Agri25: Value Creation Rating Model for Agricultural Enterprises - Comparison of Logistic and Discriminant Analysis in Czech Conditions

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Abstract

This study develops a sector-specific value creation rating model for Czech agricultural enterprises using Economic Value Added (EVA) as the classification criterion. Based on accounting data from the CRIBIS database covering period 2019-2023, we compare logistic regression and discriminant analysis for distinguishing value-creating from value-destroying firms. Results demonstrate that logistic regression provides superior predictive accuracy, with efficient return on invested capital and adequate working capital relative to long-term financing emerging as the primary determinants of positive EVA. The findings confirm that traditional rating models developed for industrial enterprises exhibit limited applicability in agriculture due to the sector's unique characteristics, including Common Agricultural Policy (CAP) subsidies that suppress bankruptcy rates and create distinct financial dynamics. This research highlights the necessity of sector-adapted analytical tools that shift focus from bankruptcy prediction to value creation assessment, providing practical frameworks for financial institutions, farm managers, and policy-makers evaluating agricultural financial performance and sustainability.

Keywords

Agriculture, creditworthiness, logistic regression, discriminant analysis, economic value added, financial health, Czech farms.

Špička, J. and Náglová, Z. (2026) "Agri25: Value Creation Rating Model for Agricultural Enterprises - Comparison of Logistic and Discriminant Analysis in Czech Conditions", *AGRIS on-line Papers in Economics and Informatics*, Vol. 18, No. 3, pp. 60-77. ISSN 1804-1930. DOI 10.7160/aol.2026.180306.

Introduction

Predicting financial condition and bankruptcy remains an important topic in finance and risk management. For the agricultural sector, however, the applicability of traditional models remains a matter of controversy. Agriculture is highly influenced by structural, climatic, and policy risks (Dai, 2025), making financial results volatile and often poorly captured by models originally designed for industrial or other types of firms (Wu et al., 2022).

Agricultural enterprises in the European Union exhibit substantially lower bankruptcy risk compared to firms in other sectors due to operational subsidies provided under the Common Agricultural Policy (CAP). These direct payments stabilize farm incomes and create a financial safety net that mitigates insolvency risk, as regular public funding ensures baseline liquidity regardless of market performance (Mazancová et al., 2025). Consequently, traditional bankruptcy prediction models, which are designed to identify firms at risk of failure in competitive market environments, have limited applicability in the agricultural sector. Instead, rating models that assess the overall financial health and operational efficiency of farms provide more meaningful analytical insights for EU agricultural holdings.

The primary objective of this study is to develop and validate a sector-specific value creation rating model for Czech agricultural enterprises that effectively distinguishes between value-creating and value-destroying firms. To achieve this overarching goal, the following specific objectives are pursued:

- To construct a comprehensive dataset of Czech agricultural enterprises using accounting data from the CRIBIS database for the period 2019-2023, ensuring adequate representation of the sector's financial characteristics.
- To implement Economic Value Added (EVA) as the key performance criterion for classifying enterprises, thereby shifting focus from bankruptcy prediction to economic value creation assessment.
- To develop and estimate both logistic regression and discriminant analysis models using relevant financial ratios that capture profitability, liquidity, capital structure, and operational efficiency.
- To systematically compare the predictive accuracy and reliability of these two statistical approaches through appropriate validation techniques.
- To identify the most significant financial determinants that differentiate value-creating from value-destroying agricultural enterprises in the Czech context. Finally, to evaluate the practical applicability of the developed model for financial institutions, agricultural policy-makers, and farm managers in assessing financial performance and sustainability of agricultural operations.

Literature review

This literature review synthesizes key approaches to bankruptcy prediction and credit rating assessment, with a focus on European agriculture, and highlights the limitations of existing models when applied to Czech agricultural enterprises.

To traditional bankruptcy models applied to agriculture belongs Altman's Z-score and its variants. The Altman's Z-score (1968) and its subsequent modifications have been widely applied in agriculture. Novotná and Svoboda (2010) tested Altman's model alongside Czech-specific indices (IN95, IN99, IN01), the Kralicek quick test, and the Bonity index on 150 Czech farms between 2003 and 2007, differentiated by less-favored area (LFA) classifications. Their findings showed inconsistencies, as profitable farms were often misclassified into the grey zone due to the mismatch between model assumptions and agricultural realities. Similarly, Baryshnikov et al. (2019) confirmed that Altman's model does not provide sufficient assessment for agricultural enterprises.

In the international literature, Altman's model has also been applied by Milić et al. (2022) in Serbian agriculture and food-processing enterprises of varying sizes, by Srebro et al. (2021) on Serbian farms, and by Kiaupaite-Grushniene (2016) in Lithuania. Results range from partial usefulness to serious misclassification problems. This underlines the fact that the Z-score, though historically important, cannot be reliably generalized to agriculture.

The Bonity index (Grünwald, 2001) and Kralicek's quick test are popular in Czech and Slovak literature. Their applications to agriculture (Novotná and Svoboda, 2010; Vavrek et al., 2021a) have revealed mixed results. Vavrek et al. (2021) applied Altman's, Taffler's, and Bonity indices to Slovak agricultural enterprises and showed that each model produced divergent classifications—Altman pointed to future risk, Bonity was neutral, and Taffler suggested no near-term threats.

In the Czech and Slovak Republic, there were also developer-specific models. Neumaier and Neumaierová (2002, 2005) developed the IN indices, which were tailored for Czech firms (mostly industrial companies) in transition economies. The progression from IN95 to IN05 sought to improve accuracy and adaptability. Applications in agriculture, however, remain a subject of controversy. For example, Kopta (2009) tested IN99 alongside Gurčík's index and others on Czech agricultural enterprises (between 1996 and 2006) and concluded that while there is a statistical relationship between index values and future performance, predictive power for bankruptcy was limited.

Gurčík (2002) developed a proprietary discriminant index specifically for Slovak agricultural enterprises, based on a sample of 60 farms. The model was intended not only for bankruptcy prediction but also for assessing future growth potential. Similarly, Chrastinová (1998) introduced the Ch-index as a tool for predicting bankruptcy. Both have been tested in Czech contexts (Kopta, 2009), where they are often classified into the "grey zone" with limited discriminatory power.

Špička et al. (2018) criticized Gurčík's index for overemphasizing profitability (four out of five indicators), while neglecting liquidity, capital structure, and working capital management.

Likewise, the Ch-index was found to misclassify many enterprises into neutral categories, limiting its practical usability.

Karas et al. (2017) tested Altman's model and IN05 on Czech active companies and bankrupt firms (2011-2014). They concluded that traditional models developed for industrial and processing enterprises demonstrate lower predictive accuracy when applied to agriculture. This confirms the need for sector-specific models.

Recent advances suggest that statistical and AI-based methods may outperform traditional indices. Gajdosikova et al. (2025) employed logistic regression, decision trees, machine learning, and artificial neural networks across farms in Central and Eastern Europe. These methods demonstrated high predictive accuracy but also revealed strong heterogeneity across economies, emphasizing the importance of localized models and continuous monitoring of financial risks.

There are also studies beyond Central Europe, for example, from Ukraine, where Dorohan-Pysarenko (2021) combined discriminant analysis with expert scoring to include non-financial risk factors such as environmental threats. Tyshchenko et al. (2023) tested several models (Altman, Springate, Tereshchenko, Matviychuk) on Ukrainian farms, with mixed outcomes—some models successfully flagged bankruptcies but also produced many false positives. These findings align with the central and eastern European experience: the structural volatility of agriculture reduces the transferability of generic models.

Meanwhile, alternative approaches, such as Data Envelopment Analysis (DEA), were explored by Horváthová and Mokrišová (2018) in the tourism sector, showing potential as a methodological alternative that is also adaptable to agriculture.

Across the reviewed studies, one consistent observation emerges: traditional bankruptcy models (Altman, Taffler, Bonity, IN) provide non-uniform and often contradictory results when applied to agricultural enterprises. Profitable farms are often categorized as being at risk (the grey zone), while long-term distressed firms may escape early warning signs.

The evidence suggests that no single existing model—whether Altman's Z-score, Czech IN indices, or Slovak Gurčík and Ch-index —adequately captures the financial risk of agricultural enterprises in the Czech Republic. Results are often contradictory, with many firms categorized in the grey zone, regardless of their actual performance. Comparative studies confirm that industrial-based models have lower predictive validity in agriculture.

Over the past decades, a wide spectrum of analytical, statistical, and machine learning techniques has been developed to predict financial distress and corporate bankruptcy. Early studies relied primarily on traditional statistical models, which laid the foundation for understanding the relationship between financial ratios and business failure. Beaver (1966) introduced univariate ratio analysis as one of the first quantitative approaches to assess financial distress, while Altman (1968) or McKee (1976) expanded this concept through multivariate discriminant analysis (MDA). These models were simple and interpretable but limited by their assumption of linearity and inability to capture.

Among the early approaches stated above, McKee (2000) provided additional methods for assessing and predicting financial distress, including subsequent advancements such as linear probability models (Meyer and Pifer, 1970) and multivariate conditional probability models, such as logit and probit frameworks (Ohlson, 1980). Other methodological innovations encompass recursive partitioning models (Marais et al., 1984; Frydman et al., 1985), survival analysis using proportional hazard models (Lane et al., 1986), expert systems (Messier and Hansen, 1988), and mathematical programming approaches (Gupta et al., 1990). More recent developments have incorporated artificial intelligence techniques, including neural networks (Tam and Kiang, 1992; Bell et al., 1990), as well as the rough sets approach (Slowinski and Zopoudnis, 1995). These methods collectively represent a diverse set of quantitative tools for evaluating corporate financial health and predicting potential financial distress.

As computational technologies evolved, traditional statistical methods such as discriminant analysis and univariate models were gradually replaced by data-driven algorithms capable of uncovering complex patterns in financial data—a transformation often referred to as the advent of data mining (Papíková and Papík, 2022). Techniques such as support vector machines (SVM), decision trees (DT), and random forests (RF) have demonstrated an improved ability to capture nonlinear relationships (Xie et al., 2011; Geng et al., 2015), although challenges related to overfitting and interpretability persist.

The use of neural networks (NNs) further enhances predictive performance, allowing for nonlinear modelling of financial variables; however, issues with class imbalance remain (Tumpach et al., 2020). More recently, ensemble learning and hybrid artificial intelligence methods —including AdaBoost, XGBoost, and CatBoost —have become state-of-the-art, achieving outstanding accuracy and robustness even in imbalanced datasets (Lahmiri et al., 2020; Jabeur et al., 2021). Among these, CatBoost has proven particularly effective for small and medium-sized enterprises, reaching an AUC close to 99% (Papíková and Papík, 2022).

This motivates the development of a new model for predicting financial situations tailored to Czech agriculture on a larger scale, encompassing multiple farms. Such a model should combine the strengths of existing indices (profitability and solvency) with additional sector-specific indicators (liquidity, subsidies, working capital, and market volatility). Furthermore, it should strike a balance between statistical accuracy and practical transparency, providing a reliable decision-support tool for farmers, policymakers, and creditors alike.

Research gap

Previous studies have predominantly focused on bankruptcy prediction rather than comprehensive value creation rating model, which is more relevant for evaluating the overall financial health and operational efficiency of subsidized agricultural holdings. The Czech agricultural sector lacks a sector-specific model that accounts for its unique characteristics and employs appropriate performance criteria beyond mere bankruptcy risk. While recent advances in statistical and artificial intelligence methods show promise, there is a lack of research comparing traditional statistical approaches in the specific context of Czech agriculture using value creation metrics. This study addresses these gaps by developing and validating a predictive model specifically tailored to Czech agricultural enterprises, employing EVA as the classification criterion rather than bankruptcy, and systematically comparing logistic regression with discriminant analysis to identify the most reliable methodological approach for this sector.

Materials and methods

Materials

Data cleaning

The accounting data of agricultural enterprises were obtained from the financial statements in the CRIBIS database (2025). The CRIBIS database, developed by CRIF-Czech Credit Bureau, a.s., is a comprehensive information system that contains detailed financial, credit, and identification data on businesses operating in the Czech Republic and abroad. It integrates data from public registers, financial statements, and payment behaviour analyses to assess the risk profile of enterprises. The data were processed and cleaned prior to the application of statistical methods in the following manner. The initial dataset contained agricultural enterprises with reported land area in the Land Parcel Identification System (LPIS). The cleaning procedure began by removing observations with missing values for the key variable LAND_AREA, ensuring that only complete cases with valid agricultural area measurements were retained for analysis.

Subsequently, a comprehensive filtering process was implemented to eliminate nonsensical or economically implausible values that could distort the statistical analysis. This involved removing enterprises with non-positive values for critical financial statement items, as negative values for these variables would indicate data entry errors or reporting inconsistencies. Specifically, observations were excluded if they reported non-positive values for total liabilities, fixed assets, tangible fixed assets, current assets, inventories, short-term receivables, cash and cash equivalents, external financing sources, short-term liabilities, product sales revenue, and material and energy consumption.

Additional filters were applied to remove observations with negative values for long-term receivables, loans and credits, long-term liabilities, depreciation, netbook value of assets, and interest expenses, as these negative values would be economically meaningless. Enterprises with missing registered capital were also excluded from the analysis. Importantly, over-indebted firms with non-positive equity were removed, as assessing the financial health of such enterprises would be economically irrelevant (it biases profitability ratios).

Following the initial data cleaning, twenty-seven financial health indicators were calculated covering four main categories: profitability ratios (including return on assets, return on equity, return on sales, return on fixed assets, return on capital employed, and return on invested capital), activity ratios (such as total asset turnover, fixed asset turnover, inventory turnover, and receivables turnover), liquidity ratios (comprising current, quick, and cash ratios, along with working capital ratios), and leverage ratios (including various debt ratios and coverage ratios).

To address the presence of extreme values that could unduly influence the statistical analysis, a trimming approach was employed (Dehnel, 2014). The first and ninety-ninth percentiles were calculated for each financial indicator, and observations falling outside this range were systematically removed from the dataset. This trimming procedure helps ensure that the subsequent statistical tests are not dominated by outliers while preserving the central distribution characteristics of the financial health indicators.

This multi-stage cleaning process yielded a refined dataset comprising only enterprises with economically plausible financial data and indicator values within reasonable bounds, thereby providing a solid foundation for the subsequent statistical analysis of the financial health of agricultural enterprises.

Calculation of Economic Value Added (EVA)

The value creation is defined as positive EVA for the purpose of this research. The EVA methodology was employed to assess whether agricultural enterprises generated value beyond the expectations of equity investors. This approach compares the actual Return on Equity (ROE) achieved by each enterprise with the expected return on equity derived from the Capital Asset Pricing Model (CAPM) (Elbannan, 2015).

The calculation of EVA involved a two-step process. First, the ROE was computed for each agricultural enterprise using the standard formula: *ROE = Net Income / Shareholders' Equity × 100*. This metric represents the actual return generated on shareholders' invested capital during the reporting period.

Second, the expected return on equity (r_e) was determined using the CAPM framework, which establishes the minimum return that equity investors should require given the systematic risk associated with the investment. The CAPM-based expected return on equity was calculated using several key parameters obtained from Professor Damodaran's database[1]. The risk-free rate (r_f) served as the baseline return for risk-free investments. The unlevered beta captures the systematic risk of the agricultural sector, excluding the influence of financial leverage. The effective tax rate (*t*) and debt-to-equity ratio (*D/E*) were used to calculate the levered beta (beta levered), which reflects the additional financial risk imposed by the enterprise's capital structure through formula: *beta levered = beta unlevered* × [1 + (1-*t*) × *D/E*]. The Czech Republic equity risk premium (Total Equity Risk Premium) represented the additional return required by investors for bearing market risk above the risk-free rate. Finally, the expected return on equity (r_e) was computed using the CAPM equation: $r_e = r_f$ + *beta levered × Total Equity Risk Premium*. Table 1 provides an overview of re computed in this study.

Indicator	2019	2020	2021	2022	2023
r_e	4.74 %	3.87 %	5.46 %	10.42 %	9.06 %

Source: Own processing

Table 1: Expected Return on Equity (r_e) in Czech agriculture based on the CAPM framework.

The EVA calculation then compared these two measures: *EVA* = (*Actual ROE* - r_e) × *Shareholders' Equity*. A positive EVA indicates that the enterprise generated returns above investor expectations, thereby creating economic value, while a zero or negative EVA suggests value destruction, as the enterprise failed to meet the minimum return requirements dictated by its systematic risk profile.

This methodology provides a more sophisticated assessment of enterprise performance than traditional accounting-based profitability measures, as it explicitly accounts for the cost of equity capital and the risk-return relationship inherent in financial markets. By incorporating market-based expectations through the CAPM framework, the EVA approach offers insights into whether agricultural enterprises are generating genuine economic value for their shareholders beyond mere accounting profits.

An approach based on the EVA indicator was therefore adopted, and the choice of the value creation rating model was made accordingly. This decision was also motivated by the fact that, in the agricultural sector (Agriculture, Forestry and Fishing, NACE A), the bankruptcy rate —defined as the number of bankruptcies per year relative to the number of economically active entities—is very low compared to other industries. According to the study conducted by Insolcentrum (n.d.), the bankruptcy rate in Czech agriculture, forestry, and fishing was 2 % in 2021. Consequently, the sample of bankrupt enterprises would be very limited.

[1] https://pages.stern.nyu.edu/~adamodar/

Data description

Our analysis covers the accounting years 2019-2023, as the database used contains the necessary accounting data. One-fifth of the enterprises in the panel data specialize in crop production, one-fifth specialize in livestock production, and more than half engage in a combination of crop and livestock production (Table 2). The average farm size in the sample is 1,062 hectares, with the smallest enterprises having zero area and the largest enterprise having more than 10,000 hectares (Table 3).

Type of farming	Relative frequency (%)
Specialized crop production	20.6 %
Specialized livestock production	21.1 %
Mixed crop and livestock production	58.2 %

Source: Own processing

Table 2: Distribution by type of farming.

Mean	Standard Deviation	Minimum	Maximum
1,062.08	1,105.42	0	10,160.26

Source: Own processing

Table 3: Distribution by land area (hectares).

Based on the frequency table (Table 4), the results demonstrate the distribution of enterprises achieving positive versus negative Economic Value Added (EVA) across the analyzed sample.

Table 4 shows that, in most years, farms with negative EVA (denoted as EVA-) predominated. A combination of rapidly increasing capital costs (due to high interest rates of the Czech National Bank resulting from inflation), a sharp rise in operating expenses, and a simultaneous decline in revenues created a situation in which operating profit was insufficient to cover capital costs. This led to negative EVA in a substantial proportion of agricultural enterprises in 2022 and 2023.

These findings suggest that a substantial number of agricultural enterprises in the sample failed to meet the minimum return expectations of equity investors, as determined by the CAPM model. The enterprises with zero or negative EVA values (EVA-) represent firms that, despite potentially generating accounting profits, failed to provide returns sufficient to compensate shareholders for the systematic risk associated with their investments. Conversely, the enterprises achieving positive EVA (EVA+) successfully created economic value by generating returns above the risk-adjusted cost of equity capital. These firms demonstrated superior performance in converting shareholder investments into returns that exceeded market expectations, given their respective risk profiles.

The substantial presence of both value-creating and value-destroying enterprises within the agricultural sector suggests significant heterogeneity in financial performance and management effectiveness. This distribution pattern indicates that while some agricultural enterprises effectively manage their resources to generate superior returns, a notable portion struggles to meet the fundamental requirement of covering their cost of equity capital, highlighting potential inefficiencies or structural challenges within parts of the agricultural sector.

Methods

Comparison of discriminant analysis and logistic regression

In the development of agricultural financial performance models, researchers frequently encounter the need to classify enterprises into distinct performance categories based on multiple financial indicators. Two statistical methodologies that have gained considerable attention for such classification tasks are discriminant analysis (e.g., Neumaier and Neumaierová, 2005) and logistic regression (e.g. Ohlson, 1980; Zmijewski, 1984). While both techniques serve the fundamental purpose of predicting group membership based on predictor variables, they differ substantially in their underlying assumptions, mathematical frameworks, and practical applications within the field of agricultural economics research.

Indicator	Unit	2019	2020	2021	2022	2023
Sample size	number	1260	1340	1353	1325	983
Share of companies with EVA+	%	43.17	54.63	47.60	35.62	18.31
Share of companies with EVA-	%	56.83	45.37	52.40	64.38	81.69

Source: Own processing

Table 4: Sample size by year and EVA.

Theoretical foundations

Discriminant analysis operates under the premise of identifying linear combinations of predictor variables that maximize the separation between predefined groups. In the context of agricultural financial performance modeling, this technique assumes that the predictor variables follow a multivariate normal distribution within each performance category and that the covariance matrices across groups are homogeneous. The method seeks to construct discriminant functions that optimize the ratio of between-group variance to within-group variance, thereby creating decision boundaries that effectively distinguish between different levels of financial performance (Hatcher, 2013).

Logistic regression, by contrast, employs a probabilistic approach that models the log-odds of group membership as a linear function of predictor variables. This methodology does not require the stringent distributional assumptions inherent in discriminant analysis, making it particularly appealing for agricultural data that often violate normality assumptions due to seasonal variations, extreme weather events, or market volatilities. The logistic function ensures that predicted probabilities remain bounded between zero and one, providing intuitive interpretations of the likelihood that a particular agricultural enterprise belongs to a specific performance category (Pampel, 2011).

Assumptions and data requirements

The assumption structure represents perhaps the most critical distinction between these methodologies. Discriminant analysis requires that predictor variables exhibit multivariate normality within each group, expressed formally as:

$$x_i|G = g \sim N(\mu_g, \sum) \text{ for all } g = 1,2,\ldots,G \tag{1}$$

This condition may prove challenging in agricultural applications where financial ratios often display skewed distributions or contain outliers resulting from extraordinary circumstances such as crop failures or commodity price spikes. Additionally, the homoscedasticity assumption demands equal covariance matrices across performance groups:

$$\sum_1 = \sum{}_2 = \cdots = \sum{}_G = \sum \tag{2}$$

This equality may not hold when comparing small-scale family farms with large agricultural corporations, as the variance structures of financial indicators may differ systematically across farm types (Klecka, 1980).

Logistic regression demonstrates considerably more flexibility in its assumption requirements. The technique does not mandate specific distributional forms for predictor variables, though it does assume a linear relationship between predictors and the log-odds of the outcome variable:

$$E\left[\ln\left(\frac{P(Y=1|x}{1-P(Y=1|x}\right)\right] = \beta_0 + \sum_{i=1}^{p} \beta_i x_i \tag{3}$$

This linearity assumption can be validated through various diagnostic procedures and, if violated, can often be addressed through variable transformations or the inclusion of polynomial terms. The logit model also assumes independence of observations:

$$P(Y_1, Y_2, \ldots, Y_n|X) = \prod_{i=1}^{n} P(Y_i|x_i) \tag{4}$$

Furthermore, logistic regression accommodates both continuous and categorical predictor variables without additional modifications, a feature particularly valuable in agricultural research where factors such as farm type, geographic region, or crop diversity may serve as important classification variables (Timming, 2022).

Model estimation and implementation

The estimation procedures for these methodologies reflect their different theoretical orientations. Discriminant analysis typically employs maximum likelihood estimation under the assumption of multivariate normality, calculating sample means and pooled covariance matrices to construct discriminant functions. The classification rule assigns observations to the group with the smallest Mahalanobis distance or, equivalently, the highest posterior probability based on Bayes' theorem (Hatcher, 2013).

Logistic regression utilizes iterative maximum likelihood estimation, as closed-form solutions generally do not exist. The iterative reweighted least squares algorithm or similar optimization procedures are employed to determine parameter estimates that maximize the likelihood function. This process continues until convergence criteria are satisfied, typically involving minimal changes in parameter estimates or log-likelihood values between iterations (Pampel, 2011).

Performance evaluation and diagnostic capabilities

In evaluating the quality of a predictive model that classifies firms into value-creating and value-destroying categories, we employ concordant and discordant pairs. The fundamental concept involves comparing all possible pairs of firms in which one firm belongs to the value-creating category (EVA+; denoted by the value 1) and the other to the value-destroying category (EVA-; denoted by the value 0). For each such pair, we then examine whether the model assigned a higher predicted probability to the correct firm. Specifically, we refer to a concordant pair when the model assigns a higher probability to the firm that is actually value-creating. Conversely, a discordant pair arises when the model assigns a higher probability to the firm that is actually value-destroying. In the case of discriminant analysis, rather than comparing probabilities, we work with discriminant scores, or values of the discriminant function (Pampel, 2011). Discriminant analysis calculates a discriminant score for each firm, which expresses its position along the discriminant axis. This score determines the group to which the firm is classified—higher values typically indicate membership in the value-creating category, while lower values indicate membership in the value-destroying category. The score itself is not a probability in the classical sense but serves as a measure of the firm's "distance" from the centroids of the respective groups (Brown and Wicker, 2000).

Key model evaluation metrics are derived from the ratio of concordant and discordant pairs. The most important of these is the C-statistic, which is calculated as the ratio of concordant pairs (plus half of the tied pairs) to the total number of pairs. A pair is concordant if the model assigns a higher predicted probability (or discriminant score) to the firm that is actually profitable, and discordant otherwise. The C-statistic (or concordance index) is calculated as the share of concordant pairs (plus half of tied pairs) relative to all possible pairs, with values ranging from 0.5 (random prediction) to 1.0 (perfect prediction).

Both methodologies provide comprehensive frameworks for model evaluation, although their diagnostic capabilities differ in significant ways. Discriminant analysis provides canonical correlation coefficients that indicate the strength of association between discriminant functions and group membership, while Wilks' lambda tests assess the statistical significance of group differences. The technique also generates structure coefficients that reveal the contribution of individual variables to group separation (Brown and Wicker, 2000).

Logistic regression provides a comprehensive suite of diagnostic tools, including goodness-of-fit statistics such as the Hosmer-Lemeshow test, pseudo R-squared measures for evaluating model explanatory power, and residual analyses for identifying influential observations or model inadequacies. The availability of odds ratios provides direct interpretation of the multiplicative effect of predictor variables on the odds of group membership, facilitating communication of results to agricultural practitioners and policymakers (Pampel, 2011).

Practical considerations for agricultural applications

The choice between discriminant analysis and logistic regression in modeling agricultural financial performance often depends on the specific characteristics of the dataset and research objectives. Discriminant analysis may prove advantageous when predictor variables approximate multivariate normality and when the primary goal is to understand the underlying structure that distinguishes between performance groups. The technique's ability to generate multiple discriminant functions can provide valuable insights into the dimensionality of group separation in complex agricultural systems.

Logistic regression is typically the preferred approach when dealing with non-normal data distributions, unequal group sizes, or when the research emphasis is on prediction accuracy rather than understanding group structure. Its robustness to assumption violations and flexibility in handling various data types make it particularly suitable for agricultural datasets that incorporate diverse financial metrics, operational characteristics, and environmental factors.

Limitations and considerations

Despite their widespread application, both methodologies possess inherent limitations that researchers must acknowledge. Discriminant analysis's sensitivity to outliers can prove problematic in agricultural contexts where extreme events may generate atypical financial observations. The technique's performance may deteriorate significantly when sample sizes are small relative to the number of predictor variables, a common scenario in specialized agricultural sectors (Klecka, 1980).

Logistic regression, while more robust to distributional violations, can experience difficulties with complete or quasi-complete separation, particularly when dealing with perfectly predictive variables or small sample sizes. Additionally, the technique's reliance on large-sample theory for statistical inference may prove inadequate in studies with limited observations, necessitating alternative approaches such as exact logistic regression or bootstrap procedures (Pampel, 2011).

Results and discussion

Statistically significant predictors of firm profitability in at least one of the analyzed years are shown in Tables 5 (Logistic Regression) and 6 (Discriminant Analysis). A positive sign indicates a direct relationship, while a negative sign denotes an inverse effect of the given financial indicator on EVA. To ensure the temporal stability of the models, predictors were selected based on their frequent occurrence across the observation period and low correlation with other selected variables.

According to logistic regression results,

Indicator	Symbol	2019	2020	2021	2022	2023	Note
Return on Assets	ROA	+				-	
Return on Tangible Assets	ROTA					+	
Return on Capital Employed	ROCE		+	+	+	+	
Return on Invested Capital	ROIC	+	+	+	+	+	Selected
Cash Ratio	CR					-	
Working Capital to Long-term Capital	WCLTC	-			+	+	Selected
Working Capital to Assets	WCA	+			-	-	
Net Debt Payback Period	NDPP	-			-		
Equity Ratio	ER	-			-		
Debt to Equity Ratio	DER				+	+	
Short-term Debt Ratio	SDR				-		
Acid-Test Ratio	ATR	-					
Total Debt Ratio	TDR					-	
Fixed Assets Coverage	FAC	-	-			-	Selected
Debt to Sales Ratio	DSR	+					
Fixed Assets Turnover	FAT					-	

Note: "+" = direct significant relationship (significance level 0.01), "-" inverse significant relationship (significance level 0.01)
Source: Own processing

Table 5: Statistically significant predictors - logistic regression.

Indicator	Symbol	2019	2020	2021	2022	2023	Note
Return on Assets	ROA	+	+	+	+	+	Selected
Return on Sales	ROS	+	+	+			
Return on Tangible Assets	ROTA	-	-	-	-		
Return on Invested Capital	ROIC	+			+	+	
Working Capital to Sales Ratio	WCS				+		
Net Debt Payback Period	NDPP	-	-	-	-	-	Selected
Equity Ratio	ER	-			-	-	Selected
Debt to Equity Ratio	DER			+		+	
Total Debt Ratio	TDR			+			
Loan Burden Coverage	LBC				+	+	
Long-term Debt Ratio	LDR		+				
Interest Coverage Ratio	ICR			+			
Fixed Assets Turnover	FAT		+	+			

Note: "+" = direct significant relationship (significance level 0.01), "-" inverse significant relationship (significance level 0.01)
Source: Own processing

Table 6: Statistically significant predictors - discriminant analysis.

the statistically significant predictors of firm profitability are Return on Invested Capital (ROIC), Working Capital to Long-term Capital (WCLTC), and Fixed Assets Coverage (FAC). The resulting equation for the entire period is as follows:

$$Agri25L = -1.828 + 0.5198\ ROIC + 0.0087\ WCLTC - 0.0113\ FAC \qquad (5)$$

Return on Invested Capital (ROIC) = Net Profit / (Fixed Assets + Non-Cash Net Working Capital) * 100

Working Capital to Long-term Capital (WCLTC) = Net Working Capital / (Equity + Long-term Liabilities) * 100

Fixed Assets Coverage (FAC) = Equity / Fixed Assets * 100

A Max-rescaled R-Square value of 0.6542 (Nagelkerke R-Square) means that your model explains approximately 65% of the variability in the data (according to this metric). This is typically considered a reasonably good model fit.

The Return on Invested Capital (ROIC) exhibits the strongest positive effect on EVA, with a coefficient of 0.5198, making it the dominant factor in the predictive model. This result aligns with fundamental principles of financial management—firms that more efficiently transform invested capital into profit generate greater value for their owners and exhibit a higher capacity to produce cash flows (Brealey et al., 2025). A high ROIC reflects not only operational efficiency but also the quality of managerial investment decisions. Firms with higher ROIC are better able to cover capital costs, contributing to long-term financial stability and lowering the likelihood of financial distress (Gibson, 2013).

Working Capital to Long-term Capital (WCLTC) also exerts a positive, though substantially weaker, influence on EVA (coefficient 0.0087). This indicator reflects a firm's liquidity relative to its long-term financing sources (Gibson, 2013). The positive relationship can be interpreted as the importance of maintaining sufficient financial flexibility—firms with higher net working capital possess greater operational maneuverability and are better prepared to absorb short-term financial fluctuations. However, the small coefficient value suggests that, while liquidity contributes to profitability, its impact is secondary to investment returns. Excessively conservative working capital management may even lead to suboptimal resource utilization and reduced overall profitability.

Fixed Assets Coverage (FAC) exhibits a negative relationship with EVA (coefficient -0.0113). This implies that enterprises with extremely high fixed asset coverage by equity may paradoxically be less value-creating. This can be explained by several mechanisms. First, an overly conservative capital structure, with minimal debt utilization, forgoes the tax benefits of debt and reduces the return on equity through the loss of leverage effects. Second, excessive reliance on equity may indicate limited access to external financing, signaling lower perceived creditworthiness (Brealey et al., 2025). A very high FAC may thus reflect insufficient expansion and investment activity, where firms accumulate equity without utilizing growth opportunities. The low absolute coefficient value, however, suggests that this effect is relatively moderate and likely occurs only in cases of excessive capitalization.

Descriptive statistics of the variables included in equation (5) and the resulting Agri25L profitability scores (Table 7) were used to determine the boundary of the value-creating zone, defined by the 5th and 95th percentiles.

Based on the logistic regression results, the boundary of the value-creating zone was set at Agri25L > 0.707 (the 95th percentile of Agri25L for firms with negative EVA). The boundary

Indicator	N	Mean	Std Dev	5th pctl	95th pctl
ROIC	6261	5.622	10.535	-5.403	23.075
WCLTC	6261	22.248	34.962	-26.155	66.431
FAC	6261	121.069	97.081	28.100	272.501
Agri25L	6261	-0.089	5.234	-6.113	8.515
Agri25L (EVA-)	3689	-2.541	2.861	-7.500	0.707
Agri25L (EVA+)	2572	3.427	5.829	-1.008	13.834

Source: Own processing

Table 7: Descriptive statistics of indicators in the logistic regression (2019 - 2023).

of the value-destroying zone was set at Agri25L < -1.008 (5th percentile of Agri25L for firms with positive EVA). Values between -1.008 and 0.707 represent the "gray zone," where the model cannot reliably classify firms.

According to discriminant analysis, the statistically significant predictors are ROA, NDPP, and ER. The resulting equation for the entire period is:

$$Agri25D = 0.4162 + 0.0515\ ROA - 0.0044\ NDPP - 0.0042\ \mathrm{ER} \quad (6)$$

Return on Assets (ROA) = Operating Profit / Total Assets * 100

Net Debt Payback Period (NDPP) = Net debt / (Net Profit + Depreciation)

Equity Ratio (ER) = Equity / Total Assets * 100

The discriminant function demonstrated statistically significant separation between groups (Wilks' $\lambda = 0.560$, $F(3, 6257) = 1636.0$, $p < 0.0001$). The eigenvalue of 0.784 indicated a moderate to good ratio of between-group to within-group variance. The canonical correlation of 0.663 revealed that the discriminant function accounted for approximately 44% of the variance in group membership (canonical $R^2 = 0.44$), representing a medium to strong effect size.

These findings indicate that the groups are meaningfully distinguishable based on the predictor variables included in the model. The discriminant function demonstrates adequate discriminatory power, though 56% of the variance in group classification remains unexplained. The highly significant F-statistic, combined with the substantial sample size, provides strong evidence for reliable group separation.

Return on Assets (ROA) demonstrates a positive effect on EVA (coefficient 0.0515), making it the most significant discriminant factor. This finding reflects the fundamental principle that a firm's ability to generate operating profit from its total assets is a key indicator of performance and financial stability (Gibson, 2013). Unlike equity-based measures, ROA provides a more comprehensive view of the efficiency of all resources, regardless of financing structure. Higher ROA indicates both operational effectiveness and competitiveness. Firms with higher ROA can better cover financial costs, reinvest in growth, and build reserves to withstand downturns.

Net Debt Payback Period (NDPP) has a negative relationship with EVA (coefficient -0.0044). This metric measures how long it would take a firm to repay its net debt from internally generated funds (net profit and depreciation). A longer payback period indicates higher financial burden and lower debt-servicing capacity, signaling over-leverage and elevated refinancing risk.

Equity Ratio (ER) also shows a negative impact on EVA (coefficient -0.0042). A higher share of equity, typically seen as a sign of stability, here correlates with lower profitability. This can result from an overly conservative capital structure with limited leverage, which reduces return on equity and overall capital efficiency (Brealey et al., 2025). A very high ER may also indicate restricted access to external financing or a cautious strategy that limits growth opportunities and tax advantages from debt use. This effect mirrors that of FAC in the logistic regression model.

Descriptive statistics of the variables used in equation (6) and the resulting Agri25D scores (Table 8) were used to determine the boundary of the value-creating zone, defined by the 5th and 95th percentiles.

In all analyzed years, both models effectively distinguished between value-creating and value-destroying firms, as the Cohen's d values were well above 0.8, indicating a large effect size.

To further assess model accuracy, we compared the effectiveness of each model in classifying firms into their correct zones (value-creating or value-

	Logistic Regression (Agri25L)				Discriminant Analysis (Agri25D)			
Year	Mean(0)	Mean(1)	Std Dev	Cohen's d	Mean(0)	Mean(1)	Std Dev	Cohen's d
2019	-2.9682	2.5952	4.0424	1.376262	0.1891	0.5980	0.2189	1.867976
2020	-3.054	2.4009	4.2292	1.289818	0.1763	0.5798	0.2352	1.715561
2021	-2.5618	3.2756	4.6169	1.264355	0.2164	0.6656	0.2368	1.896959
2022	-1.4451	5.5581	4.2773	1.637295	0.3285	0.8535	0.2383	2.203105
2023	-2.9255	5.2232	3.9845	2.04510	0.2156	0.7856	0.2245	2.53898

Source: Own processing

Table 9: Practical significance of classification by Cohen's d.

destroying). This was evaluated using concordant and discordant pairs (Table 10).

Logistic Regression		Discriminant Analysis	
Percent Concordant	94.4 %	Percent Concordant	84.0 %
Percent Discordant	5.6 %	Percent Discordant	16.0 %
C	0.944	C	0.840

Source: own processing

Table 10: Comparison of the predictive power of logistic regression and discriminant analysis models

The comparison indicates that both models exhibit high predictive accuracy, correctly classifying over 80% of cases. Logistic regression outperformed discriminant analysis.

The superior performance of logistic regression stems primarily from the differing methodological assumptions underlying the two approaches. Discriminant analysis imposes strict requirements on the data—multivariate normality of explanatory variables and equality of covariance matrices across groups (Klecka, 1980). These conditions are rarely satisfied in corporate financial data, which typically exhibit skewness, contain outliers, and display heterogeneous characteristics between financially sound and distressed firms. This is corroborated by Morris (1998), who demonstrates that financial ratios calculated from accounting statements tend to follow skewed distributions, with the dispersion of values around the mean varying substantially across industries. Furthermore, the practice of maintaining balanced samples of healthy and bankrupt firms, while common in empirical studies, is not mathematically necessary from a statistical perspective (Rencher and Christensen, 2012). When these parametric assumptions are violated, discriminant analysis experiences a significant deterioration in predictive accuracy. Nevertheless, despite these limitations, discriminant analysis remains the most frequently employed method for constructing bankruptcy prediction models according to Čámská (2014) and De Laurentis et al. (2010).

In contrast, logistic regression is more robust. It does not require normality or homogeneity of variance and naturally constrains extreme values within the (0,1) probability range. It models relationships through the logit transformation, effectively capturing non-linear patterns between predictors and the dependent variable (Pampel, 2011). This flexibility is especially valuable in financial analysis, which often involves heterogeneous enterprises of varying sizes and sectors.

Finally, discriminant analysis assumes that groups are linearly separable in predictor space. If the relationship between financial indicators and EVA involves non-linear effects or interactions that the discriminant function cannot capture, logistic regression will model these relationships more effectively (Hatcher, 2013).

Discussion of results at the national level within the agricultural sector is feasible only through comparison with the IN99 index (Neumaierová and Neumaier, 2002), which is classified as a predictive model based on whether a firm creates value in terms of positive economic value added (EVA), consistent with the approach adopted by the authors. The IN99 index comprises four financial ratios: the total assets to external financing ratio (i.e., total debt ratio), EBIT to assets, revenues to assets, and the current ratio (the proportion of current assets to short-term liabilities). Within the agricultural sector, the profitability indicator (EBIT/assets) and current ratio carry the greatest weight. All indicators demonstrate a positive effect on creditworthiness. When comparing the estimated Agri25L model with IN99, both models incorporate return on capital in narrower and broader conceptions. Agri25L focuses solely on return on investment, whereas IN99 encompasses return on total capital through two distinct indicators. IN99 does not consider the coverage of fixed assets by equity capital; instead, it directly assesses liquidity. Agri25L does not directly measure liquidity; instead, it addresses it indirectly through working capital. In the case of Agri25D, both models utilize the return on assets metric. The Agri25D model includes an equity risk indicator that reduces creditworthiness, while the IN99 model employs total indebtedness, which enhances creditworthiness. Both models incorporate debt servicing capacity: in Agri25D, the debt maturity period has a negative effect on creditworthiness, whereas in IN99, the firm's ability to meet its obligations contributes positively to its creditworthiness.

Additional models, such as IN01 and IN05 (Neumaierová and Neumaier, 2005), are constructed on the same principle as the preceding model, with the addition of the EBIT-to-interest coverage ratio. The developed Agri25 models do not incorporate this variable.

Kralicek's Quick Test (Kralicek, 1991) represents another established creditworthiness assessment tool that evaluates financial health through four key indicators divided into two dimensions:

financial stability (equity ratio and debt repayment period from cash flow) and profitability (cash flow to sales ratio and return on assets). The resulting creditworthiness index combines these dimensions to provide an overall assessment of firm viability. Comparing Kralicek's approach with the Agri25 models reveals both convergence and divergence: both methodologies incorporate return on assets as a profitability measure, and both address capital structure, though from different perspectives —Kralicek through the equity ratio (positively affecting creditworthiness) and Agri25D through equity risk (negatively affecting creditworthiness). A distinctive feature of Kralicek's Quick Test is the explicit incorporation of cash flow metrics, particularly the debt repayment capacity measured through cash flow, which is not directly captured in the Agri25 models. However, debt servicing capability is indirectly reflected in Agri25D through the debt maturity period indicator.

Grünwald (2001) presents a method for evaluating corporate financial health without reference to production orientation (creditworthiness index), which employs six indicators (ROA, ROE, quick ratio, working capital-to-inventory ratio, cash flow-to-external financing ratio, and EBIT-to-interest ratio). Liquidity is assessed indirectly in the Agri models, and debt is also approached differently. The variables defining creditworthiness are thus considerably differentiated, focusing primarily on profitability and debt servicing capacity.

The system of balance sheet analysis developed by Rudolf Doucha (1996)—also not a sector-specific model, but of Czech origin—focuses on creditworthiness assessment. The model incorporates indicators from the domains of leverage, liquidity, activity, and profitability. This balance sheet analysis corresponds to some extent with previous models, utilizing the self-financing coefficient (as does Agri25D), the ratio of output to liabilities (as in IN99), ROE (Grünwald 2001, IN99), and the quick ratio (also employed by Grünwald 2001, and conceptually related to the current ratio in IN99). These models were developed during comparable periods.

Existing models specifically oriented toward agriculture include the Chratinová index and Gurčík's index. However, both indices are bankruptcy prediction models and, therefore, comparison with creditworthiness models is not methodologically appropriate.

Conclusion

This study developed and validated a sector-specific value creation rating model for Czech agricultural enterprises using Economic Value Added (EVA) as the classification criterion. Based on accounting data from 2019 to 2023, the analysis demonstrates that logistic regression provides superior predictive accuracy compared to discriminant analysis in distinguishing between value-creating and value-destroying agricultural firms. The most significant determinants of positive EVA were identified as efficient return on invested capital and adequate working capital relative to long-term financing.

From a methodological perspective, this research contributes to statistical modeling in agricultural finance by demonstrating that the relaxed distributional assumptions of logistic regression enhance model robustness when dealing with heterogeneous agricultural financial data. The adoption of EVA as a classification criterion, rather than bankruptcy status, represents an innovation that better captures the unique risk profile of subsidized agricultural sectors, where bankruptcy rates are artificially suppressed by CAP interventions. The study validates the principle that financial risk assessment frameworks must be adapted to the structural, regulatory, and operational characteristics of the agricultural sector rather than relying on generic industrial models.

The practical implications are substantial for multiple stakeholders. Financial institutions can utilize the model as a decision-support tool for risk assessment and loan approval processes, enabling more accurate evaluation of agricultural borrowers beyond traditional collateral-based approaches. For agricultural enterprises, the model provides a diagnostic framework for self-assessment, enabling farm managers to benchmark their performance and identify areas that require strategic adjustment. Policy-makers can employ the model to evaluate the financial sustainability of agricultural support programs and design targeted interventions for distressed farms. The model's emphasis on value creation aligns with contemporary agricultural policy objectives focused on competitiveness and sustainable growth.

Several limitations must be acknowledged. The analysis is restricted to Czech agricultural enterprises from 2019 to 2023, which limits its generalizability to other countries and may be potentially affected by COVID-19 disruptions. Reliance on commercial databases introduces selection bias, potentially underrepresenting smaller family farms and specific subsectors. The binary classification approach fails to capture the magnitude of value creation, and the model overlooks non-financial factors such as management quality, technological adoption, and environmental practices. Additionally, static financial ratios fail to capture the temporal dynamics and seasonal variations of agriculture.

Future research should address these limitations through cross-country comparative studies to understand how different policy frameworks affect model applicability, expand samples to include underrepresented farm types, and incorporate machine learning techniques to capture non-linear relationships. Developing dynamic models using time-series data would better account for agricultural volatility. Integrating non-financial variables, such as environmental performance and digital adoption, would create more comprehensive assessment frameworks. Finally, longitudinal validation studies tracking predictions against actual performance over extended periods would provide empirical support for continuous model refinement and enhanced reliability of value creation rating model for the agricultural sector.

Acknowledgements

The research was Supported by the Ministry of Agriculture of the Czech Republic, internal research Project (No. 1150/2025) of the Institute of Agricultural Economics and Information.

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