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Refining the Best-Performing V4 Bankruptcy Prediction Models: Coefficient Re-Estimation for Crisis Periods

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Abstract: Bankruptcy prediction models have been extensively utilized to assess the financial health of companies. However, their predictive accuracy can be significantly affected by extraordinary economic disruptions, such as the COVID-19 pandemic. Traditional models, particularly those designed for stable economic conditions, necessitate evaluation and potential adaptation to maintain their effectiveness during unprecedented circumstances. This study seeks to evaluate the performance of financial distress prediction models developed by authors from the Visegrad Four (V4) when applied to Slovak automotive companies before, during, and after the COVID-19 pandemic. Initially, the best-performing models from those selected were identified in the pre-pandemic period (2017-2019). The performances of these models were subsequently analysed during the pandemic and post-pandemic periods (2020-2022). Finally, their coefficients were re-estimated to enhance accuracy while preserving the original variables, ensuring the interpretability of any changes. The objective is to identify the models with the highest performance during the pre-pandemic period, assess their reliability under crisis conditions, and suggest improvements through coefficient re-estimation. While the majority of models experienced significant declines in performance during the pandemic, some retained adequate predictive accuracy. The re-estimated coefficients improved the overall accuracy of the models and also enhanced the sensitivity of some, offering stakeholders the option to utilize either the original or adjusted models based on their specific context. This study provides a framework for adapting financial prediction models to unprecedented economic conditions, contributing valuable insights for researchers and practitioners seeking to enhance predictive tools within dynamic economic environments.

Keywords: bankruptcy prediction; financial distress; COVID-19 pandemic; coefficient re-estimation; Visegrad models

1. Introduction

The ability to predict financial distress in companies is critical in economic forecasting, enabling stakeholders to mitigate risks, allocate resources effectively, and prevent severe financial repercussions. Accurate financial distress prediction is especially vital in industries such as the automotive sector, which is highly susceptible to global economic fluctuations. Over recent decades, numerous models have been developed and utilised to assess companies' financial stability, with notable contributions from researchers in Central and Eastern Europe, particularly from the Visegrad countries (the Czech Republic, Hungary, Poland, and Slovakia). [1–3] These models have

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traditionally relied on financial indicators and statistical methods that reflect the economic conditions in the region, providing a region-specific foundation for evaluating company health. [4,5]

However, the COVID-19 pandemic introduced unprecedented disruptions to global economies, significantly affecting businesses' operational and financial performance across all sectors. [6,7] These new and non-standard factors can significantly impact companies' financial stability and can affect the effectiveness of existing prediction models. Although existing bankruptcy models may be built on robust mathematical and statistical principles, their ability to predict bankruptcy in a pandemic period may be limited [8]. New and unexpected factors such as government stimulus measures, moratoriums on loan repayments, temporary closures of businesses and fluctuations in markets can affect the performance of these models. In this context, models that were once reliable under stable economic conditions may exhibit reduced accuracy in times of crisis. This raises a critical question about the robustness and adaptability of traditional financial distress prediction models when applied to post-pandemic conditions. Therefore, much attention is currently being paid to the analysis and updating of existing bankruptcy models to take into account new factors and improve their accuracy in a pandemic environment. This may include adjusting weighting factors, adding new predictive variables, or modifying mathematical algorithms based on new data and experience gained during the pandemic.

Although the automotive industry faced particular challenges, including supply chain disruptions and shifts in consumer demand, research exploring the pandemic's impact on model performance remains limited. To address these gaps, this study evaluates the effectiveness of financial distress prediction models originally developed by authors from Visegrad countries when applied to Slovak automotive companies' financial data across two periods. The analysis first assesses the models' performance during the pre-pandemic period (2017-2019), identifying the models with the highest prediction performance. Subsequently, the top-performing models are selected and applied to data from the pandemic period (2020-2022) to examine any changes in predictive performance. Observing a notable decline in performance during the pandemic, we proceeded to re-estimate the coefficients within each model. This re-estimation approach preserves the original variables and statistical methods, adapting the models to better reflect the changed economic conditions.

By examining financial distress prediction models under varying economic conditions, this study offers valuable insights into the limitations of traditional models under unprecedented challenges like the COVID-19 pandemic. The findings underscore the importance of continuous evaluation of predictive models' performance to ensure their reliability in times of economic instability. For practitioners and policymakers, the study provides a framework for enhancing financial risk assessment tools, especially within sectors like automotive sensitive to global disruptions. For researchers, the study offers a methodology for evaluating and refining existing models.

The next parts of this paper are organised as follows. In the Literature review section, we highlight the current state of financial distress prediction, focusing on the situation within the Visegrad region. Methodology and Data section describes the data used in the study, explains the study methodology and describes the models selected for the study. The results section presents the empirical results, first analysing the predictive accuracy of the selected models during the pre-pandemic period, then contrasting these findings with the models' performance in the pandemic period, and, finally re-estimating the models' coefficients to address pandemic-induced economic changes. The discussion section offers a discussion of the key insights and practical implications of our findings while also mentioning the main study limitations and suggesting directions for future research. The last section concludes the study.

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1.1. Literature Review

Predicting companies' financial condition is a widespread area of economic research. Since Fitzpatrick published the first study on this topic in 1932, bankruptcy prediction has become a subject of interest for various researchers and industry professionals.

Bankruptcy prediction models are especially prevalent in economically advanced Western countries. Models developed in the latter half of the 20th century are still used today. Beaver [9] introduced univariate analysis, becoming a pioneer in the field of bankruptcy prediction. Building on this research, Altman [10] applied multivariate discriminant analysis to create a model for predicting bankruptcy. Later in 1980, Ohlson developed a new model based on logistic regression [11]. In 1984, Zmijewski proposed the application of a probit model for predicting company bankruptcy [12]. Altman's model, as well as Ohlson's logit model, were developed within the context of the US economy. Since then, numerous other models have been created across various countries worldwide. In addition to modern machine learning techniques, traditional methods such as logistic regression, multivariate discriminant analysis, and classification trees remain commonly used [13–15].

Dasgupta et al. [16] compared the performance of logistic regression and discriminant analysis models using neural networks. Their research found that the performance of neural networks was higher compared to the other two mentioned methods. However, the authors also noted that the performance of neural networks was not significantly higher than that of the other models. Huo et al. [17] conducted a comparative study on bankruptcy prediction for restaurant firms using multivariate discriminant analysis (MDA) and logistic regression models. The study revealed that while both models were effective, logistic regression provided more accurate predictions, especially in volatile industries like hospitality.

Inam et al. [18] applied artificial neural networks (ANN), logistic regression, and multivariate discriminant analysis to predict the bankruptcy of companies in Pakistan. The study compared the predictive power of these techniques, highlighting the performance of ANNs over classical statistical methods. Logistic regression and discriminant analysis, while still effective, showed limitations in handling non-linear relationships.

The first ex-ante analysis in Slovakia was published by Chrastinova [19]. The so-called CH-index model was designed specifically for Slovak agricultural enterprises based on discriminant analysis. Another well-known Slovak model is the G-index, developed using a discriminant analysis for agricultural enterprises [20]. Since then, several authors have created new models or examined the applicability of existing models within the Slovak context. Gavurova et al. [21] explored the accuracy of various bankruptcy prediction models within the Slovak business environment. The study highlighted that traditional model like Altman's Z-score required customisation for specific regions, as macroeconomic variables such as inflation and interest rates affected the models' predictive accuracy. This research underlines the need to adapt prediction models to local economic conditions to enhance their utility [21]. Horvathova et al. [22] conducted a comparative analysis of neural networks and classical discriminant analysis in predicting bankruptcy. The study demonstrated that neural networks offered greater accuracy than discriminant analysis. However, the researchers acknowledged the continued relevance of classical methods like discriminant analysis for simpler datasets and interpretability [22].

In addition, several new models have been developed by Slovak researchers. The V4 bankruptcy prediction model was developed by Kliestik et al. [1] based on the data on enterprises from V4 countries during the periods of 2015 and 2016 using the multiple discriminant analysis by the authors [1,23]. Valaskova et al. [6] developed models for enterprises in V4 countries, achieving over 88% accuracy using multiple discriminant analysis. The study identified total indebtedness ratios as the most significant predictor, providing valuable insights into the post-pandemic economic environment. Kovacova and Kliestik [24] created the logit and probit models in their study. The study's results indicate that the model based on logit functions slightly outperforms the classification ability of the probit model in predicting bankruptcies in the Slovak Republic. Durica and Adamko

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[25] created a bankruptcy prediction model for Slovak companies based on multiple discriminant analysis with a classification accuracy of over 82%.

In the Czech Republic, Neumaier and Neumaierová family of bankruptcy prediction models – IN95, IN99, IN01, and IN05 – are the most well-known Czech predictive models and represent a significant contribution to financial health assessment in the Czech Republic. These models were designed to adapt to local economic conditions and provide robust predictions of financial distress by evaluating various financial indicators [26,27]. These models are often used for predicting the financial state of the companies also in Slovakia.

Karas and Srbova [28] developed a bankruptcy prediction model specifically for the Czech construction industry, addressing the sector's unique financial characteristics. Their study critiques traditional models like the Altman Z-score, highlighting their limited applicability to construction firms. Horak et al. [29] compared multivariate discriminant analysis (MDA), artificial neural networks (ANNs), and support vector machines (SVMs) for bankruptcy prediction of Czech industrial companies. Their findings indicated that ANNs and SVMs performed better than MDA, however, the authors emphasised the continued use of classical methods like MDA in certain practical applications due to their simplicity and ease of interpretation. Pech et al. [30] analysed the performance of various bankruptcy prediction models over a five-year period, finding that Zmijevski's model achieved the highest overall success rate. Their study highlighted significant variations in model accuracy across industries, recommending sector-specific adjustments to improve predictions.

Recent studies from Polish authors have introduced innovative approaches to bankruptcy prediction, leveraging both traditional and advanced methodologies. Machine learning models, enhanced with oversampling techniques, achieved up to 99% predictive accuracy, highlighting the utility of ensemble learning for addressing imbalanced datasets in financial forecasting [31,32]. Ensemble classifier models, including boosting and bagging, outperformed traditional single-classifier approaches when tested on data on Polish firms, providing robust early warnings of bankruptcy over a two-year horizon [33]. Another study focused on logit and discriminant models tailored to the Polish industrial sector, emphasising the need for locally adapted prediction methods over unadjusted global models [34]. Hybrid machine learning techniques, such as those combining XGBoost and artificial neural networks, further improved predictive accuracy by dynamically integrating advanced algorithms and addressing imbalances in Polish financial datasets [32]. Multivariable models also outperformed univariate approaches for Polish manufacturing companies, confirming that combining multiple financial indicators yields better predictions of financial distress [35].

In Hungary, the first Hungarian model was constructed by Virag and Hajdu [36] based on the data on Hungarian enterprises covering the period 1990-1991. The authors created a model using both MDA and logistic regression. However, many studies related to prediction models from Hungarian authors are in their national language, so they are difficult to use for an international reader.

As visible, bankruptcy prediction models have historically been widely used to predict the financial distress of firms. In recent years, the development of bankruptcy prediction models has gained further attention due to the global economic shocks triggered by the COVID-19 pandemic. The pandemic significantly impacted global economies, leading to widespread financial distress across numerous sectors. Several studies have analysed the performance and adaptations of existing bankruptcy prediction models during the pandemic. However, several authors found that the pandemic revealed several limitations in using traditional bankruptcy prediction models and the need for more dynamic models capable of incorporating sudden economic shocks.

For instance, Lubis and Gandakusuma [37] conducted a re-estimation of traditional bankruptcy models, finding that the original Altman Z-score required significant adjustments to remain accurate during the pandemic. Candera [38] conducted a comparative analysis of service companies during the pandemic period and found that traditional models such as the Springate and Altman Z-scores underperformed, as they failed to account for non-financial variables that became critical during the pandemic.

Al Qamashoui and Mishrif [39] conducted a study focused on predicting bankruptcy risks in distressed insurance companies in Oman during the pandemic period. The authors used the Altman Z-score model to assess financial distress in both pre- and post-pandemic periods (2019-2020). The study revealed that while traditional financial models, such as the Z-score, could predict financial distress to some extent, they were less effective when used in the volatile insurance sector, mainly due to external factors such as market instability and government intervention during the pandemic. The authors recommended incorporating real-time data and non-financial factors to improve model accuracy. Similarly, Dengang and Oktafiani [40], have called for the inclusion of external factors like market conditions, government interventions, and non-financial metrics.. Putri et al. [41] analyzed the financial health of Indonesian state-owned construction companies during 2019-2023. The study used existing bankruptcy prediction models, including the Altman Z-score. The findings suggested that while the Z-score model provided reasonable predictions, adjustments to account for government policies and market fluctuations during the pandemic were necessary to enhance accuracy.

Stoyancheva et al. [42] conducted an assessment of the bankruptcy risk in Bulgarian agricultural enterprises using several classical models, including the Altman, Springate, and Fulmer models. The study highlighted that while these models provided accurate predictions before the pandemic (2019), they required adjustments during the pandemic period. The research suggests that sector-specific factors must be integrated to improve prediction accuracy. Similarly, Purwanti et al. [43] analysed the banking sector in Indonesia and found that model accuracy during the pandemic was significantly reduced, emphasising the need for real-time data and adaptive algorithms.

2. Materials and Methods

For the purpose of this study, we collected data on 80 enterprises from the automotive industry. The main reason for choosing this sector was that the industry has been a dominant economic sector in the Slovak Republic for a long time. It creates conditions for the development of other economic activities and is also the most important component of GDP creation in the economy of the Slovak Republic. Data were collected from publicly available financial statements of Slovak companies at the website www.finanstat.sk. The period under the study covers the pre-pandemic years, 2017-2019, and then three pandemic years, 2020-2022.

The next step was the assessment of the financial state of the companies each year, i.e., classifying the companies into one of the two groups: healthy or in crisis. The rule for determining the company's financial state was based on the Commercial Code, defining a business in crisis or decline as follows. According to Act no. 513/1991 Coll. in the Commercial Code, a company is in crisis if it is in bankruptcy or about to go bankrupt. A company is bankrupt if its debt-to-equity ratio is lower than 8 to 100. Therefore, if the company's value of the debt-to-equity ratio (equity to liabilities) in a particular year was lower than 0.08, the company was considered in crisis, i.e. having financial troubles (denoted by the value Y=1). Contrary, if the ratio was higher or equal to 0.08, the company was considered to be in a healthy financial condition (denoted by the value Y=0). The distribution of the companies' states in individual years is in Table 1.

Table 1. Distribution of companies into the groups of healthy companies and companies in crisis.

Company state / Num. of companies	2018	2019	2020	2021	2022
In crisis	13	15	13	13	11
Healty	67	65	67	67	69

The purpose of this study is to find the predictive models from the V4 countries with the highest prediction performance in the period before the pandemic. For this reason, we collected 12 models listed in Table 2. Three of them were the models from Slovak authors, three from Czech authors, three from Polish and one from Hungarian authors. The reason for using only one Hungarian model was that Hungarian authors usually publish their studies in their native language; thus, they are hardly understandable to international readers. Therefore, we used the study written in English containing such a prediction model that could be easily used to evaluate the companies' financial state. Moreover, for comparison, we used also Altman's model and Taffler's model as well-known benchmarks. We used Altman's model in the modified Z"score version from 1999. We chose this modified model because it was created to assess the financial health of non-US companies, which was an acceptable element for our analysis.

Table 2. Selected models and their coefficients.

Variable name	Variable description	Altman	Taffler - Tishawa	IN 99	IN 01	IN 05	Durica - Adamko	Kliestik et al. V4	Kliestik et al. SK	Zmijevski	Poznanski	Tomczak	Virág - Hajdu
1	Working Capital / Total Assets	1.20											
X2	Retained Earnings / Total Assets	1.40											
X3	EBIT / Total Assets	3.30											
X4	Book value of equity/Book value of total liabilities	0.60											
X5	Total Sales / Total Assets	1.00	0.16										
X6	EBIT / Current liabilities		0.53										
X7	Current assets / Liabilities		0.13										
X8	Current liabilities / Total assets		0.18					1.03					
X9	FIXED Assets / Total assets										4.288		
X10	Total assets / Liabilities			-0.017	0.13	0.13							
X11	EBIT / Total assets (=Total liabilities)			4.573	0.04	0.04	0.51					-1.30	
X12	Total revenue / Total assets			0.481	3.92	3.97							
X13	Current assets / Current liabilities			0.015	0.21	0.21							
X14	EBIT / Interest				0.09	0.09							
X15	Current assets / Current liabilities						0.25	0.024		-0.004	1.588		
X16	Current liabilities / Total Sales						-0.207						
X17	Working capital / Total assets						0.282						
X18	Equity / Total liabilities						0.618					1.95	
X19	Net income / Shareholders equity							-0.589					
X20	Net income / Total assets							-1.158		-4.513	3.562		
X21	Total liabilities / Total assets							1.87		5.679			
X22	Current assets / Total assets							-0.452					3.66

X23	Cash and cash equivalents / Total assets							0.613					
X24	Cash and cash equivalents / Current liabilities							-0.012					
X25	Return on assets							0.731	-0.004			2.19	
X26	Return on equity							0.173					
X27	Return of sales (EBIT)											2.70	
X28	Profit margin							-0.475					
X29	(Cash and Cash Equivalents + Short-term Investments) / Current liabilities								0.003				1.36
X30	Debt / Shareholders equity								0.0004				
X31	Net working capital / Total assets								0.0003				
X32	Profit(loss) on sales/ net revenues for sales										6.791		
X33	(Short-term liabilities ·365)/ sales											-0.001	
X34	CashFlow/total liabilities												1.63
X35	CashFlow/ Total assets												0.034
Constant		-	-	-				-1.47	-0.24	-4.336	-2.368	-1.303	-0.62
Safe zone – financially health company		Z > 2.9	T > 0.3	IN99 > 2.07	IN01 > 1.77	IN05 > 1.6	DA > 0.02	Z < 0	Z < 0	X < 0	PM > 0	ST < 0.51	MVH >0
Red zone – company in financial distress		Z <=1.81	T <0.2	IN99 <0.684	IN01 <=0.75	IN05 < 0.9	DA < -0.06	Z >= 0	Z >= 0	X >= 0	PM <=0	ST >= 0.51	MVH <=0
Grey zone		1.81 < Z <= 2.9	0.2 <= T <= 0.3	0.684 <= IN99 <= 2.07	0.75 < IN01 <= 1.6	0.9 <= IN05 <= 1.6	-0.06 <= DA <= 0.02	-					

All these models were used to predict the financial state of companies in the pre-pandemic period. For this purpose, we used the original variables from these models. The predictions for these models were then compared to the company's actual state in the following year. As the models are all created to predict the financial state of the company over a one-year period, we were able to assess the performance of the models in the pre-pandemic period by comparing the predictions with the actual state of the company. For example, the predictions that used values of financial ratios from the year 2017 were compared to the companies' states in 2018, etc.

The performance of the models was evaluated based on the confusion matrix, see Table 3. In the confusion matrix, a true negative case (TN) is a company that was correctly predicted as financially healthy (marked by Y=0, both actual and predicted), a true positive case (TP) is a company that was correctly predicted to be in financial distress (marked by Y=1, both actual and predicted). Moreover, a false positive case (FP) is a company that was predicted to be in financial distress (predicted Y=1), although in fact, it was in a good financial state (actual Y=0) and a false negative (FN) case is a company that was predicted to be financial healthy (predicted Y=0), although in fact, it was in financial distress (actual Y=1).

Table 3. Confusion matrix.

		Predicted ***Y***	
		0	**1**
Actual Y	0	True Negative (TN)	False Positive (FP)

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1	False Negative (FN)	True Positive (TP)

Some of the selected prediction models classify companies not only in the mentioned two groups but also contain a grey zone. However, when processing the confusion matrix, we only worked with companies classified as healthy and in crisis. We decided not to include companies in the uncertain grey zone, for which we cannot determine with certainty whether they are healthy and in a good financial situation or whether they are in crisis with a bad financial situation.

For evaluating the performance of the selected models, we considered the most important metric, the model's accuracy, given as the ratio of correctly predicted companies among all companies (equation (1)).

$$\boldsymbol{Acc} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{FP} + \boldsymbol{TN} + \boldsymbol{FN}} \tag{1}$$

and the model's sensitivity, given as the ratio of correctly predicted financial troubles among all the companies with financial troubles (equation (2))

$$\boldsymbol{Sen} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}} \tag{2}$$

Then, we selected five models with the highest performance (accuracy and sensitivity) of their predictions in the pre-pandemic period (one benchmark model and one model from each country). These models were further used to evaluate their performance in the pandemic period covering 2020-2022. Similarly, as before, the prediction of the company's financial state for each pandemic year was compared to its actual state in the following year.

Finally, if the performance of the selected models in the pandemic period dropped significantly, we re-estimated the models' coefficients and their thresholds, preserving the original models' variables. These adjusted models were created using the same technique as the original models (most of them by discriminant analysis). Finally, the adjusted models were compared to the original ones in terms of the economic interpretation of the model's coefficients and their changes during the pandemic period.

All selected models in the study were originally created using discriminant analysis. Therefore, we briefly characterise this method.

2.2. Discriminant Analysis

Discriminant analysis (DA) is a statistical technique employed to classify entities into at least two distinct groups based on predictor variables. It achieves this by constructing a discriminant function that maximises group separation. DA has been widely applied in various disciplines, including finance, where it aids in predicting corporate financial health ([44,45]. In the context of assessing corporate financial health, the models created by DA serve for the differentiation between financially robust and distressed companies by analysing financial ratios and other pertinent indicators.

Mathematically, DA aims to determine a linear combination of independent variables $X_1, X_2, \dots, X_p$, which forms the discriminant score expressed as:

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p \tag{3}$$

where D is the discriminant score, p is the number of the predictor variables, $X_1, X_2, \dots, X_p$ are the predictor variables, and $\beta_0, \beta_1, \dots, \beta_p$ are the coefficients to be estimated; their estimations are often denoted by $b_0, b_1, \dots, b_p$.

The estimation of the coefficients relies most commonly on maximizing the ratio of between-group variance (S_B)to within-group variance (S_W), defined as the objective function

$$\frac{w^T S_B w}{w^T S_W w} \tag{4}$$

Here, w represents the vector of discriminant coefficients. The matrices S_B and S_W are computed as:

$$S_B = \sum_{g=1}^{G} n_g(\mu_g - \mu)(\mu_g - \mu)^T \tag{5}$$

$$S_W = \sum_{g=1}^{G}\sum_{i=1}^{n_g}(X_{gi} - \mu_g)(X_{gi} - \mu_g)^T \tag{6}$$

where G is the number of groups, n_g is the sample size in group g, μ_g is the mean vector of group g, μ is the overall mean vector, and X_{gi} represents the observations in group g. The optimal solution for w is obtained by solving the generalized eigenvalue problem

$$S_B w = \lambda S_W w \tag{7}$$

where λ represents the eigenvalue, indicating the separation achieved by the discriminant function [46].

The discriminant function is validated using metrics such as Wilks' Lambda, which tests the significance of the discriminant power and classification accuracy through cross-validation [44]. Assumptions such as multivariate normality and homogeneity of covariance matrices are essential for the validity of DA. In practice, normality assumption is often violated; for example, financial data often exhibit non-normality. While deviations from these assumptions may impact the results, DA remains robust under moderate violations [45], and DA can still proceed with caution.

3. Results

Tables 4–8 present the confusion matrices and evaluation measures for predictions of the financial state of the companies in the pre-pandemic period in 2018 and 2019. The tables are separated for the benchmark models (Altman's and Taffler-Tishawa) and models from individual V4 countries. The actual state of the companies is in rows marked by the values 0 for financially healthy companies and 1 for companies in financial distress. The predicted values are in columns with the same notation of the company's financial state.

Table 4. Application of Altman's and Taffler-Tishawa models in the pre-pandemic period.

Altman		2018			2019			**Taffler - Tishawa**		**2018**			**2019**		
		Predicted		**Total**	**Predicted**		**Total**			**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**				**1**	**0**		**1**	**0**	
Actual	**1**	9	20	29	11	21	32	**Actual**	**1**	0	3	3	2	1	3
	0	2	37	39	1	33	34		**0**	11	59	70	12	61	73
Total		11	57	68	12	54	66	**Total**		11	62	73	14	62	76
Accuracy		67.60%			66.70%			**Accuracy**		80.80%			82.90%		
Sensitivity		31.00%			34.40%			**Sensitivity**		0.00%			66.70%		

Table 5. Application of Slovak models in the pre-pandemic period.

Durica – Adamko		**2018**			**2019**			**Kliestik et al. V4**		**2018**			**2019**			**Kliestik et al. SK**		**2018**			**2019**		
		Predicted		**Total**	**Predicted**		**Total**			**Predicted**		**Total**	**Predicted**		**Total**			**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**				**1**	**0**		**1**	**0**				**1**	**0**		**1**	**0**	
Actual	**1**	5	2	7	7	1	8	**Actual**	**1**	8	55	63	5	54	59	**Actual**	**1**	5	8	13	7	5	12
	0	7	63	70	7	64	71		**0**	5	12	17	10	11	21		**0**	8	59	67	8	60	68
Total		12	65	77	14	65	79	**Total**		13	67	80	15	65	80	**Total**		13	67	80	15	65	80
Accuracy		88.30%			88.90%			**Accuracy**		25.00%			20.00%			**Accuracy**		80.00%			83.80%		
Sensitivity		71.40%			87.50%			**Sensitivity**		12.70%			8.50%			**Sensitivity**		38.50%			58.30%		

Table 6. Application of Czech models in the pre-pandemic period.

IN 99		2018			2019			IN 01		2018			2019			IN 05		2018			2019		
		Predicted		Total	Predicted		Total			Predicted		Total	Predicted		Total			Predicted		Total	Predicted		Total
		1	0		1	0				1	0		1	0				1	0		1	0	
Actual	1	4	10	14	7	7	14	Actual	1	10	19	29	11	17	28	Actual	1	10	23	33	12	20	32
	0	2	13	15	1	9	10		0	2	28	30	0	26	26		0	2	31	33	0	29	29
Total		6	23	29	8	16	24	Total		12	47	59	11	43	54	Total		12	54	66	12	49	61
Accuracy		58.60%			66.70%			Accuracy		64.40%			68.50%			Accuracy		62.10%			67.20%		
Sensitivity		28.60%			50.00%			Sensitivity		34.50%			39.30%			Sensitivity		30.30%			37.50%		

Table 7. Application of Polish models in the pre-pandemic period.

Zmijevski		2018			2019			Poznanski		2018			2019			Tomczak		2018			2019		
		Predicted		Total	Predicted		Total			Predicted		Total	Predicted		Total			Predicted		Total	Predicted		Total
		1	0		1	0				1	0		1	0				1	0		1	0	
Actual	1	9	4	13	9	3	12	Actual	1	3	10	13	2	10	12	Actual	1	6	7	13	10	2	12
	0	36	31	67	40	28	68		0	63	4	67	11	57	68		0	29	38	67	32	36	68
Total		45	35	80	49	31	80	Total		66	14	80	13	67	80	Total		35	45	80	42	38	80
Accuracy		50.00%			46.25%			Accuracy		8.75%			73.75%			Accuracy		55.00%			57.50%		
Sensitivity		69.23%			75.00%			Sensitivity		23.08%			16.67%			Sensitivity		46.15%			83.33%		

Table 8. Application of Hungarian model in the pre-pandemic period.

Virág – Hajdu		2018			2019		
		Predicted		Total	Predicted		Total
		1	0		1	0	
Actual	1	6	7	13	8	4	12
	0	36	31	67	36	32	68
Total		42	38	80	44	36	80
Accuracy		46.25%			50.00%		
Sensitivity		46.15%			66.67%		

These tables would serve to select the models with the highest prediction performance.

3.1. Summary of Models' Performance in the Pre-Pandemic Period

A summary of the models based on sensitivity and overall accuracy shows their effectiveness in classifying companies into healthy and in crisis. The combination of these two metrics offers a comprehensive view of the success and reliability of prediction models in identifying future financial troubles of companies one year in advance.

Sensitivity is an important indicator that takes into account the ability of the model to identify true positive cases from the total number of all positive cases, i.e. correctly predict the crisis one year in advance. On the other hand, the model's accuracy provides an overview of the overall classification success regardless of whether the cases are positive or negative, i.e. correct predictions of both healthy and in-crisis companies one year in advance. Taking into account both these evaluation measures, we can identify the models from the selected ones with the highest performance of prediction of financial troubles of Slovak automotive companies in the period before the pandemic, i.e. under normal economic circumstances. Table 9 provides an overview of the selected evaluation metrics for all models in the pre-pandemic period.

Table 9. Summary of evaluation metrics for all models and their average values in pre-pandemic period.

Metrics	Year	Altman	Taffler – Tishawa	Durica – Adamko	Kliestik et al. V4	Kliestik et al. SK	IN99	IN01	IN05	Zmijevski	Poznanski	Tomczak	Virag - Hajdu

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Accuracy in %	**2018**	67.6	80.8	88.3	25.0	80.0	58.6	64.4	62.1	50.0	8.8	55.0	46.3
	2019	66.7	82.9	88.9	20.0	83.8	66.7	68.5	67.2	46.3	73.8	57.5	50.0
	avg	67.2	81.9	88.6	22.5	81.9	62.7	66.5	64.7	48.1	41.3	56.3	48.1
Sensitivity in %	**2018**	31.0	0.0	71.4	12.7	38.5	28.6	34.5	30.3	69.2	23.1	46.2	46.2
	2019	34.4	66.7	87.5	8.5	58.3	50.0	39.3	37.5	75.0	16.7	83.3	66.7
	avg	32.7	33.4	79.5	10.6	48.4	39.3	36.9	33.9	72.1	19.9	64.7	56.4

Since our main goal is to identify positive cases (e.g., companies' financial crises), we consider sensitivity more important than other evaluation metrics because it focuses on the model's ability to identify all truly positive cases. Of course, we also take into account the overall accuracy values.

Based on this, we selected the following five models as the most suitable for verifying the functionality of their predictions during the pandemic period. Among the two benchmark models, we chose the Taffler-Tishawa model, and among the SK models, we chose the Durica-Adamko model. Among the CZ models, we chose the IN 01. From the PL models, we selected the Zmijevski model and the Virag-Hajdu model was also selected as the only HU model.

The further evaluation of the financial state of the companies during the pandemic years 2020 – 2021 and 2022 after the pandemic continues with the selected five models with the highest performance in the pre-pandemic period. Table 10 presents the confusion matrices of the selected five models in the pandemic and post-pandemic period. The total number of companies varies because some models contain not only financial prosperity and non-prosperity but also grey zones, which we did not include in the tables. Therefore, only the companies where the predictions were unambiguous are included in the table.

Table 10. Prediction performance of selected five models in pandemic and post-pandemic period.

Taffler - Tishawa		**2020**			**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**		**1**	**0**	
Actual	**1**	0	1	1	1	12	13	1	9	10
	0	12	61	73	4	56	60	4	62	66
Total		12	62	74	5	68	73	5	71	76
Accuracy		82.43%			78.10%			82.89%		
Sensitivity		0.00%			20.00%			10.00%		
Durica - Adamko (SK)		**2020**			**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**		**1**	**0**	
Actual	**1**	7	3	10	6	3	9	6	5	11
	0	5	64	69	5	62	67	3	66	69
Total		12	67	79	11	65	76	9	71	80
Accuracy		89.87%			89.47%			90.00%		
Sensitivity		70.00%			66.67%			54.55%		
IN 01 (CZ)		**2020**			**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**		**1**	**0**	
Actual	**1**	7	2	9	9	1	10	19	2	21
	0	22	22	44	21	24	45	19	26	45
Total		29	24	53	30	25	55	38	28	66
Accuracy		54.72%			60.00%			68.18%		
Sensitivity		77.78%			90.00%			90.48%		
Zmijevski (PL)		**2020**			**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**		**1**	**0**	

Actual	**1**	2	10	12	0	13	13	0	11	11
	0	50	18	68	48	19	67	51	18	69
Total		52	28	80	48	32	80	51	29	80
Accuracy		25.00%			23.75%			22.50%		
Sensitivity		16.67%			0.00%			0.00%		
Virág - Hajdu (HU)		**2020**			**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**		**1**	**0**	
Actual	**1**	9	4	13	5	8	13	8	3	11
	0	40	27	67	36	31	67	38	31	69
Total		49	31	80	41	39	80	46	34	80
Accuracy		45.00%			45.00%			48.75%		
Sensitivity		69.23%			38.46%			72.73%		

Table 11 summarizes the total accuracy and sensitivity of the selected models together with the averages of these evaluation measures.

Table 11. Summary of evaluation metrics for selected five models and their average values in pandemic and post-pandemic period.

Metrics	Year	Taffler – Tishawa	Durica – Adamko	IN01	Zmijevski	Virag - Hajdu
Accuracy in %	2020	82.4	89.9	54.7	25.0	45.0
	2021	78.1	89.5	60.0	23.8	45.0
	2022	82.9	90.0	68.2	22.5	48.8
	avg	81.1	89.8	61.0	23.8	46.3
Sensitivity in %	2020	0.0	70.0	77.8	16.7	69.2
	2021	20.0	66.7	90.0	0.0	38.5
	2022	10.0	54.6	90.5	0.0	72.7
	avg	10.0	63.7	86.1	5.6	60.1

Compared to the period before the pandemic, we can say that the prediction accuracy of some of the selected high-performance models dropped significantly (the Polish model of Zmijevski) or stayed at the same average level (the other models). Regarding the sensitivity, the models' performance dropped significantly (Taffler-Tishawa benchmark model, Durica-Adamko Slovak model and Zmijevski Polish model) or even rose significantly during the pandemic and post-pandemic period (IN01 Czech model and Virag-Hajdu Hungarian model). Comparing the pandemic years 2020 and 2021 with the post-pandemic year 2022, we can say that with some exceptions, the models showed lowered accuracy and sensitivity levels during the pandemic.

During and after the COVID-19 pandemic, the coefficients of bankruptcy models changed for several reasons. The most important factors of these changes include: (i) Changes in the economic environment; the pandemic caused a global economic crisis, a sharp decrease in demand in some sectors (such as tourism and retail), and increased uncertainty, which led to a higher risk of bankruptcy for many companies and thus affected the weight of individual factors in the prediction models. (ii) Increased corporate indebtedness; many companies had to take out loans to survive the period of lower income. Higher indebtedness increased their financial risk, which could have caused the short-term debt ratio (X8) and the short-term liabilities to sales ratio (X16) to gain more weight in the models and, conversely, the interest coverage ratio (X14) to gain less weight in the analyzed models, which was due to factor number three described in the following lines. (iii) Government measures and support; many governments introduced stimulus packages, subsidies, or loan repayment moratoriums. These measures temporarily improved the financial health of some companies, which may have distorted the traditional relationships between financial indicators and the probability of bankruptcy. (iv) Sectoral differences; The pandemic affected different sectors in

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different ways. While some sectors may have benefited, others faced serious losses, i.e., the adjustment of some coefficients helped to better reflect sectoral differences. (v) Change in liquidity indicators; the importance of short-term liquidity was demonstrated during the pandemic. Companies that had better cash management and sufficient reserves had a higher chance of surviving the crisis, which affected the weights of individual liquidity indicators (X15) and cash flow (X35). (vi) Uncertainty and predictive ability; the pandemic increased volatility and uncertainty, which made traditional bankruptcy predictions more difficult. The models needed to be adjusted to better capture unexpected factors, such as sudden changes in cash flow or fluctuations in revenue.

In short, the individual coefficients had to change during and after the pandemic because financial indicators and risk factors took on new meaning in the context of unprecedented economic conditions. These changes reflect the models' efforts to better capture current realities and predict bankruptcy risk in a highly uncertain environment. Table 12 presents the newly estimated coefficients of the selected five models valid during the pandemic and post-pandemic period. The table contains only the variables included in at least one model; the other variables were omitted.

Table 12. Adjusted coefficients of five selected models for pandemic and post-pandemic period.

Variable name	Taffler – Tishawa			IN 01			Durica - Adamko			Zmijevski			Virág – Hajdu		
	Original	**2021**	**2022**	**original**	**2021**	**2022**	**Original**	**2021**	**2022**	**original**	**2021**	**2022**	**original**	**2021**	**2022**
X5	0.16	0.345	0.449												
X6	0.53	0.171	0.072												
X7	0.13	-0.058	0.151												
X8	0.18	-3.861	-3.466												
X10				0.13	0.508	0.640									
X11				0.04	4.0E-7	-0.001	0.51	4.851	6.89						
X12				3.92	4.369	8.443									
X13				0.21	0.258	0.065									
X14				0.09	0.073	-0.072									
X15							0.25	0.122	-0.757	-0.004	0.395	0.295			
X16							-0.207	-2.835	2.336						
X17							0.282	-3.89	0.321						
X18							0.618	0.015	0.562						
X20										-4.513	0.133	-2.659			
X21										5.679	5.143	4.174			
X22													3.66	-3.514	-0.194
X29													1.36	0.224	0.335
X34													1.63	0.19	-1.387
X35													0.034	7.356	12.868
Constant	-	1.233	0.493	-	-1.54	-1.273		2.99	0.963	-4.336	-4.109	-3.329	-2.616	2.03	0.025
Safe zone	T > 0.3	T > 0	T > 0	IN01 > 1.77	IN01 > 0	IN01 > 0	DA > 0.02	DA > 0	DA > 0	X < 0	X < 0	X < 0	MVH >0	MVH >0	MVH >0
Red zone	T < 0.2	T < 0	T < 0	IN01 <=0.75	IN01 < 0	IN01 < 0	DA < -0.06	DA < 0	DA < 0	X >= 0	X >= 0	X >= 0	MVH <=0	MVH <=0	MVH <=0
Grey zone	0.2 <= T <= 0.3	-	-	-			-0.06 <= DA <= 0.02	-	-	-	-	-	-	-	-

We also listed the original coefficients for comparison with their changes during the pandemic year 2021 and the post-pandemic year 2022. Moreover, Table 13 presents the confusion matrices representing the prediction performance of the selected models with the adjusted coefficients.

Table 13. Confusion matrices for adjusted models.

Taffler – Tishawa	2021			2022		
	Predicted		**Total**	**Predicted**		**Total**
	1	**0**		**1**	**0**	

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Actual	**1**	10	3	13	7	4	11
	0	10	57	67	9	60	69
Total		20	60	80	16	64	80
Durica - Adamko (SK)		**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**	
Actual	**1**	8	4	12	7	3	10
	0	8	60	68	10	60	70
Total		16	64	80	17	63	80
IN 01 (CZ)		**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**	
Actual	**1**	11	2	13	6	4	10
	0	18	44	62	7	54	61
Total		29	46	75	13	58	71
Zmijevski (PL)		**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**	
Actual	**1**	12	1	13	8	3	11
	0	6	61	67	4	65	69
Total		18	62	80	12	68	80
Virág - Hajdu (HU)		**2021**			**2022**		
		Predicted		**Total**	**Predicted**		**Total**
		1	**0**		**1**	**0**	
Actual	**1**	7	6	13	6	5	11
	0	6	61	67	6	63	69
Total		13	67	80	12	68	80

Table 14 presents the performance measures of the adjusted models compared to the original models' performance during the pandemic and post-pandemic periods.

Table 14. Prediction performance measures of original and adjusted models.

Metrics	Year	Taffler – Tishawa	Durica – Adamko	IN01	Zmijevski	Virag - Hajdu
Accuracy in %	original 2021	78.1	89.5	60.0	23.8	45.0
	adjusted 2021	83.75	85.00	73.33	91.25	85.00
	original 2022	82.9	90.0	68.2	22.5	48.8
	adjusted 2022	83.8	83.8	84.5	91.3	86.3
	avg original	80.5	89.7	64.1	23.1	46.9
	avg adjusted	83.8	84.4	78.9	91.3	85.6
Sensitivity in %	original 2021	0.0	70.0	77.8	16.7	69.2
	adjusted 2021	76.9	66.7	84.6	92.3	53.8
	original 2022	20.0	66.7	90.0	0.0	38.5
	adjusted 2022	63.6	70.0	60.0	72.7	54.5
	avg original	10.0	68.3	83.9	8.3	53.8
	avg adjusted	70.3	68.3	72.3	82.5	54.2

Regarding accuracy, it is visible that it is significantly higher for the models with adjusted coefficients than for the original models, except for the Durica-Adamko model, where it was pretty high already for the original model. Sensitivity also significantly arose for the Taffler-Tishawa and Poznanski models in both years and for IN01 in 2021, Durica-Adamko in 2022 and the Virag-Hajdu

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model in 2022. In averages, the performance of the models either arose slightly or significantly or stayed approximately at the same level. From this point of view, the adjustment of the model's coefficients during an extraordinary period, such as COVID-19, is highly recommendable, especially when the prediction performance of the original model significantly dropped compared to normal circumstances.

4. Discussion

This study highlights the necessity of updating financial distress prediction models to address pandemic-induced economic disruptions. It also contributes to the broader understanding of how traditional models can be adapted for unprecedented circumstances. The findings highlight the necessity of re-estimating the models, maintaining their original variables chosen by their authors, to enhance their applicability in diverse economic conditions.

The findings of this study align with previous research that highlights the limitations of traditional bankruptcy prediction models during the COVID-19 pandemic and underscores the necessity of adapting these models to incorporate pandemic-specific economic factors. Several studies cited in the Literature Review reached similar conclusions, recommending adjustments to model coefficients or the inclusion of external variables to enhance predictive performance.

For instance, Lubis and Gandakusuma [31] evaluated the Altman Z-score model and found that significant adjustments were required to maintain its predictive accuracy during the pandemic. Their findings emphasised that financial variables alone were insufficient for reliable predictions in the volatile economic environment caused by COVID-19 and highlighted the importance of including external factors such as government policies and market shocks. Similarly, Candera [32] found that traditional models like the Springate and Altman Z-scores underperformed when applied to service companies, as these models failed to account for critical non-financial variables that emerged during the pandemic. Our study corroborates these conclusions, demonstrating that the original coefficients of the selected models developed by V4 authors were inadequate in the pandemic context, and re-estimation of the coefficients significantly improved model performance. However, the authors recommended models adjustments by incorporating macroeconomic indicators to enhance the prediction performance in predicting bankruptcies during this period. Dengang and Oktafiani [34] also advocated for integrating external factors such as government interventions and market conditions into prediction models. This approach aligns with the recommendations of Al Qamashoui and Mishrif [33], who found that incorporating real-time data and adjusting existing models improved predictions for distressed insurance companies in Oman during the pandemic period. Similarly, the research by Putri et al. [35] analyzed Indonesian construction companies and highlighted the necessity of model adjustments to account for government policies and market fluctuations during the pandemic. Stoyancheva et al. [36] conducted a similar assessment of traditional models like Altman, Springate, and Fulmer in Bulgarian agricultural enterprises. They observed that these models required sector-specific adjustments to improve their predictive accuracy during the pandemic. These findings resonate with our study, where the models tailored for pre-pandemic conditions failed to deliver reliable predictions until their coefficients were recalibrated. The coefficient re-estimation was pivotal in restoring the accuracy of the selected models. However, our study did not explicitly include external factors, the re-estimation of coefficients implicitly accounted for the shifts in financial ratios caused by such external influences.

Our results also highlight significant variations in the performance of adjusted models compared to their original versions. For example, while the sensitivity of certain models, such as Zmijevski model, dropped significantly during the pandemic, recalibration substantially enhanced their predictive capabilities. This observation is consistent with the findings of Purwanti et al. [37] who noted similar performance improvements following model adjustments in the Indonesian banking sector.

Despite its contributions, this study has several limitations. First, its focus on the automotive sector within Slovakia makes it country- and sector-specific, which may limit the generalizability of its findings to other industries or regions with different economic structures. Nevertheless, this study holds significant value for an international audience as it offers a detailed methodology for adapting financial prediction models to extraordinary economic disruptions, such as the COVID-19 pandemic. By demonstrating the process of coefficient re-estimation and its impact on model performance, the study provides a replicable framework that can be applied to diverse contexts, making it a valuable reference for both researchers and practitioners. Second, the study relies exclusively on financial data, omitting potentially significant non-financial variables such as management decisions or macroeconomic policies, which could further refine the models. However, our approach assumes that any changed macroeconomic conditions would be reflected in a change in the companies' financial indicators. The primary objective was to maintain the same variables in the models established by previous authors, re-estimating only their parameters. This approach was crucial for comparing the newly estimated coefficients with the original ones and deriving the economic interpretation of any identified changes. Introducing new variables would lead to entirely different models, making it impossible to compare them with the original models regarding the economic implications of the coefficient changes.

Future research could explore several directions. First, expanding the scope of analysis to include additional industries and countries would provide a broader understanding of how economic disruptions impact bankruptcy prediction models. Second, adding more post-pandemic years to the analysis could offer deeper insights into the long-term effects of economic shocks on financial prediction models, helping to determine whether the observed coefficient changes persist or diminish over time. This extended timeline would enhance the robustness of the findings and provide further validation of the adjusted models' utility in post-pandemic environments. However, this would be possible only in case of the availability of the necessary data. Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5. Conclusions

This study evaluates the performance of bankruptcy prediction models from Visegrad authors in the Slovak automotive sector during the COVID-19 pandemic and post-pandemic periods. The research followed a systematic methodology: first, the best-performing models were identified during the pre-pandemic period. Then, their performance was evaluated during the pandemic and post-pandemic years. Finally, the coefficients of these models were re-estimated to reflect the economic disruptions caused by the pandemic while maintaining their original variables and the methodology used by their authors.

The findings revealed that some models experienced significant declines in predictive accuracy during the pandemic, necessitating adjustments to their coefficients to restore performance. However, certain models continued to perform sufficiently well even during the pandemic, providing researchers and stakeholders with the flexibility to choose between the original models or their adjusted versions, depending on their specific needs and context.

While the research is country- and sector-specific, its implications extend beyond Slovakia and the automotive industry. The methodological framework of coefficient re-estimation provides a scalable approach for adapting financial prediction models to various regions and sectors facing economic disruptions. The study highlights the importance of continuous evaluation and refinement of predictive models to ensure their reliability in dynamic environments.

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