Modelling credit risk for small and medium-sized enterprises (SMEs)

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Abstract: SMEs are vital to the global economy yet encounter significant financing constraints. This study analyzes 5 years of data from 3,040 SMEs using 33 annual financial indicators, dummy variables, and logistic regression. The results yield a universally applicable and accurate credit risk assessment equation. Key determinants of SME default include stock turnover, collection period, credit period, solvency ratios, gearing, operating revenue per employee, employee cost ratios, average employee cost, working capital per employee, total assets per employee, current liabilities, cash equivalents, and operating revenue. This model enables banks and creditors to effectively evaluate SME credit risk, thereby facilitating SME financing and promoting mutually beneficial outcomes.

Keywords: Small and medium-sized enterprises (SMEs)；credit risk；default

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Introduction

Despite their economic significance and operational agility, SMEs face persistent difficulties in accessing finance. Bank lending remains limited due to perceived high credit risks and significant information asymmetry. This leads to cautious lending behavior, even though the Basel II Accord and research by Altman and Sabato (2005) suggest that SME lending can reduce banks' capital requirements due to portfolio diversification effects[1].

Addressing this information gap requires robust, tailored credit risk assessment tools for SMEs. Traditional models, designed for large corporations, perform poorly when applied to SMEs due to differences in risk profiles and data availability. Studies in Germany and France show SMEs have higher bankruptcy probabilities and lower asset correlations than large firms (Dietsch & Petey, 2004)[2]. Similarly, research in Italy indicates that predictive accuracy of standard models decreases with firm size, underscoring the need for SME-specific models (Vallini et al., 2008)[3].

2 Testable Hypotheses and Research Methodology

It can be concluded from the literature research that there are abnormal financial indicators before the default of SMEs. Hence, the hypothesis is: SMEs have abnormal and observable financial indicators before default. Therefore, the goal of this research is to identify these financial indicators and construct a regression.

3 Data Collection and Variable Construction

3.1 Data Screening and Sample Selection

Data were sourced from the ORBIS database, with a multi-stage filter for sample quality:SMEs met EC criteria (assets ≤ €43M/turnover ≤ €50M, <250 employees);firms active in the last 5 years; prior-year financials used, listed/unlisted SMEs with complete data included; distress (1=distressed, 0=healthy) defined by default/insolvency etc. The screening gave 20,583 initial firm-year observations.

3.2 Variable Selection

The selection of predictive variables was guided by a synthesis of academic literature and pragmatic data availability. Benn and Kramar (2011) established that liquidity, profitability, leverage, coverage, and activity ratios are particularly influential for SME credit risk[4]. Besides, liquidity and leverage are among the most powerful predictors across contexts

(Terdpaopong & Mihret, 2011)[5].

Table.1: Financial indicators

Category	Symbol	Financial indicators(Year-1)
Profitability Ratios	X_1	ROE using P/L before tax (%)
	X_2	ROCE using P/L before tax (%)
	X_3	ROA using P/L before tax (%)
	X_4	ROE using Net income (%)
	X_5	ROCE using Net income (%)
	X_6	ROA using Net income (%)
	X_7	Profit margin (%)
	X_8	EBITDA margin (%)
	X_9	EBIT margin (%)
	X_{10}	Cash flow / Operating revenue (%)
Operational Ratios	X_{11}	Net assets turnover
	X_{12}	Interest cover
	X_{13}	Stock turnover
	X_{14}	Collection period (days)
	X_{15}	Credit period (days)
Structure Ratios	X_{16}	Current ratio
	X_{17}	Liquidity ratio
	X_{18}	Shareholder's liquidity ratio
	X_{19}	Solvency ratio (Asset based) (%)
	X_{20}	Solvency ratio (Liability based) (%)
	X_{21}	Gearing (%)
Per employee ratios	X_{22}	Profit per employee (th) (th)th EUR
	X_{23}	Operating revenue per employee (th) (th) th EUR
	X_{24}	Costs of employees / Operating revenue (%)
	X_{25}	Average cost of employee (th) (th)th EUR
	X_{26}	Shareholders' funds per employee (th) (th)th EUR
	X_{27}	Working capital per employee (th) (th)th EUR
	X_{28}	Total assets per employee (th) (th) th EUR
Others	X_{29}	Current assets EUR
	X_{30}	Current liabilities EUR
	X_{31}	Cash & cash equivalent EUR
	X_{32}	Operating revenue (Turnover) EUR
	X_{33}	Quick ratio

3.3 Final Data Cleansing and Modelling Dataset Construction

Based on the availability of these 33 financial indicators, only 2,082 SMEs possessed sufficient financial information for inclusion. To ensure a robust comparative analysis and enhance model precision, an additional 958 financially healthy SMEs were incorporated into the final modeling sample.

4 Analysis and Results

4.1 One sample K-S test

H_0: financial indicators obey a normal distribution

The one sample K-S test for normality is based on the maximum difference between the sample cumulative distribution and the hypothesized cumulative distributionIf the P-value close to zero, the null hyporesearch will be rejected.

For SMEs with financial distress:

Table.2:One sample K-S test for SMEs with financial distress

Financial indicators(Year-1)	Test statistic	P-value	Reject or not
ROE using P/L before tax (%)	0.238922081	0.00	Reject
ROCE using P/L before tax (%)	0.216123297	0.00	Reject
ROA using P/L before tax (%)	0.163718764	0.00	Reject
ROE using Net income (%)	0.251564193	0.00	Reject
ROCE using Net income (%)	0.236867826	0.00	Reject
ROA using Net income (%)	0.178969839	0.00	Reject
Profit margin (%)	0.216236274	0.00	Reject
EBITDA margin (%)	0.167401814	0.00	Reject
EBIT margin (%)	0.202501795	0.00	Reject
Cash flow / Operating revenue (%)	0.196953725	0.00	Reject
Net assets turnover	0.389734053	0.00	Reject
Interest cover	0.35644884	0.00	Reject
Stock turnover	0.341808059	0.00	Reject
Collection period (days)	0.219364133	0.00	Reject
Credit period (days)	0.190488582	0.00	Reject
Current ratio	0.229353101	0.00	Reject
Liquidity ratio	0.208083814	0.00	Reject
Shareholder’s liquidity ratio	0.428393125	0.00	Reject
Solvency ratio (Asset based) (%)	0.07724753	0.00	Reject
Solvency ratio (Liability based) (%)	0.114530172	0.00	Reject
Gearing (%)	0.149101639	0.00	Reject
Profit per employee (th) (th)th EUR	0.349555562	0.00	Reject
Operating revenue per employee (th) (th) th EUR	0.344016856	0.00	Reject
Costs of employees / Operating revenue (%)	0.0702213	0.00	Reject
Average cost of employee (th) (th)th EUR	0.139219984	0.00	Reject
Shareholders’ funds per employee (th) (th)th EUR	0.404991477	0.00	Reject
Working capital per employee (th) (th)th EUR	0.307941856	0.00	Reject
Total assets per employee (th) (th) th EUR	0.355500246	0.00	Reject
Current assets EUR	0.343922909	0.00	Reject
Current liabilities EUR	0.352308781	0.00	Reject
Cash & cash equivalent EUR	0.378957095	0.00	Reject
Operating revenue (Turnover) EUR	0.29495475	0.00	Reject
Quick ratio	0.228952445	0.00	Reject

For SMEs without financial distress:

Table.3:One sample K-S test for SMEs without financial distress

Financial indicators(Year-1)	Test statistic	P-value	Reject or not
ROE using P/L before tax (%)	0.263338893	0.000	Reject
ROCE using P/L before tax (%)	0.250423266	0.000	Reject
ROA using P/L before tax (%)	0.200964075	0.000	Reject
ROE using Net income (%)	0.290878107	0.000	Reject
ROCE using Net income (%)	0.275790411	0.000	Reject
ROA using Net income (%)	0.236102032	0.000	Reject

Profit margin (%)	0.231824808	0.000	Reject
EBITDA margin (%)	0.196568886	0.000	Reject
EBIT margin (%)	0.220422703	0.000	Reject
Cash flow / Operating revenue (%)	0.211923788	0.000	Reject
Net assets turnover	0.319108281	0.000	Reject
Interest cover	0.341093582	0.000	Reject
Stock turnover	0.352701842	0.000	Reject
Collection period (days)	0.124491596	0.000	Reject
Credit period (days)	0.114356622	0.000	Reject
Current ratio	0.309553128	0.000	Reject
Liquidity ratio	0.230421138	0.000	Reject
Shareholder's liquidity ratio	0.417885483	0.000	Reject
Solvency ratio (Asset based) (%)	0.052115007	0.011	Reject
Solvency ratio (Liability based) (%)	0.07745091	0.000	Reject
Gearing (%)	0.172282723	0.000	Reject
Profit per employee (th) (th)th EUR	0.336682548	0.000	Reject
Operating revenue per employee (th) (th) th EUR	0.351833682	0.000	Reject
Costs of employees / Operating revenue (%)	0.140860891	0.000	Reject
Average cost of employee (th) (th)th EUR	0.128796485	0.000	Reject
Shareholders' funds per employee (th) (th)th EUR	0.345375743	0.000	Reject
Working capital per employee (th) (th)th EUR	0.336925059	0.000	Reject
Total assets per employee (th) (th) th EUR	0.393827923	0.000	Reject
Current assets EUR	0.193887769	0.000	Reject
Current liabilities EUR	0.168004383	0.000	Reject
Cash & cash equivalent EUR	0.286367801	0.000	Reject
Operating revenue (Turnover) EUR	0.1748218	0.000	Reject
Quick ratio	0.309093354	0.000	Reject

According to Table 2&3 in the above text. The P-values of all financial indicators are close to zero. Therefore, none of the above 33 financial indicators follow a normal distribution.

4.2 Two sample K-S test

H_0:the distributions of the two groups are the same.

Using two-sample K-S test to test if the distributions of two groups are the same and analyze the ability of each financial indicator to distinguish between the SMEs with financial distress and the SMEs without financial distress.

Table.4:Two sample K-S test

Financial indicators(Year-1)	Test statistic	P-value	Reject or not
ROE using P/L before tax (%)	0.158958117	0.000	Reject
ROCE using P/L before tax (%)	0.129363405	0.000	Reject
ROA using P/L before tax (%)	0.208733082	0.000	Reject
ROE using Net income (%)	0.158653174	0.000	Reject
ROCE using Net income (%)	0.107697195	0.000	Reject
ROA using Net income (%)	0.200052422	0.000	Reject
Profit margin (%)	0.160345146	0.000	Reject
EBITDA margin (%)	0.085787746	0.000	Reject
EBIT margin (%)	0.078055059	0.001	Reject
Cash flow / Operating revenue (%)	0.125009051	0.000	Reject

Net assets turnover	0.06831169	0.004	Reject
Interest cover	0.212019117	0.000	Reject
Stock turnover	0.130193072	0.000	Reject
Collection period (days)	0.130931971	0.000	Reject
Credit period (days)	0.119496121	0.000	Reject
Current ratio	0.089019727	0.000	Reject
Liquidity ratio	0.063829342	0.009	Reject
Shareholder's liquidity ratio	0.225120932	0.000	Reject
Solvency ratio (Asset based) (%)	0.205351178	0.000	Reject
Solvency ratio (Liability based) (%)	0.205772896	0.000	Reject
Gearing (%)	0.181062362	0.000	Reject
Profit per employee (th) (th)th EUR	0.407911471	0.000	Reject
Operating revenue per employee (th) (th) th EUR	0.611163748	0.000	Reject
Costs of employees / Operating revenue (%)	0.333593231	0.000	Reject
Average cost of employee (th) (th)th EUR	0.567919548	0.000	Reject
Shareholders' funds per employee (th) (th)th EUR	0.498236637	0.000	Reject
Working capital per employee (th) (th)th EUR	0.318791796	0.000	Reject
Total assets per employee (th) (th) th EUR	0.487865026	0.000	Reject
Current assets EUR	0.767469172	0.000	Reject
Current liabilities EUR	0.769824061	0.000	Reject
Cash & cash equivalent EUR	0.653911779	0.000	Reject
Operating revenue (Turnover) EUR	0.817093705	0.000	Reject
Quick ratio	0.089019727	0.000	Reject

From the results in Table 4, the P-value is very low. Hence, the null hyporesearch can be rejected. Therefore, all 33 financial indicators can be used to differentiate the SMEs with or without financial distress.

5.4 Modelling credit risk for SMEs

5.4.1 Divide the training set and the test set

Following the amalgamation of the two groups, a binary target variable named 'default' was constructed for classification. Observations from the regular group were assigned a value of 0, whereas those from the non-default group were assigned a value of 1.

The combined dataset comprises 3,040 samples. For model development, the dataset was partitioned into a training set of 2,000 observations to train the model, and a testing set of the remaining observations to evaluate its predictive accuracy.

5.4.2 Variable Selection and Regression

As detailed previously, a stepwise regression procedure was employed to refine the set of predictors. This process yielded a subset of 14 significant variables from the original 33. A logistic regression was then performed using this refined subset, the outcomes of which are summarized as follows.

Table. 5:Regression

Financial indicators(Year-1)	Variable name	Coefficient	Standard error	Wald statistic	P-value
Stock turnover Year - 1	x13	0.0006	0.001	0.235225	0.628
Collection period (days) Year - 1	x14	-0.0004	0.002	0.074529	0.785
Credit period (days) Year - 1	x15	0.0124	0.002	24.910081	0
Solvency ratio (Asset based) (%) Year - 1	x19	0.3385	0.036	89.756676	0
Solvency ratio (Liability based) (%) Year - 1	x20	-0.1531	0.019	67.289209	0

Gearing (%) Year - 1	x21	0.0051	0.001	80.156209	0
Operating revenue per employee (th)(th)th EUR Year - 1	x23	0.0002	7.50E-05	8.145316	0.004
Costs of employees / Operating revenueYear (%)- 1	x24	-0.0111	0.006	3.189796	0.074
Average cost of employee (th) (th) th EUR Year - 1	x25	-0.0112	0.004	8.508889	0.004
Working capital per employee (th) (th) th EUR Year - 1	x27	0.0002	0	0.401956	0.526
Total assets per employee (th) (th) th EUR Year - 1	x28	-0.0007	0	11.6281	0.001
Current liabilities EUR Year - 1	x30	-4.34E-09	1.34E-08	0.104329	0.746
Cash & cash equivalent EUR Year - 1	x31	0.746	8.18E-08	16.916769	0
Operating revenue (Turnover) EUR Year - 1	x32	1.07E-08	1.50E-08	0.511225	0.475
Log-likelihood	-374.37				
Pseudo R-square	70.14%				

The Pseudo R-square of the model is 70.14%, which indicates that the model fits the data well. Moreover, there are six variables whosep-values are greater than 0.05, and their Wald statistics are pretty good, so these financial indicators have a strong relationship with the target variable.

For regression equation:

$$\mathrm{Ln}\left(\frac{p}{1-p}\right)=0.0006X_{13}-0.0004X_{14}+0.0124X_{15}+0.3385X_{19}-0.1531X_{20}$$
$$+0.0051X_{21}+0.0002X_{23}-0.0111X_{24}-0.0112X_{25}+0.0002X_{27}$$
$$-0.0007X_{28}-4.34*\ 10-9X_{30}+0.746X_{31}+1.07*\ 10-9X_{32}$$

Then transform the above linear equation into anon-linear form:

$$P=\frac{1}{1+e^{-(0.0006X_{13}-0.0004X_{14}+0.0124X_{15}+0.3385X_{19}-0.1531X_{20}+0.0051X_{21}+0.0002X_{23}-0.0111X_{24}-0.0112X_{25}+0.0002X_{27}-0.0007X_{28}-4.34*10^{-9}X_{30}+0.746X_{31}+1.07*10^{-9}X_{32}}}$$

Therefore, the equation can calculate the corresponding value of P directly by using the financial indicators of SMEs and determine the probability of default.

5.4.3 Accuracy Test

After fitting the data, the confusion matrix as follows:

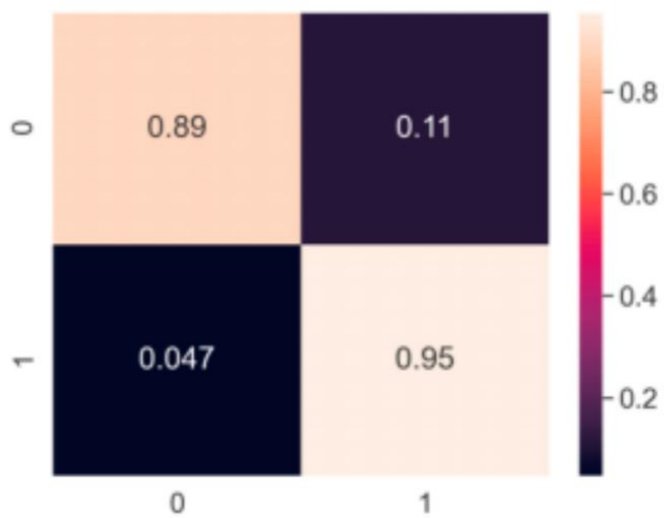

Figure. 2. the confusion matrix

The confusion matrix implies that: for the SMEs without financial distress, the predicting accuracy is 89%; For the default SMEs, the predicting accuracy is 95%. Hence, the model has a good performance in predicting the default of SMEs.

6 Discussion of Key Predictive Variables

6.1 Stock Turnover

Consistent with Bhimani et al. (2010), stock turnover was a significant predictor, serving as a gauge of operational efficiency[6][7]. A lower ratio indicates prolonged inventory holding, leading to higher costs and capital immobilization, thereby straining working capital and increasing default probability.

6.2 Collection Period

Corroborating Pourdarab et al. (2011) and Zainudin & Regupathi (2010), the collection period influences credit risk [8][9]. The model's slight negative coefficient may suggest marginally longer terms are associated with securing more stable clients, though beyond a threshold, protracted periods severely hamper cash flow.

5.3 Credit Period

Mirroring Wu et al. (2017), the credit period exhibited a strong positive relationship with default risk [10]. Generous credit terms pose a significant liquidity risk for capital-constrained SMEs, potentially leading to a cash flow crisis.

5.4 Solvency and Leverage

As established by Brîndescu-Olariu (2016), the solvency ratio is a pivotal bankruptcy predictor[11]. A higher ratio signifies a stronger equity base and greater resilience.Additionally， High gearing significantly increases financial risk. Operational setbacks can impair debt-servicing ability, as shown by the clear positive correlation in the model.

5.5 Per Employee Ratios

The importance of per-employee ratios aligns with Chong (2003), who highlighted human capital efficiency's impact on SME performance[12]. These ratios offer a granular view of operational efficiency particularly pertinent for smaller firms.

5.6 Liquidity and Cash Management

Jayadev (2006) identified current liabilities as a primary financial risk factor[13]. Interestingly, the model yielded a slight negative relationship, a potential anomaly warranting further investigation.The relationship between cash and default is nuanced. While vital for liquidity, excessively high cash may indicate suboptimal asset allocation (Amidu & Hinson, 2006)[14].

5.7 Operating Revenue

Wang & Ma (2012) documented operating revenue's significant effect on SME financial standing[15]. Contrary to expectations, the model estimated a very small positive coefficient, a discrepancy that could stem from data biases and highlights an area for future refinement.

6 Conclusion

This study yields several key findings: the asset-based solvency ratio and cash equivalents are critical predictors of SME credit status, warranting particular attention in risk assessment; innovatively, per-employee ratios—including operating revenue, cost metrics, working capital, and total assets per employee—significantly influence credit risk, reflecting the characteristic integration of founders and staff in small-scale operations; the model demonstrates superior fit with a Pseudo R^2 of 70.14% and robust predictive accuracy via confusion matrix analysis; methodologically, employing stepwise regression to sequentially eliminate correlated variables, rather than their outright deletion, enhanced the model’s final fitting performance.

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