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ORIGINAL ARTICLE

Corporate failure prediction in crisis periods: the case of Visegrad Four large corporates

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Abstract

This article demonstrates that crisis conditions significantly impact the efficacy of corporate bankruptcy prediction models developed with pre-crisis data pertaining to large corporates in the Visegrad Four (V4) countries. Empirical research includes 245,974 firm-year observations and 3091 failure occurrences. Model development was accomplished using a combination of chi-squared automatic interaction detection (CHAID) decision trees and logistic regression (LR) methods, constituting a novel technique in V4-level bankruptcy prediction. Model performance was evaluated by area under the ROC curve (AUROC) analysis. Evidence from V4 large corporates indicates that the classification accuracy of the corporate failure prediction model developed in the pre-crisis period substantially declines during a crisis; thus, it was essential to create a new point-in-time model based only on crisis data. The results indicate that the model design underwent substantial alterations compared to the pre-crisis model. The current ratio is the strongest predictor; however, country and sector classifications also significantly contribute to elucidating corporate failure throughout the crisis era.

Keywords Corporate failure · Credit risk modeling · Bankruptcy prediction · Classification

JEL Classification C38 · C58 · G32 · G33

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Introduction

Multivariate corporate failure prediction is a thoroughly examined topic. Several decades have passed since Altman (1968) introduced the first significant multivariate statistical bankruptcy model in international literature. In statistical practice, failure prediction is a multivariate classification problem in which the target variable denotes the occurrence of a failure event, while the input variables seek to elucidate the reasons for the failure.

Failure prediction pertains to credit risk, which receives heightened attention during crisis moments (Barboza et al. 2017). In academic literature, it is predominantly evident as a result of the South-East Asian crisis in the late 1990s, the global financial crisis (GFC) at the close of the 2000s, the financial crisis affecting certain eurozone countries in the early 2010s, and the COVID-19 crisis from 2020 to 2021.

It may be contended that, irrespective of the bankruptcy model employed, moments of crisis exacerbate going concern dilemmas and result in adverse modifications to bankruptcy alarm signs (Avi and Baldassa 2022). Implicit risk variables in crises differ from those identified in previous research conducted in stable external environments (Zheng and Chen 2010; Dellepiane et al. 2015). The financial position of companies can be significantly compromised during recessionary periods, many of them could get to precarious situations or immediately exposing them to bankruptcy risks (Repousis et al. 2021; Muhammad and Rahadi 2023).

Previous empirical research suggest that the efficacy of company failure prediction models created during stable periods may be considerably diminished during crises (Camska and Klecka 2020; Papík and Papíková 2023). It has been demonstrated to possess both commendable accuracy and robustness (Nam and Jinn 2002). Several prior empirical research shown downward biases in the utilization of financial data during periods of turbulence (Kwak et al. 2012; Boratyńska 2021).

The COVID-19 crisis precipitated a shift from a prolonged benign credit cycle to a distressed one, due to the ongoing overvaluation of the non-financial corporate loan market since the last financial crisis (Altman 2022). Country-specific characteristics utilized as control variables have increasingly surpassed firm-specific characteristics in predicting insolvency and financial hardship (Bozkurt and Kaya 2023).

The Visegrad Four (V4) countries comprise Poland, Czechia, Slovakia, and Hungary. This quartet of nations functions as a regional integration inside the European Union (EU), with both a comparable historical background and an analogous economic landscape. V4 serves as an optimal subject for examining financial behavior in international empirical research for various objectives (Valaskova et al. 2023).

Consequently, challenging research questions may arise about whether the observed issues were also present during the COVID-19 era in V4 nations and what factors necessitated the revision of credit risk model architecture during this period.

The primary aim of this article is to develop a unique V4-wide failure prediction model by focusing on large V4 corporations utilizing long-term historical

data. Corporate failure is characterized in the article by conventional legal failure situations. Model construction is achieved by the integration of chi-squared automatic interaction detection (CHAID) and logistic regression (LR) techniques, which have demonstrated reliability in business failure modeling (Chen 2011) constituting a novel technique in V4-level bankruptcy prediction. Results are assessed using the commonly utilized area under the ROC (AUROC) analysis approach (Stein 2005). Furthermore, classification matrices are analyzed to demonstrate predictive accuracy.

The study seeks to analyze the impact of COVID-19 on failure behavior and predictability among V4 large corporations. The empirical investigation is substantiated by the analysis of the subsequent three hypotheses:

- *Hypothesis 1*: A universally applicable V4-wide large corporate failure prediction model exists with substantial classification accuracy, whereby country and sector classifications are not significant. This hypothesis is evaluated by parameter testing of the developed model.
- *Hypothesis 2*: A generally V4-wide applicable large corporate failure prediction model exists that demonstrates high classification accuracy for non-COVID-19 financial ratios and failure events (2018/2019), non-COVID-19 financial ratios and COVID-19 failure events (2019/2020), and COVID-19 financial ratios and failure events (2020/2021). This hypothesis is evaluated by AUROC analysis.
- *Hypothesis 3*: A novel corporate failure prediction model should be created throughout the crisis period to accommodate the evolving environment and enhance model efficacy. This hypothesis is additionally evaluated by AUROC analysis.

Although several empirical studies on corporate bankruptcy prediction have been published for specific countries, research including firms from all V4 nations remains limited, with just eight journal articles empirically addressing this subject. This study aims to enhance the current body of literature by presenting original empirical research on corporate failure prediction in the overall V4 region. This article contributes to the literature through its combined methodology, the comparative analysis of predictive efficacy across markedly distinct environments, and the inclusion of crisis observations, especially regarding the evolving requirements for model redevelopment in a rapidly changing environment.

This article is organized as follows. The *literature review* section assesses previously published V4-level corporate bankruptcy models. The *methodology and data* section presents rationale for data collection, the formulation of variables, and the assessment of applied classification methods. The *results* section delineates the outcomes of model development and offers a comparative assessment of model performance. The *discussion* section assesses the findings of empirical research in relation to other studies. The *conclusion* section summarizes the findings of this work and suggests potential avenues for further research.

Literature review

To the authors' knowledge, eight journal articles have been published to date that developed empirical corporate failure prediction models using data from all four nations of the Visegrad Group. The research scope and results of these empirical research are assessed below.

The first article concerning V4-level bankruptcy prediction was published in 2013, outlining the use of data envelopment analysis (DEA) and production function-based economic performance assessment (PFEP) for agribusiness firms in the four nations (Vavřina et al. 2013). Data were obtained from the Amadeus database provided by Bureau Van Dijk, covering the period from 1998 to 2012. A comparative analysis was conducted to evaluate the outputs of statistical models using discriminant analysis (DA) and LR. It was concluded that all applied approaches had both benefits and limitations for the accurate classification of financial health status.

Režňáková and Karas (2014) sought to find critical financial indicators for predicting bankruptcy across diverse environments. The dataset included data from manufacturing companies in the V4 region, covering the years 2007 to 2012. The information was obtained from Bureau Van Dijk's Amadeus database. Boosted trees (BT) were used to construct a bankruptcy model for each nation with similar data. The evaluation of variable significance in the models indicated statistically significant factors across all nations and specific variables relevant to individual countries.

Klieštik et al. (2018) created DA-based models for each country and an overarching Visegrad Group model to elucidate the financial status of enterprises in these nations. Data from around 450,000 companies operating in the V4 countries were obtained from the Amadeus database, including the years 2015 and 2016. The most significant model variables were the current assets to current liabilities ratio, the net income to total assets ratio, the non-current and current liabilities to total assets ratio, the cash and cash equivalents to total assets ratio, and return on equity. All models have a classification accuracy of over 80%.

Durica et al. (2019b) identified critical predictors of corporate insolvency one year before using LR modeling. The research used a dataset of financial indicators from more than 173,000 firms in the V4 countries for the years 2016 and 2017. Statistically significant variables were identified that suggest impending company failure. The developed model has a prediction accuracy over 88%. The model's prediction power is akin to that of sophisticated artificial intelligence (AI) techniques.

Pavlicko et al. (2021) developed a prediction model for several industries to evaluate corporate bankruptcy within the Visegrad Group, using an ensemble methodology that combined RobustBoost, classification and regression trees (CART), and k-nearest neighbor (KNN) techniques. More than 550,000 corporate records were extracted from the Amadeus database of Moody's Analytics, using 27 financial ratios. The model was trained and validated using financial data from 2016 to predict financial distress in 2017. The model's effectiveness was then

assessed using financial data from 2017 to forecast the financial conditions of 2018. Five variables were recognized as important predictors in the model: current ratio, return on equity, return on assets, debt ratio, and net working capital. The model's benefit is in its interpretability and enhanced accuracy.

Pavlicko and Mazanec (2022) presented a minimalist LR model for predicting financial difficulty among Visegrad Group companies, using a limited set of factors. Evaluating the significance of progress in the incremental development of the predictor set was used to choose the minimal set. Data was gathered from the Amadeus database from 2016 to 2018. Cross-validation was used in the modeling process. The model was assessed in comparison to other locally and globally used LR-based models on the same comprehensive dataset, underscoring its validity and robustness. The developed model achieved improved performance metrics compared to competing models.

Tomczak (2023) developed regional and general DA and LR models for small and medium enterprises (SMEs) in the construction industry of Visegrad Group countries. Data were acquired from the Emerging Markets Information Service (EMIS) database for the period from 2009 to 2018. A total of 32 unique models were developed and evaluated in conjunction with the Altman model for emerging markets. The stability of the created models was assessed over time. The results demonstrated that regional models had more accuracy than global models. Nevertheless, generic models may be adjusted for the analyzed Visegrad Group with an accuracy of around 90%. The model was considered preferable which had relatively high accuracy and stability over time.

Valaskova et al. (2023) created DA-based models to predict bankruptcy using the financial data of 20,693 enterprises from diverse industries within the Visegrad Group countries throughout the COVID-19 pandemic (2020–2021). Data were acquired from the Moody's Analytics Orbis database. A predictive model was created for each Visegrad Group country, along with an overarching model for the whole V4, using pertinent financial indicators as predictors. The constructed models included 6 to 14 indicators using diverse combinations of predictors and coefficients. The total indebtedness ratio had the greatest discriminative power and was included into every developed model.

Methodology and data

In order to conduct empirical research to meet research objectives, financial data of V4 large corporates was collected from Moody's Analytics Orbis Europe database. Orbis constitutes a reliable data source for corporate records and is extensively used in empirical corporate failure modeling studies, i.e., Altman et al. (2017), Sucorro (2017), Kainth and Wahlstrøm (2021), Pilch (2021). By use of Orbis Europe 'Large' and 'Very Large' (L/VL) Corporate database, no size filtering was needed to collect data.

At the time of data collection records of 44,722 V4 large corporates were accessible in Orbis. Screenings were essential to ensure consistency and manage data quality issues. Company records were discarded in the following cases:

- where no financial data was available between 2012 and 2020;
- where the status of the company was unknown;
- in cases of organizations listed in Banking, Insurance and Financial Services, or Public Administration, Education, and Health Social Services classification sectors.

There were also companies present in the Orbis database with limited periods of data availability. No firm-year observations were created for absent financial periods in these instances.

The selection of financial ratios might be challenging (Lončarski and Vidovič 2019). A number of studies have been undertaken in the V4 countries to ascertain financial indicators that possess significant discriminatory characteristics between solvent and insolvent entities (Prusak and Karas 2024). Based on prior bankruptcy prediction research (Klieštik et al. 2020) and in conformity with corporate financial standards, the following financial ratios were used as input variables:

- ROE using Net income (%);
- ROCE using Net income (%);
- ROA using Net income (%);
- Profit margin (%);
- EBITDA margin (%);
- EBIT margin (%);
- Cash flow /operating revenue (%);
- Net assets turnover;
- Interest cover;
- Stock turnover;
- Collection period (days);
- Credit period (days);
- Current ratio;
- Liquidity ratio;
- Shareholders liquidity ratio;
- Solvency ratio (Asset based) (%);
- Solvency ratio (Liability based) (%);
- Gearing (%);
- Profit per employee (000 EUR);
- Operating revenue per employee (000 EUR);
- Costs of employees/Operating revenue (%);
- Average cost of employee (000 EUR).

Missing values for one or more variables detected in Orbis were substituted by means of median imputation. Variables with a substantial proportion of missing data were excluded from consideration in the modeling process.

A total of 245,974 firm-year observations comprised the modeling database for the period between the 2012 and 2020 financial years. The country and financial year breakdown of the database is summarized in Table 1.

Table 1 Breakdown of the modeling database by V4 country and financial year. *Source* Orbis Europe

	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
CZ	6,433	6,427	6,481	6,410	6,555	6,563	6,516	6,120	4,491	55,996
HU	4,130	4,221	4,304	4,364	4,404	4,578	4,640	4,633	4,696	39,970
PL	11,917	12,390	12,910	13,487	14,305	15,034	15,337	15,089	14,091	124,560
SK	2,676	2,721	2,763	2,773	2,830	2,864	2,878	2,859	3,084	25,448
V4 Total	25,156	25,759	26,458	27,034	28,094	29,039	29,371	28,701	26,362	245,974

Corporate failure is conventionally characterized by legal failure events including bankruptcy, insolvency proceedings, reorganization, rescue plans, compulsory strike-off, or liquidation. Reasons for failure were not distinguished for the purpose of further calculations. In order to create a binary target variable, firm-year observations were denoted as 1 when a failure event occurred and as 0 when no failure occurred. This was applied in the subsequent year after the final date of the financial report.

It is generally well known that large corporates possess lower vulnerability to failure risk than SMEs (Kotaskova et al. 2020). Hence, the application of multivariate classification methods is challenging due to the presence of a highly imbalanced sample. Table 2 delineates the annual and country distribution of failure events. It can be observed that except for Czechia, the COVID-19 pandemic is associated with increased failure levels in the V4 countries. This phenomenon is seen in failure data from 2020 and 2021. The total V4-level failure rate throughout the examined period is 1.26%.

To enable model validation on data not used during model development, the database was partitioned into training and testing subsets. The training subset included firm-year observations from between 2012 and 2017 and associated failure occurrences between 2013 and 2018, constituting 65.7% of the modeling database. The testing subset incorporates subsequent firm-year-observations and associated failure events constituting 34.3% of the database. Table 3 delineates the attributes of the partitioned database facilitating model performance evaluation based on

- non-COVID-19 financial data (2018) and associated non-COVID-19 failure events (2019);

Table 2 Breakdown of failed observations by V4 country and failure year. *Source* Orbis Europe

	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
CZ	72	79	70	53	62	44	37	44	25	486
HU	67	56	43	39	36	32	30	63	73	439
PL	112	128	126	165	207	232	200	253	323	1,746
SK	54	51	53	43	43	42	34	50	50	420
V4 Total	305	314	292	300	348	350	301	410	471	3,091

Table 3 Breakdown of the database after partitioning (the period refers to financial reporting dates). *Source* own calculations

Partition	Non-failed	Failed	Total	Failure rate
Training subset (2012–2017)	159,633	1,907	161,540	1.18%
Testing subset (2018–2020)	83,250	1,184	84,434	1.40%
Total	242,883	3,091	245,974	1.26%

- non-COVID-19 financial data (2019) and associated COVID-19 failure events (2020); and
- COVID-19 financial data (2020) and associated COVID-19 failure events (2021).

Prior experience has demonstrated that the combined use of CHAID and LR methods is beneficial in corporate failure modeling (Kristóf and Virág 2012). CHAID as a standalone method can provide high classification accuracy in itself (Durica et al. 2019a). The univariate CHAID-based categorization method can more effectively handle outliers than the winsorization approach (Nyitrai and Virág 2019). It might also identify critical intervals for non-linear and non-monotonic variables. Consequently, it was decided to apply the univariate CHAID to categorize continuous financial ratios and to develop a LR model using the categorized variables.

CHAID, a nonparametric classification technique, attempts to optimally split sets of financial ratios based on critical intervals using the chi-squared homogeneity test (Kass 1980). The primary aim is to categorize data that represent the behavior of the target variable so that intragroup variance is minimized, and intergroup variance is maximized. CHAID offers a distinct edge over other decision tree methodologies by its ability to generate more than two categories. It is not constrained by a distribution assumption and can accommodate both continuous and categorical data types (Delen et al. 2013).

In accordance with the previously specified requirements critical intervals were determined ratio by ratio using the univariate CHAID method. Membership in established categories was indicated by flag (1/0) variables serving as decision rules with binary outcomes for further modeling steps.

The multivariate failure prediction model was constructed using LR which is widely applied in V4 countries to develop corporate failure models (Kovácová and Kliestik 2017; Durica et al. 2019a, b; Tomczak 2023). It employs a logistic function to assess the likelihood of a binary dependent variable's occurrence based on independent variables. The log-odds for the class designated as '1' is constituted by a linear combination of input variables. The logistic function is fitted by the maximum likelihood method which transforms log-odds into probabilities (Ohlson 1980) as described in the following formula:

$$\Pr(\text{failure}) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_j X_j)}} \tag{1}$$

where β_j is the regression parameters; X_j is the input variable; $j = 1,.., m,$ where m is the number of input variables.

LR is not constrained by a distribution assumption and can accommodate both continuous and categorical data types. Furthermore, LR modeling necessitates the handling of outliers which has previously been addressed with CHAID. The significance of the LR model is evaluated by use of the Omnibus Chi-squared test, while its parameters are assessed by use of the Wald test.

Model performance is evaluated by use of the ROC curve method in line with established model validation standards. The ROC curve evaluates the accuracy of predicted probabilities in representing output category membership when the original classification is known (Stein 2005). The AUROC serves as an objective statistical metric for predictive power. An AUROC score over 50% indicates a benefit over random guessing. A satisfactory model must possess an AUROC score of no less than 75%.

Results

The Wald forward stepwise procedure was applied to develop the LR model using the flag variables obtained from CHAID categorization. The entry criterion was set at 0.05 and the removal criterion at 0.1. Table 4 delineates the features of the constructed LR model.

Table 4 Model design, parameters, and results of statistical tests. *Source* own calculations

Model variable (Decision rule; 1—true, 0—false)	β	Standard error	Wald test	p value
ROE using Net income (%) ≤ -3.435	1.061	0.117	82.131	0.000
− 3.435 < ROE using Net income (%) ≤ 1.542	0.382	0.101	14.240	0.000
ROA using Net income (%) ≤ -2.858	1.158	0.095	148.638	0.000
− 2.858 < ROA using Net income (%) ≤ 0.152	0.780	0.094	69.252	0.000
EBIT margin (%) ≤ -1.119	0.328	0.067	24.195	0.000
Cash flow/Operating revenue (%) ≤ 0.290	0.530	0.094	31.650	0.000
0.290 < Cash flow/Operating revenue (%) ≤ 8.842	0.273	0.080	11.651	0.001
6.237 < Net assets turnover	0.742	0.056	173.728	0.000
Credit period (days) ≤ 38.198	− 0.738	0.063	135.269	0.000
38.198 < Credit period (days) ≤ 82.037	− 0.259	0.061	18.254	0.000
Current ratio ≤ 0.617	1.673	0.064	677.578	0.000
0.617 < Current ratio ≤ 0.908	0.919	0.074	153.178	0.000
0.908 < Current ratio ≤ 1.062	0.594	0.088	45.705	0.000
Shareholders liquidity ratio ≤ 0.377	0.858	0.077	124.600	0.000
0.377 < Shareholders liquidity ratio ≤ 31.925	0.360	0.065	30.473	0.000
Solvency ratio (Liability based) (%) ≤ 13.776	− 0.374	0.072	26.883	0.000
Operating revenue per employee (000 EUR) ≤ 52.430	0.178	0.052	11.938	0.001
Constant	− 6.697	0.132	2567.393	0.000

The most significant variable is that of the current ratio falling below a value of 0.617 indicating that inadequate liquidity is the primary factor explaining failure risk of V4 large corporates. This is followed by high net assets turnover, the second lowest category for current ratio, and subsequently the poor ROA value.

The Omnibus Chi-squared test yielded a result of 4,540.6 with a 0.000 p value indicating that the model is significant. All input variables are also significant. It can be concluded that parameter signs and effects comply with professional standards of corporate finance. The AUROC value for the training subset is 88.2% indicating robust performance and classification power. Figure 1 depicts the ROC curve.

It was attempted to include country and sector classifications as categorical variables in the model. Nonetheless, none was deemed significant outside the scope of financial ratios, hence supporting the adoption of Hypothesis 1.

To illustrate that the CHAID categorization enhanced model predictive power, a benchmark LR model was constructed utilizing the original continuous variables and the forward stepwise procedure with identical entry and removal criteria. The most significant predictor was the continuous ROA, followed by the credit period days, as determined by the Wald test. The Omnibus test yielded a value of 2783.8 with a p value of 0.000, indicating a statistically significant model, albeit with a reduced Chi-squared statistic. Nevertheless, the AUROC was 83.0%, indicating inferior classification accuracy relative to the previously presented model.

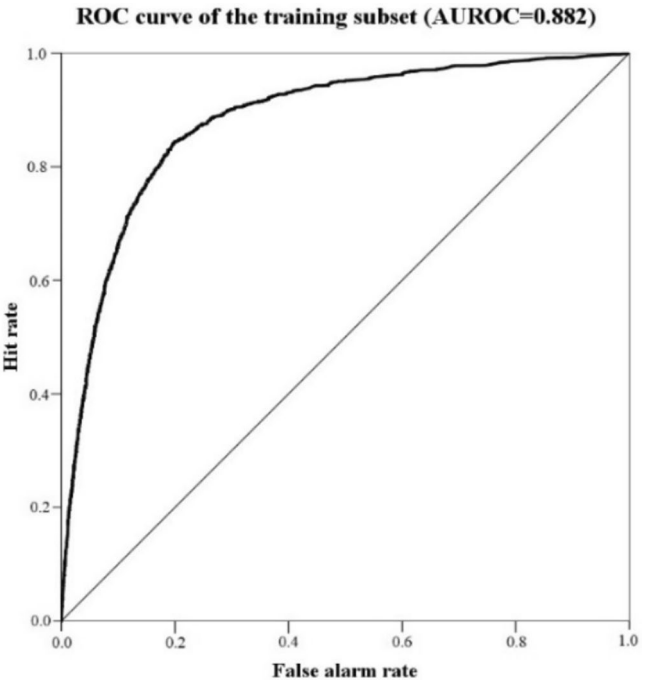

Fig. 1 ROC curve for the training subset (2012–2017 financial data; 2013–2018 failure events). *Source* own calculations

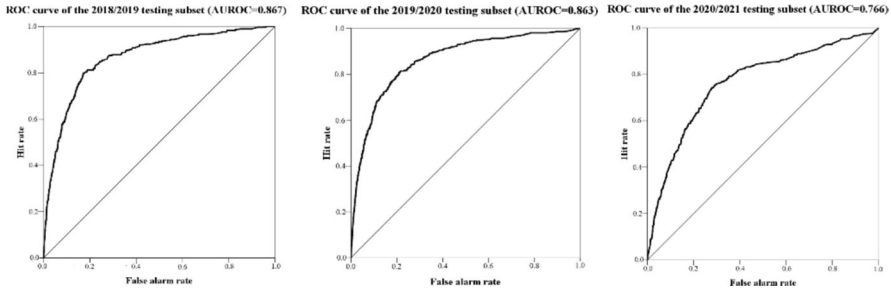

Fig. 2 ROC curve analysis for the testing years. *Source* own calculations

Figure 2 illustrates the outcomes of model evaluation throughout the three temporal intervals. The AUROC value is 86.7% for 2018 financial data and 2019 failures, 86.3% for 2019 financial data and 2020 failures, whereas it is only 76.6% for 2020 financial data and 2021 failures. This trend indicates that the developed model maintained its favorable predictive power for the first two years, but substantially deteriorated during the testing year characterized by COVID-19 associated financial data and failure behavior. The tendency resembles that of the former GFC when pre-crisis models managed to predict the occurrence of failure with significantly lower reliability levels. Consequently, Hypothesis 2 is dismissed since COVID-19 has created conditions in firm data that were insufficiently captured by the model.

The classification matrices, utilizing a 2.5% cut-off value, are presented in Table 5 to convey classification accuracy during the testing periods. The increasing misclassification of genuinely failed observations during the 2020/2021 period exemplifies the reduced usability of the pre-crisis model in times of crisis.

In addition to classification power, the consideration of probability of failure calibration, to determine to what extent predicted probabilities line up with observed failure rates in each period, is also key to evaluate the applicability of the developed model. Table 6 presents statistics on the predicted versus actual failure rates, along with the Brier scores, which is a validated method for assessing the calibration of a predictive model. The rise in the Brier score indicates a decline in the pre-crisis model's usability; however, the Brier scores across all periods do not necessarily appear excessively unfavorable.

Table 5 Classification matrices for the testing periods**.** *Source* own calculations

		2018/2019 Testing subset			2019/2020 Testing subset			2020/2021 Testing subset		
		Predicted class			Predicted class			Predicted class		
		0	1	Total	0	1	Total	0	1	Total
Actual class	0	25,895	3,172	29,067	25,446	2,846	28,292	23,146	2,745	25,891
	1	107	197	304	148	261	409	269	202	471
Total		26,002	3,369	29,371	25,594	3,107	28,701	23,415	2,947	26,362

Table 6 Calibration metrics for the testing periods. *Source* own calculations

	Average estimated probability of failure	Actual failure rate	Brier score
2018 Financials, 2019 defaults	0.0120	0.0103	0.0098
2019 Financials, 2020 defaults	0.0116	0.0143	0.0132
2020 Financials, 2021 defaults	0.0118	0.0179	0.0173

For the abovementioned findings, it was decided to create an alternative point-in-time model by just using 2020 financial data and 2021 failure occurrences to address the identified issues with the previously constructed model. The reduced modeling database included 26,362 firm-year observations, of which 471 companies failed, resulting in a failure rate of 1.79%.

Initially, the financial ratios were recategorized using CHAID. Results demonstrated that failure statistics significantly altered across sectors in comparison to data gathered during the pre-COVID period. The critical intervals of the majority of financial ratios grew more conservative, and the disparities in failure rates across V4 nations became large. The database was then divided into training and testing subsets using random sampling. The training subset constituted 70% of the data, whereas the testing subset accounted for 30%. So, the 2020/2021 model was developed using a singular snapshot of financial indicators, precluding the possibility of out-of-time or out-of-universe validation; instead, an out-of-sample validation was employed. This indicates that firm identities did not overlap between the training and testing samples. To maintain the integrity of the model's applicability, the selection of the two subsets was conducted randomly, ensuring the model's usability across any large corporate entity within the V4 framework without distortions. Table 7 delineates the characteristics of the partitioning exercise.

By intending to develop a better model, a forward stepwise LR modeling was applied to the training subset. Table 8 illustrates the model design together with parameters and statistical test results.

While the current ratio remained the strongest variable, the model design underwent substantial alterations compared to the prior model. The result of the Omnibus Chi-squared test is 487.6 with a 0.000 p value indicating that the model is significant. All parameter signs and effects again satisfy the broad requirements of corporate finance. The AUROC for the training subset is 81.8%, while for the testing subset it is 81.5% suggesting favorable model performance and absence of overtraining. Figure 3 illustrates the ROC curves for the point-in-time model.

Table 7 Breakdown of the 2020/2021 database after partitioning. *Source* own calculations

Partition	Non-failed	Failed	Total	Failure rate (%)
Training subset (70%)	18,086	332	18,418	1.80
Testing subset (30%)	7,805	139	7,944	1.75
Total	25,891	471	26,362	1.79

Table 8 Variables, parameters, and statistical values for the 2020/2021 model. *Source* own calculations

Model variable (decision rule; 1—true, 0—false)	β	Standard error	Wald test	p value
ROE using net income (%) ≤ 1.114	0.381	0.172	4.920	0.027
− 1.065 < ROCE using net income (%) ≤ 2.697	0.521	0.126	17.048	0.000
ROA using net income (%) ≤ 0.044	0.558	0.208	7.179	0.007
0.044 < ROA using net income (%) ≤ 1.269	0.558	0.194	8.291	0.004
Cash flow/operating revenue (%) ≤ 0.169	0.673	0.156	18.569	0.000
5.610 < Net assets turnover	0.442	0.126	12.218	0.000
53.397 < Stock turnover	0.383	0.128	8.981	0.003
58.672 < Collection period (days)	0.445	0.119	13.948	0.000
Current ratio ≤ 0.634	0.997	0.173	33.088	0.000
0.634 < Current ratio ≤ 0.946	0.579	0.173	11.147	0.001
Liquidity ratio ≤ 0.327	0.411	0.170	5.812	0.016
Gearing (%) ≤ 79.614	− 0.326	0.125	6.769	0.009
1.891 < Cost of employees/Operating revenue (%) ≤ 14.238	− 0.303	0.141	4.652	0.031
Is the company in Czech Republic?	− 0.779	0.287	7.349	0.007
Is the company in Poland?	0.332	0.134	6.117	0.013
Is the company in Agriculture; Horticulture and Livestock; Biotechnology and Life Sciences; Industrial, Electric and Electronic Machinery; Miscellaneous Manufacturing; Transport Manufacturing; or Wholesale sector?	− 0.534	0.168	10.030	0.002
Is the company in Communications; Computer Hardware; Information Services; or Retail sector?	− 1.878	0.589	10.165	0.001
Constant	− 5.339	0.226	558.747	0.000

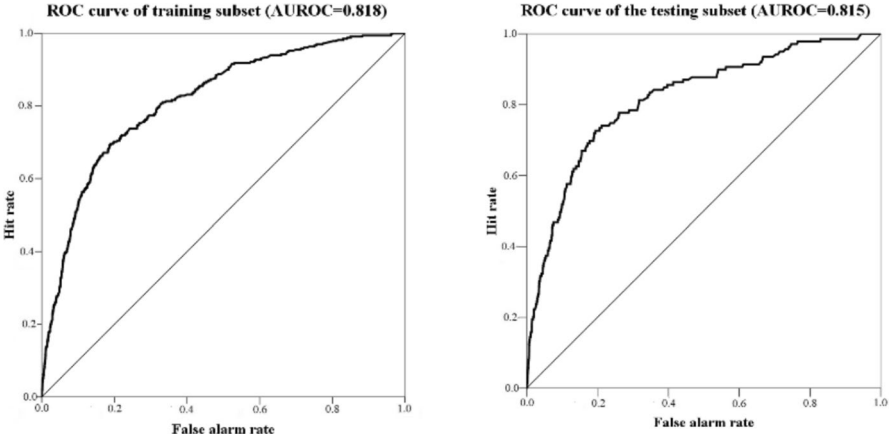

Fig. 3 ROC curves of the 2020/2021 model *Source* own calculations

Table 9 Classification matrix for the testing period *Source* own calculations

		2020/2021 testing subset		
		Predicted class		
		0	1	Total
Actual class	0	6,460	1,345	7,805
	1	44	95	139
Total		6,504	1,440	7,944

Table 9 displays the classification matrix for the testing subset, employing the previously utilized 2.5% cut-off threshold. The Type I error significantly decreases with the implementation of the point-in-time model, which is a crucial element in bankruptcy prediction.

A benchmark LR model was constructed also for this period using the original continuous variables and the same modeling strategy. The strongest predictor was the continuous ROA, succeeded by the asset-based solvency ratio, as established by the Wald test. The Omnibus test produced a value of 163.0 and a p value of 0.000, signifying a statistically significant model, accompanied by a diminished Chi-squared statistic. The AUROC was 70.1%, signifying markedly inferior classification accuracy compared to the CHAID-based model.

Ultimately, Hypothesis 1 is rejected owing to the significance of both country and sector classifications in the revised model. Hypothesis 2 has already been rejected in light of prior findings. However, due to the need for novel model design during the COVID-19 era, Hypothesis 3 is accepted.

Discussion

In response to the core research question of this article, historical crisis experience has indeed seemed to repeat itself in the COVID-19 era in V4 countries. Since the pre-COVID-19 model showed lower predictive power when it was projected onto COVID-19 related financial data and failures, it was deemed necessary to develop a point-in-time model to exclusively consider the most recent observations. This aspect also emerged during the 2007–10 financial crisis (Camska and Klecka 2020). The point-in-time model possessed altogether lower (but still high) classification accuracy, and backtesting of it was successful.

Instances of COVID-19 related failure have revealed that sector classification is significant in predicting corporate failure. The point-in-time model incorporated two sector groups which produced the two lowest failure rates in the COVID-19 crisis. Therefore, if a company belongs to either of these sectors, it faces lower probability of failure. It is also notable that before the COVID-19 crisis the sector classification did not produce significant variables beyond consideration of financial ratios.

The developed models can to a certain extent be compared to previously published V4-level corporate failure prediction models. However, it is notable that previous V4-level models mostly included small and medium enterprises as well as

large corporates. Their target variable was not necessarily that of unique legal failure, and they did not consider the same period of observations. In certain empirical studies differentiated models were also developed for the four countries (Tomczak 2023; Valaskova et al. 2023). The sector classification was not inevitably examined by former models and backtesting was not always accomplished in subsequent periods of observations at least one year later. Moreover, it was not possible prior to the COVID-19 crisis to research its business-related effects.

With regard to the significance of country classification, not all studies considered it as a model variable. The current COVID-19 model considered Czechia and Poland as significant input variables. In contrast, Klieštik et al. (2018) found Czechia and Slovakia to be significant categorical variables, as did Durica et al. (2019b) in the case of the Czechia, Hungary, and Poland.

We demonstrate the effects of country and sector classification in our point-in-time model. For instance, we analyzed a Polish company (BVDID: PL140353224) in the Travel, Personal and Leisure sector, which faces compounded adversity due to its classification during the crisis. The estimated probability of failure for this company in 2021, based solely on financial indicators, is 5.190%, whereas the point-in-time model yields a probability of 6.747%. Conversely, a Czech company in the Computer Hardware sector (BVDID: CZ25965361) represents a favorable country and sector combination during the crisis. Its probability of failure, based on financial ratios alone, is 0.200%, while the point-in-time model indicates 0.103%. Thus, these impacts align with business and financial rationales and accurately reflect the effects of COVID-19.

A notable point of discussion is the diversity of financial ratio variables employed, which differ markedly across the formerly referred models. The current ratio emerged as the most significant variable in this investigation, similar to the findings of Klieštik et al. (2018) and Pavlicko et al. (2021). The return on equity or the return on assets were included in all models, but with differing importance. The asset turnover ratio was significant in this analysis, consistent with the findings of Klieštik et al. (2018) and Durica et al. (2019b). The indebtedness ratio, or its proxy (shareholders' liquidity ratio in this study), emerged as a major variable in the research conducted by Pavlicko et al. (2021), Pavlicko and Mazanec (2022), Tomczak (2023), and Valaskova et al. (2023). Conversely, contrary to previous studies, size indicators emerged as the most effective predictors according to Režňáková and Karas (2014). It is also advisable to select indicators that illustrate the variations in values prior to and during the COVID-19 pandemic, while assessing the stability of ratios over time (Tomczak 2021).

In light of a methodological comparison with previous V4-level empirical investigations, it can be concluded that diverse solutions and modeling methodologies are employed by V4 researchers. The initial V4-level article indicated that the PFEP might be advantageous when company information is minimal, as it depended just on three attributes, whereas DEA seems to be a more effective strategy (Vavřina et al. 2013). Mainstream DA and LR methodologies yielded good outcomes as demonstrated by Kliestik et al. (2018), Durica et al. (2019b), Pavlicko and Mazanec (2022), Tomczak (2023), and Valaskova et al. (2023), albeit across varying timeframes. Režňáková & Karas (2014) and Pavlicko et al. (2021) employed ensemble

approaches, illustrating the development and effective utilization of machine learning techniques in V4-level corporate failure modeling. The current empirical research methodologically showed that the combined use of CHAID and LR approaches is effective for constructing credible corporate failure models. Given the global advancements in classification methods, there is undoubtedly potential for more experimentation in future V4-level predictive modeling.

Conclusion

In this article, a V4-level corporate failure prediction model concentrating on V4 large corporates using longer term historical data has been presented. It has examined how COVID-19 has affected failure behavior of V4 large corporates. A total of 245,974 firm-year observations and 3,091 failure events comprised the modeling database.

A model from the pre-COVID-19 period was initially created with CHAID and LR methodologies and subsequently evaluated with actual data gathered over the subsequent three years. Results were positive until the release of the 2019 financial figures and the failures of 2020. Furthermore, the predictive power was significantly diminished when applied to the financial data of 2020 and the failures of 2021. Consequently, it was considered essential to develop a new point-in-time model utilizing just data gathered in 2021. The testing was successful.

Results demonstrate that in the turbulent economic environment amid crisis periods failure prediction models must be reviewed at least annually. If earlier applied models fail in revalidation, new models should be developed to reflect features of actual failure behavior.

However, a research limitation is evident in the fact that large corporations maintain a low failure rate while experiencing many crises. This fact results in a restricted quantity of failed observations for multivariate classification modeling. Future emerging crises may reveal unprecedented patterns in company failure behavior that historical data cannot elucidate.

Future research will involve replicating this empirical study by integrating findings from subsequent periods. Contemporary machine learning approaches are also intended to be implemented in V4 large corporates to enhance predictive power.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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