“Financial reporting frameworks and distress prediction models in SME auditing: Evidence from the Visegrad Four countries”

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FINANCIAL REPORTING FRAMEWORKS AND DISTRESS PREDICTION MODELS IN SME AUDITING: EVIDENCE FROM THE VISEGRAD FOUR COUNTRIES

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Abstract

Although financial reporting and auditing standards are substantially harmonized across the European Union, important differences remain in national accounting regulations, audit thresholds, and the practical application of the going concern principle. These differences are particularly relevant for small and medium-sized enterprises (SMEs), which constitute the dominant segment of the Visegrad Four (V4) economies. This paper examines differences in financial reporting and auditing frameworks among the Czech Republic, Hungary, Poland, and Slovakia and develops sector-specific distress prediction models to support going-concern assessments in SME auditing.

The empirical analysis is based on financial statement data for 66,988 active firms obtained from the Orbis database. After data cleaning and consistency checks, a modelling sample of approximately 41,000 SMEs was constructed. Financial distress is defined as a persistent inability to cover interest obligations, represented by two consecutive years in which earnings before interest and taxes (EBIT) are lower than interest expenses. Distress status is modelled using financial ratios, firm-size indicators, industry characteristics, and selected variables inspired by ISA 570. Separate binomial logistic regression models are estimated for country–industry groups derived from NACE classifications and evaluated using hold-out samples.

The results confirm that country- and sector-specific models achieve satisfactory predictive performance and provide useful support for assessing going-concern risks. The results also show that the most informative predictors differ across countries and industries, reflecting differences in regulatory environments and economic structures. The study highlights the importance of local calibration when developing distress prediction models and demonstrates that a universal approach may lead to reduced predictive accuracy. The proposed models provide a practical screening tool for auditors, lenders, and SME managers, complementing professional judgement and broader audit procedures.

Keywords auditing, SMEs, distress prediction, going concern principle, financial reporting, Visegrad group countries

JEL Classification G33, M41, M42

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INTRODUCTION

The harmonization of financial reporting and assurance standards in the European Union has, in theory, created a uniform basis for corporate transparency in the common market. In practice, however, the transposition of these international standards into the national legal systems of the Visegrad Group (V4) – the Czech Republic, Hungary, Poland, and Slovakia – reveals significant local divergences. These differences are particularly pronounced in the application of the *going concern principle*, the categorization of economic entities, and the determination of thresholds for mandatory auditing. As the region grapples with economic volatility

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stemming from the post-pandemic recovery and geopolitical instability, the reliability of the going-concern assumption has become a critical issue for all stakeholders, from managers, auditors, credit risk analysts to regulatory authorities.

This paper presents, in the context of the functioning of small and medium-sized enterprises, an overview of the financial reporting and auditing regulatory environment in the V4 region, with a particular focus on legislative changes referring to the going concern principle that took effect in 2024 and 2025. The choice of the SME sector is mainly due to the fact that these differences are more visible there than in large entities, which apply international standards to a greater extent. The study focuses on the qualitative assessments of the going concern principle required by the International Standard on Auditing (ISA) 570 and quantitative distress prediction models. The use of such models, especially in relation to small and medium-sized enterprises, can be helpful for business partners. This is because many managers and contractors of small and medium-sized enterprises have significantly fewer analytical resources at their disposal compared to larger entities. They can also be helpful to auditors, who will be able to obtain preliminary information on the financial condition of the audited company in a short time and without significant resources.

1. LITERATURE REVIEW

The literature review was organized into key areas related to the objectives of the study. These include a presentation of key differences in accounting systems among the four countries analyzed, a description and characterization of the going concern principle with regard to the regional context, and a critical review of the literature on distress forecasting models for SMEs to assess compliance with the going concern principle.

1.1. Regulatory frameworks and financial reporting thresholds in the V4 region

Although the V4 countries operate within the common framework of European Union accounting harmonization, financial reporting and statutory audit requirements continue to be shaped by national legislation and supervisory practice. These institutional differences are particularly relevant for small and medium-sized enterprises (SMEs), as they influence both the scope of accounting obligations and the amount of reliable financial information available to auditors, lenders, investors, and other stakeholders.

In Poland, the accounting framework is governed primarily by the Accounting Act of September 29, 1994 with later amendments (Legislation of Poland, 1994). The legislation distinguishes between simplified bookkeeping and full accounting systems, with the obligation to maintain accounting books applying to natural persons and partnerships once specified revenue thresholds are exceeded. The Polish audit regime is regulated by the same Act, under which joint-stock companies are generally subject to statutory audit irrespective of size, while other entities become subject to audit when they satisfy at least two of three criteria relating to employment, total assets, and revenues. Consequently, a substantial proportion of smaller Polish entities may operate under simplified reporting arrangements, which can reduce the availability and comparability of publicly accessible financial information.

The Hungarian accounting environment is based on Act C of 2000 on Accounting (Legislation of the Hungarian, 2000). Recent amendments effective from January 2025 substantially increased the thresholds for exemption from mandatory audit requirements. In particular, the annual net sales revenue threshold relevant to audit exemption was increased from HUF 300 million to HUF 600 million, while the employment criterion remained unchanged. At the same time, the thresholds for simplified annual financial statements were also raised, thereby extending the population of SMEs permitted to prepare less detailed financial reports. Although these changes reduce administrative burdens for smaller enterprises, they also decrease the proportion of firms whose financial statements are externally verified and fully comparable across jurisdictions.

In the Czech Republic, accounting regulation is based on Act No. 563/1991 Coll., on Accounting (Legislation of the Czech Republic, 1991). Amendments effective from 2025 significantly increased the thresholds used for categorizing accounting entities into micro, small, medium-sized, and large firms. Under the revised framework, small entities are defined by thresholds of CZK 120 million in assets, CZK 240 million in turnover, and 50 employees, while medium-sized entities are defined by thresholds of CZK 600 million in assets, CZK 1.2 billion in turnover, and 250 employees. These categorization criteria directly affect statutory audit obligations. For accounting periods beginning on or after 1 January 2026, mandatory audits are generally restricted to medium-sized and large entities, while most small entities are exempt unless they fall under special regulatory regimes such as public-interest entities.

In Slovakia, financial reporting is governed primarily by Act No. 431/2002 Coll. on Accounting and Act No. 423/2015 Coll. on Statutory Audit (Legislation of the Slovak Republic, 2002, 2015). Compared with some neighboring countries, the Slovak framework is characterized by a relatively formalized legal structure and standardized reporting requirements. This approach supports consistency and comparability of financial information, although it may provide less flexibility regarding reporting alternatives available to SMEs. As in the other V4 countries, statutory audit obligations are determined through size-related criteria that influence the proportion of firms subject to external verification.

From a comparative perspective, these differences are not merely formal. Although all V4 countries operate within the broader framework established by EU accounting directives, significant variation remains in audit coverage, reporting thresholds, disclosure obligations, and the institutional interpretation of accounting requirements. Such differences directly affect the quantity, quality, and reliability of accounting information available for financial analysis and distress prediction modelling.

Consequently, a distress prediction model developed using accounting data from one V4 country cannot automatically be assumed to perform equally well in another. Differences in reporting regimes, audit coverage, financial statement structures, and disclosure requirements may substantially influence the informational content of accounting variables and, ultimately, the predictive performance of distress models. These institutional differences, therefore, provide an important justification for the development of country-specific and sector-specific distress prediction models within the V4 region.

1.2. Going concern principle: ISA 570 and its regional application

The going concern principle is a fundamental assumption underlying financial reporting and auditing because it presumes that an entity will continue its operations for the foreseeable future and therefore prepares its financial statements on a basis other than liquidation. Within the V4 region, this principle is particularly significant for SMEs, whose financial resilience is often more sensitive to adverse economic conditions, customer concentration, financing constraints, and short-term liquidity shocks than that of larger corporations.

The auditor's responsibilities regarding the assessment of going concern are defined by International Standard on Auditing (ISA) 570, *Going Concern* (IAASB, 2024). The revised version of ISA 570 strengthens the auditor's responsibilities in several areas, including risk assessment procedures, the evaluation of management's going-concern assessment, and communication with those charged with governance. The revision reflects growing regulatory and professional concerns regarding situations in which auditors failed to identify or adequately communicate material uncertainties related to business continuity before major corporate failures (IAASB, 2024).

From an analytical perspective, ISA 570 is particularly relevant because it explicitly links the assessment of going concern to indicators of financial and operational distress. The standard highlights recurring operating losses, negative operating cash flows, adverse financial ratios, difficulties in meeting debt obligations, and breaches of loan covenants as important warning signals. At the same time, ISA 570 emphasizes that financial indicators should be assessed together with operational and external factors, including

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the loss of key customers or suppliers, labor-related difficulties, management intentions, regulatory uncertainties, and other circumstances that may affect an entity's ability to continue its operations (IAASB, 2024).

This broader perspective is especially important in the SME sector. Financial difficulties experienced by smaller firms are often temporary and may not necessarily indicate a genuine threat to business continuity. Conversely, some firms may report acceptable financial ratios while facing significant operational or strategic challenges that threaten their long-term viability. Consequently, the assessment of going concern requires a combination of quantitative analysis and professional judgment.

Although ISA 570 provides a common international framework, its practical application remains embedded within national auditing environments. The relevance of going-concern assessments in the Hungarian environment has also been illustrated in studies of the financial sector, where violations of capital adequacy requirements and weaknesses in business continuity assessments were identified as important warning signals (Gulyás & Papp, 2024). In Poland, for example, ISA 570 has been incorporated into professional practice through KSB 570 (Z), which represents the national implementation of the international standard (PIBR, 2019). Similar mechanisms exist across the V4 countries, where international auditing requirements are implemented through domestic professional and regulatory structures. As a result, the practical evaluation of going concern may be influenced not only by the wording of ISA 570 itself but also by national reporting traditions, audit coverage, supervisory practices, and the quality of available accounting information.

For this reason, distress prediction models should be viewed as complementary tools supporting the going-concern assessment process rather than as substitutes for auditors' professional judgement. Such models can help identify entities exhibiting elevated levels of financial risk and can provide an efficient initial screening mechanism for auditors, lenders, investors, and business partners. Nevertheless, they cannot fully capture qualitative information, management intentions, future financing arrangements, or other entity-specific circumstances that are essential components of a comprehensive going-concern evaluation. Their role is therefore best understood as providing additional evidence within a broader assessment framework consistent with the requirements of ISA 570.

1.3. Structural divergences in accounting data: The example of the "Costs vs. Functions" problem

One of the principal obstacles to constructing comparable distress prediction models across the V4 countries is the limited homogeneity of accounting information, despite the common framework established by European Union accounting directives. Differences remain not only in audit coverage and disclosure requirements but also in the structure of financial statements and the classification of selected accounting items. These technical differences are highly relevant for empirical modelling because they directly affect the interpretation and comparability of commonly used financial ratios.

A particularly important distinction concerns the presentation of operating expenses. In the Czech Republic, Hungary, and Slovakia, SMEs predominantly report expenses according to their nature, whereas in Poland, the functional classification of expenses is more common, particularly in reporting environments influenced by IFRS principles (Lőrinczová, 2021). Although both approaches satisfy statutory accounting requirements, they do not necessarily generate equivalent analytical inputs. Consequently, ratios related to operating efficiency, gross profitability, or cost structure may reflect somewhat different economic realities depending on the reporting format adopted by a firm.

The implications of this difference become especially apparent when distress prediction models rely on variables derived from sales revenues, operating costs, or cost-of-sales categories. Under a cost-by-nature reporting system, analysts frequently cannot identify a measure directly equivalent to the cost of sales. Instead, proxy variables must be constructed using material expenses and related cost categories, which may contain elements that would be classified differently under a functional presentation format. As a result, variables that appear identical in name may not be fully comparable across countries or industries.

Another important divergence concerns the treatment of internally generated production and changes in inventories of own production. In the Czech accounting system, changes in internally generated inventories and capitalized own work are commonly presented as adjustments to expenses. In contrast, accounting practices in Slovakia, Hungary, and Poland often present similar items in a manner that more closely resembles revenue recognition or production output (Lőrinczová, 2021). Although the resulting effect on net profit may be identical, the composition of revenues and operating costs differs, thereby influencing ratios such as asset turnover, operating margin, cost efficiency, and other indicators frequently employed in distress prediction models.

These accounting differences have important methodological implications. First, they support the argument that distress prediction models developed in one V4 country should not automatically be transferred to another without adaptation. Second, they provide a strong rationale for the development of country-specific and sector-specific model specifications, as identical financial variables may contain different accounting content depending on the reporting framework and industrial context in which they are generated.

Therefore, accounting heterogeneity should not be viewed merely as a descriptive institutional characteristic of the V4 region. Rather, it represents a direct empirical constraint affecting variable selection, model construction, interpretation of results, and the transferability of distress prediction models across national environments.

1.4. Distress prediction models and auditor opinions in the V4

The theoretical purpose of distress prediction models overlaps with one of the central objectives of auditing, namely the timely identification of circumstances that may cast significant doubt on an entity's ability to continue as a going concern. In practice, however, the two approaches are not identical. Audit judgments incorporate qualitative, forward-looking, and entity-specific information, whereas statistical distress prediction models rely primarily on structured quantitative data derived from financial statements and, in some cases, selected non-financial variables. Consequently, distress prediction models should be viewed as supporting tools rather than substitutes for auditors' professional assessments.

The literature on business failure and distress prediction is extensive and methodologically diverse, covering both bankruptcy prediction models and going-concern evaluation frameworks (Paquette & Skender, 1996; Bellovary et al., 2007b). Classical studies based on discriminant analysis and logistic regression continue to form the foundation of this research stream, while more recent contributions increasingly apply machine-learning techniques and ensemble methods (Altman, 1968; Ohlson, 1980; Dimitras et al., 1996; Balcaen & Ooghe, 2006; Bellovary et al., 2007a; Du Jardin, 2009; Jones, 2023). Nevertheless, within the V4 environment, traditional statistical approaches remain particularly attractive in SME auditing due to their transparency, ease of interpretation, relatively low data requirements, and practical applicability in auditing and credit-risk assessment (Kliestik et al., 2018; Kovacova et al., 2019; Svabová et al., 2020; Prusak & Karas, 2024; Režňáková et al., 2025).

Existing research further demonstrates that no universal set of predictors performs equally well across all institutional and industrial environments. Financial statement indicators remain the dominant explanatory variables in most models, although firm size, business activity, governance characteristics, and selected non-financial variables have also been shown to possess predictive value (Wilson et al., 2016; Karas & Srbová, 2019; Kliestik et al., 2020; Ptak-Chmielewska, 2021; Pavlíčko et al., 2021; Veganzones & Severin, 2021; Michalková et al., 2022; Svabová et al., 2022; Valaskova et al., 2023; Papík et al., 2023; Filatova et al., 2024). This issue is particularly relevant in the V4 region, where differences in reporting systems, audit coverage, and accounting practices may alter the informational content of otherwise similar financial ratios. Consequently, the literature generally supports developing country- and sector-spe-

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cific distress prediction models rather than a fully pooled international specification (Režňáková & Karas, 2014; Valaskova et al., 2020; Tomczak, 2023; Prusak & Karas, 2024).

An additional issue concerns the relationship between model outputs and auditors' going-concern evaluations. The two do not always lead to identical conclusions, and the literature offers several explanations for such discrepancies. Auditors may be reluctant to issue a modified going-concern opinion because such a signal can itself contribute to the deterioration of a firm's financial position by influencing creditors, suppliers, customers, and investors. At the same time, auditors frequently consider qualitative information such as recovery plans, expected refinancing arrangements, support from parent entities, strategic restructuring initiatives, and other circumstances that are difficult to capture in quantitative models (Bosman, 2025).

These issues become even more pronounced in the SME sector. Smaller firms often operate with limited access to external finance, less sophisticated reporting systems, and higher levels of information asymmetry, while many remain outside the scope of mandatory statutory audits. Higher levels of information asymmetry are frequently associated with lower financial reporting quality and reduced transparency for external stakeholders (Ayagi & Salisu, 2023). Under such conditions, distress prediction models can provide valuable early-warning signals for auditors, lenders, investors, and business partners. This issue is particularly relevant for SMEs operating in the Visegrad region, where financial risk management remains an important challenge (Kotaskova et al., 2020). Nevertheless, their design should reflect the specific informational constraints of SME reporting and the institutional characteristics of the country in which they are applied. This provides the rationale for the present study's focus on segmented country-specific and industry-specific distress prediction models within the V4 region.

1.5. Aim

This paper aims to examine differences in financial reporting and auditing requirements across the Visegrad Four countries and to develop and validate country- and sector-specific distress prediction models for supporting going-concern evaluations in SME auditing.

2. METHODS

To develop distress prediction models for small and medium-sized enterprises operating in the V4 countries, we initially extracted financial statements for 66,988 active companies from the Orbis database (update from December 2024). Firms were selected from the Czech Republic, Hungary, Poland, and Slovakia, and restricted to entities with SMErelevant size bands, defined as operating revenue between EUR 2-50 million and total assets between EUR 2–43 million. Public authorities and government bodies were excluded from the outset.

The Orbis export, however, did not contain fully complete and internally consistent data for all firms. A substantial number of observations had missing or implausible values for key financial statement items, incomplete NACE codes, or inconsistent time series for EBIT and interest expenses. After applying data quality filters and restricting the sample to firms with complete information for the candidate predictors listed in Table 1, the usable modeling sample was reduced to approximately 41,000 firms. Within this cleaned subsample, 40,706 companies had complete information on industry classification and distress status and were therefore used for the CART-based industry clustering and subsequent model estimation, as summarized in Table 2.

The construction of the dependent variable follows Tinoco and Wilson's (2013) notion of persistent financial distress. In line with their approach, we define financial distress as a sustained inability of the firm to generate sufficient operating profit to cover its interest obligations. Specifically, a firm is classified as distressed if its EBIT remains below interest expenses for two consecutive years. For this purpose, we use at least a two-year history of EBIT and interest expenses to identify distressed firms, while the explanatory variables in the logistic models are calculated from the most recent available set of annual accounts. The models, therefore, relate a cross-sectional snapshot of financial indicators to a distress outcome that is defined over a two-year horizon.

An important limitation of this design is that some of the explanatory variables used in the models are algebraically related to the distress definition itself. In particular, ratios such as EBIT/interest expenses (EBITINT) or total liabilities/EBIT (TLEBIT) are mechanically close to the rule classifying firms as distressed whenever EBIT falls short of interest expenses in two consecutive years. As a result, the reported values of Cox–Snell R^2 and the area under the ROC curve (AUC) may partly reflect this mechanical linkage rather than a broader ability to capture going-concern risk. The models should therefore be interpreted as providing an upper bound on discriminatory power under this specific definition of distress, rather than as fully independent measures of auditors' goingconcern assessment capabilities.

To ensure independence between model estimation and performance assessment, the cleaned modeling sample was randomly split into a 70% training subsample and a 30% test subsample, preserving the joint distribution of countries and industry groups. All model parameters and cut-off points were selected exclusively on the training data, while the out-of-sample performance was evaluated on the hold-out test set.

Given the wide set of candidate accounting ratios listed in Table 1, the initial selection of explanatory variables relied on a predictor screening procedure based on Cramer's V coefficient. Only variables that simultaneously (I) exhibited a statistically meaningful association with distress and (II) showed an economically plausible direction of influence were retained for further modeling.

This two-step selection logic ensures coherence with prior empirical findings and reduces the risk of multicollinearity or variable redundancy, a challenge that is particularly salient in SME datasets characterized by reporting heterogeneity.

The next stage involved an industry classification process and an analysis of sector homogeneity. The initial industry classification followed the NACE Rev. 2 main sections, which, although commonly used, bundle together activities with heterogeneous relationships between sector-specific risk factors and distress probability. To address this, a Classification and Regression Tree (CART) model was estimated using distress as the dependent variable and NACE sections as the splitting criterion. The resulting four terminal nodes define homogeneous industry clusters that balance sector specificity with sufficient sample size and form the basis for the segmented modeling strategy.

In the final stage, empirical models for predicting distress were estimated using binomial logistic regression. We adopted a fully segmented approach, estimating a separate model for each country–industry cluster identified in the previous step. For each model, the probability of non-distress was coded as $P(Y = 1)$ and the probability of distress as $P(Y = 0)$; firms with a predicted probability at or above the cut-off point are classified as non-distressed, while those below the cut-off are classified as distressed. The optimal decision threshold in each segment was determined using Youden's J statistic, with the cut-off value that maximizes Youden's J statistic on the training sample subsequently applied to the test sample.

Based on the literature discussed in Section 1.4 and the practical constraints of SME reporting in the V4 region, the initial set of potential predictors focused on widely available financial ratios, simple size measures, industry classifications, and a small number of ISA 570-inspired indicators. The aim was to balance predictive power with interpretability and data availability, so that the models can be used in SME auditing and credit-risk practice. Table 1 shows the variables subsequently used in the process of constructing distress prediction models.

Table 1. List of potential predictors of distress of SMEs operating in V4 countries applied in own research

Source: Own elaboration.

Measures	Formulas
Financial	
Liquidity measures	
X1 – CACL	current assets/current liabilities
X2 – CAINCL	(current assets – inventories)/current liabilities
X3 – CCL	cash & cash equivalents / current liabilities
Profitability measures	
X4 – EBITOR	EBIT (operating profit) / net revenues

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Table 1 (cont.). List of potential predictors of distress of SMEs operating in V4 countries applied in own research

Measures	Formulas
X5 – NITA	net income/total assets
Activity measures	
X6 – STA	net revenues / total assets
X7 – SDEB	net revenues / total receivables
X8 – SCL	net revenues / short-term liabilities
X9 – SINV	net revenues / inventories
X10 – NWCTA	working capital (current assets – short-term liabilities) / total assets
X11 – CAS	current assets / net revenues
Debt measures	
X12 – TLTA	total liabilities / total assets
X13 – CLTA	short-term liabilities / total assets
X14 – TLEBIT	total liabilities/EBIT (operating profit)
X15 – EBITINT	EBIT (operating profit)/interest expenses
Other measures	
X16 – cashTA	cash & cash equivalents / total assets
X17 – sizeTA	ln(assets)
X18 – sizeS	ln(net revenues)
Non-financial	
X19 – IND group	classification into business activity based on NACE codes, merged categories of NACE main sections
ISA 570 measures	
X20 – EQvRC	shareholders' funds < registered capital, binary measure: 1-if shareholders' funds is less than registered capital, 0 – otherwise
X21 – negEQ	shareholders' funds < 0, binary measure: 1 – negative shareholders' funds for the given year, 0-otherwise
X22 – negOPERCF	EBITDA – change of NWC < 0, binary measure: 1 – negative operating cash flow (EBITDA – change of NWC), 0-otherwise

In summary, in addition to typical financial indicators, variables reflecting the size of economic activity (sizeTA and sizeS) were taken into account; the type of business activity, which is determined using NACE codes; and relevant selected financial information that should be analyzed when assessing the risks associated with continuing economic activity, as contained in ISA 570.

3. RESULTS

The presentation of the results follows a structured procedure. First, the results of grouping industry classification are presented. Second, industry sectors were grouped using CART, which provided four homogeneous industry clusters better suited for estimation than the original NACE structure. The results are then presented in three steps: overall model discrimination assessed by Cox–Snell R^2, regression outputs summarizing coefficient estimates and variable significance, and finally, the evaluation of optimal cutoff values based on Youden's J statistic is used to assess classification performance.

3.1. Grouping industry classification

A CART model was applied to the original NACE industry sections to create more homogeneous groups of sectors with respect to distress risk. The administrative NACE structure proved too granular and too smooth for modeling purposes. The second level of the CART split provided the most interpretable and statistically meaningful separation, producing four balanced and distinct industry clusters. These four groups represent a compromise between preserving industry-specific risk patterns and maintaining sufficient sample size for model estimation. The resulting clusters and their distress rates are summarized in Table 2.

Cramer's V was used as a preliminary variable-selection tool to identify which financial ratios are most strongly associated with distress in each country–industry model.

3.2. Logistic regression results

The results are presented in several steps. First, overall model discrimination is evaluated using the Cox-Snell R^2, which provides a summary mea-

Table 2. Grouping the industry categories using the CART approach

Source: Own elaboration.

Terminal Node (group)	NACE main sections code	Distress %	Nondistress %	n (Total)
Node (group) 1	G, O	17.0%	83.0%	7,625
Node (group) 2	N, C, M, B, U, F, H, J	25.1%	74.9%	24,374
Node (group) 3	Q, E, S, A	33.8%	66.2%	4,242
Node (group) 4	D, K, P, I, L, R	44.5%	55.5%	4,465

sure of explanatory power across all country-industry models. Second, the logistic regression coefficients and their statistical significance (p-values) are reported to identify the key predictors of distress in each segment. In the next stages, the optimal classification cutoff is determined and tested, and the created models are tested using the learning and validation sample.

Considering models' discrimination, the Cox-Snell R^2 values in Table 3 demonstrate that all country–industry models achieve solid explanatory power, with consistent differences between countries. The Czech models reach the highest values (e.g., CZ1: 0.9163; CZ2: 0.9078), followed closely by the Polish specifications (PL1: 0.9144; PL2: 0.9038). Slovak and Hungarian models also show substantial model fit (e.g., SK4: 0.8691; HU1: 0.8564).

However, these values should be interpreted with caution because part of the explanatory power may reflect the close relationship between the distress definition and selected profitability and coverage indicators. In particular, variables such as EBITINT and TLEBIT are conceptually linked to the criterion used to identify distressed firms and may therefore contribute to higher pseudo-R^2 values.

Table 3. Cox-Snell pseudo R^2 results

Source: Own elaboration.

Version	Cox-Snell R^2	Version	Cox-Snell R^2
CZ1	0.9163	PL1	0.9144
CZ2	0.9078	PL2	0.9038
CZ3	0.8399	PL3	0.8402
CZ4	0.8471	PL4	0.8131
SK1	0.8150	HU 1	0.8564
SK2	0.8209	HU 2	0.7995
SK3	0.8330	HU 3	0.8126
SK4	0.8691	HU 4	0.8061

Tables 4-7 present the estimated logistic regression coefficients together with their statistical significance (p-values) for each country-industry model.

The Czech models reveal strong and welldefined distress patterns. Indebtedness indicators (TLEBIT) consistently show highly significant coefficients (typically $p < 0.01$). Leverage measures, especially EQvRC, are also significant in several industry groups ($p < 0.05$). Liquidity and activity ratios display weaker or inconsistent effects across the industry groups. The high explanatory strength of the Czech models is reflected in their Cox–Snell R2 values (e.g., 0.9163 for CZ1; 0.8471 for CZ4), confirming a clear distress pattern in the Czech SME environment.

Table 4. Regression results – CZ models

Source: Own elaboration.

Version	CZ1		CZ2		CZ3		CZ4	
Stat/var	Est.	p-value	Est.	p-value	Est.	p-value	Est.	p-value
Intercept	–1.4075	< 0.001	–1.7326	< 0.001	0.8192	< 0.001	0.1332	0.1174
CACL	–0.0615	< 0.001	–0.0999	< 0.001				
CAS	0.0156	0.2964		< 0.001				
EBITINT	0.0075	< 0.001	0.0198	< 0.001			0.0064	< 0.001
NITA	17.9066	< 0.001		< 0.001	17.3465	< 0.001	15.6052	< 0.001
NWCTA	0.8536	< 0.001	1.3529	< 0.001			0.5642	< 0.001
SCL	0.0862	< 0.001	0.1013	< 0.001				< 0.001
TLEBIT	0.0029	< 0.001	0.0038	< 0.001	0.0057	< 0.001	0.0049	< 0.001
TLTA	1.4053	< 0.001	–0.0830	0.5819			–0.0503	0.6334
EQvRC	0.0847	0.0657	0.3661	< 0.001	0.2330	< 0.001	0.2812	< 0.001
cashTA			2.1451	< 0.001				< 0.001
CCL			0.0290	0.3786				< 0.001
CLTA			1.6868	< 0.001			0.8544	< 0.001
STA							0.3410	< 0.001
negEQ							–0.2434	< 0.001

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Table 5. Regression results – SK models

Source: Own elaboration.

Version	SK1		SK2		SK3		SK4	
Stat/var	Est.	p-value	Est.	p-value	Est.	p-value	Est.	p-value
Intercept	0.6619	< 0.001	0.0024	0.9811	0.6177	< 0.001	0.7045	< 0.001
CAS			−0.0516	0.0001				
EBITINT	0.0232	< 0.001	0.0199	< 0.001	0.0046	< 0.001	0.0049	< 0.001
NITA					9.0761	< 0.001	12.3296	< 0.001
NWCTA	1.1549	< 0.001	0.9618	< 0.001				
SCL	0.0763	< 0.001	0.0282	0.0001				
TLEBIT	0.0057	< 0.001	0.0050	< 0.001	0.0059	< 0.001	0.0064	< 0.001
TLTA	−1.5172	< 0.001	−0.5575	< 0.001				
EQvRC			0.5255	< 0.001			0.2505	< 0.001
CLTA	2.0084	< 0.001	1.0430	< 0.001	0.6885	< 0.001		
STA			0.2439	< 0.001				
negEQ			0.0836	0.0991				

Table 6. Regression results – PL models

Source: Own elaboration.

Version	PL1		PL2		PL3		PL4	
Stat/var	Est.	p-value	Est.	p-value	Est.	p-value	Est.	p-value
Intercept	−1.3792	< 0.001	−1.5516	< 0.001	−0.4283	< 0.001	0.9634	< 0.001
CACL	−0.0461	0.0045	−0.0768	< 0.001				
CAS			0.0743	0.0001	−0.0826	< 0.001		
EBITINT	0.0082	< 0.001	0.0223	< 0.001	0.0069	< 0.001	0.0234	< 0.001
NITA	17.0884	< 0.001			14.7278	< 0.001		
NWCTA	1.3832	< 0.001	1.2994	< 0.001	0.9753	< 0.001		
SCL	0.0829	< 0.001	0.0527	0.0001	0.0573	< 0.001	0.1105	< 0.001
TLEBIT	0.0030	< 0.001	0.0033	< 0.001	0.0044	< 0.001	0.0055	< 0.001
TLTA	0.1493	0.4663	0.5812	0.0006	0.3029	0.0122	−0.6335	< 0.001
EQvRC	0.0382	0.5575	0.2991	< 0.001	0.2234	< 0.001		
CCL							−0.2034	< 0.001
CLTA	1.9578	< 0.001			1.8492	< 0.001		
STA			0.2698	< 0.001				
negEQ	−0.1861	0.0547	0.0842	0.3389				

Table 7. Regression results – HU models

Source: Own elaboration.

Version	HU1		HU2		HU3		HU4	
Stat/var	Est.	p-value	Est.	p-value	Est.	p-value	Est.	p-value
Intercept	4.2150	< 0.001	0.4792	0.1011	1.1405	< 0.001	0.9558	< 0.001
CACL	−0.1327	< 0.001						
CAS	0.0819	0.1156						
EBITINT			0.0201	< 0.001	0.0060	< 0.001		
NITA					19.8172	< 0.001	22.9122	< 0.001
NWCTA	1.3635	< 0.001	0.3212	0.1937				
SCL	0.1692	< 0.001	0.0474	0.1421				
TLEBIT	0.0056	< 0.001	0.0053	< 0.001	0.0045	< 0.001	0.0049	< 0.001
TLTA	−0.6977	0.0892	−1.0515	0.0008			0.0980	0.6850
EQvRC	1.0170	< 0.001	0.5303	< 0.001			0.0876	0.4776
CLTA	0.8072	0.0419	0.1731	0.6396				
STA			0.3140	0.0005				
negEQ	−0.2407	0.3510	0.3480	0.0361			0.0628	0.7348
sizeTA	−0.5442	< 0.001						
EBITOR					−0.0007	0.9882	0.0119	0.8339

In the Slovak models, indebtedness variables (TLEBIT, EBITINT) remain the strongest and most consistent predictors, typically significant at $p < 0.05$. Liquidity variables mostly fail to achieve significance, indicating limited predictive strength.

The Polish models combine high overall model fit with weaker predictorlevel significance. Indebtedness measures (EBITINT, TLEBIT, SCL) are again significant. Liquidity metrics (NWCTA) contribute significantly, except for the group 4 industry

Hungarian models display the sharpest and most statistically robust patterns of all four industries. Indebtedness ratios (EBITINT, TLEBIT, TLTA, EQvRC) appear as stable predictors ($p < 0.05$) across multiple industry groups. Liquidity indicators reveal mixed behavior,

Across all countries, indebtedness measures consistently emerge as the strongest predictors of distress, while liquidity indicators provide an additional – but more context-dependent – signal. Hungarian models show the sharpest statistical patterns, followed by the Czech models with high explanatory strength across most groups. Slovak models demonstrate balanced but weaker predictor significance, whereas Polish models display diffuse predistress signals despite high overall model fit.

3.3. Model testing results

The discriminatory ability of the models was evaluated using ROC analysis, with the AUC values reported in Table 8. The models exhibit strong to excellent discrimination across all country–industry segments, with AUC values consistently exceeding 0.80 and in many cases above 0.90, indicating that the predicted probabilities reliably distinguish distressed from nondistressed firms.

The ROC analysis shows that all country–industry models achieve strong discriminatory performance, with AUC values consistently above 0.80 and in many cases exceeding 0.90, confirming excellent separation between distressed and nondistressed firms. However, meaningful differences appear across countries. Polish models reach the highest AUC values overall (often above 0.94), indicating very strong classification ability. Czech models also perform robustly, with most AUC values above 0.90, especially in liquiditybased specifications. Hungarian models show more variation, with several AUC values in the 0.72-0.93 range, indicating weaker discrimination in some segments. Slovak models fall between these extremes, producing consistently solid results (mostly 0.84-0.92). These differences suggest varying intensity and clarity of pre-distress patterns across the V4 countries.

Part of this strong discriminatory power is mechanically driven by the specification of the distress definition. Because distress is defined through the relationship between EBIT and interest expenses, and several key predictors are constructed from the same components (for example, EBITINT and TLEBIT), the models partly reproduce the classification rule itself. The reported AUC values should therefore be interpreted as upper-bound estimates of discriminatory ability under this particular distress proxy.

At the same time, the distress proxy is defined over two consecutive years, whereas all explanatory ratios, including EBITINT and TLEBIT, are based on a single year of financial data. Moreover, sev-

Table 8. ROC testing results (AUC values)

Source: Own elaboration.

Version	Learn	Test	Version	Learn	Test
CZ1	0.933	0.922	PL1	0.948	0.944
CZ2	0.902	0.869	PL2	0.921	0.906
CZ3	0.838	0.777	PL3	0.919	0.923
CZ4	0.863	0.867	PL4	0.868	0.846
HU1	0.726	0.732	SK1	0.882	0.854
HU2	0.890	0.887	SK2	0.861	0.874
HU3	0.935	0.925	SK3	0.918	0.878
HU4	0.899	0.858	SK4	0.84	0.804

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eral country-industry models that do not include EBIT-to-interest coverage ratios among their final predictors still achieve strong discriminatory performance. This indicates that the models capture not only the mechanical relationship embedded in the distress definition, but also broader patterns in profitability, leverage, liquidity, and firm size that are consistent with the going-concern perspective.

3.4. Deriving optimal cut-off score

Based on the ROC results, optimal classification thresholds were derived using Youden's J statistic, which identifies the cutoff that maximizes the balance between sensitivity and specificity. Table 9 presents the optimal cutoff values and corresponding classification probabilities, showing clear variation across country–industry models and confirming the need for segmentspecific decision thresholds.

Table 9. Youden's J statistic and optimal cutoff

Source: Own elaboration.

Version	Youden's J statistic	Cut-off point	Prob.
CZ1	0.760612	0.5577	55.8%
CZ2	0.707031	0.4961	49.6%
CZ3	0.658669	0.6780	67.8%
CZ4	0.646937	0.6060	60.6%
HU1	0.372751	0.5168	51.7%
HU2	0.620322	0.6398	64.0%
HU3	0.814418	0.8052	80.5%
HU4	0.738174	0.7732	77.3%
PL1	0.817627	0.7138	71.4%
PL2	0.725168	0.4866	48.7%
PL3	0.737842	0.5855	58.5%
PL4	0.618018	0.6645	66.4%
SK1	0.661548	0.7584	75.8%
SK2	0.56692	0.6583	65.8%
SK3	0.857729	0.6861	68.6%
SK4	0.642215	0.6927	69.3%

Youden's J statistic identifies the cut-off that maximizes the joint performance of sensitivity and specificity, so that the selected thresholds balance the costs of false positives and false negatives in each country–industry segment.

The optimal cutoff values derived from Youden's J statistic (Table 9) show clear differences across country-industry segments, reflecting variation in the underlying distress patterns. Models with stronger ROC performance – such as CZ1, CZ2, PL1, PL2, and HU3 – tend to achieve higher Youden's J statistic values (often above 0.70), indicating a wellbalanced tradeoff between sensitivity and specificity. In contrast, segments with weaker discriminatory strength, such as HU1 or selected Slovak models, yield lower Youden's J statistic values and correspondingly higher or lower cutoff thresholds. These results demonstrate that a single universal threshold would be inappropriate, and that segmentspecific cutoffs materially improve classification accuracy.

3.5. Applying optimal cut-off and the corresponding accuracies

The final step of the model evaluation examines the classification performance, expressed as the percentage of correctly classified distress and nondistress cases (Table 10).

Table 10. True positive and true negative rates

Source: Own elaboration.

Version	Nondistress		Distress	
	Learn	Test	Learn	*Test*
CZ1	90.43%	86.25%	89.08%	89.33%
CZ2	80.37%	62.89%	94.66%	96.14%
CZ3	74.36%	70.61%	87.80%	81.75%
CZ4	84.97%	79.62%	84.38%	80.77%
HU1	88.43%	68.63%	57.63%	67.86%
HU2	83.98%	82.41%	80.43%	76.98%
HU3	92.08%	94.16%	73.53%	86.84%
HU4	84.87%	89.58%	80.00%	70.59%
PL1	87.06%	88.48%	89.89%	91.80%
PL2	82.81%	70.77%	96.18%	95.60%
PL3	90.15%	84.07%	85.19%	85.86%
PL4	83.75%	81.34%	74.93%	74.40%
SK1	81.81%	88.82%	64.80%	65.38%
SK2	80.70%	80.12%	75.80%	79.02%
SK3	94.13%	94.96%	90.67%	83.33%
SK4	82.35%	78.67%	77.67%	76.47%

The classification results in Table 10 show that the models achieve solid accuracy for both distress and nondistress firms in the test samples. Nondistress classification rates mostly fall within the 70-90 % range, while classification reaches 75-95 % in several segments. The strongest performance is observed in Polish and Slovak models (e.g., PL1, PL2, SK3), whereas some Hungarian segments show lower accuracy but remain stable across learning and test samples.

4. DISCUSSION

Research shows that, despite efforts to standardize accounting practices across EU countries, certain regulatory differences still exist, even in countries as economically closely linked as Poland, Hungary, the Czech Republic, and Slovakia. Therefore, to develop distress prediction models intended to assess compliance with the going concern principle, models specific to the various V4 countries and additionally sector-specific have been proposed. This approach is consistent with the findings of studies conducted by Režňáková and Karas (2014), Kovacova et al. (2019), Valaskova et al. (2020), and Tomczak (2023). Universal models for the V4 countries could, on the one hand, provide an opportunity to compare distress risk between firms operating in different countries; on the other hand, however, this would entail lower effectiveness and distortions in the calculation of certain metrics due to differences in accounting practices across these countries.

It is also important to distinguish between models for predicting distress based on business size, specifically those designed for small or small and medium-sized enterprises. This approach is also represented in the V4 countries by, among others: Svabova et al. (2020), Ptak-Chmielewska (2021), and Režňáková et al. (2025). This stems from a number of factors, including the varying bargaining power of these entities compared to large firms; in some cases, the possibility of using a less advanced form of reporting (e.g., without a cash flow statement); and the fact that some of these entities are not subject to audits. Assessing the risk of distress among micro entrepreneurs, who in some countries are allowed to use significantly simplified accounting methods, remains a research challenge. It appears that, due to limited access to financial data of these entities, standard distress prediction models used for larger enterprises will not be suitable in this case.

The research also shows that financial variables derived from financial statements continue to be the main explanatory variables in models for predicting distress, although the effectiveness of non-financial measures is increasingly being explored. This finding is consistent with previous studies, including those of Svabova et al. (2020), Ptak-Chmielewska (2021), and Papík et al. (2023). The results further highlight the importance of firm characteristics and industry context when constructing distress prediction models. In particular, the segmentation of firms according to industry groups improved model specification and reflects the heterogeneity of distress patterns across sectors.

At the same time, the results should be interpreted with caution because the distress definition is partially linked to some of the financial indicators included among the candidate predictors. In particular, measures based on EBIT and interest coverage may capture elements that are closely related to the classification rule used to identify distressed firms. Although these indicators are consistent with the practical requirements of going-concern assessment and ISA 570, future research could examine alternative model specifications excluding such variables in order to evaluate the robustness and transferability of the reported results.

CONCLUSIONS

The objective of this paper was to compare the financial reporting and auditing frameworks of the Visegrad Four countries and to develop country-specific and sector-specific distress prediction models that support going-concern assessments in SME auditing.

The results demonstrate that despite the ongoing harmonization of accounting and auditing regulations within the European Union, significant differences remain among the Visegrad Four countries. The developed logistic regression models achieved satisfactory predictive performance and confirmed that the most relevant distress indicators vary across both countries and industries. The findings further indicate that sector-specific calibration improves predictive accuracy compared with a universal modelling approach.

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These results suggest that the assessment of going-concern risks in SMEs should reflect both national regulatory environments and industry-specific characteristics. The recent increases in audit thresholds may reduce administrative burdens for SMEs; however, they may also decrease the availability of independently verified financial information, potentially affecting the reliability of distress prediction models. The developed models provide a practical tool for auditors, lenders, investors, and SME managers and can complement professional judgement in the early identification of financial difficulties. Their public availability further enhances their practical applicability and contributes to improving the quality of going-concern evaluations within the Visegrad Four region.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The data used in this study were obtained from the Bureau van Dijk's Orbis database under subscription agreements and cannot be made publicly available. Derived results and model specifications are available from the authors upon reasonable request.

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