The bankruptcy determinants of Swedish SMEs

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Abstract

The failure rate of Small and medium enterprises (SMEs), is high in Sweden. Around 6000 SMEs go into bankruptcy every year. This paper attempts to identify the main determinants that are perceived to have contribution to the failure of Swedish SMEs. The research is in principle based on the analysis of panel data matched sample consisting of 1991 bankrupted and 1991 non-bankrupted Swedish SMEs. The statistical techniques of discriminant and logit models are used for analyzing the data. The results, which have a high accuracy rate, indicate a set of three factors - solvency, quick ratio and return on assets - that have significant impact on bankruptcy probability of sample firms in the preceding year of bankruptcy. Furthermore, the results of the multiple discriminant analysis (MDA) for one year before bankruptcy are consistent with the results of logit model.

Keywords: Failure determinants, bankruptcy prediction, SME finance, credit risk management, financial ratio.

Introduction

Despite the fact that SMEs represent a vital portion of national economies throughout the world, according to many previous studies, they have high income volatility, high failure probability and a short life span (Bradley et al. 1984; Long and Malitz 1985; Harris and Raviv 1991; Rajan and Zingales 1995; DiPietro & Sawhney 1977; Fredland & Morris 1976; Monk, 2000). The Swedish Institute for Growth Policy Studies (ITPS) reports that less than half of new SMEs survive their first five years of business (ITPS, 2007). Recent Statistics Sweden data also show that around 6000 firms, 1% of the total number of firms in Sweden, go bankrupt annually (Ibid). The bankruptcy study is of interest not only to academics, but also to managers, owners, creditor, government and other actors in any economy. Thus, various actors are continuously seeking an optimal solution for performance forecasting, as an approach to rationalize the decision-making process and manage bankruptcy risks. It should be emphasized that business bankruptcies affect several parties and generates large costs. The costs of the bankruptcy of a firm with a large network of related firms may cause a downward spiral for an industry or the economy as a whole.

Purpose

The purpose of this study is to identify the set of financial ratios that discriminates bankrupted from non- bankrupted Swedish SMEs and thereby establish a financial bankruptcy prediction model.

The basic assumption is that firms with certain financial structures have a higher probability of bankruptcy than firms with other characteristics. In addition, since the bankruptcies of firms are usually preceded by a multistage process, there is a possibility that this can be observed.

The main research questions are accordingly:

* Which are the financial ratios that explain bankruptcies among Swedish SMEs?

* Are there any distinct characteristics in the financial situation of Swedish SMEs before bankruptcy?

Since the bankruptcy occurs gradually in a multistage process it is possible to anticipate the upcoming bankruptcy. Research in this field usually includes applications of bankruptcy prediction models based on financial ratios. The results of the research, as mentioned above, could be relevant to explain various aspects of firm bankruptcies.

Previous studies

Over the past three decades, a considerable amount of research has focused on explaining firm failure by analyzing financial ratios and through the development of statistical models for bankruptcy prediction, such as the Multiple discriminant analysis (MDA) and logit models. The researches in this field are based primarily on the assumption that financial ratios such as profitability, cash flow, and leverage ratios can be used as bankruptcy predictor variables. Historically, the bankruptcy research is developed through three phases. In the first phase, Multiple discriminant analysis (MDA) is introduced as important methodology by Altman (1968) and Beaver (1966, 1968). The next phase of bankruptcy studies is dominated by the logit/probit models presented by Ohlson (1980), and Zmijewski (1984) amongst others. In the third phase the Artificial Neural Networks (ANN) is introduced as new methodology. Even though the Artificial Neural Networks (ANN) is the most recently introduced method, the Multiple discriminant analysis (MDA) and logit model method has kept its importance as the most widely-used statistical techniques in research. The following pages provide additional detail about previous researches.

Beaver (1966) is usually considered as one of most influential authors in bankruptcy research. In order to analyze a sample of 79 failed and 79 non-failed firms and 30 financial ratios from five years prior to failure for the period 1954 to 1964, Beaver (1966) employs a paired-sampling method to construct the univariate approach of the multiple discriminant model. The model indicates with a predictive accuracy of 87%, that cash flow to total-debt ratio was significant in predicting failure.

In the same way, Altman (1968) investigates a set of 22 financial ratios from five categories: liquidity, profitability, leverage, solvency and activity ratios as potential determinants of bankruptcy using multiple discriminant analysis. The analysis with satisfactory accuracy around 95% exhibits that the firms with certain financial structures have a higher probability of failure than firms with other characteristics. The classification accuracy of the model is satisfactory and stable over various data samples. Furthermore, the author develops a Z-Score model including the five financial ratios with the highest predictive power in a multivariate discriminant analysis model (MDA). Accordingly, the bankruptcy probability enhances as the Z-Score decreases.

Similarly, Deakin (1972) applies the multiple discriminant method to analyze a paired-sample with 97 failed and 97 non-failed firms, using 14 explanatory financial ratios for a period of 3 years. The study finds that the MDA model can successfully predict bankruptcy in 94% of the firms in the sample in the year prior to bankruptcy. The ratios used are cash/current debts, cash/sales, cash/total assets, cash flow/total debts, current assets/current debts, current assets/sales, current assets/total assets, net income/total assets, quick assets/current debts, quick assets/sales, quick assets/total assets, total debts/total assets, working capital/sales, and working capital/total assets. The model was 97% effective in classifying the firms in the year prior to failure.

Dambolena and Khoury (1980) study a matched-pair sample consisting of 34 bankrupted and 34 non-bankrupted firms, applying discriminant analysis. In addition they employ financial ratios for economical situation, exploitation, cash flow and provisions provided. The model generate the correct classification of companies – 96% and the financial ratios with significant predictive power are the current debt/net worth, inventory/working capital, net income/fixed assets, standard deviation of current debt/net worth, standard deviation of total debt/total assets, and total debts/total assets.

Ohlson (1980) implements a conditional logit analysis to overcome the disadvantages associated with MDA, thus starting a new type of research in the field. The sample included 2058 non-bankrupt and 9 bankrupt firms and implied 9 financial and non-financial ratios for the period 1970-1976. The explanation of the application of the logit model is that some of the problems of the MDA can be avoided and that there is no need for a matched sample. The results of the study suggest that the ratios representing current liquidity, financial structure, performance, and firm size are associated with bankruptcy within one year.

Fulmer (1984) employs 40 financial ratios and applies them to a matched sample consisting of 30 bankrupted and 30 non- bankrupted firms in the US. The results of the employed multiple discriminant analysis (MDA) confirm predictive power of 9 financial ratios and a 98% accuracy rate in classifying the test firms one year prior to failure and an 81% accuracy rate more than one year prior to bankruptcy.

Zmijewski (1984) argues that the use of matched-pair research design leads to biased statistical results. Thus, he (1984) develops a new type of research using a probit model to analyze a sample constructed of 40 bankrupted and 800 non-bankrupted firms. The explanatory variables in the model are financial ratios that measure firm performance, leverage, and liquidity. According to the empirical results the choice-based sample bias decreases as the failure/non-failure ratio moves toward the population probability. There is also a considerable bias in the majority of the tests. On the other hand, the results do not entail significant changes in overall classification and prediction rates.

Andrew (1986) applies both logit and discriminant analysis methods on a matched sample containing 38 bankrupted 38 and non-bankrupted in the same industry for the period 1975-1983. The empirical results confirm that the discriminant method shows a better predictive power and higher accuracy than the logit model.

Pantalone and Platt (1987) apply Logit regression analysis to study the explanatory variables which discriminate between bankrupted and non-bankrupted banks in the US. The sample they use consists of 113 bankrupted and 226 non-bankrupted banks for the period 1983-84. The empirical findings demonstrate that the main reasons of bankruptcy are inefficient credit risk management, excess risk, inefficient control and monitoring.

Raghupathi, et. al., (1991) develop an Artificial Neural Network (ANN) method to analyze bankruptcy among firms included in the Wall Street Journal Index during the period 1980-1988. They apply the model on 105 firms and 51 bankrupted firms are matched with non-bankrupted firms in same industry during the last three years before the bankruptcy year. The empirical results exhibit that the financial ratios are not exact predictors to bankruptcy.

Similarly, Leshno and Spector (1996) analyze bankruptcy prediction using the Artificial Neural Network (ANN). The authors apply the model on a sample consisting 44 firms for the period 1984-1988. The classification percentage they obtained was very high for the studied financial service industry. The problem, as the authors affirm, is to establish the procedure that follows the neural network for the classification of the firm.

Grice and Ingram (2001) test the generalizability of the Altman model using data from 1985 to 1991 which included non-manufacturing firms as well as manufacturing firms. The results of the research prove that the accuracy of the Altman model declines for more recent data and the accuracy is lower for non-manufacturing firms than for manufacturing firms. They suggest that a powerful predicting bankruptcy model requires continuous updating due to changing industries, markets and business environments.

Becchetti and Sierra (2003) apply a logit model using non-financial variables to identify bankruptcy determinants in three representative unbalanced samples of Italian firms for the periods 1989–91, 1992–94 and 1995–97. The authors conclude that qualitative variables such as customers' concentration are significant explanatory powers.

Pompe and Bilderbeek (2005) apply multiple discriminant analysis (MDA) and a Neural Network model to analyze an initial sample of 1500 bankrupted and 1500 active SME's in Belgian during 1986-1994. The main purpose of this research is to test the predictive power of different ratio categories during successive phases before bankruptcy and the association between the age of a firm and the bankruptcy predictability. The study employs 73 ratios from four categories: profitability, activity, liquidity, and solvency ratios. The results show that it is more difficult to predict bankruptcy in starting firms than in old and established ones.

Chi and Tang (2006) use logit models to analyze a sample of 240 publicly traded firms including 60 bankrupted firms listed in seven Asia-Pacific capital markets during 2001-2003. Every bankrupted firm is matched with three non- bankrupted ones with regard to 20 independent explanatory variables classified in three categories: financial ratios, firm-specific characteristics and country risk. The empirical results that were obtained from this study show that the logit method gives satisfying prediction accuracy.

In order to evaluate different models' prediction accuracy, Kim and Gu (2006), use 12 financial rations and both discriminant analysis and a logit method for a sample of 18 bankrupted and 18 active restaurants in the US for the period 1986-1988. The empirical results show that the logit method provides better results with an accuracy rate of 94%, while the multivariate discriminant analysis (MDA) generates an accuracy rate of 92%.

Data

The sample contains SMEs of the Swedish legal form 'Aktiebolag', i.e. limited liability firms, which are featured in the Swedish business database 'Affärsdata'. This database covers standardized yearly financial data of all Swedish limited liability firms. An SME is defined according to Statistics Sweden (SCB) as having fewer than 200 employees. The initial sample of non-bankrupt firms consists of a total of 65550 independent, unlisted, randomly selected firms. Moreover, the initial matched-pair sample includes 6154 firms. In order to exclude non-operative firms and firms established or maintained for tax advantages, the sample selection was modified according to the following criteria:

- Independent;
- Complete accounting statements for the last three years prior to bankruptcy;
- Number of employees greater than one;
- Included in a bankruptcy process;
- Operating revenue greater than 120,000 Swedish kronor annually before bankruptcy;
- Total assets greater than 100,000 Swedish kronor annually before bankruptcy;
- Same financial year for all firms;
- Bankrupted firms must have municipal court code for bankruptcy 20, 21, 22, 25

Also excluded from the sample- to eliminate outliers- are firms with abnormal observations for independent variables which are outside the interval defined by three times the difference between the 25th and 75th percentile. The analysis in this paper is thus based on the remaining matched-pair sample consisting of 1991 bankrupted and 1991 non-bankrupted firms. Table 1 provides descriptive statistics of the sample. As the table reveals, the long- and short-term debt of firms varies among industries. The above criteria are set as to ensure a minimum bias in selection of the sample. Furthermore, the use of the matched-pairs approach is consistent with previous studies. The industry variable is not included in this study. The reason for this is that a considerable number of the sample firms have two or more industry codes. Consequently, it is difficult to identify entirely the industry affiliation of all the firms and to examine the effect of the industry variable on bankruptcy.

Methodology

The previous and dominant bankruptcy researches usually focus on explaining firm failure by using financial ratios and developing models for bankruptcy prediction. The four broad categories of methods used in the research field are:

(1) The multiple discriminant models (MDA);
(2) Logistic regression model (logit),
(3) The regression probit model (Probit),
(4) Artificial Neural Network (ANN)

All of these models have a potential capability to identify financial variables that have significant statistical explanatory power in differentiating bankrupted from non-bankrupted firms. Each method is based on specific assumptions and is associated with some advantages and disadvantages. The first two models, the multiple discriminant (MD) and logistic regression (Logit) models have been used predominantly in previous studies. Despite the advantages of these approaches, they are also criticized for some of their shortcomings. As instance, the application of the multiple discriminant analysis models requires that the data follow normal distribution to generate powerful results (Beaver 1966, Altman 1968, Deakin 1972, Ohlson 1980, Zmijewski 1983, Platt and Platt 1990). The financial data and ratios infrequently have a normal distribution. Despite this shortcoming, the idea of developing bankruptcy models- especially discriminant analysis and logit models- based on these assumptions have been widely accepted by researchers in the field. A solution to the non-normality challenge is rank transformation of data. The use of this procedure makes the models less sensitive to non-normal distributions (Kane et al. 1998). Moreover, the Logit model is somewhat less challenging in terms of basic distributional assumptions. An additional advantage of logit model is that it is based on nonlinear transformation of the input data which minimizes the effects of outliers on the results. In order to improve the quality of this study as well as the accuracy of the results a combination of (MDA) and (logit) is applied. In addition, a stepwise analysis, as opposed to direct simultaneous entry of all independent variables, is applied since the large number of initial explanatory variables selected for analysis can worsen the overall Wilke's Lambda.

Selection of variables and hypotheses

Dependent variable

The dependent variable is defined by coding an indicator binary variable, i.e. a dummy-variable with a 0 (bankrupt) or a 1 (non-bankrupt). Consequently, the effect of changes in the explanatory variables on the crisis probability depends on its initial level. A given change in an explanatory variable will make little difference to the probability of bankruptcy if the probability is initially very low (or very high).

Independent variables and hypotheses

Financial ratios are assumed to be powerful prediction models for assessing the financial distress of a firm (Hossari & Rahman, 2005). Since Beaver’s (1966) influential article, financial ratio analysis has become the predominant approach in investigating the characteristics of corporate bankruptcy (Altman, 1983; Altman 1993). With regard to theoretical framework and the previous literature, 30 variables are selected as preliminary explanatory independent variables in the models. The variables are classified into groups containing financial ratios (including capital structure ratios, liquidity ratios, profitability ratios, cash flow and efficiency ratios, turnover ratios, and operational efficiency) and firm-specific characteristics (i.e. size and age). Each of these groups contains several variables. These variables, their definitions and references are shown in the following table.

Table 1: An overview of the independent variables, their definitions and references

Categories	Variables and definitions	Pervious studies
I. CAPITAL STRUCTURE VARIABLE	X1. Long Term Debt to Total Asset	Beaver 1966; Ohlson 1980; Gu and Gao, 2000
	X2. Short and Long Term Debt to Equity	Zmijewski,1984, Chi et al 2006

	X3. Short & Long Term Debt to Tot. Assets	Beaver 1966; Lennox, 1999, Laitinen et al 2000
	X4. Cash-Holdings to Total Assets	Dugan et al 1989; Laitinen et al 2000
	X5. Equity Share of Total Assets (Solvency)	Altman,1968; Pantalone and Platt, 1987; Shumway, 2001; Cielen et al 2004; Charitou et al , 2004, Pompe et al 2005
	X6. Current Liabilities to Total Assets	Zmijewski,1984, Lo 1985; Pantalone and Platt ,1987; Gu and Gao, 2000
II. LIQUIDITY RATIOS	X7.Quick Ratio	Altman,1968; Shumways, 2001; Nam and Jinn ,2001, Cielen et al 2004; Charitou et al , 2004
	X8. Cash to Long & Short Term Debt	Dugan and Zavgren 1989; Charitou et al , 2004
III. PROFITABILITY RATIOS	X9. Return on Equity	Altman,1968; Shumways, 2001; Pompe et al 2005
	X10. Return on Assets	Ohlson, 1980; Dambolena and Khoury 1980; Zmijewski,1984, Becchetti et al 2003;
	X11. Net Profit Margin	Beaver 1966; Kim et al 2006
	X12. Gross Profit Margin	Cielen et al 2004; Kim et al 2006
	X13. Profit Margin	Becchetti et al 2003; Pompe et al 2005
IV. CASHFLOW AND EFFICIENCY RATIOS	X15. Cash flow to Sales	Beaver 1966
	X16. Cash flow to Total Assets	Aziz et al. , 1988;Young et al 2005; Pompe et al 2005
	X17. Cash flow to long & short term debt	Beaver 1966
	X18. Sales to Total Assets	Altman 1968; Raghupathi et al 1991
	X19. EBITA to Total Assets	Altman 1968; Gu and Gao, 2000; Young et al 2005;
	X20. Retained Earnings to Total Assets	Altman 1968
	X21. Financial Expenses to Sales	Becchetti et al 2003
V. DEVELOPMENT AND FIRM SPECIFICS	X22. Change in Sales from Last Year	Pompe et al 2005; Arshad 1985
	X23. Change in Total Assets from Last Year	Becchetti et al 2003; Arshad 1985
	X24. Firms Age	Beaver 1966; Kim et al 2006; Altman, 2000
	X25. Firm Size (Natural Logarithm of Sales)	Cielen et al 2004; Kim et al 2006
	X26. Firm Size (Natural Logarithm of total assets)	Ohlson, 1980; Beynon, and Peel, 2001; Wilson and Summers 2002
VI. TURNOVER RATIOS	X27. Accounts Receivable to Sales	Beaver 1966
	X28. Accounts Receivable to Total Assets	
	X29. Inventory to Sales	Beaver 1966; Young et al 2005
	X30. Inventory to Total Assets	Cielen et al 2004

Based on the previous empirical studies, the following hypotheses are developed:
Hypothesis 1: solvency (leverage) ratios discriminate bankrupted from non-bankrupted firms**.** Due to the negative (positive) relationship between solvency (leverage) and bankruptcy the firm's bankruptcy probability decreases as the firm's solvency (leverage) increases (decrease).

Hypothesis 2: liquidity ratios discriminate bankrupted from non-bankrupted firms**.** Due to the negative relationship between liquidity and bankruptcy the firm's bankruptcy probability decreases as the firm's liquidity increases.

Hypothesis 3: profitability ratios discriminate bankrupted from non-bankrupted firms**.** Due to the negative relationship between profitability and bankruptcy the firm's bankruptcy probability decreases as the firm's profitability increases.

Hypothesis 4: cash flow and efficiency ratios discriminate bankrupted from non-bankrupted firms**.** Due to the negative relationship between efficiency and bankruptcy the firm's bankruptcy probability decreases as the firm's efficiency increases.

Hypothesis 5: development and firm specific ratios discriminate bankrupted from non-bankrupted firms.

Hypothesis 6: turnover ratios discriminate bankrupted from non-bankrupted firms.

Empirical results

Description of Sample and examination of independent variables

To describe the firms included in the data sample, the firms' size, expressed by the number of employees in 2006, the firm's age, and three important financial ratios are employed. The average size of the non-bankrupt group is 1.18 while the average size of the bankrupt group is 9.13. The average age of the non-bankrupt and bankrupt firms is 15.1 and 16.1 respectively. It is evident from the descriptive statistics table that the mean of solvency¸ quick ratio and return on total assets (ROA) of non-bankrupt firms look higher on average than their bankrupt counterparts. The standard deviation of solvency and return on total assets are higher for the bankrupt firms than for the non-bankrupt firms. On the other hand, the quick ratio of the standard deviation of this group is higher than the bankrupt group. The bankrupt firms are on average older and, in terms of number of employees, larger than the non-bankrupt firms. Furthermore, standard deviations of these two variables are higher for bankrupt firms in comparison to the non-bankrupt firms.

Before starting the multivariate analysis, the following procedures are employed:
(1) Test of the statistical significance of all the initial independent variables;
(2) Determination of the relative contributions of each independent variable;
(3) Examination of intercorrelations among the relevant variables;
(4) Examination of the predictive accuracy of each independent variable

Test of the statistical significance

The significance test is carried out to examine which variables are statistically significant to explain the differences between the non-bankrupt group and the bankrupt group. The null hypothesis is the following: H0: No significant difference between the two groups.

Table 2: All variables, group Mean, and F-tests based on one period before Bankruptcy

	Non-bankrupt firms		Bankrupt firms		F-test	ANOVA
	Mean	STDEVA	Mean	STDEVA		Sig.
Long Term Debt to Total Asset	9%	0.178815	25%	0.35655	327.392	0,0000
Short Term Debt to Equity	147%	12.71005	356%	32.13163	7.264	0,0070
Short Term Debt to Total Asset	32%	0.215587	78%	0.76679	663.805	0,0000
Short and Long Term Debt to Equity	200%	13.09299	477%	46.74115	6.493	0,0110
Short & Long Term Debt to Total Assets	41%	0.245949	104%	0.811317	1070.588	0,0000
Cash-Holdings to Total Assets	44%	0.288777	31%	0.245176	252.174	0,0000
Equity Share of Total Assets (Solvency)	52%	0.228065	-6%	0.804889	944.218	0,0000
Current Liabilities to Total Assets	38%	0.278766	109%	1.044808	850.965	0,0000
Quick Ratio	279%	11.97944	41%	0.583814	78.471	0,0000
Return on Equity	9%	3.07644	-11%	9.649793	0.795	0,3730
Return on Assets	6%	0.259899	-14%	0.507806	231.229	0,0000
Net Profit Margin	-3%	6.209254	-11%	1.049289	0.399	0,5280
Gross Profit Margin	6%	0.628702	-7%	0.914728	25.998	0,0000
Cash flow to Sales	3%	6.208068	-8%	1.005346	0.542	0,4620
Cash flow to Total Assets	9%	0.244143	-11%	0.505952	235.106	0,0000
Cash flow to long & short term debt	94%	16.92885	-3%	0.551876	6.546	0,0110
Sales to Total Assets	151%	1.682618	336%	3.411195	469.547	0,0000

EBITA to Total Assets	10%	0.257982	-7%	0.497437	186.628	0,0000
Retained Earnings to Total Assets	4%	0.244961	-17%	0.517703	284.643	0,0000
EBITA per Employee	23507%	3269.13	-2986%	850.2113	12.248	0,0000
Financial Expenses to Sales	17%	5.807604	4%	0.231748	1.122	0,2900
Financial Expenses to debt	7%	0.574024	5%	0.135946	2.229	0,1360
Change in Sales from Last Year	45%	7.856301	71%	9.932291	0.873	0,3500
Change in Total Assets from Last Year	12%	0.631148	21%	1.77244	4.125	0,0420
Firms Age	16.1	11.1	15.1	10.5	9.3	0,0020
Firm Size (Natural Logarithm of Sales)	297%	0.429538	369%	0.616033	1815.069	0,0000
Accounts Receivable to Sales	12%	0.178515	10%	0.217436	4.473	0,0340
Accounts Receivable to Total Assets	31%	0.263648	9%	0.151975	978.609	0,0000
Inventory to Sales	9%	0.431459	13%	0.591551	6.215	0,0130
Inventory to Total Assets	9%	0.195344	22%	0.262408	321.884	0,0000
Number of employees	1.18	0.77	16.1	11.13	375.565	000

Based on the results in table 2, significant differences are found between bankrupt and non-bankrupt groups one year prior to bankruptcy with regard to 24 significant variables. Subsequently, only these variables are used in the multiple discriminant analysis.

Multiple discriminant analysis (MDA) results

The stepwise discriminant analysis is initially started with the significant independent variables and finally arrives at 3 financial ratios which best discriminate between bankrupt and non-bankrupt sample firms. The results of this analysis are shown in table 4.

Table 4: Results of the stepwise MDA, the Classification functions coefficients

Financial ratios	1 year period prior to bankruptcy	2 year period prior to bankruptcy	3 year period prior to bankruptcy
Solvency	0.897581	0.667746	0.69298
Quick ratio	0.218504	0.129283	0.051087
Return on assets(ROA)	0.150185	0.0132	
Return on equity			0.050897
Accounts receivable to total assets		0.584307	0.593303

The MDA results show that the three financial ratios solvency, quick ratio and return on assets are significant in discriminating between bankrupt and non-bankrupt firms for a one-year prediction horizon. The positive coefficients signify that the higher the solvency, quick ratio and return on assets, the lower is the probability of bankruptcy. This finding is consistent with the hypotheses of the present study. Solvency displays a firm capital structure. Theoretically, it is expected that the more equity financed a firm is the less likely it is to go bankrupt due to the lower financial costs. The obtained sign denotes consistency with this expectation. The quick ratio measures liquidity and expresses a firm's ability to repay short-term creditors out of its most liquid assets. In general, it is expected that the higher the quick ratio, the lower the risk of bankruptcy is. The obtained sign is positive and thus consistent with the expectation. Return on Assets expresses firm profitability. In general, it is expected that the more profitable a firm is the less likely it is to go bankrupt. The obtained sign is negative thus consistent with the expectation. Several attempts are carried out to add other variables. However, it could not significantly improve the results. In other words, any other linear combination of the predictors will result in a smaller ratio. The discriminant coefficient of the first variable solvency is generally higher than other variables. Furthermore, this discriminant coefficient loses significance as a bankruptcy prediction measure when the time horizon exceeds one year. Similarly, the discriminant coefficients of quick ratio for a two and three-year prediction horizon are lower than that for a one-year prediction horizon. Similar patterns can be observed when considering return on assets and accounts receivable to total assets.

The findings confirm in general that financial crisis of sample firms begins several years before bankruptcy. Three years before bankruptcy, the solvency and the account receivable to total asset have higher discriminate coefficients than other predictors. This can be interpreted as a combination of low solvency and low revenue which is expressed in low account receivable to total asset; which, in turn, reduces profitability and quick ratio during subsequent year. Consequently, the reduced profitability leads to a gradual decrease in solvency, profitability and quick ratio one year prior to bankruptcy. In this situation, when a firm loses its ability to pay back debts, a further decline in operations and accordingly bankruptcy will occur.

Since the accuracy and reliability of the three selected variables have been confirmed, the linear MDA function can be developed as follow:

$$Z = 0.89X6 + 0.21X8 + 0.150X11$$

Z < 1.25 indicates a bankruptcy condition).

The interpretation of Z score for the first year prior to bankruptcy is that the firms with Z values less than 1.25 have a high probability (82.8%) of going bankrupt.

As is shown in table 5, the MDA can correctly classify 78% of the bankrupted firms and 86% of the non- bankrupted firms one year before bankruptcy. The model seems to be more effective in classifying non-bankrupt firms than bankrupt ones. An explanation is that the financial ratios of the non- bankrupted group are more stable than those of the bankrupted group. The overall predictive power of the model to identify bankrupt firms from the non-bankrupt firms is 82.8%, which is relatively high. Moreover, the model can also predict bankruptcy two and three years prior to the fact with an overall accuracy rate of 78.1 and 75.4% respectively. The accuracy rates are inversely related to prediction horizons. This means that the shorter the prediction horizons, the higher the accuracy rate.

Table 5: Accuracy of discriminant classification

1 year prior to bankruptcy	Predicted Group Membership			2 year prior to bankruptcy	Predicted Group Membership			3 year prior to bankruptcy	Predicted Group Membership		
	Bankrupt	Non-bankrupt	Total		Bankrupt	Non-bankrupt	Total		Bankrupt	Non-bankrupt	Total
Bankrupt	1571	420	1991	Bankrupt	1680	311	1991	Bankrupt	1606	385	1991
Non-bankrupt	263	1728	1991	Non-bankrupt	563	1428	1991	Non-bankrupt	595	1396	1991
Bankrupt	78.90%	21.10%	100%	Bankrupt	84.40%	15.60%	100	Bankrupt	80.70%	19.30%	100%
Non-bankrupt	13.20%	86.80%	100%	Non-bankrupt	28.30%	71.70%	100	Non-bankrupt	29.90%	70.10%	100%
a. 82.8% of original grouped cases correctly classified.				a. 78.1% of original grouped cases correctly classified.				a. 75.4% of original grouped cases correctly classified.			

In order to test the significance of the discriminant function as a whole, the following sets of tests are performed: F and Wilk's Lambda statistics to evaluate the statistical significance of each individual ratio, and relative importance of each independent variable (the standardized values of their coefficients). Within sample discriminatory power of these ratios' best combinations. Chi-square statistic as test of the overall significance of various discriminant functions.

Table 6: summary of canonical discriminant for different horizons prior to bankruptcy

	Wilks' Lambda			Eigenvalues of the discriminant functions			
	1 Prior	2 Prior	3 Prior		1 Prior	2 Prior	3 Prior
Wilks'	0.797394	0.709611	0.7537	Eigenvalue	0.254085	0.409223	0.326789

Lambda							
Chi-square	900.7581	1364.78	1124.825	% of Variance	100	100	100
Df	3	3	4	Cumulative %	100	100	100
Sig.	0.00	0.00	0.00	Canonical Correlation	0.450118	0.538878	0.496287

Even if the Wilks' Lambda is high, it indicates that the group means are different from each other. Furthermore, Wilks' Lambda for one year prior to bankruptcy is higher than that of two and thee year horizons. The Chi-square with a high value signifies a high level of significance. Although the eigenvalues and their associated canonical correlation coefficients, which express the power of the discriminant function, explain 100% of the variation of the dependent variables, it is around 0.25 and even less. This means, eigenvalues have a small discriminatory power. The tests imply a low cross-correlation between the financial ratios used for the discriminant function construction, as well as the significance of the variables. However, there is a possibility to increase the explanatory power of the models by employing irrelevant independent variables which in turn decreases the accuracy rate of the models.

Correlation analysis

High correlation between independent variables often indicates multicollinearity which, in turn, may cause bias in the t-values of estimated coefficients. In order to identify possible risk for multicollinearity, a correlation analysis between the selected independent variables is performed. The results of correlation confirm that all indicators representing the selected predictors are lowly correlated. In addition, the correlation between four of the six variables are not significant. The correlation pattern implies that all of these three indicators should be included in a well specified model.

Table 3: Results of the Pearson correlation analysis among the selected financial ratios for one-year prediction horizon

	Solvency	Sig.		Quick Ratio	Sig.		Return on Assets	Sig.	
	Correlation	(2-tailed)	N	Pearson Correlation	(2-tailed)	N	Pearson Correlation	(2-tailed)	N
Solvency	1		3982	0.11884	00000	3982	-0.013	0.41	3982
Quick Ratio	0.11884	0000	3982	1		3982	0.00099	0.95	3982
Return on Assets	-0.013	0.41	3982	0.00099	0.95	3982	1		3982

**. Correlation is significant at the 0.01 level

Moreover, when the tests of Variance Inflating Factors (VIF) are performed, all the above variables present a figure below 10. For the MDA sample, the VIF ranges in between 1.3 to 3.57. Consequently, it can be concluded that the degree of multicollinearity problem is not a risk for the results.

Logit Regression

A stepwise logistic regression model (Forward Conditional Model) is employed to examine the performance of Multiple Discriminant Analysis (MDA). The technique fits linear logistic regression model for binary or ordinal response data by the method of maximum likelihood. Similar to discriminant analysis, this technique weights the independent variables and assigns a Z-score in a form of bankruptcy probability to each firm in a sample. Discriminant analysis and logit analysis have different assumptions concerning the relationships between the independent variables. While linear discriminant analysis is based on linear combination of independent variables, logit analysis uses the logistic cumulative probability function in predicting bankruptcy.

Table 7 : Results of the best fitting logit Regression

1 year period prior to bankruptcy	B	S.E.	Wald	df	Sig.	Exp(B)
Solvency	6.214847	0.253148	602.7134	1	0.0000	500.1194
Quick ratio	0.619585	0.076869	64.96736	1	0.0000	1.858158
Return on assets	0.657458	0.158776	17.14605	1	0.0000	1.92988
Constant	-2.31275	0.084968	740.8849	1	0.0000	0.098988
2 year period prior to bankruptcy						
Solvency	5.215199	0.227454	525.7189	1	0.0000	184.0485
Quick ratio	0.332478	0.071153	21.83439	1	0.0000	1.394419
Accounts receivable to total assets	1.842735	0.252464	53.27541	1	0.0000	6.313783
Constant	-2.20549	0.078332	792.74	1	0.0000	0.110197
3 year period prior to bankruptcy						
Solvency	4.872127	0.197373	609.3424	1	0.0000	130.5984
Accounts receivable to total assets	2.435308	0.204998	141.1265	1	0.0000	11.41934
Constant	-1.91793	0.072205	705.5574	1	0.0000	0.146911

The B coefficients, standard error, Wald statistic and Exp (B) (likelihood) in the logistic regression table indicate that all of the selected independent variables in the model are related to changes in bankruptcy probability. The coefficient of the solvency, quick ratio and return on assets variable are found to be positive, indicating an inverse relationship between these variables and bankruptcy probability. Thus the higher solvency, quick ratio and return on assets, the lower the bankruptcy probability. The results are consistent with the finding of the Multiple Discriminant Analysis (MDA) and supports the hypothesis. Exp (B) expresses odds ratios for each variable and implies for example that the chance to be non-bankrupt is 1.8 times higher when the value of the predictor, quick ratio, increases by one unit. Evidently, Exp (B) of solvency for all three reporting years is considerably higher than other predictors.

Table 8: Classification table at probability Level 0.5

	Predicted Group Membership				Predicted Group Membership				Predicted Group Membership		
1 year prior to bankruptcy	Bankrupt	Non-bankrupt	%age Correct	2 year prior to bankruptcy	Bankrupt	Non-bankrupt	%age Correct	3 year prior to bankruptcy	Bankrupt	Non-bankrupt	%age Correct
Bankrupt	1703	288	85.5	Bankrupt	1667	324	83.7	Bankrupt	1608	383	80.7
Non-bankrupt	369	1622	81.5	Non-bankrupt	452	1539	77.3	Non-bankrupt	501	1490	74.8
Overall %age			83.5	Overall %age			80.5	Overall %age			77.8

The classification accuracy rate varies from 83.5% for one period prior to bankruptcy to 77.8% for three annual reporting periods prior to bankruptcy. In addition, the rates for bankrupted firms are lower than non-bankrupted ones. However, the logit model has generally a higher accuracy than Multiple Discriminant Analysis for all three periods. There is an inverse relationship between the accuracy rate and the prediction horizon. Thus, the longer the prediction horizon, the lower the accuracy rate. Moreover, the result of Hosmer and Lemesho´s Goodness of Fit test demonstrates that the chi-square is 84,592 with 8 degrees of freedom and the observed significance level of the chi-square value is 0.0000 implying that the model's estimates fit the data at an acceptable level.

The empirical results support the first three hypotheses that solvency, liquidity and profitability ratios discriminate bankrupted from non-bankrupted firms one year before bankruptcy***.*** However, the role of the specific development factors, cash flow and efficiency ratios are not significant.

CONCLUSIONS

Overall, the study reveals that a combination of three predictors: capital structure in terms of solvency; quick ratio; and profitability are obvious determinants of bankruptcy in one year prior to firm failure. The results also suggest that solvency, both as a separate financial ratio and as part of different combinations of financial ratios, is more apparent than other bankruptcy determinants for one to three years before bankruptcy. This appears to be reasonable because the financing is widely regarded as a major challenge for small businesses. In contrast, other independent variables are not obvious bankruptcy determinants during the three reporting years. To ensure validity of the results of MDA a Logit model is applied to analyze the data sample. Estimation and validation results of the Logit model support the hypotheses that solvency, quick ratio and return on assets are important in identifying bankruptcy among sample firms one year before failure. The results imply that the selected financial ratios lead to useful predictions with both techniques, where logistic regression perform superior to discriminant analysis. The results can widely be used for a range of purposes, including the monitoring of firm solvency by banks, creditors, regulators and auditors. The model can also be used by owners/managers to predict problems in time to avoid financial distress which can lead to bankruptcy.

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