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Is it possible to build a stable ex-ante bankruptcy prediction model for Visegrad Group companies? A multi-year approach

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Abstract. Corporate bankruptcies pose significant challenges, impacting a wide range of stakeholders. While valuable, existing research on bankruptcy prediction primarily focuses on ex-post analysis, identifying financial indicators associated with past failures. This approach offers limited utility in proactively mitigating the negative consequences of future corporate distress. This study addresses this critical gap by developing ex-ante bankruptcy prediction models for the Visegrad Group countries. Employing Multiple Discriminant Analysis, these models are aimed at identifying companies at risk of bankruptcy up to five years before the event. A multi-model approach is utilized to construct a comprehensive V4 model that encompasses all four nations and develop individual models for each member country. Data from a sample of 25,084 companies incorporates 15 key financial ratios and 5 non-financial variables. The ratios differ significantly between bankrupt and solvent companies, and each model is calibrated with a single cut-off that caps the in-sample Type II error at 10%. Ex-ante evaluation, however, shows that this restriction does not halt the erosion of correct identification of failed firms. Rather, it drops from 90% in the test year to about one-third at a five-year horizon, even though classification of healthy firms

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remains above 95% and overall accuracy stays above 92%. The V4 model performed well, indicating that companies across the region share similar financial characteristics. Notably, two financial ratios, Net Income to Total Liabilities / Total Assets (X06) and Net Income / Total Assets (X04), consistently proved to be reliable indicators of financial health in all the examined models. These ratios are important because they help identify companies with strong financial stability across the V4 countries.

Keywords: bankruptcy, ex-ante prediction model, multiple discriminant analysis, Visegrad Group countries

JEL Classification: G33, C54

1. INTRODUCTION

The consequences of corporate bankruptcies serve as a powerful motivator for developing methods and models that can predict bankruptcy well in advance. Bankruptcy prediction models, functioning as early warning systems, offer a valuable tool for assessing a company's financial situation and gauging its future prospects. These models leverage the assumption that financially troubled companies often exhibit unique patterns in their financial performance compared to healthy businesses, even before a bankruptcy event occurs. Researchers have dedicated decades to developing and refining bankruptcy prediction models, resulting in many approaches. However, these models often vary in methodology, explanatory variables, and timeframes, which raises the question of their generalizability (Zvarikova et al., 2017).

The Visegrad Group (V4), comprised of Slovakia, Hungary, Poland, and the Czech Republic, presents a compelling case study for examining bankruptcy phenomena. Sharing a common history, similar economic development trajectories (Piotrowicz, 2015), and broadly similar insolvency laws (Crhova et al., 2016), these nations offer a unique environment with a high degree of comparability. This uniformity allows researchers to focus on core financial metrics without excessive interference from different legal or economic systems.

The inception of bankruptcy prediction models in the V4 region can be traced back to the late 1990s, with pioneering research employing the MDA approach for specific countries within the group (Chrastinová, 1998; etc.). A subsequent surge of research focused on bankruptcy prediction in Slovakia using MDA models (Svabova et al., 2022; Gajdosikova & Valaskova, 2023; etc.). Similar research efforts emerged in Hungary (Bozsik, 2010; Ekes & Koloszar, 2014; etc.) and Poland (Antonowicz & Antonowicz, 2023; Kitowski et al., 2022; etc.). The Czech Republic also saw extensive research employing MDA models (Rowland et al., 2021; Yakymova & Kuz, 2019; etc.). Beyond country-specific models, some researchers explored creating universal models encompassing all V4 countries (Kliestik et al., 2018; Valaskova, 2023). This existing body of research highlights the extensive application of MDA in bankruptcy prediction within the V4 since the late 1990s, with a primary focus on individual countries and sectors.

This research addresses a critical gap in financial risk assessment for the V4 countries – Slovakia, Hungary, Poland, and the Czech Republic. It aims to develop an ex-ante bankruptcy prediction model capable of identifying bankruptcy up to five years in advance. Our multi-pronged approach involves constructing five distinct models: a comprehensive V4 model including all countries and individual models for each member country. This strategy allows us to capture regional trends and potential country-specific nuances in financial health. Leveraging a rich dataset from the Orbis private database, encompassing 15 key financial ratios and 5 non-financial variables for 25,084 companies across the V4 region, the effectiveness of these models in predicting bankruptcy is investigated. Calibration with a single cut-off that caps the in-sample false-negative rate at 10 % yields models that retain very high precision for healthy firms (≥ 95 %) and overall accuracies above 92 % even at the five-year horizon, although recall of bankruptcies diminishes with lead time, indicating that the strategy to cap Type II error at 10% did not work. Importantly, the pooled V4 scorecard performs almost on par with the best national models, indicating a substantial degree of financial homogeneity across the bloc. Among the predictors, Total Liabilities / Total Assets (X06) emerges as the dominant discriminant variable, with profitability and working-capital measures - especially Net Income / Total Assets (X04) - providing complementary explanatory power. These findings lay the groundwork for a region-wide early-warning system that can be tailored, when necessary, to country-level specificities.

2. LITERATURE REVIEW

Building upon Fitzpatrick's work, Smith and Winakor (1936) analyzed a larger sample of 183 failed firms across various industries. Their research highlighted the Working Capital to Total Assets ratio as the most effective predictor of financial distress (Smith & Winakor, 1936). Similarly, Merwin (1942) further emphasized the importance of Working Capital to Total Assets, along with the Current Ratio and Net Worth to Total Debt, in identifying financially troubled companies. These early studies, while limited in scope, established the foundation for future research by demonstrating the potential of specific financial ratios in predicting corporate failure. However, Beaver's (1966) work marked a significant shift in the field. Utilizing a larger sample and a more systematic univariate discriminant analysis, Beaver identified Net Income to Total Debt as the strongest predictor of bankruptcy, followed by Net Income to Sales. Importantly, Beaver recognized the limitations of relying solely on individual ratios and advocated for developing multivariate models that combine the predictive power of multiple financial ratios for a more comprehensive assessment.

Altman's (1968) Z-score model marked a significant paradigm shift in bankruptcy prediction. This groundbreaking work departed from the univariate approach, pioneering multivariate discriminant analysis (MDA). By incorporating five key financial ratios – working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total liabilities, and sales to total assets – the Z-score model achieved an impressive 95% accuracy in predicting bankruptcy one year ahead (Altman, 1968). This multi-faceted approach effectively addressed the limitations and scepticism surrounding traditional single-ratio analysis.

Despite its introduction in 1968, Altman's Z-score model, built upon multiple discriminant analysis (MDA), remains a prominent tool in bankruptcy prediction research (Altman, 1968). The model's enduring relevance is evident in the numerous studies that have validated its effectiveness (Kim-Soon et al., 2013; Lifschutz, 2010; Machek, 2014; Meeampol, 2014; Reisz & Perlich, 2007; Sulub, 2014; etc.). Other studies focused their efforts on re-weighting the original Z-score ratios to enhance their predictive power (Grice & Ingram, 2001; Pindado et al., 2008) and developing hybrid models that combine the Z-score with other prediction techniques (Kwak et al., 2004; Merkevicius et al., 2006; Xu & Zhang, 2009). However, research also highlights limitations associated with the generalizability of Altman's Z score models across diverse economic contexts. Studies by Chava and Jarrow (2004), Gerantonis et al. (2009), Grice and Ingram (2001), Wu et al. (2010), Plíhal et al. (2018) demonstrate that the accuracy of these models can significantly deteriorate when applied in settings that substantially differ from the environments in which they were developed. This underscores the inherent industry-specificity and time dependency of many bankruptcy prediction models. Consequently, several researchers have focused on developing models tailored to specific sectors or time periods, such as the industry-specific models proposed by Bilderbeek (1979), Deakin (1972), Laitinen (1991), Platt and Platt (1990), and others. The time dependency of many bankruptcy prediction models is further highlighted by studies analyzing the pre- and post-effects of events like COVID-19 on specific industries, such as the insurance sector (Macovei et al., 2024). The shift towards more sophisticated methodologies is evident in research exploring artificial intelligence for bankruptcy prediction, particularly in specific sectors like the engineering industry (Letkovsky et al., 2023).

Given our research interest in the V4 countries, we now turn our attention to the existing literature on bankruptcy prediction models specifically developed or applied within this region. Researchers in the V4 countries began developing bankruptcy prediction models in the late 1990s. Pioneering research employed the MDA approach, with applications for specific countries, including Slovakia (Chrastinová, 1998), Hungary (Virág & Hajdu, 1996), Poland (Maczynska, 1994), and the Czech Republic (Neumaierová & Neumaier, 1996). Following this initial wave, a surge of studies emerged that focused on bankruptcy prediction in the Slovak Republic using MDA models. (Gurčík, 2002; Horváthová et al., 2021; Mihalovič, 2016; Svabova et al., 2018, 2020, 2022; Katarina Valaskova et al., 2018). Similar research efforts emerged in Hungary (Virág & Kristóf, 2005), and Poland (Balina et al., 2021; Gajdka & Stos, 1996; Kopczyński, 2020; Pawełek et al., 2020; Ptak-Chmielewska, 2021). The research in the Czech Republic also extensively employed MDA models (Dvoracek & Sousedikova, 2006; Kalouda & Vanicek, 2013; Yakymova & Kuz, 2019). Beyond country-specific models, some researchers explored the possibility of creating universal models encompassing all V4 countries. These efforts included global models (Kliestik et al., 2018; Valaskova, 2023) and partial discriminant models (Michalkova et al., 2022). This literature review highlights the extensive application of MDA in bankruptcy prediction research within the V4 since the late 1990s. The focus has primarily been on individual countries and sectors. While traditional financial ratios remain fundamental, newer approaches such as textual analysis (Gupta & Banerjee, 2023) are also being explored. Beyond core financial ratios, external factors like the influence of interest rates on outstanding loans of enterprises on their structure in the bankruptcy warning system (Butyrskyi et al., 2023) are also crucial for a comprehensive bankruptcy warning system. The evolving financial landscape also necessitates considering the impact of financial technology adoption on bank stability, particularly in emerging economies (Okoli, 2024). Understanding financial resilience, as explored in studies comparing Sharia and conventional banking during financial crises (Suripto et al., 2023), also contributes to the broader landscape of financial stability research. Beyond direct bankruptcy prediction, research also examines broader financial market dynamics, such as the effect of bank performance on stock price returns in European high-income countries (Yenni et al., 2024). Moreover, a comprehensive understanding of financial stability extends to the macro level, encompassing state financial security and its diverse impact factors (Shkolnyk et al., 2020), which indirectly influence the environment for businesses.

3. METHODOLOGY

The paper aims to develop ex-ante models for predicting the bankruptcy of V4 companies up to 5 years before bankruptcy. This study utilized financial data from the Orbis database to develop bankruptcy prediction models for the V4 companies. Due to the vast number of businesses analyzed, determining individual details like the number and duration of overdue financial obligations or the precise count of creditors is not feasible directly from their financial statements. Therefore, to categorize companies as bankrupt or non-bankrupt, the following criteria will be employed:

$$\text{assets} - (\text{liabilities} + \text{accrued liabilities}) < 0 \tag{1}$$

$$\text{profit after taxes} \leq 0 \tag{2}$$

$$\frac{\text{equity}}{\text{liabilities} + \text{accrued liabilities}} < 0.08 \tag{3}$$

Companies are categorized as bankrupt if they met either condition (1) or conditions (2) and (3) simultaneously. The original dataset comprised 111,460 companies. Upon calculation of all variables and categorization of the data, adjustments were made to account for missing values. Enterprises with incomplete information were removed, resulting in a final dataset of 25,084 companies and 20 variables, out of which 15 were financial variables and 5 categorical. Table 1 presents a comprehensive review of the number of non-bankrupt and bankrupt companies over the studied period.

Table 1

Number of non-bankrupt and bankrupt companies in V4 countries

Country	Category	2018	2019	2020	2021	2022	2023
V4	Non-Bankrupt	23705	23818	23806	24022	24144	24080
	Bankrupt	1371	1261	1272	1059	937	1001
SK	Non-Bankrupt	3814	3834	3849	3875	3909	3894
	Bankrupt	338	317	302	277	243	258
HU	Non-Bankrupt	12870	12903	12861	12991	13047	13020
	Bankrupt	454	425	466	336	280	309
PL	Non-Bankrupt	2092	2113	2114	2135	2158	2142
	Bankrupt	201	181	180	159	136	152
CZ	Non-Bankrupt	4929	4968	4982	5021	5030	5024
	Bankrupt	378	338	324	287	278	282

Since the primary objective is to construct a bankruptcy prediction model leveraging the MDA framework, this section outlines a step-by-step approach for its successful development. Discriminant analysis is a suitable statistical technique when the dependent variable (Y) has distinct categories potentially influenced by at least one of the independent variables (X_1,..., Xn). The following null and alternative hypotheses demonstrate this:

H_0: The dependent variable (Y) is independent of all independent variables (X_1,..., Xn).
H_1: The dependent variable (Y) is dependent on at least one of the independent variables (X_1,..., Xn).

Building upon the valuable insights from prior research by prominent scholars in the field (Bellovary et al., 2007; Klieštik et al., 2018; Valaskova et al., 2023), a crucial step involves identifying the specific independent variables employed in their financial health prediction models. These variables serve as critical indicators for assessing the financial well-being of firms. Table 2 outlines the chosen financial indicators along with the necessary relationships for the calculation of the discriminant function.

Table 2

Overview of Financial Indicators Calculations

Indicator	**Calculation Algorithm**
X01	Short-term Assets/Short-term Liabilities
X02	Sales/Total Assets
X03	Net income/equity
X04	Working Capital/Total Assets
X05	Net Income/Total Assets
X06	(Long-term + Short-term Liabilities)/Total Assets
X07	Short-term assets/Total assets
X08	Operating income/Total assets
X09	Short-term Liabilities/Total Assets
X10	Short-term Assets/Sales
X11	Inventories/Sales
X12	Long-term Liabilities/Total Assets
X13	Return on Assets (Operating Income/total assets)
X14	(Short-term Assets - Inventory)/Short-term Liabilities
X15	Working Capital

Following established practice, the data was divided into training and test sets using an 80/20 split. The training set was employed to estimate the model parameters, while the test set served to evaluate its classification accuracy. Notably, calculations for variable ratios and data visualizations were performed using Microsoft Excel. RStudio (R Core Team, 2022), an integrated development environment featuring the R statistical programming language, was utilized to conduct the core statistical analysis.

This research design incorporates a multi-step process for firm classification, drawing inspiration from the well-established body of research on MDA (Klieštik et al., 2018; Valaskova et al., 2023). The methodology leverages MDA to develop a bankruptcy prediction model encompassing the V4 countries as a whole, along with individual models for each member nation. The following section details the methodological process in a step-by-step manner:

1. The first step involves classifying companies into two distinct groups: (1) bankrupt and (2) non-bankrupt. The specific criteria used for this categorization are detailed in Equation 1, 2 and 3.
2. The next step focuses on identifying the variables for model creation. Here, the research adopts a common approach within the field of bankruptcy prediction models. This approach involves examining past research articles and selecting the variables most frequently utilized in such models. It's important to note that this research paper prioritizes variables with the highest discriminatory power, opting for a focused selection over an all-inclusive approach (the complete list is in Table 2).
3. After constructing the full set of candidate predictors, we applied a step-wise forward selection grounded in multivariate analysis of variance (MANOVA). At each step the variable that produced the largest improvement in the multivariate F-statistic entered the model, provided its marginal F value was significant at the 5 % level ($\alpha = 0.05$). Predictors that failed to meet this criterion were judged to add no statistically meaningful explanatory power and were omitted. The procedure was implemented in R by combining the manova() routine with the step() function, thereby retaining only those variables that demonstrably enhance the joint discrimination between bankrupt and non-bankrupt firms.
4. The following step involves testing the assumption of homogeneity using Box's M test. This test assesses the equality of variance-covariance matrices in the two groups: (1) bankrupt and (2) non-bankrupt. Generally, a high Box's M value with a low p-value (indicating rejection of the null hypothesis) signifies the absence of a homogeneity problem within the two groups. The <boxM> function from the heplots package (Fox et al., 2009) is utilized for this analysis.
5. Rejecting the null hypothesis of equal co-variation in groups, a canonical discriminant function can be constructed using a "Stepwise selection" approach. This process involves making selections based on a simultaneous assessment of standardized canonical coefficients and canonical correlation of the canonical discriminant function in individual steps. Only the variables exhibiting the highest discriminatory power are incorporated into the final model. The <candisc> function from the candisc package (Friendly & Fox, 2021) is used to create the canonical discriminant function. Once the model is constructed, the variables as mentioned above are extracted from the results.
6. Following the completion of the variable selection process, the final model is presented. Individual coefficients are extracted from the "raw coefficients" section of the canonical discriminant function results. A critical research component involves a thorough assessment of the model's discriminatory ability. This evaluation is conducted using a two-pronged approach:
   - Ex-Post Prediction Accuracy: The models are first calibrated on the 2018 estimation sample by fixing the Type II error (false-negative rate) at 10 %. This procedure yields a single Z-score cutoff for each specification; no intermediate "grey zone" is retained. The calibrated

thresholds are then applied to the 20 % hold-out test sample for 2018 to gauge out-of-sample performance. By explicitly capping the share of bankrupt firms that escape detection, the approach prioritises economic relevance while allowing the resulting Type I error (false positives) and overall hit rate to be assessed transparently. Once the cutoff points are set, the models ex-post prediction power on the whole year of 2018 is evaluated.

- Ex-Ante Prediction Accuracy: Secondly, the model's ex-ante prediction power is assessed for 1, 2, 3, 4, and 5 years before bankruptcy.

4. EMPIRICAL RESULTS AND DISCUSSION

Given the potential for MDA to predict group membership, it is crucial to assess the presence of statistically significant differences between groups across each independent variable. This evaluation utilizes group means and the results of the Multivariate Analysis of Variance (MANOVA) test presented in Table 3. Generally, if the MANOVA tests reveal an absence of substantial differences in the means between groups for the chosen independent variables, it suggests limited discriminatory power for these variables. Consequently, under such circumstances, it may not be worthwhile to proceed further with the investigation utilizing MDA.

Table 3

Test results of equality of means for V4 countries

	V4		SK		HU		PL		CZ	
	F-stat	**Sig.**	**F-stat**	**Sig.**	**F-stat**	**Sig.**	**F-stat**	**Sig.**	**F-stat**	**Sig.**
X01	182.734	0.000	64.659	0.000	54.299	0.000	7.349	0.007	52.482	0.000
X02	94.024	0.000	12.003	0.001	32.551	0.000	35.615	0.000	35.554	0.000
X03	27.843	0.000	186.299	0.000	8.907	0.003	1.816	0.178	0.043	0.836
X04	2155.455	0.000	547.080	0.000	933.521	0.000	126.213	0.000	553.882	0.000
X05	1641.573	0.000	315.272	0.000	711.687	0.000	260.848	0.000	478.646	0.000
X06	5648.249	0.000	1161.567	0.000	1832.891	0.000	1118.598	0.000	1799.019	0.000
X07	8.463	0.004	0.090	0.765	6.879	0.009	13.611	0.000	9.343	0.002
X08	1316.251	0.000	238.522	0.000	587.422	0.000	198.616	0.000	357.355	0.000
X09										
X10	17.375	0.000	7.388	0.007	27.600	0.000	0.774	0.379	0.291	0.590
X11	0.104	0.747	0.079	0.778	4.780	0.029	3.949	0.047	0.138	0.710
X12										
X13										
X14	175.296	0.000	56.466	0.000			5.531	0.019	50.124	0.000
X15	244.592	0.000	112.423	0.000	135.076	0.000	25.187	0.000	51.025	0.000
Small	8.980	0.003	11.028	0.001	2.883	0.090	4.755	0.029	59.136	0.000
Medium	1.843	0.175	2.207	0.138	0.525	0.469	1.792	0.181	3.041	0.081
Large	3.046	0.081	4.604	0.032	119.870	0.000	6.731	0.010	8.284	0.004
Very large										
Age	309.381	0.000	50.352	0.000	0.344	0.558	43.817	0.000	142.620	0.000

A suitable discriminant can be identified when a variable has a statistically significant p-value at a level below $\alpha = 0.05$, meaning the variable can discriminate the mean values between non-bankrupt and bankrupt companies. As indicated in the output above, all variables are appropriate except for:

- X11, Medium, and Large in the V4
- X07, X11. and Medium in Slovakia
- Small, Medium, and Age in Hungary
- X03, X10, and Medium in Poland
- X03, X10, X11, and Medium in the Czech Republic

According to the Box's test (Table 5), the covariance matrices cannot be considered identical. As a result, when conducting calculations, the assumption of varying covariance matrices was made using RStudio. The log determinants of the covariance-variance matrices for each group are notably distinct.

Table 4

Log determinants table

Test Results					
Y_2018	**V4**	**SK**	**HU**	**PL**	**CZ**
0	-24.005	-29.769	-24.554	-24.535	-24.248
1	-13.062	-16.633	-13.772	-8.684	-15.213

Table 5

The Box's M Test results for Equal Covariance Matrices

Test Results						
		V4	**SK**	**HU**	**PL**	**CZ**
Chi-Sq	Approx.	96615.21	18145.32	40171	13502	26666.2
	df	120	120	120	120	120
	p-value	.000	.000	.000	.000	.000

The subsequent part of the output includes the canonical correlation of the discriminant function and a test of its statistical significance, which can be found in Table 6. These values are utilized to assess the overall effectiveness of the model and determine if the canonical discriminant functions effectively differentiate between the individual groups. Table 6 reveals statistically significant canonical correlations for the V4 countries as a whole and all individual models for each member nation. However, the strength of these correlations varies. The V4 (.362), and Hungary (.258) exhibit relatively low values, while Poland (.630) and the Czech Republic (.559) boasts a medium-strong correlation. Slovakia (.843) achieved the highest canonical correlation among the group. These findings highlight the overall discriminatory power of the model while suggesting potential for further improvement in certain countries.

The individual discriminant ability of variables is obtained from the standardized coefficients of the canonical discriminant function. Generally, variables with values close to zero have a low discriminant ability and are thus excluded. The sign of the coefficients indicates the group membership; for instance, a negative coefficient assigns the company to the category of bankrupt. The highest discriminant ability was attained by the variables marked in bold.

Table 6

The canonical correlation between the discriminant function and explanatory variables

	Function	**Eigenvalue**	**Canonical Correlation**		
V4	1	0.362	0.266		
SK	1	0.843	0.457		
HU	1	0.258	0.205		
PL	1	0.630	0.387		
CZ	1	0.559	0.358		
Wilks' Lambda					
	Test of Function(s)	**LR test stat**	**F-statistics**	**df**	**Sig.**
V4	1	0.734	452.82	16	.000
SK	1	0.614	129.41	16	.000
HU	1	0.795	182.8	15	.000
PL	1	0.543	95.677	16	.000
CZ	1	0.642	147.14	16	.000

The examination of the models reveals that the variables with the highest discriminatory power varied across the V4 countries. For the overall V4 model, variable X06 (0.891) emerged as the most significant discriminant. Similarly, country-specific models identified the variables with the highest discriminatory power for each nation: X05 for Slovakia (-0.790), X05 for Hungary (-0.945), X06 for Poland (1.136), and X06 again for the Czech Republic (0.916). Certain variables exhibited consistent discriminatory power across multiple countries. Notably, variable X05 and X06 plays a crucial role in the models for all countries, while variable X04, Small and Medium contributed significantly to four models.

Table 7

Standardized coefficients of the canonical discriminant function table

V4		**SK**		**HU**		**PL**		**CZ**	
X01	0.155	X01	**0.570**	X01	**0.403**	X01	-0.157	X01	0.036
X02	0.101	X02	0.038	X02	0.129	X02	0.020	X02	-0.052
X03	-0.070	X03	**-0.425**	X03	**0.300**	X03	-0.057	X03	-0.055
X04	**-0.293**	X04	**-0.675**	X04	**-0.638**	X04	0.165	X04	**-0.255**
X05	**-0.416**	X05	**-0.790**	X05	**-0.945**	X05	**-0.398**	X05	**-0.409**
X06	**0.891**	X06	**0.783**	X06	**0.428**	X06	**1.136**	X06	**0.916**
X07	0.086	X07	**0.305**	X07	**0.313**	X07	-0.161	X07	0.110
X08	**0.219**	X08	**0.752**	X08	**0.473**	X08	0.128	X08	0.155
X09		X09		X09		X09		X09	
X10	0.118	X10	0.136	X10	**0.198**	X10	-0.071	X10	-0.001
X11	-0.008	X11	-0.030	X11	-0.050	X11	0.167	X11	0.049
X12		X12		X12		X12		X12	
X13		X13		X13		X13		X13	
X14	**0.282**	X14	0.017	X14		X14	**0.516**	X14	**0.364**
X15	0.074	X15	0.110	X15	-0.005	X15	0.064	X15	0.157
Small	**0.211**	Small	**0.211**	Small	0.025	Small	**0.263**	Small	**0.311**
Medium	**0.204**	Medium	**0.169**	Medium	-0.007	Medium	**0.310**	Medium	**0.321**
Large	0.037	Large	0.041	Large	-0.030	Large	0.098	Large	0.129
Very large		Very large		Very large		Very large		Very large	
Age	-0.014	Age	0.021	Age	-0.035	Age	0.041	Age	-0.020

The correlation coefficients between the discriminant function and individual explanatory variables reveal a markedly different pattern with the updated estimates (Table 8). In the V4 as a whole, X06 now shows the strongest positive association with the discriminant function (coefficient = 0.910), and it likewise dominates in each member country: Slovakia (0.821), Hungary (0.846), Poland (0.911) and the Czech Republic (0.912). This consistency suggests that X06 is the primary driver differentiating bankrupt from non-bankrupt firms across the region. By contrast, X04 exhibits a uniformly strong negative correlation: –0.605 for the V4 aggregate, and –0.606 (SK), –0.627 (HU), –0.375 (PL) and –0.568 (CZ) at the country level. Other variables such as X05 (–0.534 V4; range: –0.475 to –0.553) and X08 (–0.482 V4; –0.418 to –0.505) also display moderate negative correlations, indicating they contribute inversely to the discriminant score.

Several additional variables – including X01, X02, X07, X10 and X15—show only weak to moderate correlations (absolute values generally below 0.25), implying a more limited discriminant role. Only those predictors with high canonical correlations and strong discriminant loadings (not marked with "a" in Table 8) were retained in the final model to guard against overfitting and maximize predictive power.

Table 8

Canonical correlation coefficients table

V4		SK		HU		PL		CZ	
X01	-0.184	X01	-0.223	X01	-0.157	X01	-0.093	X01[a]	-0.185
X02	0.133	X02[a]	0.097	X02	0.122	X02[a]	0.204	X02[a]	0.153
X03[a]	-0.072	X03	-0.372	X03	0.064	X03[a]	0.047	X03[a]	-0.005
X04	-0.605	X04	-0.606	X04	-0.627	X04	-0.375	X04	-0.568
X05	-0.534	X05	-0.475	X05	-0.553	X05	-0.522	X05	-0.533
X06	0.910	X06	0.821	X06	0.846	X06	0.911	X06	0.912
X07[a]	0.040	X07[a]	0.008	X07[a]	0.056	X07	0.127	X07[a]	0.078
X08	-0.482	X08	-0.418	X08	-0.505	X08	-0.462	X08	-0.466
X09[a]		X09[a]		X09[a]		X09[a]		X09[a]	
X10	0.057	X10	0.076	X10	0.112	X10[a]	-0.030	X10[a]	0.014
X11[a]	-0.004	X11[a]	-0.008	X11[a]	0.047	X11	-0.069	X11[a]	-0.010
X12[a]		X12[a]		X12[a]				X12[a]	
X13[a]		X13[a]		X13[a]		X13[a]		X13[a]	
X14	-0.181	X14[a]	-0.209	X14[a]		X14	-0.081	X14	-0.181
X15	-0.213	X15[a]	-0.292	X15[a]	-0.247	X15[a]	-0.172	X15	-0.182
Small	0.041	Small	0.093	Small[a]	0.013	Small	0.075	Small	0.196
Medium	-0.019	Medium	-0.042	Medium[a]	-0.036	Medium	0.046	Medium	-0.045
Large[a]	-0.024	Large[a]	-0.060	Large[a]	0.016	Large[a]	-0.089	Large	-0.074
Very large[a]		Very large[a]		Very large[a]		Very large[a]		Very large[a]	
Age[a]	-0.239	Age[a]	-0.197	Age[a]	-0.233	Age[a]	-0.226	Age[a]	-0.302

a. variables not selected

note: Based on concerns regarding overfitting, the analysis in certain cases excluded variables deemed to have the lowest contribution to the model's predictive power.

A company's discriminant score (Z-score) can be calculated using raw coefficients (non-standardized coefficients) from the canonical discriminant function. This score can then be compared to the centroids to determine whether the enterprise belongs to the group of prosperous or non-prosperous enterprises.

Prediction model of the V4 countries

$$y_{V4} = 0.0326\mathrm{X}_{01} + 0.0608\mathrm{X}_{02} - 0.9722\mathrm{X}_{04} - 3.3777\mathrm{X}_{05} + 3.462\mathrm{X}_{06} + 1.635\mathrm{X}_{08} + 0.1791\mathrm{X}_{10} + 0.0755\mathrm{X}_{14} + 0.00004\mathrm{X}_{15} + 0.5306\mathrm{Small} + 0.4484\mathrm{Medium} \quad (4)$$

Prediction model of Slovakia

$$y_{SK} = 0.2598\mathrm{X}_{01} - 1.0749\mathrm{X}_{03} - 2.1056X_{04} - 8.6452\mathrm{X}_{05} + 3.2114X_{06} + 6.875\mathrm{X}_{08} + 0.1468\mathrm{X}_{10} + 0.529\mathrm{Small} + 0.3882\mathrm{Medium} \quad (5)$$

Prediction model of Hungary

$$y_{HU} = 0.0706\mathrm{X}_{01} + 0.07297\mathrm{X}_{02} + 1.025\mathrm{X}_{03} - 2.1552X_{04} - 6.8344X_{05} + 1.682X_{06} + 3.2272 + 0.3128X_{10} \quad (6)$$

Prediction model of Poland

$$y_{PL} = -0.02666X_{01} + 0.57864X_{04} - 3.3895X_{05} + 434179X_{06} - 0.5311X_{07} + 1.0175X_{08} + 0.6440X_{11} + 0.12294\mathrm{X}_{14} + 0.85519\mathrm{Small} + 0.69757\mathrm{Medium} \quad (7)$$

Prediction model of the Czech Republic

$$y_{CZ} = -0.90653X_{04} - 4.3079X_{05} + 3.58643X_{06} + 1.38556X_{08} + 0.09757X_{14} + 0.00003\mathrm{X}_{15} + 0.92939\mathrm{Small} + 0.69045\mathrm{Medium} + 0.39735\mathrm{Large} \quad (8)$$

Where:

X01 Short-term Assets/Short-term Liabilities
X02 Sales/Total Assets
X03 Net income/equity
X04 Working Capital/Total Assets
X05 Net Income/Total Assets
X06 (Long-term + Short-term Liabilities) /Total Assets
X07 Short-term assets / Total assets
X08 Operating income / Total assets
X10 Short-term Assets/Sales
X11 Inventories/Sales
X14 (Short-term Assets - Inventory)/Short-term Liabilities
X15 Working Capital

The next stage is the specification of cutoff scores for each discriminant model. Because overall accuracy depends on the location of this threshold, the selection procedure must be transparent. In the present study a single cutoff per model is chosen so that the Type II error (false-negative rate) is fixed at 10 %. This criterion reflects the greater economic cost of failing to identify a bankrupt firm, while allowing the Type I error (false positives) to adjust endogenously to the sample characteristics. Although dual-threshold schemes can yield superficially higher hit rates, they confound the underlying error trade-off and are therefore eschewed in favour of a single, explicit decision boundary.

To gauge genuine predictive power, every model is validated on out-of-sample observations several years before the event of failure. Table 9 lists the resulting cutoff values for the V4 aggregate and for each country-specific specification. Firms with discriminant scores above their model's cutoff are classified as Bankrupt; those below are classified as Non-Bankrupt. This parsimonious rule provides a consistent and academically rigorous basis for comparative analysis across the region.

Table 9

Cutoff points estimation based on 10% Type II error

	V4	SK	HU	PL	CZ
Bankrupt	>4.688	>6.033	>3.699	>5.353	>4.737
Non-Bankrupt	<4.688	<6.033	<3.699	<5.353	<4.737

Following the estimation and out-of-sample validation of the MDAs reported in Table 10, the next task is to compare their classification performance. In this study the evaluation framework is anchored on a fixed 10 % Type II error ceiling – that is, no more than one-tenth of genuinely distressed firms may be misclassified as safe. This choice reflects the asymmetry of economic losses: for academics analysing the dynamics of failure, and for lenders or regulators charged with safeguarding financial stability, overlooking a future bankrupt entity is typically more costly than issuing a false alarm.

Because the decision boundary is calibrated to control Type II error, the Type I error rate (false positives) is allowed to adjust endogenously and is reported as a diagnostic rather than a constraint. Practitioners who give equal or greater weight to Type I costs can therefore gauge, ex post, whether the implied trade-off is acceptable for their particular application. By making the tolerance for false negatives explicit and transparent, the comparison of models in Table 10 remains academically rigorous while still providing actionable information for investors, credit analysts, and other stakeholders.

Table 10

Classification results calculated

	V4	SK	HU	PL	CZ
Correctly classified bankrupt companies					
2018	90%	90.51%	89.19%	83.33%	87.72%
I year	65.45%	67.09%	58.74%	71.78%	69%
2 years	50.83%	53.16%	45.74%	61.35%	56.46%
3 years	42.75%	48.73%	30.94%	52.15%	52.40%
4 years	34.99%	43.67%	22.42%	44.17%	44.28%
5 years	33.44%	35.44%	23.32%	45.40%	42.44%
Correctly classified non-bankrupt companies					
2018	97.82%	95.12%	98.21%	97.16%	97.00%
I year	97.23%	94.69%	97.75%	97%	96.98%
2 years	96.63%	94.52%	97.21%	96.25%	96.59%
3 years	97.22%	94.99%	97.95%	96.53%	97.14%
4 years	97.43%	95.64%	98.23%	97%	96.88%
5 years	97.11%	94.94%	98.04%	96.34%	96.66%
Overall classification accuracy					
2018	97.52%	94.94%	98.09%	96.08%	96.50%
I year	96.09%	93.64%	97.10%	95.21%	95.57%
2 years	94.99%	92.94%	96.35%	93.77%	94.55%
3 years	95.26%	93.23%	96.83%	93.37%	94.84%
4 years	95.18%	93.67%	96.97%	93.24%	94.18%
5 years	94.82%	92.68%	96.79%	92.72%	93.91%

Although the cut-off values were calibrated to impose a uniform 10 % Type II ceiling, ex-post results show that this constraint did not preserve the models' discriminating capacity over time: the proportion of correctly identified bankrupt firms plummets from roughly 90 % in the 2018 test year (peaking at 90.51 % for Slovakia) to little more than one-third five years before failure, whereas recognition of solvent firms remains uniformly high (≥ 94.9 %), so overall accuracy, while still respectable (> 92 %), declines steadily with the forecast horizon. In contemporaneous tests Slovakia performs best, but Poland overtakes all rivals from one to five years ahead, making these two the only national models that ever exceed the regional V4 benchmark. By contrast, the Hungarian specification achieves the lowest Type I error and, consequently, the strongest aggregate accuracy across all horizons; it is followed by the V4, Czech and Polish models, with Slovakia lagging. Despite never ranking first on any single criterion, the unified V4 model—estimated without country dummies—remains competitively robust, suggesting that a single, region-wide set of cut-offs can accommodate the financial homogeneity of Visegrád firms, even though the fixed 10 % Type II calibration entails a rapid erosion of forward-looking bankruptcy detection.

The existing literature on V4 bankruptcy prediction demonstrates a prevalent reliance on ex-post analysis. In this approach, models are constructed using historical financial data from companies that have declared bankruptcy. This retrospective approach limits the practical application of the models for real-world decision-making. The prediction horizon in these studies has also been typically short, often focused on identifying bankruptcies within one year of the event.

A noteworthy contribution comes from Valaskova et al. (2023), who successfully developed a model encompassing all V4 countries using an ex-post approach. This model achieved a commendable overall classification accuracy of 89.6% for bankrupt and non-bankrupt companies. However, the individual models achieved higher classification rates, except for Poland where the correct classification rate of Bankrupt companies declined to 67.5%.

To the best of our knowledge, Karas and Reznakova (2013) are the sole authors in all the V4 countries' literature to focus on a multi-year approach, although again using an ex-post analysis and only for the Czech Republic industrial companies. Their model achieved promising results, demonstrating the ability to predict bankruptcies with an accuracy of 92.11%, 85.53%, and 90% for 1, 2, and 3 years before bankruptcy event, respectively. However, for identifying non-bankrupt companies, the model's accuracy varied more significantly across the prediction horizon. While the accuracy reached a high of 97.42% for companies two years before bankruptcy, it was lower at 78.26% for companies on the verge of bankruptcy (one year prior). The overall classification accuracy also reflected this trend, reaching 94.07% and 94.66% for two and three years before bankruptcy, respectively. However, similar to other existing studies, their analysis remained ex-post, meaning it doesn't directly translate to predicting future bankruptcies for companies that haven't yet filed.

The studies above highlight valuable research efforts in bankruptcy prediction within the V4 region. However, a fundamental limitation lies in their reliance on ex-post analysis. For practical purposes, financial institutions and investors require models to forecast bankruptcy likelihood ex-ante. This research breaks new ground by employing an ex-ante prediction approach. Our model aims to predict bankruptcy probabilities for V4 companies based on their current financial data, enabling proactive decision-making. This represents a significant advancement in the V4 bankruptcy prediction field, offering valuable insights for various stakeholders concerned with financial risk assessment.

Building on the previous discussion of the fundamental limitation in relying on ex-post analysis for bankruptcy prediction within the V4 region, it is imperative to also consider the specific constraints of traditional methodologies such as MDA. In discussing the limitations of MDA in bankruptcy prediction, it is crucial to acknowledge both the strengths and weaknesses inherent in the method. MDA provides a straightforward analytical solution, making it both fast and accessible, particularly beneficial given its effectiveness when multidimensional normality and homoskedasticity assumptions are met (Tufféry, 2011). However, its utility is constrained by several significant limitations. Firstly, MDA is inherently linear and therefore only effective in identifying linear relationships, which can be a critical shortcoming when dealing with complex, non-linear financial data (Tufféry, 2011). This method also demands continuous independent variables without missing values, though it can tolerate discrete variables to some extent. A major challenge arises with the presence of outliers or multicollinearity among variables, which can lead to unreliable solutions and potential heteroskedasticity, thereby undermining the stability and accuracy of the predictive model.

To further enhance the robustness and applicability of bankruptcy prediction, models such as Neural Networks (NNs) and Support Vector Machines (SVMs) offer substantial benefits due to their ability to handle non-linear data interactions. Both models excel in environments where traditional linear methods like MDA falter, particularly in capturing subtle, complex patterns in financial datasets. However, they require careful handling to mitigate their inherent drawbacks, notably the difficulty in interpreting NNs and the complex parameter tuning in SVMs (Tam & Kiang, 1992; Min & Lee, 2005). Additionally, ensemble methods like Random Forests and probabilistic approaches like Logistic Regression present valuable alternatives. Random Forests are effective for their robustness against overfitting and ability to provide variable importance metrics, though they may become computationally intensive (Breiman, 2001). Logistic Regression, while less equipped for non-linear relationships, offers greater model transparency and ease of interpretation, making it suitable for applications requiring straightforward explanatory factors (Ohlson, 1980). These models collectively represent a suite of tools that can be tailored to specific predictive needs in bankruptcy analysis, balancing complexity, interpretability, and predictive power to overcome the limitations of MDA.

The practical implementation of our bankruptcy prediction models offer substantial benefits to stakeholders in the V4 countries by providing a robust framework for proactive financial risk assessment. Beyond simply predicting potential bankruptcies, our models leverage current financial data, allowing financial institutions, investors, and policymakers to make informed, timely decisions that enhance economic stability and prevent financial distress. Additionally, for those stakeholders who may choose not to directly employ our models, our research includes a comprehensive guide on constructing these MDA models using R with specific packages, making it a valuable resource for anyone interested in developing similar predictive tools. This dual approach ensures that our work can be utilized to its fullest potential, supporting a range of applications from direct model use to facilitating customized model development. Our analysis leveraged a comprehensive database encompassing various companies across the V4 countries. While not exclusively focused on small and medium-sized enterprises (SMEs), SMEs constituted a significant portion of the data. Future research utilizing such extensive databases could further leverage the recent findings on SMEs from the V4 countries and incorporate them into their bankruptcy prediction models (Dvorsky et al., 2023; Machova et al., 2023).

5. CONCLUSION

This research sought to address a critical gap in financial risk assessment for the Visegrad Group countries – Czech Republic, Hungary, Poland, and Slovakia. It aimed to develop ex-ante bankruptcy prediction models capable of identifying bankruptcy up to five years before bankruptcy. To achieve this objective, we employed a multi-pronged approach. First, five distinct models were constructed: a comprehensive V4 model encompassing all four nations and individual models for each member country. This strategy allowed us to capture regional trends and potential country-specific nuances in financial health indicators. The data sample leveraged a rich dataset from the Orbis private database. This dataset encompassed 15 key financial ratios alongside 5 non-financial dummy variables. Following a rigorous reduction process, the final sample size consisted of a robust 25,084 companies across the V4 region.

The empirical tests confirm that the selected ratios differ significantly between bankrupt and solvent firms, validating their usefulness as early-warning indicators. Each model maintains very high precision in recognising healthy companies (≥ 95 %), which keeps overall accuracy above 92 % even five years before failure; however, the share of correctly identified bankrupt firms falls from roughly 90 % in the test year to about one-third at the longest horizon, revealing the limits of a static 10 % Type II cut-off. The region-wide V4 specification performs almost on par with the best country models, supporting the financial homogeneity of Visegrád firms. Across all five discriminant functions the ratio Total Liabilities / Total Assets (X06) emerges as the dominant predictor, while profitability and working-capital measures–most notably Net Income / Total Assets (X04)–provide additional explanatory power in signalling impending bankruptcy.

The successful application of these models provides significant value for financial institutions, investors, and corporations within the V4 region. By incorporating these models into their decision-making processes, stakeholders gain a clearer picture of a company's financial trajectory over a multi-year horizon. This enhanced foresight empowers them to make informed choices regarding credit risk management, investment strategies, and potential restructuring initiatives.

While the findings of this research regarding bankruptcy prediction in the V4 region are promising, it's crucial to acknowledge certain methodological limitations. These limitations are inherent to the field of bankruptcy prediction and deserve careful consideration. The very nature of bankruptcy prediction models necessitates a reliance on financial metrics that signal potential bankruptcy rather than definitive indicators of actual bankruptcy. This is particularly relevant when dealing with a vast dataset encompassing a significant number of companies. While these financial ratios offer valuable insights, they may not always capture the nuanced dynamics that can lead to bankruptcy or recovery within a single year. It's conceivable that a company exhibiting concerning financial metrics in one year could experience a turnaround and avoid bankruptcy the following year due to unforeseen improvements.

In conclusion, while methodological limitations are inherent to bankruptcy prediction, they need not negate the value of this research. By acknowledging these limitations and continuously seeking ways to refine the models, we can contribute to a more robust and informative approach to financial risk assessment within the V4 economies.

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