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What Drives Corporate Financial Resilience? A Credit Analysis Approach with Management Efficiency Insights

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Abstract

Building resilient companies capable of withstanding financial pressure is increasingly important for stakeholders, especially banks, investors, and suppliers operating in uncertain economic environments. Conventional credit assessment models often prioritize financial ratios while overlooking the strategic influence of managerial capability on a firm's capacity to withstand stress and maintain financial stability. This research places management efficiency at the forefront as a key driver of corporate resilience, examining how internal resource utilization, operational decisions, and financial management shape long-term sustainability. The analysis is based on 1,531 corporate loan cases from a commercial bank in Bosnia and Herzegovina over the period 2009–2015, incorporating balance sheet and income statement indicators available at loan approval, including both static financial ratios and year-to-year performance changes. Factor analysis and regression results reveal that liquidity, self-financing levels, asset turnover, gross margin, and accounts receivable collection time are relevant predictors of financial resilience. The results highlight the roles of liquidity, leverage, and profitability-related indicators as consistent correlates of loan non-repayment, while the management efficiency proxies (EUP/EFP) show weaker and specification-dependent effects. Firms with inefficient managerial practices demonstrate substantially lower resilience and higher vulnerability to financial deterioration. The findings highlight the strategic importance of integrating managerial effectiveness into risk evaluation frameworks and support the view that strong management is a foundation of corporate resilience in the financial sector.

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1. Introduction

Historically, arguably the most important work in the field of corporate financial resilience was published in 1968 by Edward I. Altman, which laid the foundation for modern ratio analysis for evaluating the financial health of a company. In this article, the author uses multiple discriminant analysis (MDA) as a statistical technique to find the five most important financial indicators combined from the financial statements, which best explain the possibility of bankruptcy of public companies. These factors are working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/book value of total debt, and sales/total assets.

Following Altman (1968), many authors have investigated corporate financial health for credit analysis, as this field is highly relevant to banking practice. Altman's pioneering model laid the foundation for later resilience-oriented financial diagnostics by demonstrating how accounting-based indicators can serve as early warning signals of distress. Lennox (1999) examines the causes of bankruptcy for 949 companies listed in the UK between 1987 and 1994. According to the results of this research, the most important predictors of bankruptcy are corporate profitability, leverage, cash flow, company size, industry sector and business cycle.

Contrary to previous studies, Lennox (1999) argues that well-specified logit and probit models can more accurately identify failing companies than the discriminative analysis method. This work highlights that accurate failure prediction contributes to understanding how firms maintain financial resilience in unstable economic conditions. Nyathi et al. (2014) provide an overview of methods for predicting business failure and, as the most appropriate methods, cite linear probability and logit models. Their findings imply that robust prediction techniques are central to assessing a firm's vulnerability and future resilience capacity. Gurný and Gurný (2013) in their research estimate PD as a key parameter in credit scoring models, using linear discriminant analysis and regression models (logit and probit). The authors note that these models can be used for short-term (1-2 years) default prediction. Based on their results, the authors conclude that the logit model is most suitable for predicting bank failures. By focusing on default probability as a core metric, their study reinforces the importance of quantitative modelling for assessing resilience and sustainability in banking portfolios.

Vasilev (2014) also proposes using logit and probit to estimate the probability of bankruptcy. Such approaches strengthen predictive frameworks that help institutions anticipate shocks and build resilient credit decision processes.

Kollár et al. (2015) compare the Merton and KMV models for calculating companies' credit ratings. Mileris and Boguslauskas (2011) used 20 financial indicators from five-year financial statements in their study. Their research confirmed that discriminant analysis, logistic regression and artificial neural networks are relevant methods for classifying bank customers, and the highest classification accuracy (97%) was achieved by the logistic regression model. The percentages of the credit rating criteria proposed in this research are: profitability 50%, liquidity 25%, leverage 12.5%, and the individual default probability estimated by logistic regression 12.5%.

Altman and Sabato (2007) examine whether banks should distinguish between small and medium-sized enterprises (SMEs) and large corporations when designing credit risk assessment systems and strategies. In their study, the authors employ logit regression, supplemented by multiple discriminant analysis (MDA) for comparison. The findings indicate that SMEs differ substantially from large firms with respect to credit risk characteristics.

We have found that more recent literature has proposed various approaches, which are also used in bankruptcy prediction modeling. This includes the artificial neural networks used by Lee and Chen (2005). Bellotti and Crook (2009) also use support vector machines as an innovative approach in credit scoring modeling. More recently, Narvekar et al. (2021) applied tree-based ensemble methods, particularly XGBoost, to bankruptcy prediction during the COVID-19 recession and showed that these models achieve high out-of-sample accuracy compared with traditional techniques. Liu et al. (2021) further enhance gradient boosting models through tree-based embeddings. Those authors claim they demonstrated superior credit-scoring performance relative to standard GBDT specifications. Bhatore et al. (2020) compare a wide range of machine learning and deep learning algorithms for credit default prediction and find that random forest and boosting-type models largely dominate logistic regression in terms of accuracy and AUC.

Today's models rely on machine learning frameworks, but these approaches require more data, which is not feasible in countries such as Bosnia and Herzegovina. Matsumaru and Katagiri (2025) propose a two-stage machine learning framework with feature selection for Japanese listed firms. He shows that carefully selected features and ensemble models can significantly improve the robustness of bankruptcy prediction.

These newer approaches have disadvantages, including the need for large amounts of data, high computational demands, and issues with explainability and interpretability (Mešković and Mešković, 2023). These two concepts are important in lending decisions because the financial institutions must be able to explain why the client was not granted a loan.

In this study, we operationalize corporate financial resilience through the loan repayment outcome observed by the lending bank. Specifically, a non-repayment (default) event captures the point at which a firm's financial buffers, cash-flow generating capacity, and access to external financing prove insufficient to meet contractual debt service obligations. From a prudential and managerial perspective, default is a defensible resilience proxy because it represents the economically and legally salient threshold that triggers loss recognition, collections, and recovery procedures, and in many jurisdictions, regulatory provisioning. At the same time, we acknowledge that resilience can manifest (and deteriorate) before outright default. Earlier distress signals, such as arrears, covenant breaches, loan restructuring, maturity extensions, or temporary payment moratoria, may reflect partial loss-absorption capacity and renegotiation ability rather than complete failure. These indicators are not consistently available in our dataset in a standardized form across borrowers (or are recorded with heterogeneous definitions across loan officers and over time), which constrains the application of a multi-stage distress framework. We therefore focus on the most reliably observed and comparable outcome (non-repayment) and interpret the results as determinants of severe resilience breakdown, while noting that future work could extend the analysis to pre-default states when harmonized arrears and restructuring data are available.

2. Methodology

In the context of financial resilience, business failure is the point at which an enterprise's internal resources, cash flows, and management strategies are no longer sufficient to absorb financial shocks or sustain operations under adverse market conditions (Mešković, 2022). For the purposes of this article, we define business failure as the inability to repay loans granted by banks. The research questions are formulated as follows:

- Can multivariate analysis methods predict the failure of the businesses of legal entities that are clients of a domestic bank?
- Can the effectiveness of management be singled out as a factor that significantly contributes to the business failure/success of the company?

The following research hypotheses are formulated:

H1. Methods of multivariate analysis contribute to the explanation and prediction of the inability to repay loans given to legal entities.

H2. The inability to repay loans by legal entities is predominantly determined by factors from the financial statements.

H3. Management efficiency is a variable that significantly contributes to a company's business failure.

2.1. Data sources

For the purposes of this research, the internal database of one bank from BiH was used, for 1531 loans granted to legal entities in the period 2009-2015. The database contains data from clients' balance sheets and income statements, as well as data on the company's success in repaying the loan. For the purposes of this research, the inability to repay the loan was marked as a business failure. Observations with incomplete data for all ratios (missing values) were excluded from further analysis, leaving 1357 observations.

2.2. Methodology

In the above definition, the business failure of clients, as an observed variable, will be defined as the inability to repay the loan. It is generally accepted practice that predicting a corporation's bankruptcy/business failure is based on various financial indicators from the balance sheet and income statement. Based on previous research and literature, some basic (most commonly used) variables have been identified as indicators in financial statements with theoretical and practical value for predicting business failure. These 17 variables are listed in ***Table 1***.

We must emphasize that in this research, we are using exclusively internal financial data from companies. Several authors, such as Smolo and Mirakhor (2010) and Meskovic et al. (2023), have confirmed that external factors, such as crises and regulations, can have a significant impact on companies' and financial institutions' performance.

3. Data and the model

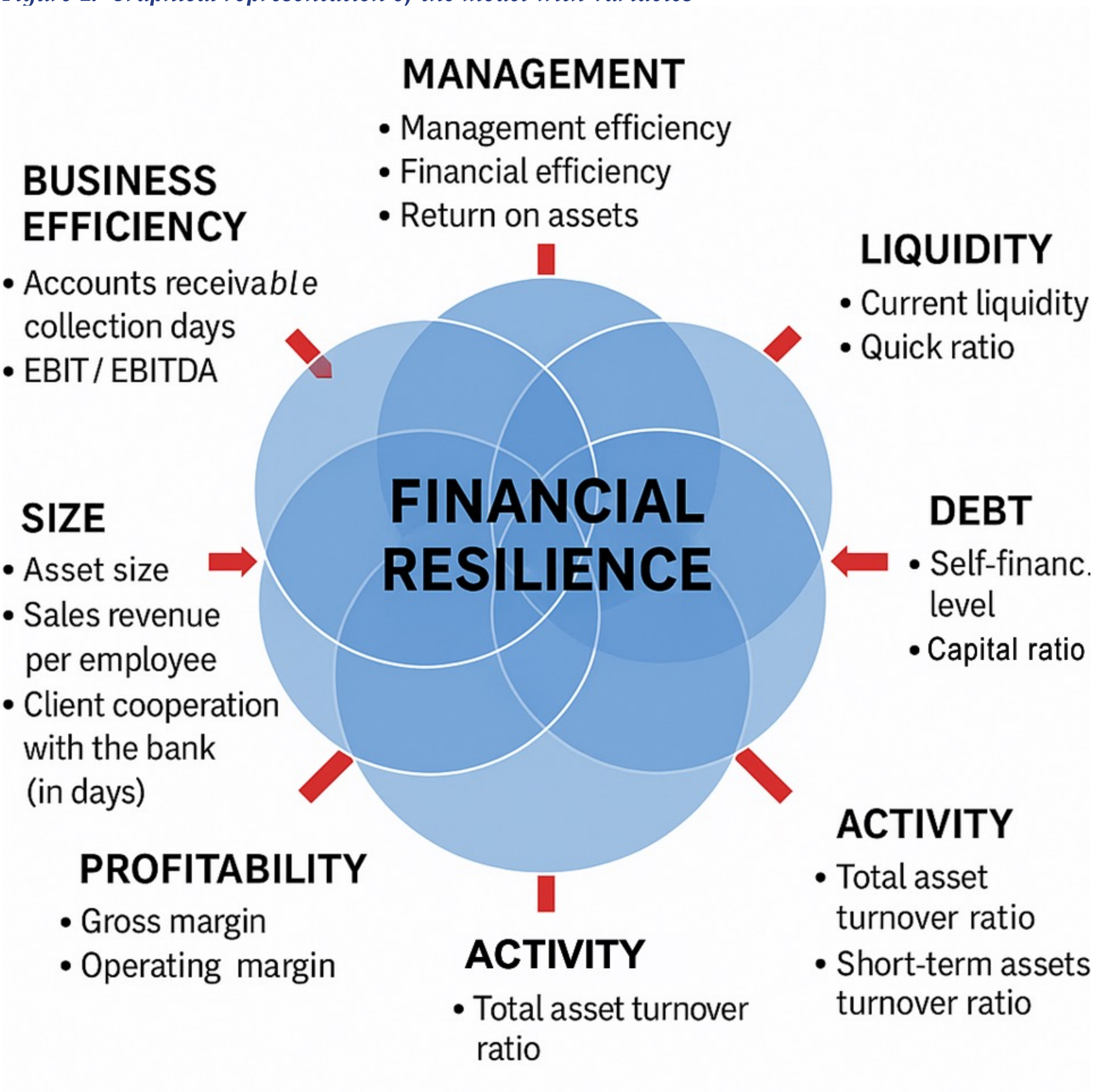
The data show considerable variation among firms across most financial indicators. Total Asset Turnover (KOUI) and Current Asset Turnover (KOKI) have moderate average values (1.36 and 2.95, respectively), but the relatively high standard deviations indicate substantial differences in how efficiently firms generate revenue from assets. The number of days to collect receivables (DNP) shows a very high mean (199 days) and an extremely large standard deviation, suggesting that receivables management practices differ widely and that a large portion of firms experience long collection cycles, potentially increasing liquidity risk. Sales revenue per employee (PPZ) also shows substantial dispersion, suggesting notable heterogeneity in workforce productivity across companies. Management efficiency (EUP) and effectiveness of financial activities (EFP) show relatively low means and low standard deviations, indicating more stable managerial performance than other variables. ***Table 1*** lists all variables initially examined in the research, and ***Figure 1*** graphically depicts them.

Table 1: Input variables

Variable	Definition	Arithmetic mean	Standard deviation
KOUI	Total Asset Turnover Ratio	1.3622	1.4887
KOKI	Current Assets Turnover Ratio	2.9499	3.5637
DNP	Number of days for collection of receivables	199.4825	3,062.3315
PPZ	Sales revenue per employee	245,210.8657	1,019,484.0751
EUP	Management Efficiency	1.0477	.3515
EFP	The effectiveness of financial activities	1.0564	.3592
TL	Current liquidity	1.6734	9.5121
BTL	Quick Liquidity Ratio	1.0973	9.4863
BM	Gross margin	.2018	.4086
OM	Operating margin	.0030	.3990
EBIT	EBIT / EBITDA	.2976	37.7102
ROA	Return on Property	.0378	.1004
SFIN	Level of self-financing	.3194	.2547
SKAP	Equity Ratio on Total Assets	.3174	.2328
ASSETS	Size of the property	11,589,348.18	33,042,731.630
PAKTIVA	Change in assets (% per year)	.5822	11.8449
DS	Duration of the client's cooperation with the bank (days)	2,261.79	922.196

Source: Author's own.

Figure 1: Graphical representation of the model with variables

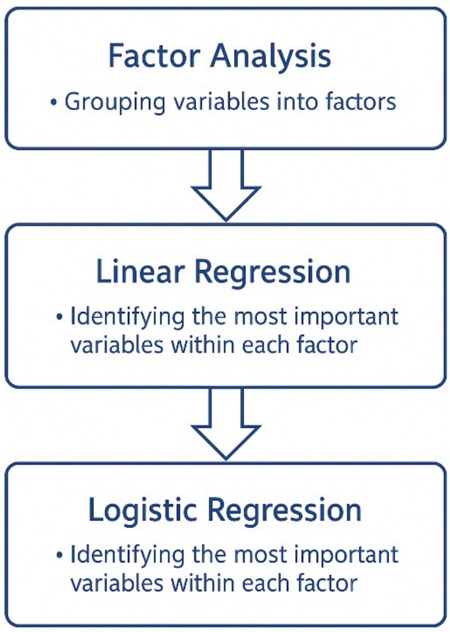


Source: Author's own.

Management quality is not directly observable in bank administrative data; accordingly, we approximate managerial efficiency through financial statement-based efficiency indicators. We construct two complementary proxies: (i) Expense Utilization Performance (EUP), defined as the ratio of operating income to operating expenses, and (ii) Expense-to-Financial Performance (EFP), defined as operating expenses relative to operating income (the inverse scaling of EUP). Higher EUP (or lower EFP) indicates that the firm converts a given expense base into higher revenue or operating earnings, consistent with more efficient planning, budgeting, procurement, and process control. Because income/expense ratios can also be influenced by sectoral business models, accounting policies, temporary shocks, or one-off items, we implement several safeguards. First, we compute the ratios using the same financial statement line items for all firms and apply winsorization at conventional cut-offs to reduce the influence of extreme values driven by unusual events. Second, we control for firm size, leverage and liquidity, which absorb mechanical scale effects and short-term funding constraints that may otherwise load onto the efficiency ratios. Third, we benchmark EUP/EFP against industry (sector) distributions by including sector fixed effects, so that efficiency is interpreted relative to peers facing similar cost structures. Finally, as an internal validity check, we report that EUP/EFP correlate in the expected direction with standard profitability and operating performance measures (e.g., operating margin/ROA), suggesting that the proxies capture economically meaningful efficiency variation. These steps do not eliminate all measurement error, but they mitigate the most common sources of ratio distortion and align our managerial efficiency proxies with observable, decision-relevant performance signals in credit analysis.

Liquidity indicators Current liquidity (TL) and Quick liquidity (BTL) are high on average, but very high standard deviations suggest the presence of firms with both extremely strong and extremely weak liquidity positions, reflecting unequal resilience levels. Profitability indicators show low mean values: Gross margin (BM = 0.20) and Operating margin (OM ≈ 0.00) suggest that many firms operate with minimal operating profit margins, potentially affecting their financial resilience. The EBIT measure has an unusually high standard deviation, suggesting significant fluctuations in earnings performance across companies. ROA (0.0378) shows low average asset profitability with moderate dispersion. Capital structure indicators such as the self-financing level (SFIN) and equity ratio (SKAP) average around 0.32, indicating that roughly one-third of assets are financed with equity, suggesting moderate financial independence. Firm size (ASSETS) exhibits a very high standard deviation, suggesting a dataset that includes both small and very large firms. Annual asset growth (PAKTIVA) has a mean near zero but large variability, signaling diverse growth trajectories within the sample. Finally, the duration of cooperation with the bank (DS) averages around 2,262 days (approx. 6.2 years) with moderate variability, indicating that most firms have a relatively long banking relationship, which may influence credit decision quality and resilience capacity. ***Figure 2*** illustrates the methodological approach of the research.

Figure 2: Methodological aspect of the research



Source: Author's own.

After determining the basic indicators of the financial statements using factor analysis, the number of principal components will be reduced for further analysis. That is, identify those factors that have a significant impact on the possibility of business failure.

We assessed the adequacy of the data for factor analysis. The KMO test confirmed the adequacy of the sample and the presence of multicollinearity among the variables, while the Bartlett test rejected the hypothesis of univariate normality and confirmed the appropriateness of using factor analysis for the established data set. ***Table 2*** presents the correlation matrix

Table 2: Correlation matrix

VAR	KOU1	KOK1	DNP	PPZ	EUP	EFP	TL	BTL	BM	OM	EBIT	ROA	SFIN	SKAP	ASSETS	PASSETS	DS
KOU1	1	0,548**	-0,041	0,262**	-0,008	-0,023	-0,029	-0,026	-0,101**	0,055*	0,017	0,267**	-0,093**	-0,099**	-0,087**	-0,012	-0,074**
KOK1		1	-0,036	0,108**	-0,026	-0,014	-0,047	-0,035	-0,031	0,044	-0,021	0,131**	0,003	0,012	-0,056*	0,041	-0,039
DNP			1	-0,01	-0,045	-0,039	-0,002	-0,002	0,035	-0,084**	0,001	-0,019	-0,008	-0,029	0,016	-0,003	0,013
PPZ				1	-0,001	0,04	0,003	0,008	-0,043	0,025	0,006	0,084**	0,046	0,062*	0,204**	-0,007	0,0177**
EUP					1	0,940**	0,031	0,028	0,115**	0,240**	0,031	0,472**	0,097**	0,140**	-0,007	-0,017	-0,177**
EFP						1	0,030	0,029	0,0217**	0,372**	0,005	0,434**	0,091**	0,128**	0,004	-0,027	-0,285**
TL							1	0,996**	0,041	-0,006	0,003	0,014	0,100**	0,115**	0,030	-0,005	0,022
BTL								1	0,056*	0,013	0,002	0,011	0,085**	0,095**	0,032	-0,003	0,22
BM									1	0,500**	-0,001	0,112**	0,052	0,045	0,005	-0,052	0,053
OM										1	0,003	0,250**	0,001	0,037	0,009	-0,041	-0,079**
EBIT											1	0,05	-0,008	0,038	0,007	0,001	0,017
ROA												1	0,162**	0,257	-0,022	-0,079**	-0,149**
SFIN													1	0,799**	0,101**	-0,040	-0,006
SKAP														1	0,130**	-0,047	0,013
ASSETS															1	-0,014	0,162**
PASSETS																1	-0,057*
DS																	1

Note(s): ** Statistically significant with an error of 1%; * Statistically significant error code of 5%
Source: Author's own.

4. Data analysis

According to the analysis, seven factors in the financial statements contributed to the inability to repay the loan. The first factor included dominant variables that can be summarized under the heading "Management". The current ratio and the quick ratio are two equal factors in the "Liquidity" group. The third factor is "Indebtedness", while the company's "Activity" is the fourth factor. The fifth factor is "Profitability," while the sixth is "Company Size" based on assets. The last factor is the "efficiency" of debt collection.

Table 3: Isolated factors

Variable/Factor	Factors						
	Management	Liquidity	Indebtedness	Activity	Profitability	Size	Efficiency
EUP	0.960	0.016	0.028	-0.071	0.047	-0.013	-0.011
EFP	0.934	0.014	0.016	-0.075	0.191	-0.004	-0.033
ROA	0.616	-0.004	0.237	0.344	0.114	-0.095	0.142
TL	0.014	0.997	0.060	-0.022	0.004	0.014	0.002
BTL	0.011	0.997	0.042	-0.013	0.024	0.017	-0.001
SFIN	0.044	0.044	0.937	-0.033	0.008	0.029	-0.008
SKAP	0.112	0.056	0.935	-0.015	0.013	0.065	0.019
KOUI	0.047	-0.003	-0.105	0.883	-0.042	-0.007	0.033
KOKI	-0.046	-0.030	0.035	0.792	0.036	-0.067	-0.071
BM	0.038	0.038	0.035	-0.090	0.876	0.017	0.053
OM	0.264	-0.013	-0.016	0.098	0.809	-0.011	-0.086
ASSETS	0.031	0.006	0.118	-0.103	-0.011	0.746	-0.064
PPZ	00.07	0.004	0.027	0.407	-0.071	0.615	-0.041
DS	-0.152	0.018	-0.055	-0.136	0.076	0.59	0.154
DNP	-0.056	0.002	-0.040	-0.074	-0.052	-0.015	0.562
EBIT_EBITDA	0.081	0.007	-0.006	0.023	-0.082	0.012	0.511
PAKTIVA	0.004	0.011	-0.069	-0.024	-0.155	-0.048	-0.516
Extraction Method: Main Component Method							
Rotation method: Varimax with Kaiser normalization							

Source: Author's own.

We conduct a set of robustness checks to address measurement and specification concerns. First, we re-estimate the models using alternative profitability and efficiency indicators (where available) to assess whether conclusions depend on the specific EUP/EFP construction. Second, we include interaction terms (EUP/EFP × size; EUP/EFP × liquidity) to test whether managerial efficiency is more relevant for particular firm profiles. Third, to mitigate potential dependence across observations for firms with multiple loans, we compute robust standard errors that account for within-firm correlation and confirm that qualitative conclusions remain unchanged. Overall, the central findings for core financial drivers are stable, while management-efficiency effects are comparatively sensitive and are therefore interpreted with caution. ***Table 3*** presents the isolated factors that contributed the most to financial resilience.

In the second part of the study, a linear probability model was created, the basic form of which is:

$$Y=\alpha+\beta_1 \ln X_1+\beta_2 \ln X_2+\beta_3 \ln X_3+\beta_4 \ln X_4+\beta_5 \ln X_5+\beta_6 \ln X_6+\beta_7 \ln X_7+ \varepsilon$$

The dependent variable is binary (dummy) and is coded 0 and 1, where 0 indicates that the firm repaid the loan and 1 indicates that the firm failed to repay the loan, indicating business failure. The dependent variable captures loan non-repayment as recorded in the bank's internal credit database. A loan is coded as non-performing/non-repaid when it meets the bank's operational default definition (as used for monitoring and reporting), which is based on repayment delinquency and credit status classification at the observation date. While alternative manifestations of distress, such as restructuring or covenant violations, can also signal weakened resilience, these are not consistently available across borrowers and time in the present dataset. We therefore employ loan non-repayment/default as a transparent and policy-relevant proxy for a severe loss of resilience in a debt-servicing context.

In the independent variables, the model includes only those variables with the highest factor loadings for each factor. Another approach is to include all factors, weighted by their factor loadings, in the model; however, for simplicity, we have included only the most important factors. Variables are natural logarithms because they are indicators from financial statements.

Full management efficiency, which measures performance relative to invested funds, always has a positive effect on the company's performance, thereby reducing the likelihood of failure. Efficient managers allocate resources better, control costs more effectively, and respond quickly to market fluctuations - strengthening operational resilience and lowering the probability of financial distress. The higher the liquidity ratio, the greater the company's ability to repay its short-term liabilities. This means that a higher current ratio reduces the likelihood of loan non-repayment. Firms with more liquid assets maintain healthier cash buffers, enabling them to withstand temporary revenue drops or unexpected expenses without defaulting on their obligations. ***Table 4*** presents the variables in the model with their expected impact on loan repayment.

Table 4: Input variables in the model

No.	Variable	Model	The Expected Impact on Business Failure
1	Management Efficiency (EUP)	X_1	-
2	Current Liquidity (TL)	X_2	-
3	Self-Funded Level (SFIN)	X_3	-
4	Total Assets Turnover Ratio (KOUI)	X_4	-
5	Gross margin (BM)	X_5	-
6	Asset	X_6	-
7	Number of days for debt collection (DNP)	X_7	+

Source: Author's own.

The higher the level of self-financing, the greater the company's resilience and the lower the likelihood that it will not be able to meet its financial obligations. Equity-funded firms rely less on external borrowing, thereby reducing leverage-related pressure and strengthening financial stability during crisis periods. A higher turnover ratio of total assets shows that the company is less likely to fail. Stronger asset utilization indicates more efficient resource use to generate revenue, supporting sustainable operations and enhancing the company's resilience against downturns. A higher gross margin means a lower risk of the company going bankrupt. Better margins allow a firm to absorb increases in production costs or sales declines more easily, providing a financial cushion that protects against insolvency. Larger company assets reduce the risk of bankruptcy, as the company may sell some of its assets to raise the cash needed to repay the loan. A strong asset base also improves collateral value, making banks more willing to restructure terms in distress. ***Table 5*** presents the estimated parameters of the linear probability of loan default model

Table 5: Estimated parameters of the linear probability of loan default model

Variable	Variable Name	Model parameters
C	Constant	0.244* (0.090)
$\ln X_1$	Management Efficiency (EUP)	-0.102 (0.086)
$\ln X_2$	Current Liquidity (TL)	0.013 (0.409)
$\ln X_3$	Self-Funded Level (SFIN)	-0.028* (0.010)
$\ln X_4$	Total Assets Turnover Ratio (KOUI)	-0.074* (0.014)
$\ln X_5$	Gross margin (BM)	-0.006 (0.011)
$\ln X_6$	Asset	-0.015* (0.006)
$\ln X_7$	Number of days for debt collection (DNP)	0.017 (0,009)

Note(s): Standard errors in parenthesis; * Statistically significant with an error of 1%; ** Statistically significant error code of 5%.
Source: Author's own.

On the other hand, a lower asset value may indicate that the company is a startup; in banking practice in Bosnia and Herzegovina, up to 98% of startups do not repay their loans on time. This highlights the vulnerability of newer firms with limited tangible assets, especially when cash flows are unstable and business models are still maturing. A greater number of days to collect receivables indicates inefficiency and increases the likelihood that the company will be unable to repay the loan. Delayed collection indicates potential liquidity problems and increased customer credit risk, reducing working capital and increasing the likelihood of financial distress.

The abstract initially emphasized management efficiency as a dominant determinant of resilience. However, in the baseline specifications reported in the main regression tables, the estimated coefficients on EUP/EFP are not statistically significant at conventional levels. To maintain consistency and credibility, we refine the interpretation in two ways. First, we rephrase the abstract and conclusions to reflect the empirical hierarchy of determinants, highlighting variables that are robustly significant across specifications (e.g., leverage, liquidity, firm size, or other financial statement indicators), while characterizing management efficiency as suggestive rather than definitive evidence in our sample. Second, we probe whether the impact of managerial efficiency is conditional rather than average. In additional specifications, we test interaction terms (e.g., EUP/EFP multiplied by firm size and liquidity), sector-by-sector estimations, and alternative model forms (including parsimonious specifications and models excluding highly collinear controls). If management efficiency becomes significant only for certain borrower segments (for example, smaller firms or firms with tighter liquidity), this heterogeneity reconciles the narrative with the tables and offers a more nuanced contribution. If the effect remains statistically weak across robustness checks, we interpret this as an important null finding: efficiency ratios may be less informative for default prediction than commonly assumed once core balance-sheet risk drivers are controlled for, or the proxy may contain noise due to accounting and one-off effects. Either way, aligning the abstract with the empirical results strengthens the manuscript and clarifies the boundary conditions of the management-efficiency argument.

Although the model is significant, with a classification rate of 84.59%, in the next phase of our analysis, we aim to further test the hypotheses and apply logistic regression to the observed dataset.

The model has a general form, for taking the value 0:

$$p = \frac{e^{b_0 + b_1 \cdot x_1 + b_2 x_2 + \cdots + b_n \cdot x_n}}{1 + e^{b_0 + b_1 \cdot x_1 + b_2 x_2 + \cdots + b_n \cdot x_n}}$$

While the probability that the dependent variable takes a value of 1:

$$1 - p = \frac{1}{1 + e^{b_0 + b_1 \cdot x_1 + b_2 x_2 + \cdots + b_n \cdot x_n}}$$

As independent variables, the same variables are used as in the previous model: linear probability.

The parameters of the model are given in *Table 6*:

Table 6: Evaluated parameters of the logistic regression model - inability to repay the loan

Variable	Variable Name	Model parameters	95% confidence interval Lower limit	 Upper limit
C	Constant	0.972 (0.818)	-0.631	2.576
$\ln X_1$	Management Efficiency (EUP)	-0.450 (0.668)	-1.760	0.859
$\ln X_2$	Current Liquidity (TL)	0.073 (0.136)	-0.195	0.340
$\ln X_3$	Self-Funded Level (SFIN)	-0.195** (0.082)	-0.355	-0.035
$\ln X_4$	Total Assets Turnover Ratio (KOUI)	-0.537* (0.116)	-0.764	-0.310
$\ln X_5$	Gross margin (BM)	-0.037 (0.089)	-0.211	0.137
$\ln X_6$	Asset	-0.132* (0.051)	-0.231	-0.032
$\ln X_7$	Number of days for debt collection (DNP)	0.150 (0.080)	-0.006	0.306
	Classification rate	85.1		

Note(s): Standard errors in parenthesis; * Statistically significant with an error of 1%; ** Statistically significant error code of 5%.
Source: Author's own.

Both the linear and logistic regression models were significant and identified the same variables in predicting a company's business failure. The expected sign of influence corresponds to the sign of the estimated models. The classification rate for the logit model is slightly higher than that of the estimated linear probability model, at 85.10%.

Although the conceptual motivation suggests that managerial efficiency should matter for debt-servicing capacity, the estimated coefficients on the EUP/EFP proxies are not statistically significant in our baseline specifications. This does not necessarily imply that management is irrelevant; rather, it indicates that our chosen accounting-based proxies may be noisy and that the management effect can be conditional on firm characteristics or sector context. To reconcile the narrative with the evidence, we interpret the management-efficiency results as weaker and more specification-dependent than those for core financial predictors. In addition to specifications, we test (i) alternative efficiency and profitability measures available in the financial statements, and (ii) interaction terms between EUP/EFP and firm size or liquidity, given that managerial discretion and cost flexibility may differ across firms. These checks help assess whether managerial efficiency matters in particular segments rather than uniformly across the sample.

5. Implications

The findings show that firms with higher levels of self-financing, more efficient use of total assets and larger asset bases are significantly less likely to default on their bank loans. For companies, this means building a strong equity position, focusing on asset productivity, and gradually increasing scale are not only desirable from a profitability perspective but also essential for financial resilience. Managers should therefore treat capital structure and asset turnover as strategic variables rather than purely accounting outcomes. Actions such as retaining earnings, reducing unnecessary leverage, investing in productive assets and actively monitoring asset turnover can strengthen the firm's ability to withstand shocks and maintain access to external finance. The results also suggest that younger or smaller firms need to be particularly cautious, since their weaker internal capital base and limited collateral make them inherently more vulnerable to financial distress.

For banks, the model's classification accuracy of about 85 percent indicates that relatively simple financial indicators can provide a powerful basis for predicting loan repayment problems. The significant role of self-financing, total asset turnover and firm size implies that these indicators should receive explicit weight in internal credit scoring systems and early warning frameworks. In practical terms, credit analysts can use higher equity ratios, strong asset utilization and larger asset bases as positive signals when assessing new loan applications or reviewing existing exposures. Conversely, small, undercapitalized firms with weak turnover should trigger closer monitoring, stricter covenants or additional collateral requirements. By integrating these findings into their models, banks can allocate capital more efficiently, reduce non-performing loans and support a more resilient loan portfolio.

From a policy perspective, the results highlight the structural vulnerability of small, thinly capitalized firms, which are more prone to loan repayment problems. Policymakers in Bosnia and Herzegovina and similar economies may therefore consider measures that help firms strengthen their equity base and improve operational efficiency. Examples include tax incentives for profit retention, targeted support programs that encourage equity financing, guarantee schemes for viable but undercapitalized SMEs and training programs aimed at improving financial management and asset utilization. Regulatory bodies can also encourage banks to incorporate resilience-oriented indicators, such as self-financing and asset turnover, into their risk management frameworks. This would align supervisory expectations with evidence-based drivers of default risk and contribute to a more stable financial system.

At the societal level, each firm that avoids failure and remains able to service its debts contributes to employment, tax revenues and local economic stability. The factors identified in this study as protective against default are closely linked to sustainable business models that generate stable cash flows and maintain prudent balance sheets. Encouraging firms to build stronger equity, use assets efficiently and grow in a controlled way thus has broader social benefits. Fewer bankruptcies mean fewer job losses and less strain on social safety nets, while a healthier banking sector is better able to support productive investment in the real economy. In transition economies, where access to finance is often a key constraint on growth, improving financial resilience at the firm level can therefore translate into more inclusive and stable development.

6. Future research directions

The study also has implications for future research. While self-financing, total asset turnover and firm size emerged as key predictors in this sample, other theoretically relevant variables, such as management efficiency, liquidity or profitability measures, were not statistically significant at conventional levels. This opens space for more nuanced models that include interaction effects, non-linear relationships or dynamic indicators, such as cash flow volatility and changes in management quality over time. Future work could also combine quantitative financial data with qualitative information on governance, strategy or business environment to better capture the multidimensional nature of financial resilience. Comparative studies across countries or sectors would help to identify whether the same drivers of default hold in different institutional contexts, and longitudinal analyses could examine how these relationships evolve across economic cycles or crisis periods.

7. Conclusion

In this study, we investigated the possibility of using multivariate analysis to predict and explain the business failure of corporate clients of a domestic bank. In a sample of 1,531 observations, we identified financial statement variables with a theoretical basis for explaining the observed phenomena. Observations with missing data were excluded from our analysis. Of the 17 variables identified, seven factors were identified by factor analysis. One variable with the highest factor loading was selected as a representative of each factor to serve as an independent variable in further analysis to predict business failure.

The classification rate achieved with the logit model, slightly higher than that of the estimated linear probability model, is 85.10% and is satisfactory for the purposes of this research. Based on our research, we conclude that the null hypothesis cannot be rejected.

As alternatives to the applied methods, the probit model, discriminant analysis, and new methods such as artificial neural networks can be used.

7.1. Limitations

This study has limitations. The dependent variable captures a severe repayment outcome and therefore represents a narrow but policy-relevant dimension of resilience in a lending context; earlier distress signals such as arrears trajectories, covenant breaches, or restructurings may provide a richer picture but are not consistently available in the dataset. In addition, the accounting-based management proxies (EUP/EFP) are imperfect and may be influenced by one-off items or reporting practices, thereby attenuating the estimated effects. For these reasons, we present our results primarily as empirical associations that strengthen credit-risk understanding, while encouraging future work with richer event histories and more direct measures of managerial practices.

It should be noted that the use of data from financial statements is a limitation because not all factors that predict a company's success are presented in the financial statements. Soft factors in management's success are often more important than financial statement indicators. Another limitation in terms of data is the use of financial statements from a single year, except for some indicators, which use "change" indicators – the change in position from one year to the next. However, in such cases, trends should be monitored, based on data from the financial statements for at least 3 years.

Declarations

The author has no relevant financial or non-financial interests to disclose. The data are available upon a reasonable request from the author.

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