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Proceeding Paper

Improving the Accuracy of Firm Failure Forecasting Using Non-Financial Variables: The Case of Croatian SME †

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Abstract: Empirical findings based on a bivariate logistic regression model with two SME categories (successful and failed) indicate that by adding non-financial indicators to the model based on financial variables, the accuracy of forecasting increases significantly. Namely, the total classification error decreases by an average of 26.99%, while the AUROC value increases by an average of 7.33%. In the additional model, with three firm categories (successful, sensitive, and failed), the findings reveal that one financial variable (self-financing) and three non-financial variables (orderly settlement of obligations, export, and age) significantly explain the occurrence of the early stage of SME failure.

Keywords: SME; firm failure; non-financial variables

1. Introduction

Firm failure modeling has been an important research topic for many years, for both academia and practitioners in banks, investment funds, and other institutions. Firm failure often has a wide range of negative effects on numerous subjects, especially for employees, investors, creditors, and suppliers. Every new economic crisis, such as Global Financial Crisis (2007–2008), Great Recession (2008–2012), or the recent COVID-19-caused economic crisis (2020), brings this issue into the spotlight again.

The problem of firm failure has been an intriguing issue in Croatia for many years, primarily due to the large number of insolvent companies. According to official statistical data (www.dzs.hr), there were 137,664 companies in Croatia at the end of 2022, while current data (February 2023) from the state agency FINAs database (www.infobiz.hr, accessed on 5 February 2023.) reveal that 13,901 companies were insolvent because of blocked accounts (EUR 406.58 million). In other words, the Croatian business environment is quite risky since 10.5% of companies have problems meeting their due liabilities. The riskiness of doing business in Croatia was confirmed by the World Bank's Doing Business data in 2020 (https://www.worldbank.org/en/home, accessed on 14 January 2023.), as only 35.2% of receivables were collected in insolvency proceedings. For comparison, the percentage of receivables collection in insolvency proceedings is 90% in Slovenia, 67.5% in the Czech Republic, and 79.8% in Germany, while the average in OECD countries is 70.2%. The reason for a low percentage of claims collection in Croatian insolvency proceedings is the late opening of proceedings and the fact that many companies enter bankruptcy procedures with negative equity. In such a business environment, predicting legal failure, i.e., bankruptcy, is not very useful, but it is much more useful to create a model for predicting firm insolvency and the early stages of firm failure [1]. This research emphasizes the modeling of firm failure in the SME segment due to the large number of such companies in Croatia and their relative importance in the national economy. According to the 2021

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aggregated data retrieved from the FINAs database (www.infobiz.hr), the SME sector in Croatia comprises 55.4% of total assets and generates 58.3% of revenue.

Our study adds to the existing literature in several ways. Firstly, we developed a unique set of non-financial variables to explore how much these variables can improve firm failure forecasting. Secondly, we developed a model for the prediction of the early stage of the firm failure process, which enables timely decision making to avoid credit losses. The estimated multinomial logistic regression model indicates that one financial variable (self-financing) and three non-financial variables (settlement of obligations, export, and firm age) significantly contribute to explaining the early stage of SME failure. Finally, we conducted research for the sample of Croatian SMEs for which this kind of modeling is almost nonexistent. In addition to confirming the theoretical assumptions about the usefulness of non-financial variables, the designed model also has the possibility of practical use, especially in commercial banks.

2. Literature Review

There is a large body of literature dealing with firm failure from different perspectives; however, the main goal of almost all papers is to design a prediction model with the lowest possible forecasting error. Early studies [2–5] put focus on the use of financial indicators in the prediction of firm failure. Given that financial indicators are based on financial statements, such studies explore the usefulness of accounting information in the context of crediting decisions and firm failure modeling. As a general conclusion of the mentioned early studies, as well as many recent studies [6–9], one can point out the finding that financial indicators are useful in predicting business failure. However, studies that analyzed the predictive power of financial indicators over time showed that as the accounting data age ($t-2$, $t-3$ ...), the predictive power of financial indicators declines sharply. The accuracy of forecasting over a long period directly depends on the stationarity of the data, which implies a stable correlation between the variables in the forecast period. Empirical research has shown that this is difficult to achieve, which is emphasized by Du Jardin and Severin [10], who analyzed 34 studies and determined that the accuracy of the model decreases by 15% in 3 years before the bankruptcy. Pervan et al. [1] report similar findings in a more recent study.

Over the years, one direction of firm failure research focuses on SMEs. Namely, the modeling of firm failure for large listed companies is not identical to modeling for SME failure. The first such study was published in the US by Edminister [11], followed by numerous recent studies for SME samples. Edminister designed the model with seven financial ratios (different from Altman's Z score ratios) with a classification accuracy of 93%. Altman and Sabato [12] developed the SME failure model and compared it with Altman's Z″ (model for unlisted firms). A comparison of the SME failure prediction model and the Z″ model indicated that the SME model outperformed Altman's Z″ model by 30%. Similar research focused on SMEs can be found for SMEs from Portugal [13], Russia [14], Belgium [15], Estonia [16], etc.

To improve the predictive power of forecasting models, authors such as Gudmundson [17], Grunert et al. [18], Altman et al. [19], Pervan and Kuvek [20], Laitinen [21], Habachi and Benbachir [22], and Altman et al. [23] use non-financial variables. The general finding from most of the mentioned studies is that the inclusion of non-financial indicators in addition to financial indicators improves the accuracy of predicting firm failure. This can be explained by the characteristics of qualitative variables that do not change over time (or only partially change) and achieve more stable correlations as compared to financial variables. Previous papers often use firm age, firm size, industry, and region as a set of non-financial variables since these data are publicly available.

3. Research Design

The research sample included 4639 SME clients of a commercial bank, while the dataset incorporated data from the period 2011–2015. An important element in firm failure modeling is the definition of the dependent variable, i.e., the firm failure variable. In countries such as Croatia, where bankruptcies are opened at the very late stage of the failure process and where the percentage of receivables collection in bankruptcy is quite low, it is much more useful to predict the early stage of firm failure than legal failure—bankruptcy. Therefore, the total sample of SMEs was divided into three categories (successful, sensitive, and failed) depending on the bank's internal credit rating and regularity in the settlement of due obligations (Table 1). The group of successful firms includes only those firms that have an intact high credit rating and that have not had any delays in settling their obligations. A firm entered the sensitive category (early stage of firm failure) if it had a reduced credit rating and a delay in meeting obligations for a duration between 30 and 90 days. Finally, the firm was classified as failed if it had the lowest credit rating with delays in the settlement of obligations longer than 90 days, accompanied by a recorded amount of loss for the bank.

Table 1. Sample structure.

SME Category	Number of Observations
Successful	3046
Sensitive	779
Failed	814
Total	4639

Following the example of similar studies, this research also uses accounting information and financial ratios as influential variables for predicting SME failure. Modern accounting frameworks (IFRS, FASB, etc.) point out that accounting information should be useful for investing and crediting decisions. Previous studies generally confirmed that accounting information and resulting financial ratios are useful as independent variables for firm failure modeling. However, some papers such as [1,3,10] point out that older accounting information results in lower prediction accuracy. In the segment of financial variables, 14 financial ratios were used, which were calculated as shown in Table 2:

Table 2. Financial variables.

Financial Variable	Acronym	Description
Return on equity	ROE	Net earnings/Equity
Return on assets	ROA	Net earnings/Assets
Operating margin	OM	Operating earnings/Sales
EBITDA to assets	EBITDAA	EBITDA/Assets
Sales to equity	SE	Sales/Equity
Operating cash flow to assets	OCFA	Net operating cash flow/Assets
Working capital	WC	Working capital/Assets
Current ratio	CR	Current assets/Current liabilities
Quick ratio	QR	Current assets-Stock/Current liabilities
Debt to assets	DA	Total debt/Assets
Self-financing	SF	Equity/Assets
Short-term debt to assets	STDA	Short-term debt/Assets
Debt to EBITDA	DEBITDA	Total debt/EBITDA
Operating cash flow to debt	OCFD	Net operating cash flow/ Total debt

To improve forecasting accuracy, further modeling of SME failure includes non-financial variables. The starting assumption is that non-financial variables (due to their characteristics) only partially change over time, which enables them to be more stable failure predictors in comparison with financial variables. A unique dataset obtained from a Croatian commercial bank enabled the development of a complex prediction model, which combines financial and non-financial variables. Therefore, this research is one of the few whose modeling includes a battery of non-financial variables, as described in Table 3.

Table 3. Non-financial variables.

Non-Financial Variable	Acronym	Description
Managerial experience	ME	Three groups (<5 years, 5–10 years, >10 years)
Business diversification	BD	Three groups (one business, two or more businesses within one industry, businesses in different industries
Settlement of obligations	SO	Four groups (late payment up to 30 days, late payment from 30 to 60 days, late payment from 60 to 90 days, late payment for more than 90 days)
Size	S	Ln of assets
County	C	One of 21 counties in Croatia
Export	EX	Four groups (export sales 0%, up to 30% export sales, export sales from 30% to 60%, export sales more than 60%)
Age	A	Three groups (<5 years, 5–10 years, >10 years)

Regarding the use of statistical methods, a review of previous studies indicates that many papers often followed Altman [3] and used multiple discriminant analysis (MDA). Here, it is important to point out that MDA has very strict requirements (normality of explanatory factors, equal variance–covariance matrices, prior groups' probabilities) which often are not met by data. After Ohlson's [24] seminal study, the majority of later studies started to use logit/probit/logistic regression since this method is much more robust. Therefore, for this study, we employed binary logit regression and multinomial logit regression.

4. Research Results

The first logit model (Table 4) includes only financial variables, and given a large number of financial variables, it was important to control for the potential problem of multicollinearity. Due to the high correlation (r > 0.8) with other variables, two variables (STDA and DA) were omitted from further analysis. In this model, the dependent variable, SME failure, can take only one of two values (failed—1; successful—0). The application of the Prabhakaran algorithm [25] in the R application resulted in the following final model with financial variables.

Table 4. Bivariate logit model with only financial variables (FVs).

Variable	Estimate	St. Error	Z Value
Const.	0.2150	0.2289	0.939
WC	−2.0607 ****	0.5271	−3.909
SF	−5.4357 ****	0.7314	−7.431
OM	−2.8503 ***	0.8898	−3.203
ROE	−0.3980	0.2327	−1.710

Significances: ***** $p \approx 0$; *** $p < 0.001$.

Three statistically significant financial variables (WC, SF, and OM) had a negative sign, which, under theoretical expectations, indicates that greater liquidity, self-financing, and profitability reduce the probability of failure. However, a model based only on financial variables shows the instability of predictions because model error increased over time (from 7.91% in 2015 to 13.27% in 2011). The same conclusion can be drawn for the AUROC value, which decreased over time (from 89.34% in 2015 to 86.36% in 2011).

To improve prediction accuracy and reduce the model instability, in the next step, we added non-financial variables from Table 3. Non-financial variables (except for the size variable) were first transformed into multi-level factor variables [26] with the initial category dropped from the regression (base category). The Prabhakaran algorithm and

R application estimated model were used with financial and non-financial variables, as presented in Table 5.

Table 5. Bivariate logit model with financial and non-financial variables (F&NFV).

Variable	Estimate	St. Error	Z Value
Const.	2.1976	1.8158	1.210
WC	−1.8168 **	0.8411	−2.160
SF	−4.0941 ****	0.9895	−4.138
OM	−3.8662 ***	1.4867	−2.600
S	−0.3061	0.2678	−1.143
A 5−10 y	−2.0328 ****	0.6100	−3.333
A > 10 y	0.3079	0.8719	0.353
ME 5−10 y	−1.5885 **	0.7128	−2.228
ME > 10 y	−1.8246 **	0.8042	−2.269
SO 30−60 d	−0.0903	1.0309	−0.088
SO 60−90 d	0.9045	0.9897	0.917
SO > 90 d	3.7638 ****	0.6429	5.854

Significances: **** $p \approx 0$; *** $p < 0.001$; ** $p < 0.01$.

Of seven non-financial variables included in the modeling, three were found to be statistically significant (age, management experience, and obligation settlement). As expected, the aging of SMEs (5–10 years) and longer management experience (>5 years) reduce the probability of SME failure. In addition, late obligation payments for more than 90 days significantly explain SME failure. Empirical findings based on a bivariate logit model (successful and failed firms) indicate that by adding non-financial indicators into the model based on financial variables, the accuracy of forecasting increases significantly (Table 6). In particular, the total classification error decreases by an average of 26.99%, while the AUROC value increases by an average of 7.33%.

Table 6. Comparison of model error and AUROC.

Year	Model Error (%)		AUROC (%)	
	FV	F&NFV	FV	F&NFV
2011	7.91	5.04	89.34	97.20
2012	7.00	4.74	90.99	96.65
2013	9.27	6.36	89.20	96.61
2014	11.21	7.65	86.87	95.04
2015	13.27	12.84	86.36	89.73

In the additional model, the dependent variable, SME failure, was grouped into three categories: successful (0Y), sensitive (1Y), and failed firms (2Y). The test for combining dependent categories [27] starts from the null hypothesis H_0, which asserts that no independent variable significantly predicts the *m* category of the dependent variable in relation to the *n* category of the dependent variable, and that categories *m* and *n* cannot be distinguished from each other in relation to the variables in the model. All combinations of the categories of the dependent variable (Table 7) in the estimation sample have statistically significant Chi2 ($p < 0.05$) values, which indicates that the categories of the dependent variable cannot be combined, as they are mutually independent, and according to the test of combining dependent variables, the conditions are met for the application of the multinomial approach.

Table 7. Test for combining dependent categories.

	Chi2	df	p > Chi2
Successful and sensitive	2113.08	10	0.0001
Successful and failed firms	3720.04	10	0.0001
Sensitive and failed firms	837.44	10	0.0001

Particular interest was in the sensitive firms' category (1Y) because it is interesting to investigate whether entering the early stage of firm failure prediction can be forecasted with the proposed set of financial and non-financial variables. The estimated multinomial logit regression model (Table 8) indicates that one financial variable (self-financing) and three non-financial variables (orderly payment of obligations, export, and age of the company) significantly explain the occurrence of the early stage of firm failure. The direction of the influence of quantitative and qualitative variables on the probability of the occurrence of the early stage of failure (1Y) concerning the successful category (0Y) is in line with theoretical expectations. The regression coefficients of self-financing (SF) and the qualitative variables' regularity of settlement of obligations (SO) and export (EX) have a negative sign, which indicates that the probability of the early stage failure is higher in SMEs that have a smaller share of self-financing, which are not exporters and which are late in settling their due obligations. The positive sign with the qualitative variable age (A) suggests that SMEs that have been present on the market for more than 5 years are less likely to enter the early stage of failure.

Table 8. Multinomial panel with financial and non-financial variables.

	Coefficient	St. Error	Z Value	p
0Y		Base Outcome		
1Y				
SF	−0.6096	0.2238	−2.72	0.006
OCFD	−0.0469	0.0412	−1.14	0.254
BD-MBI	−0.7155	0.2413	−0.30	0.767
BD-MBMI	−0.5302	0.3135	−1.69	0.091
SO 30−60 d	4.4176	0.2054	21.51	0.000
SO 60−90 d	4.8246	0.2226	21.67	0.000
SO > 90 d	6.5753	0.5190	12.67	0.000
EX < 30%	−0.7165	0.2003	−3.58	0.000
EX 30−60%	−0.8018	0.3646	−2.20	0.028
EX > 60%	−0.3717	0.3107	−1.20	0.232
A 5−10 y	−0.6534	0.2221	−2.94	0.003
A > 10 y	−0.9005	0.3541	−2.54	0.011
Const	−1.9046	0.1574	−12.10	0.000
2Y				
SF	−0.6185	0.2228	−2.71	0.007
OCFD	−0.2855	0.0907	−3.15	0.002
BD-MBI	−0.8810	0.2807	−3.14	0.002
BD-MBMI	−1.6507	0.4590	−3.60	0.000
SO 30−60 d	3.6686	0.5651	6.49	0.000
SO 60−90 d	6.0407	0.3984	15.16	0.000
SO > 90 d	10.3727	0.5884	17.63	0.000
EX < 30%	−1.1166	0.3018	−3.70	0.000
EX 30−60%	−1.0661	0.5791	−1.84	0.066
EX > 60%	−0.4927	0.5031	−0.98	0.327
A 5−10 y	−1.0914	0.2620	−4.17	0.000
A > 10 y	−0.5193	0.4147	−1.25	0.210
Const	−3.7462	0.3066	−12.22	0.000

Log likelihood = −1591.53; N = 4639.

The highest classification power, exp (b), in predicting the sensitive SME (1Y) category has the variable regularity of settlement of obligations (SO), while the exp (b) values of the other variables are much smaller (age, export, and self-financing). For example, the probability of the sensitive SME status (1Y) compared to the successful SME status (0Y) is 717.1 times higher if the delay in the settlement of obligations increases from "SO < 30 d" (base category) to "SO > 90 d".

5. Conclusions

The results of this research confirm that the inclusion of non-financial variables in addition to financial variables into SME failure modeling improves prediction accuracy. By adding non-financial variables, total classification error decreases by an average of 26.99%, while the AUROC value increases by an average of 7.33%. The evaluated model revealed that the most important financial variables are working capital, self-financing, and operating margin. The signs for all three financial variables were negative, which, in accordance with theoretical expectations, indicates that greater liquidity, self-financing, and profitability reduce the probability of SME failure. Of all the non-financial variables tested, only age, management experience, and obligation settlement were found to be statistically significant. The aging of SMEs (5–10 years) and longer management experience (>5 years) reduce the probability of firm failure. According to theoretical expectations, a lower degree of regularity in settling obligations, i.e., late obligation payment for more than 90 days, significantly contributes to SME failure. Additional modeling, based on a multinomial logit model and three SME categories (successful, sensitive, and failed), revealed that the self-financing variable and three non-financial variables (settlement of obligations, export, and age of the company) significantly explain the occurrence of the early stage of firm failure. The findings of this research confirm the theoretical viewpoints on the usefulness of non-financial indicators in predicting SME failure and can serve as guidelines for commercial banks when developing models for assessing the credit risk of SME clients.

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