. 1011–1038), and independence between variables (Marozzi & Cozzucoli *et al.*, 2016, pp. 40–57). Individual assumptions for multiple discriminant analysis implementations have been frequently questioned in published scientific studies (Joy & Tollefson, 1975, pp. 723–739), similarly to other classical, machine learnings and artificial intelligence models (as each model has its weaknesses), it belongs to the most popular classical statistical models of bankruptcy prediction (Shi & Li, 2019, pp. 114–127; Mihalovic, 2016, pp. 101–118; Kim *et al.*, 2011, pp. 740–745).

However, other methods are also used in the development of prediction models, such as logistic regression, which is the most frequently employed statistical technique. A multivariate method for predicting the likelihood that an event will occur or not, using a collection of independent factors to forecast a binary dependent result, is called logit analysis (Bateni & Asghari, 2020, pp. 335–348). Verma and Raju (2021, pp. 143–154) stated that prediction models created by logistic regression compared with multiple discriminant analysis work with the probability of bankruptcy and generally have no restrictive assumptions for bankruptcy prediction. The first logistic regression model was developed in the late 1980s. The O-score model, a multi-factor financial formula suggested as an alternative to the Altman Z-score for forecasting financial difficulties, is one of the most widely used logistic regression models (Ohlson, 1980, pp. 109–131). Zavgren (1985, pp. 19–45) proposed a logit model for manufacturing firms, whereas Wang (2004) developed a logit model for Internet enterprises. Other studies were carried out by Wertheim and Lynn (1993, pp. 529–546), Ward (1994, pp. 547–561), Platt *et al*. (1994, pp. 491–510), and Becchetti and Sierra (2003, pp. 2099–2120), and others. Similar to these are models based on probit analysis, which is an alternative when modeling categorical dependent variables (Jones *et al*., 2015, pp. 72–85). The ratio for the Zmijewski score, which predicts an enterprise's insolvency in two years, was produced using probit analysis (Zmijewski, 1984, pp. 59–82). The Zmijewski score is derived from variables such as performance, leverage, and financial liquidity. Since the output of the provided prediction models is an estimate of the chance of future corporate bankruptcy, logit and probit models have a straightforward interpretation of the results. As stated by Szetela *et al*. (2016, pp. 839–856), compared to prediction methods based on multivariate discriminant analysis, logit models do not require a normal distribution of independent variables and equality of variance-covariance matrices. In this case, there is no requirement to have two equally large and homogeneous groupings of prosperous and non-prosperous enterprises. In the same period, Black-Scholes-Merton (BSM) models were created, defined as notable differential equations for pricing options contracts (Black & Scholes, 1973, pp. 637–654; Merton, 1974, pp. 449–470). These models assume that the market reflects more information that is potentially more useful for bankruptcy prediction than for accounting. However, the BSM models do not account for changing market and environmental conditions (Wieprow & Gawlik, 2021). However, hazard models, which use accounting and market data, attempt to correct this limitation (Shumway, 2001, pp. 101–124; Hillegeist *et al*., 2004, pp. 5–34).

The development of statistical programs at the end of the last century has expanded the possibilities of empirical research (Kumar & Ravi, 2007, pp. 1–28). The models that emerged during this time, based on observations of thousands of businesses, are generally more effective. The popularity of bankruptcy prediction tools has changed over the past two decades from statistical to intelligent, such as neural networks. One of the earliest studies in which neural networks were employed in bankruptcy prediction models was by Odom and Sharda (1990, pp. 163–168). They used the financial indicators of the Altman model as inputs in the development of the model, and then trained a neural network on a sample of enterprises. Models based on the neural network approach have been developed by Dwyer (1992), Guan (1993), and others. In contrast to conventional statistical methods, new model development techniques do not require any assumptions. Consequently, they can be used with any data, leading to the idea that they operate better than conventional statistical approaches. These techniques, such as genetic algorithms (Varetto, 1998, pp. 1421–1439; Shin & Lee, 2002, pp. 321–328), fuzzy logic (Chen *et al.*, 2009, pp. 7710–7720; Korol, 2018, pp. 165–188), and support vector machines (Min & Lee, 2005 pp. 603–614; Kim & Sohn, 2010, pp. 838–846), have a higher computational complexity and frequently require the use of statistical programs, but they have a higher estimation accuracy for bankruptcy.

The performance of individual models in predicting corporate bankruptcy depends on the input data and the processing technique utilized (Valaskova *et al.*, 2022). These models are built based on empirical data from a particular economy. Only the economy from which empirical data are collected during model development is typically able to use it successfully (Krulicky & Horak, 2021, pp. 38–51). Additionally, it is impossible to regard any one model as immutable or fixed because its predictive ability could be affected by changes in a country's economic conditions.

Current state of the art for Visegrad countries

It is still difficult to estimate bankruptcy risk despite the existence of different models developed using diverse techniques to obtain the best outcomes (Dimitrova *et al.*, 2021, pp. 13–26). In Slovakia, Chrastinova (1998) and Gurcik (2002, pp. 373–378) were among the pioneers in dealing with the creation of a prediction model, applying multiple discriminant analysis to develop a model for agricultural businesses. Hurtosova (2009) was the first to use logistic regression in the Slovak national context to evaluate future corporate prosperity, and Gulka (2016, pp. 5–10) proposed the Slovak logit model. Subsequently, Mihalovic (2016, pp. 101–118) created two prediction models for Slovakia based on discriminant analysis and logistic regression. Gavurova *et al.* (2017, pp. 370–383) investigated the effects of incorporating trend variables on model construction to develop a model that is superior to those currently in use in the Slovak business environment, using decision trees in addition to discriminant analysis. As a result, decision trees were used to suggest a model with a prediction accuracy close to 85%. Kovacova and Kliestik (2017, pp. 775–791) used the logit and probit techniques to develop models for predicting bankruptcy in Slovak enterprises, which implies that the logit-based model somewhat outperforms the classification accuracy of the probit-based model. Boda and Uradnicek (2019, pp. 426–452) contributed to the theory and practice of Slovak corporate finance in this respect by critically evaluating the efficiency of three prediction models used to forecast the financial distress of Slovak agricultural firms. Horvathova and Mokrisova (2014, pp. 46–60), Kliestik *et al.* (2018a, pp. 791–803), Valaskova *et al.* (2018), Svabova *et al.* (2020), Valaskova *et al.* (2020), Kliestik *et al.* (2020, pp. 74–92), and others also dealt with the issue of developing prediction models in the conditions of Slovakia.

Models based on multiple discriminant analysis describing the conditions of the Czech business environment were created with a significant time gap. The Neumaiers, who have created several models, are considered pioneers in the development of prediction models in the Czech Republic (Neumaier & Neumaierova, 1995, pp. 798–810). Korab (2001, pp. 359–368) provided research on the failure of small- and medium-sized businesses in the Czech Republic. The threat of corporate insolvency was evaluated using fuzzy logic, and quantitative and qualitative indicators were included as explanatory variables. The bankruptcy prediction model using univariate discriminant analysis was also created by Dvoracek and Sousedikova (2006, pp. 283–286). To develop prediction models, Dvoracek *et al.* (2008, pp. 33–36; 2012, pp. 525–528) used multidimensional linear discriminant analysis, logit analysis, and artificial neural networks. Jakubik and Teply (2011, pp. 157–176) demonstrated that conventional techniques can be used to evaluate the financial health of the corporate sector. Logistic regression was used to generate a scoring model based on seven variables. Consequently, the JT index was developed as a general measure of the creditworthiness of the Czech corporate sector to estimate the risks of this sector in the future. In the same year, Pitrova (2011, pp. 66–76) applied Altman's model to 37 prosperous and 13 non-prosperous enterprises operating in the Czech Republic, and examined whether there was multicollinearity between indicators and how individual variables affected the final value of the discriminant score of the enterprises. Two national bankruptcy prediction models based on linear multidimensional discriminant analysis, CZ2 and FLKp, were suggested by Kalouda and Vanicek (2013, pp. 164–168). This study compares the reliability of bankruptcy predictions made for domestic enterprises using Altman's original Z-score with the reliability of predictions made for Czech conditions. Machek *et al.* (2015) focused on the creation of a model using linear discriminant analysis and logit analysis for enterprises operating in the cultural sector, which is unique compared to previous research. Vochozka *et al.* (2015, pp. 109–113) focused on transportation and shipping companies using logit analysis. Rudolfova and Skerlikova (2014), Kubickova and Nulicek (2016, pp. 34–41), Kubenka (2018, pp. 516–525), and Karas and Reznakova (2018, pp. 116–130; 2020, pp. 525–535; 2021, pp. 859–883) significantly contributed to the development of bankruptcy prediction under these conditions.

In Poland, pioneering research on predicting bankruptcies of enterprises was conducted using foreign models (Maczynska, 1994, pp. 42–45). Consequently, because of the limited access to the data, it was necessary to perform ratio analysis to form a model, which was followed by multivariate linear discriminant analysis (Wedzki, 2000, pp. 54–61). Hamrol *et al.* (2004, pp. 35–39) created a model known as the Poznanski model, whose classification and prediction abilities reached 96%. However, many others have been developed using discriminant analysis in the context of the Polish business environment with a larger sample size (Appenzeller & Szarzec, 2004, pp. 120–128). Many logit models have been developed (Jagiello, 2013; Karbownik, 2017). Over time, the development of statistical programs has also influenced researchers dealing with the issue of prediction models because many of them have begun to use new methods of creating models, such as artificial neural networks, genetic algorithms, and classification trees (Pisula *et al.*, 2013, pp. 113–133; 2015; pp. 7–21). In addition to universal models, several sectoral models have also been developed. For example, Brozyna *et al.* (2016, pp. 93–114) created a prediction model for enterprises operating in the logistics sector; Jagiello (2013) focused on enterprises operating in the transport, construction, service, commercial, and industrial sectors; and Siudek (2005, pp. 86–91) created a prediction model for cooperative banks.

Bankruptcy prediction models are the subject of numerous publications in Hungary, where insolvency among corporations became a concern in the early 1990s. Hajdu and Virag (1996, pp. 28–46) developed the first bankruptcy prediction model using multidimensional discriminant analysis and financial data from 10,000 economic units. They concluded that all the created models had more than 90% classification accuracy. Virag and Kristof (2005, pp. 403–426) used artificial neural networks to create a different model using the database of the first Hungarian bankruptcy model, which was characterized by higher efficiency. Using the same learning sample from previous studies, Virag and Nyitrai (2013, pp. 227–248) created a model using support vector machines and the rough set theory. Szeverin and Laszlo (2014, pp. 56–73) predicted the failure of Hungarian small- and medium-sized enterprises not only by linear discriminant analysis but also by logit analysis, classification trees, and artificial neural networks. They compared the classification ability of these models with the efficiencies of other Hungarian and foreign models. Several sectoral models have been developed in the Hungarian business environment, including Rozsa (2014, pp. 938–947) for dairy firms, Peto and Rozsa (2015, pp. 801–809) for meat processing enterprises, and Dorgai *et al.* (2016, pp. 341–349) for commercial enterprises. Bauer and Edresz (2016) used a panel probit model to calculate the probability of bankruptcy.

Research methods

The ORBIS database is regarded as a source of business and financial data on more than 400 million private and public enterprises operating worldwide. The financial parameters from this database provided input data for the prediction model development for the Visegrad group countries. The dataset used to create the model contained financial data on 98,933 enterprises operating in Visegrad group countries in 2020 (for all independent variables, i.e., individual financial indicators) and 2021 (for the dependent variable, i.e., the corporate prosperity). However, not all enterprises were suitable for the practical evaluation of financial indicators. Hence, the data obtained from the database had to be appropriately adjusted. Corporations that did not provide all the input data required for the calculation of critical mathematical relationships during the monitored period were removed from the created dataset, reducing the reporting power of the obtained results. After the final adjustments (elimination of unavailable and outlying values), the dataset contained 20,693 enterprises used in the prediction model development.

The completed dataset includes the information required to build a prediction model for Visegrad Group countries. These criteria are outlined in the ORBIS database to calculate firm size characteristics: a very large enterprise satisfies at least one of the following criteria: operational revenue ≥ 100 million euros, total assets ≥ 200 million euros, and number of employees ≥ 1,000. A large enterprise has an operational revenue of 10 million euros, total assets of 20 million euros, and 150 employees. A business is considered medium-sized if it achieves at least one of the following requirements: operating revenue of at least 1 million euros, minimum 2 million euros in total assets, and more than 15 employees. Enterprises that do not fulfill these criteria are considered small enterprises. The final dataset, considering firm size, consisted of 1,296 very large enterprises, 5,576 large enterprises, 12,092 medium-sized enterprises, and 1,729 small enterprises. The ORBIS database also determines the following legal form categories. The final dataset contains 3,744 public limited companies that share capital that can be given to the public, with members solely responsible for the company's obligations up to the amount owed on their shares; 15,960 public limited companies with capital divided into shares that are not available to the general public; 920 partnerships in which at least one partner is personally accountable for corporate debts; and 69 enterprises with other legal forms.

Approaches for predicting financial health enable the classification of business entities into prosperous or non-prosperous enterprises with reasonable accuracy. Consequently, the overall financial performance of the enterprise is expressed concisely, that is, in a single-number expression. The development of such a discriminator requires identification of appropriately discriminating indicators, in addition to knowledge of methods for summarizing them (Horvathova *et al.*, 2021; Cegarra-Navarro *et al.,* 2023). Multivariate discriminant analysis, often known as Z-score analysis, is currently used to develop prediction models. Financial health is evaluated based on several weighted indicators such that the difference between the average value calculated in the group of prosperous and non-prosperous enterprises is as large as possible (Kovacova *et al*., 2019b, pp. 241–251).

Multiple discriminant analysis aims to model one quantitative variable (i.e., a dependent variable) as a linear combination of other variables (i.e., an independent variable). Its main strength is a relatively easy interpretation of between-group differences and reduction of error rates, while it suffers from several assumptions — the analysis is extremely sensitive to outliers, it needs an adequate sample size, multivariate normality, homoscedasticity, independence of observations, and low (non) multicollinearity (Svabova *et al.*, 2022). This method, despite the number of assumptions considered, is frequently used to create bankruptcy prediction models in different conditions (see Wieprow & Gawlik, 2021; Bărbuță-Mișu & Madaleno, 2020; Inam *et al.*, 2019; Kliestik *et al.*, 2018b; etc.). In the current research of Visegrad group environment, the assumptions were complied as indicated in the methodological steps of the research.

Discriminant analysis generates the discriminant function, which is a linear combination of the independent variables that best discriminate between groups in the dependent variable (Peres & Antao 2017, pp. 108–131). The primary objective of discriminant analysis is to determine whether the classification of groups in the dependent variable (Y) is affected by at least one of the independent variables (X). Based on this, the following hypotheses are proposed:

H0: *The dependent variable (Y) does not depend on any independent variable (Xi).*

H1: *The dependent variable (Y) depends on at least one independent variable (Xi).*

While focusing on the indicators highlighted by renowned researchers (e.g., Scott, 1981, pp. 317–344; Dimitras *et al.*, 1996, pp. 487–513; Bellovary *et al.*, 2007, pp. 1–42; Tian *et al.*, 2015, pp. 89–100; Kovacova *et al.*, 2019a, pp. 743–772; Gregova *et al.*, 2020; Kliestik *et al.*, 2020, pp. 74–92), identifying the independent variables that were used to build a prediction model is essential since they serve as the main indicators of financial health. Table 1 summarizes the selected financial indicators and the relationships required for the calculation.

A discriminating model required that individual companies be split into two categories. The first category consisted of businesses with an adequate level of debt but no major financial issues. The second group was composed of highly leveraged businesses that were in serious financial trouble. The regulation of the company in crisis served as the basis for the discriminatory model development. This regulation states that a company is in crisis if its equity-to-debt ratio, a measure of the company's diminishing financial independence and creditworthiness, is less than 0.08 (Kliestik *et al.*, 2020, pp. 74–92; Gregova *et al.,* 2020). If the equity-to-debt ratio is lower than this value, the level of debt is unsuitable and the company is financially unstable. Conversely, if this ratio exceeds this limit, the enterprise will not face serious financial difficulties. The limit value of the equity-to-debt ratio is legislatively given by the Slovak Commercial Code, however, it is important to monitor this ratio to prevent the company from becoming bankrupt, so the same thresh-old value was considered also in other analyzed enterprises as the business environment in these countries is very similarly developed.

Concerning the dependent variable, there are two possible future development strategies: prosperous (marked by 0) and non-prosperous enterprises (marked by 1). The final dataset contains financial and statistical data on the following:

- 8,495 Slovak enterprises divided into the group of 7,547 prosperous enterprises and 948 non-prosperous enterprises;
- 8,073 Czech enterprises with 7,642 prosperous enterprises and 431 non-prosperous ones;
- 432 Polish enterprises consisting of 392 prosperous enterprises and 40 non-prosperous enterprises (the dataset of Polish enterprises is not as robust because of different legislation, the enterprises do not report the same data as other countries, and some indicators could not be computed; however the overall quality of the model was not affected by the number of enterprises as this country was chosen as a reference category in dummy coding).
- 3,693 Hungarian enterprises divided into the group of 3,489 prosperous enterprises and 204 non-prosperous enterprises.

The multivariate discriminant analysis consists of several methodological steps (Ogbogo, 2019, pp. 50–57), which were followed in this study.

1. A suitably large sample that accepts some of the principles of sample size determination needs to be determined. Generally, the dataset should include 5 cases for each independent variable; however, at least 20 cases are suitable. The sample of analyzed variables is sufficiently large, and thus the data is considered approximately multivariate normally distributed (multivariate central limit theorem). If the normality test of a set of companies proves that the data do not come from a mul-

tivariate normal distribution, the significance tests are not valid, which subsequently affects the results of the classification of companies into individual groups (Svabova *et al*., 2022). It is recommended to transform such data so that their distribution approaches a normal distribution. However, a study by some authors showed that the total classification error is not a violation of the assumption of multivariate normality, which is violated, because the classification ability of the model is then underestimated in one group and overestimated in the other group (Sharma, 1996). As this method is highly sensitive to the inclusion of outliers, we run Grubbs′ and Dixon′s tests, and the IQR method to identify the outlying values and eliminate them.

2. Discriminant analysis can predict group membership and identify any significant difference between groups on any of the independent variables, by using group means and ANOVA results. A test of equality of group means was conducted. If the p-value is higher than the chosen significance level, the variable probably does not contribute to the model.
3. Box's M test examines the assumption of equality of variance-covariance matrices in the groups. A large Box's M with a small p-value suggests that this assumption is violated. However, Box's M value is usually high when the sample size is large.
4. The canonical correlation measures the relationship between the groups in the dependent variable and the discriminant function, which utilizes two measurements: Eigenvalue and Wilk's lambda. Eigenvalue, generally known as the characteristic root, is the ratio of the explained to unexplained variance in a model. Large eigenvalues imply superior functionality. Wilk's lambda, which is one minus the explained variation mathematically, is used to determine the relevance of the discriminant functions.
5. Subsequently, the values of the standardized canonical discriminant function and correlation coefficients that help to identify the best discriminants should be evaluated. The standardized discriminant function coefficients are used as multipliers when the variables have been standardized to a mean of 0 and a variance of 1. The closer the coefficient is to zero, the less impact it has on the discriminant function. Otherwise, the correlation coefficients are used to calculate the strength of the link between the dependent and independent variables. The higher the value, the better is the discrimination ability of the indicator.

6. Another technique to interpret discriminant analysis results is to explain each group in terms of its profile using the group means of the predictor variables. In general, for each discriminant function, the group centroids are the mean discriminant scores of each group in the dependent variable. Each group's center is one of the centroids placed in a one-dimensional space. The weighted average of the centroid (weighted by the number of enterprises in the individual groups) is zero because SPSS uses the model constant to make an intended adjustment for centroid calculations. In this situation, the Z-score value may be contrasted to zero; a positive number denotes a less prosperous firm, whereas a negative number denotes a financially healthy company.
7. The unstandardized discriminant function coefficients are used to write down the discriminant function.
8. The classification and discrimination abilities of the model are validated.

Results

Several assumptions must be made to build the model based on the multivariate discriminant analysis (the significance level was set at 5%). Each financial ratio considered was employed as one of the input variables of the multivariate discriminant analysis, and its values were examined to determine whether they might be used as significant determinants.

Since group membership may be predicted using multivariate discriminant analysis, it is necessary to determine whether there are any significant differences between groups for each of the independent variables using group means and data from the ANOVA results. In general, if there are no substantial group differences, it is not worthwhile to continue the investigation according to the tests of equality of group means (Table 2).

The table results clearly show that all variables considered as statistical indicators can be used as the appropriate discriminator, except for those marked in bold.

– X03, X06, X11, and X18 in Slovakia,
– X03, X07, and X11 in the Czech Republic,
– X07, X14, X15, X17, and X18 in Poland,
– X08, X12, X13, and X17 in Hungary.

In multivariate discriminant analysis, the fundamental assumption is that the variance-covariance matrices are identical, in contrast to ANOVA, which assumes that the variances are equal for each group. Box's M evaluates the null hypothesis: there is no difference in the covariance matrices among the dependent groups. To maintain the null hypothesis, this test needs to be non-significant. The log-determinant results are summarized in Table 3. The variance-covariance matrices of each group have different log determinants, but in general, they should be equal.

A non-significant M is considered when using Box's M (Table 4) to test for similarity and the existence of significant differences. The assumption of different covariance matrices was applied in the SPSS calculation because Box's M cannot be regarded as identical. However, a significant result is not regarded as crucial for a large sample.

The following table of the multivariate discriminant analysis output is the eigenvalue table, which provides details on each of the generated discriminant functions (equations). Based on this table, two critical facts can be determined: (i) whether there is statistical significance for the canonical discriminant function (p-value of Wilk's lambda), and (ii) the strength of the canonical correlation. The canonical correlation, which provides an indicator of the overall model fit and is regarded as the amount of variance explained (R2), is the multiple correlation between the predictors and discriminant function. In Table 5, the results of the canonical correlation are summarized mutually with Wilk's lambda, which indicates the significance of the discriminant function. In the Visegrad group countries, the models suggest a statistically significant canonical correlation, although the value of the canonical correlation is relatively low for Slovakia (0.531), the Czech Republic (0.503), and Hungary (0.498). A medium-strong canonical correlation is considered in Poland (0.705), while this canonical correlation value is the best of all monitored Visegrad group countries.

Similar to the multiple regression, the discriminant coefficients (or weights) were interpreted. Table 6 summarizes the relevance of each predictor (the sign represents the direction of the relationship), similar to the standardized regression coefficients (beta's) of the multiple regression. All independent variables varied widely and were considerably different from one another. For all Visegrad group countries, the variable with the best discriminating power is the total indebtedness ratio. This variable stands out as one of the most significant predictors of allocation to enterprises with and without financial difficulties. Slightly worse discriminators are the debt-to-equity ratio (0.225) and return on equity ratio (0,201) for Slovakia, the financial independence ratio (0.158) and return on assets ratio (-0.121) for the Czech Republic, and the credit period ratio (0.497) and net profit margin ratio (0.418) for Poland. Lastly, the debt-to-equity ratio (0.301) and net profit margin ratio (0.213) belong to Hungary.

Table 7 includes the values of the correlation coefficients between the individual independent variables and the discriminant function, which is considered as an alternative method for expressing the relative relevance of the predictors. The correlations between each variable in the model and discriminant functions are shown by the canonical structure matrix, which evaluates correlations and determines how closely a variable is related to each function. While evaluating the correlation coefficients, the total indebtedness ratio is the best discriminator because this ratio and the discriminant function have the highest correlation. Slovakia also has the following discriminators in terms of significance, which are the return on assets ratio (-0.406) and credit period ratio (0.181). The return on assets ratio, with a correlation coefficient value of -0.347 for the Czech Republic, -0.453 for Poland, and -0.426 for Hungary, and the insolvency ratio, whose correlation coefficient value is 0.183 for the Czech Republic, 0.384 for Poland, and 0.390 for Hungary, can be considered as other statistically significant variables. Generally, the threshold between significant and insignificant variables is often set to 0.3.

It is possible to calculate the discriminant score of the prediction model for each enterprise operating in the Visegrad group countries using the non-standardized coefficients of the canonical discriminant function.

The prediction model of Slovakia

$$\begin{aligned} y_{SK} = -2.007 + 3.401X_1 - 0.016X_7 - 1.711X_{10} + 0.005X_{11} + \\ +0.010X_{13} + 0.007X_{14} - 0.054X_{17} \end{aligned} \tag{1}$$

The prediction model of the Czech Republic

$$\begin{aligned} y_{CZ} = -1.905 + 3.684X_1 + 0.001X_2 + 0.018X_5 + \\ +0.004X_6 + 0.135X_7 - 1.039X_{10} + 0.005X_{11} + \\ +0.005X_{12} + 0.002X_{14} + 0.001X_{15} - 0.015X_{17} \end{aligned} \tag{2}$$

The prediction model of Poland

$$y_{PL} = -2.313 + 3.174X_1 + 0.061X_2 + 0.107X_5 + \\ +0.037X_6 - 0.127X_{11} + 0.002X_{16} \quad (3)$$

The prediction model of Hungary

$$y_{HU} = -2.130 + 3.374X_1 + 0.012X_2 + 0.004X_4 + 0.021X_5 + 0.039X_6 + \\ +0.591X_7 - 0.127X_8 + 0.152X_9 - 1.760X_{10} + 0.002X_{15} \quad (4)$$

The coefficients of the discriminant function show how each variable contributes to the discriminant function, which corrects for all the other variables in the equation. The same variables and financial ratios but different coefficients were employed during the formation of the model in the circumstances of the individual Visegrad group countries. Thus, it was necessary to develop a distinctive model adopted by all Visegrad Group countries. Variables SK, CZ, and HU are categorical variables introduced into the discriminant function analysis using dummy variables. Dummy variables take the values 0 or 1 to indicate the absence or presence of some categorical effect. A categorical variable is divided into all of its values, minus one, using dummy variables. In a discriminant analysis, one item is always omitted as the reference group (PL was used as a reference category). The predicted differences in comparison to the reference category are then displayed by the new variables' B-coefficients.

$$y_{V4} = -1.919 + 3.592X_1 + 0.011X_5 - 0.018X_7 - 0.007X_8 + 0.003X_9 - \\ -1.171X_{10} + 0.006X_{11} + 0.002X_{12} + 0.002X_{13} + 0.002X_{14} - \\ -0.043X_{17} + 0.026SK + 0.023CZ + 0.028HU \quad (5)$$

Subsequently, the following table 8 of the output of the discriminant analysis is the classification table, also called the confusion table. The rows of this classification table represent the observed categories of the dependent categories, whereas the columns represent the predicted categories. In general, all the cases lie on the diagonal of the classification table when the prediction is perfect. However, sufficient discriminating ability is required for the model to be used practically. It is evident from the classification table (Table 8) that the developed models have a general level of discrimination that is higher than 88%. The Polish model has the best ability to discriminate because 95.6% of the enterprises were classified correctly into one of two considered groups.

The total indebtedness ratio, which is the proportion of a company's assets financed by debt, is thus an important indicator of corporate debt leverage and measure of financial stability. However, this ratio is used in all models, which indicates the comparable economic and financial environments of the countries.

Discussion

Several prediction models describing the conditions of the business environment are also created with a significant time gap in the Visegrad group countries (Reznakova & Karas, 2015, pp. 617–633; Zvarikova *et al.*, 2017, pp. 145–157; Kliestikova *et al.*, 2017, pp. 221–237; Kliestik *et al.*, 2018b, pp. 569–593; Krajewski *et al.*, 2020, pp. 593–609). Nonetheless, no other bankruptcy prediction model assesses the financial stability of enterprises using the same set of financial indicators, but many financial predictors play a significant role in bankruptcy prediction (see Sousa *et al.*, 2022 or Kliestik *et al.*, 2020, pp. 74–92; Korol, 2019). Alaminos *et al.* (2016) confirmed that the ratios of profitability and liquidity included in the model improve the total accuracy of bankruptcy prediction. The selection of indicators in the Visegrad group models affirms this claim.

Based on discriminant analysis and logistic regression, Mihalovic (2016, pp. 101–118) developed two prediction models for economic conditions in Slovakia. The created model was based on five financial indicators, of which the ratio of current assets to total assets does not discriminate between prosperous and non-prosperous enterprises well because this ratio is not significant. The remaining four variables are significant. According to the author's structural matrix, the current ratio is the best separator in the negative sense. Thus, the higher the current ratio value, the lower the probability of an enterprise failing. The importance of the current ratio is also confirmed by this study, in which this financial indicator was used as an independent variable in the model developed for the Slovak, Czech, and Visegrad group environments.

By critically assessing the effectiveness of the three prediction models developed for foreseeing the financial distress of Slovak agricultural enterprises, Boda and Uradnicek (2019, pp. 426–452) contributed to the theory and practice of Slovak corporate finance. Three variables–gross return on revenue, debt ratio, and days payables outstanding (DPO)–were crucial in predicting financial difficulty. The results confirm these findings, as the debt ratio (X03), indicating the percentage of corporate assets provided via debt, was selected as a significant predictor in the models developed for Polish, Czech, and Hungarian economies. The DPO is a very useful indicator that represents the average number of days needed for a company to pay its suppliers. In this study, a similar indicator was used (X15), and it was proven to be important in the Polish environment, which may be a consequence of a new Polish restructuring law. Considering the gross return on revenues and measuring corporate profitability based on the level of revenue generated, its relevance in bankruptcy prediction was confirmed in the Czech, Hungarian, and Visegrad models. Moreover, return on assets and return on equity also play a significant role in the assessment of corporate financial health.

Kovacova *et al.* (2019a, pp. 743–772) applied cluster and correspondence analyses to reveal the most important financial indicators in the role of explanatory variables considering the prediction models developed in individual Visegrad group countries. They noted that in the Slovak Republic and the Czech Republic, the most frequently used determinants of the financial health of enterprises are the current ratio, liabilities to total assets ratio, equity to total assets ratio, return on assets, and cash ratio. With an exception of the equity to total assets ratio, all indicators are included in the model developed for the Czech Republic, and three of them are also included in the Slovak conditions, which underlines the relevance of the current findings. Moreover, the benefit of using the current liabilities to total assets ratio in the modeling of financial stability is that it is linked to bankruptcy, showing a higher probability of financial collapse when the ratio reaches a larger value (Al-Kassar & Soileau, 2014, pp. 147–155). Kovacova *et al.* (2019a, pp. 743–772) further proved that in Hungary return on equity, total revenue to total assets, total assets to total liabilities, and quick ratio are very important. However, the results of the study were completely different and none of the indicators were confirmed. As indicated by Toth *et al.* (2022), the focus has shifted away from planning and toward analyzing the macroenvironment and corporate financial status as a result of the COVID-19 pandemic, which has changed the complementary roles of planning and analysis of Hungarian enterprises. The same situation also occurred in Poland, which could be an outcome of new legislation, the choice of the financial determinants in the model, and the conditions under which the models were formed (Kitowski *et al.*, 2022).

Tian and Yu (2017, pp. 510–526), based on the adaptive LASSO method, showed that the total debt to total asset ratio is an important predictor of bankruptcy in European countries and Japan. This fact is verified by the current research in Visegrad conditions, where this indicator is the one which is included in each model developed and with the best discriminant ability. Tomczak and Radosinski (2017, pp. 81–97) summarized the ranking of the most popular financial predictors in Central European countries. They indicated some predictors that appear more often than others — equity ratio, debt ratio, and asset turnover ratio. Comparing the models formed during the pandemic, the model developed for all Visegrad countries includes all these variables, in a combination of other predictors, confirming their important role. Ogachi *et al.* (2020) focused on the use of logistic regression to determine the predictors of corporate financial distress and revealed that asset turnover had a positive coefficient, which is in absolute contrast with the results of the current study. This could be explained by the low values of operating revenues and sales achieved during the pandemic, when the business activities of enterprises were significantly limited (Papik & Papikova, 2023; Hertina & Dari, 2022, pp. 272–282; Narvekar & Duha, 2021, pp. 180–195; etc.)

The impact of the financial crisis on bankruptcy prediction was checked and verified in Ptak-Chmielewska (2021, pp. 179–195) mapping the superiority of multidimensional discrimination over conventional linear multivariate discrimination, as demonstrated by support vector machines. The author selected almost similar financial ratios, and the results revealed that current liquidity, gross margin ratio, operating profitability of sales, and asset turnover are the most significant explanatory variables in bankruptcy prediction, proving that the outputs achieved in the Visegrad environment are plausible. Nonetheless, it was confirmed that higher gross margin values are associated with insolvent businesses, which is also an indicator that appears in each developed prediction model. Horvathova and Mokrisova (2018) stressed the importance of return on assets, return on equity, collection period, asset turnover, quick liquidity, and current liquidity ratios in the bankruptcy prediction modeling used in this study, when analyzing the risk of bankruptcy by data Envelopment Analysis in Slovak environment. Comparing the findings of this study with other relevant studies, it can be concluded that low liquidity ratios and annual profitability increase the likelihood of bankruptcy risk (Lukason & Camacho-Minano, 2019).

Conclusions

In addition to evaluating past developments, financial analysis is used to predict the financial health of enterprises. Enterprise creditors are primarily interested in this information. Individual indicators cannot accurately predict financial health development. This problem is precisely eliminated by prediction models, which usually focus on determining a single coefficient, based on which the enterprise can be classified into pre-specified categories. Although summarizing the results of the financial analysis of the enterprise into one synthetic indicator is tempting, these models do not include all the details of enterprises, so their usage is not universal.

The main aim of this study was to form a bankruptcy prediction model based on the financial data of 20,693 enterprises operating in the Visegrad Group countries to predict financial health in post-pandemic, identify the most relevant bankruptcy predictors and thus eliminate potential risks threatening all parties concerned. Using multiple discriminant analyses, a prediction model was created for each Visegrad Group country along with a complex model for the Visegrad Group, with appropriate financial indicators serving as predictors. The created models based on 6–14 indicators were developed using different predictor combinations and different coefficients. For all Visegrad group countries, the best variable with the best discriminating power was the total indebtedness ratio, which was also included in each developed model. This variable stood out as one of the most significant predictors of allocation to enterprises with and without financial difficulties. Slightly worse discriminators were the debt-to-equity ratio and return on assets ratio for Slovakia, the financial independence ratio and return on assets ratio for the Czech Republic, and the credit period ratio and net profit margin ratio for Poland. The debt-to-equity ratio and net profit margin ratio variables belong to the last observed country, Hungary. Generally, sufficient discriminating abilities are required for the model to be used practically Based on the results, the developed models have an overall discriminant ability greater than 88%. This study's major contribution is its utilization of the most recent data, which might assist in more accurate financial stability predictions for companies' post-pandemic.

Additionally, this study fills a research gap in the creation of bankruptcy prediction models in an unpredictable economic environment in the post-pandemic era in the Visegrad area. Business insolvencies have increased above pre-pandemic levels; therefore, the additional value of this research is the development of bankruptcy prediction models that consider how well businesses have performed financially throughout the crisis. However, the current bankruptcy prediction models do not reflect sufficient results and should be revalidated in the context of these new circumstances, particularly in the Visegrad area, where company bankruptcy has increased by double digits. Thus, it highlights the significance of research outputs for the academic community and financial institutions, stakeholders, and other concerned parties. The ability of managers to predict future events and corporate performance and the use of bankruptcy predictors as a foundation for pre-sent decision-making is a vital component of strategic management. In this perspective, one of the primary goals of the majority of commercial enterprises is to survive and be prosperous. As financial insolvency is one of the greatest dangers of corporate existence, bankruptcy prediction is now more crucial than ever before.

Despite the contribution of this study to the extant literature and its practical implications in the context of the accurate estimation of future financial stability and development, the following limitations need to be highlighted. For example, the findings of the multiple discriminant analysis are not sufficient as compared to other methods, such as, logistic regression or neural networks. On the other hand, increasing the number of samples in the training set can improve the predictive ability of the discriminant model. Another limitation of the study is the use of the financial data from the pandemic period, and it is not evident if and how the models' parameters would recover to their pre-crisis settings after the crisis. Future research should be broadened in the context of the specified limitations, and it should also involve further investigation to determine which method provides more accurate and precise outputs when predicting the financial health of enterprises.

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Annex

Table 1. Summarized formulas of financial indicators

	Ratio	Algorithm
X01	Total indebtedness ratio	Current and non-current liabilities to total assets
X02	Debt-to-equity ratio	Current and non-current liabilities to shareholders funds
X03	Interest coverage ratio	Earnings before interest and taxes to interests paid
X04	Debt-to-cash flow ratio	Current and non-current liabilities to cash-flow
X05	Financial independence ratio	Shareholders funds to current and non-current liabilities
X06	Insolvency ratio	Current and non-current liabilities to receivables
X07	Gross profit margin ratio	Operating revenue minus cost of goods sold to operating revenue and sales
X08	Operating profit margin ratio	Earnings before interest and taxes to operating revenue
X09	Net profit margin ratio	Profit after tax to operating revenue
X10	Return on assets ratio	Profit after tax to total assets
X11	Return on equity ratio	Profit after tax to shareholders funds
X12	Cash liquidity ratio	Cash and cash equivalents to current liabilities
X13	Quick liquidity ratio	Current assets minus stocks to current liabilities
X14	Current liquidity ratio	Current assets to current liabilities
X15	Collection period ratio	Debtors to operating revenue and sales*365
X16	Credit period ratio	Creditors to operating revenue and sales*365
X17	Asset turnover ratio	Operating revenue and sales to total assets
X18	Inventory turnover ratio	Operating revenue and sales to stocks

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

Tests of Equality of Group Means								
	SK		CZ		PL		HU	
	Wilks‘ Lambda	Sig.	Wilks‘ Lambda	Sig.	Wilks‘ Lambda	Sig.	Wilks‘ Lambda	Sig.
X01_2020	0.741	0.000	0.767	0.000	0.612	0.000	0.810	0.000
X02_2020	0.999	0.004	0.998	0.000	0.987	0.016	0.962	0.000
X03_2020	1.000	0.114	1.000	0.211	0.975	0.001	0.999	0.026
X04_2020	1.000	0.048	0.999	0.005	0.987	0.018	0.991	0.000
X05_2020	0.998	0.000	0.996	0.000	0.960	0.000	0.996	0.000
X06_2020	1.000	0.874	0.989	0.000	0.879	0.000	0.952	0.000
X07_2020	0.997	0.000	1.000	0.529	1.000	0.983	0.998	0.017
X08_2020	0.998	0.000	0.997	0.000	0.957	0.000	1.000	0.709
X09_2020	0.998	0.000	0.997	0.000	0.954	0.000	0.999	0.044
X10_2020	0.939	0.000	0.961	0.000	0.874	0.000	0.943	0.000
X11_2020	1.000	0.689	1.000	0.220	0.987	0.017	0.999	0.047
X12_2020	0.999	0.009	0.999	0.001	0.990	0.037	0.999	0.065
X13_2020	0.999	0.020	0.999	0.020	0.970	0.000	0.999	0.084

Table 2. Continued

Tests of Equality of Group Means								
	SK		CZ		PL		HU	
	Wilks' Lambda	Sig.	Wilks' Lambda	Sig.	Wilks' Lambda	Sig.	Wilks' Lambda	Sig.
X14_2020	0.999	0.012	0.998	0.000	0.996	0.190	0.998	0.015
X15_2020	0.998	0.000	0.998	0.000	1.000	0.878	0.996	0.000
X16_2020	0.987	0.000	0.999	0.005	0.912	0.000	0.999	0.030
X17_2020	0.996	0.000	0.999	0.001	0.997	0.275	0.999	0.150
X18_2020	1.000	0.912	0.999	0.005	1.000	0.928	0.995	0.000

Table 3. Log determinants table

Test Results				
	SK		CZ	
Y_2021	Rank	Log Determinant	Rank	Log Determinant
0	10	61.972	13	94.561
1	10	28.530	13	58.109
Pooled within-groups	10	51.569	13	72.413
	PL		HU	
Y_2021	Rank	Log Determinant	Rank	Log Determinant
0	7	36.883	12	73.307
1	7	17.147	12	52.357
Pooled within-groups	7	30.105	12	62.698
The ranks and natural logarithms of determinants printed are those of the group covariance matrices.				

Table 4. Box's M test results table

Test Results					
		SK	CZ	PL	HU
Box's M		163,999.583	99,769.759	4,802.047	33,917.105
F	Approx.	2,970.714	1,084.867	160.292	425.849
	df1	55	91	28	78
	df2	8,997,109.749	1,745,181.006	15,941.925	391,631.232
	Sig.	0.000	0.000	0.000	0.000
Tests null hypothesis of equal population covariance matrices.					

Table 5. Eigenvalues and Wilk's Lambda table for Visegrad Group countries

Eigenvalues					
	Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
SK	1	0.394	100.0	100.0	0.531
CZ	1	0.339	100.0	100.0	0.503
PL	1	0.988	100.0	100.0	0.705
HU	1	0.331	100.0	100.0	0.498
Wilk's Lambda					
	Test of Function(s)	**Wilks' Lambda**	**Chi-square**	**df**	**Sig.**
SK	1	0.718	2,817.667	10	0.000
CZ	1	0.747	2,355.700	13	0,000
PL	1	0.516	281.801	7	0.000
HU	1	0.752	1,052.430	12	0.000

Table 6. Standardized canonical discriminant function coefficients table

Standardized canonical discriminant function coefficients							
SK		**CZ**		**PL**		**HU**	
X01_2020	0.930	X01_2020	0.973	X01_2020	0.965	X01_2020	0.808
X02_2020	0.225	X02_2020	0.112	X02_2020	0.297	X02_2020	0.301
X04_2020	-0.040	X04_2020	-0.050	X03_2020	0.115	X03_2020	0.105
X07_2020	-0.075	X05_2020	0.158	X04_2020	-0.205	X04_2020	0.152
X10_2020	-0.176	X06_2020	0.123	X05_2020	0.268	X05_2020	0.176
X11_2020	0.201	X07_2020	0.046	X06_2020	0.249	X06_2020	0.171
X13_2020	0.063	X10_2020	-0.121	X08_2020	-0.239	X07_2020	0.106
X14_2020	0.051	X11_2020	0.054	X09_2020	0.418	X08_2020	-0.155
X16_2020	0.118	X12_2020	0.074	X10_2020	0.007	X09_2020	0.213
X17_2020	-0.150	X14_2020	0.102	X11_2020	-0.326	X10_2020	-0.205
		X15_2020	0.071	X12_2020	-0.085	X15_2020	0.137
		X17_2020	-0.048	X13_2020	0.103	X18_2020	0.124
		X18_2020	0.058	X16_2020	0.497		

Table 7. Structure matrix table

Structure matrix							
SK		**CZ**		**PL**		**HU**	
X01_2020	0.943	X01_2020	0.947	X01_2020	0.823	X01_2020	0.842
X02_2020	0.050	X02_2020	0.080	X02_2020	0.120	X02_2020	0.347
X03_2020[a]	-0.051	X03_2020[a]	-0.060	X03_2020[a]	-0.221	X03_2020	0.064
X04_2020	-0.034	X04_2020	-0.054	X04_2020	-0.118	X04_2020	0.168
X05_2020[a]	-0.097	X05_2020	-0.109	X05_2020	-0.210	X05_2020	-0.112

Table 7. Continued

Structure matrix							
SK		CZ		PL		HU	
X06_2020[a]	0.010	X06_2020	0.183	X06_2020	0.384	X06_2020	0.390
X07_2020	-0.085	X07_2020	0.012	X07_2020[a]	-0.060	X07_2020	0.069
X08_2020[a]	-0.058	X08_2020[a]	-0.118	X08_2020[a]	-0.240	X08_2020	0.011
X09_2020[a]	-0.057	X09_2020[a]	-0.109	X09_2020[a]	-0.266	X09_2020	0.058
X10_2020	-0.406	X10_2020	-0.347	X10_2020[a]	-0.453	X10_2020	-0.426
X11_2020	0.007	X11_2020	0.023	X11_2020	-0.119	X11_2020[a]	-0.001
X12_2020[a]	-0.053	X12_2020	0.062	X12_2020[a]	-0.094	X12_2020[a]	-0.026
X13_2020	-0.040	X13_2020[a]	0.049	X13_2020[a]	-0.196	X13_2020[a]	-0.034
X14_2020	-0.043	X14_2020	0.079	X14_2020[a]	-0.050	X14_2020[a]	-0.081
X15_2020[a]	0.079	X15_2020	0.067	X15_2020[a]	0.083	X15_2020	0.112
X16_2020	0.181	X16_2020[a]	0.074	X16_2020	0.321	X16_2020[a]	0.062
X17_2020	-0.096	X17_2020	0.062	X17_2020[a]	-0.053	X17_2020[a]	0.042
X18_2020[a]	-0.012	X18_2020	0.054	X18_2020[a]	0.057	X18_2020	0.125

Notes: Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.
[a] This variable not used in the analysis.

Table 8. Classification results table

Classification Results						
				Predicted Group Membership		
			Y_2021	non-prosperous	prosperous	Total
SK	Original	Count	non-prosperous	839	109	948
			prosperous	853	6,694	7,547
		%	non-prosperous	88.5	11.5	100.0
			prosperous	11.3	88.7	100.0
CZ	Original	Count	non-prosperous	380	51	431
			prosperous	532	7,110	7,642
		%	non-prosperous	88.2	11.8	100.0
			prosperous	7.0	93.0	100.0
PL	Original	Count	non-prosperous	2	13	40
			prosperous	6	386	392
		%	non-prosperous	67.5	32.5	100.0
			prosperous	1.5	98.5	100.0
HU	Original	Count	non-prosperous	179	25	204
			prosperous	292	3,197	3,489
		%	non-prosperous	87.7	12.3	100.0
			prosperous	8.4	91.6	100.0

Table 8. Continued

Classification Results						
				Predicted Group Membership		
			Y_2021	non-prosperous	prosperous	Total
V4	Original	Count	non-prosperous	1,455	168	1,623
			prosperous	1,983	17,087	19,070
		%	non-prosperous	89.6	10.4	100.0
			prosperous	10.4	89.6	100.0

For SK, 88.7 % of original grouped cases correctly classified.
For CZ, 92.8 % of original grouped cases correctly classified.
For PL, 95.6 % of original grouped cases correctly classified.
For HU, 91.4 % of original grouped cases correctly classified.
For V4, 89.6 % of original grouped cases correctly classified.