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The prediction of bankruptcy of small- and medium-sized industrial firms

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Abstract

Using large amounts of data from small- and medium-sized industrial firms, this study examines several aspects of bankruptcy prediction. We have tested a hypothesis on the predictive power of different ratio categories during the successive phases before bankruptcy, and one on the relationship between the age of a firm and the predictability of bankruptcy. It was found that virtually every ratio investigated had some predictive power, and that the univariate and multivariate importance of ratio stability were not very high.

Keywords: Bankruptcy; Small- and medium-sized industrial firms; Multiple discriminant analysis

1. Executive summary

This study focuses on the prediction of bankruptcy through the use of bankruptcy models and individual financial ratios. A model for predicting failure sets out to establish a

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relationship between bankruptcy and a number of financial ratios. These are ratios that can be calculated using information contained in a firm's annual report. Since the 1960s, researchers have shown much interest in this subject. Many studies on bankruptcy prediction have focused on large listed firms. Less frequently, small firms have been studied. However, the number of data that were collected for these small business failure studies is limited (less than 100 bankrupt firms). This seems to be a general problem with bankruptcy prediction research: because data from bankrupt firms can only be collected with much effort, researchers often use few annual reports, which limits the reliability of their findings. In Belgium, the collection and storage of data in computer files is carried out in a very systematic way. Annual reports of those firms that legally have to file their annual reports with the Belgian National Bank are stored on CD-ROM. Given the richness of this data, Belgian annual reports were selected for this research. We composed a large data set in which virtually all the firms were small- or medium-sized, i.e. virtually all the firms employed less than 50 people. The number of bankrupt firms in the data set was 1369.

To generate bankruptcy models, we applied the frequently used method of multiple discriminant analysis (MDA) and a more recent method known as neural networks (NN). Both methods produced similar results. To determine the univariate importance of ratios in the prediction of bankruptcies, we decided to use the dichotomous classification test. Although researchers rarely apply this test, we believe this test is very useful since it provides a predictive value that is directly comparable with the predictive value of a model. In total, 73 ratios were examined in this study.

We tested a hypothesis on the predictive power of different ratio categories during the successive phases before bankruptcy:

Hypothesis 1. When a firm is heading towards bankruptcy, a downward movement can be first seen in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and finally the liquidity ratios.

The hypothesis was not supported by the results. We found no fixed order in which the different categories of financial ratios started to be predictive. Apparently, ratios that evaluate different dimensions of a firm's financial position can have similar predictive powers many years before bankruptcy. Next, we tested a hypothesis on the relationship between the age of a firm and the predictability of bankruptcy:

Hypothesis 2. The bankruptcy of young firms is more difficult to predict than the bankruptcy of established firms.

The second hypothesis was supported by the results. A key reason seems to be that, with young firms, a long gradual slide towards bankruptcy is less likely, and therefore the bankruptcy is more often unexpected.

The results showed that virtually every ratio considered had some predictive power. Thus, an approaching bankruptcy is noticeable in almost every dimension of a firm's financial position. A few ratios, such as cash flow/total debt, achieved results that were close to the results of the models. In this study, we also determined the univariate and multivariate importance of ratio stability; for example, we examined the predictive power of the standard deviation in the ratio values in three successive annual reports. It was found, however, that the univariate and multivariate importance were not very high.

2. Prior research and hypotheses

In the literature on bankruptcy prediction, researchers have tended to focus on large listed firms. Less frequently, small firms have been studied, for example in Huyghebaert et al. (2000), Keasey and Watson (1987) and Laitinen (1992). However, the amount of data that were collected in these studies is small: the three studies mentioned used 81, 73 and 20 bankrupt firms, respectively. In our research, we make use of a large Belgian data set in which virtually all the firms are small- or medium-sized and which includes 1369 bankrupt firms. Using such a large quantity of data is an important contribution made by this study to existing literature, since the reliability of our findings will be much higher than in other research. We can determine the predictive values of ratios and models with more precision, and differences between predictive values become clearer.

Studies on bankruptcy prediction are nearly always purely empirical analyses: that is, one rarely encounters the development and testing of theories. One exception is Scott (1981), who presents some links between theoretical models and the variables included in certain empirical failure prediction models. Laitinen (1991) notes that financial ratios are seldom used to test hypotheses and theories on firms' financial behaviour before failure. In the present study, we test a simple hypothesis on the predictive power of different ratio categories during the successive phases before bankruptcy. This hypothesis resembles the reasoning of Luoma and Laitinen (1991). The 73 ratios selected for this study are divided into four categories: profitability ratios, activity ratios, liquidity ratios and solvency ratios. We assume that, prior to bankruptcy, a firm gradually runs into problems. The problems start when a firm no longer carries out its business operations in an effective and efficient way, which leads to lower or negative profits. This should be reflected in poor values for the activity ratios and the profitability ratios. Poor profitability over a number of years will weaken the solvency position of the firm and, therefore, the firm will have unfavourable solvency ratios. Just before bankruptcy, there will be an acute shortage of liquid assets, because the weak solvency and poor profitability leads to a situation in which creditors are no longer willing to provide credit. The liquidity ratios will reflect this (Bilderbeek, 1979). Eventually, the firm is no longer able to pay its debts and this results in bankruptcy. On the basis of this seemingly plausible reasoning, we suggest:

Hypothesis 1. When a firm is heading towards bankruptcy, a downward movement can be first seen in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and finally the liquidity ratios.

The relationship between the age of a firm and the chance of a bankruptcy is well known (e.g. Altman, 1993): the older the firm, the smaller the likelihood. However, the relationship between the age of a firm and the predictability of bankruptcy has received remarkably little attention in the literature. We have not found a study containing a similar analysis to ours, i.e. dividing the firms in the data set into different age categories, generating separate bankruptcy models for each category, and then comparing the performance of these models. Regarding the relationship between age and predictability, our hypothesis is that the bankruptcy of young firms is more difficult to predict than the bankruptcy of established firms. It seems logical that, in heading for bankruptcy, older firms will often experience a long gradual decay. Levinthal (1991) notes that older organizations tend to be organizations that had been, in previous periods, successful and this prior success will buffer them against failure for a certain time. For example, an established firm that makes a loss year after year may survive for some time by using up its retained profits reserve. Because of their short life, such a protracted period is less likely with young firms. Therefore, the bankruptcy of young firms is more likely to be unexpected and harder to predict a couple of years in advance. Furthermore, young firms tend to be smaller than old firms. We expect that, compared to larger firms, the prediction of bankruptcies is more difficult in the case of small firms. With small firms, it may be difficult to exclusively rely on financial ratios since personal and business activities may be intertwined (Caouette et al., 1998). Furthermore, Brüderl and Schüssler (1990) note that larger organizations are assumed to have more resources open to them to weather bad times and so a gradual decline towards bankruptcy would seem more likely. We hypothesize:

Hypothesis 2. The bankruptcy of young firms is more difficult to predict than the bankruptcy of established firms.

Alongside the testing of two hypotheses, other contributions of this study to existing literature are as follows. We examine the univariate and multivariate importance of ratio stability, where the multivariate importance is determined by the degree to which models that use ratios and ratio stability perform better than models that use ratios alone. Dambolena and Khoury (1980) found that the stability of ratios can have a high multivariate importance. However, they did not examine the univariate importance and, furthermore, they focused on a different population (large firms), and had very few data. Finally, to determine the predictive values of models and ratios, we follow a rigorous procedure that is not generally used in other studies on bankruptcy prediction. For example, we apply 10-fold cross-validation to the training set to determine a good parameter setting for each method.

3. Data

In Belgium, virtually all firms are legally obliged to file their annual reports with the Belgian National Bank. These annual reports are obtainable on CD-ROM. The annual reports have a standard layout, in which the items in the balance sheet, the profit-and-loss account, and the disclosure have fixed names and codes. In this research, we study the period 1986–1994 and, in order to obtain a homogeneous sample, we restrict ourselves to the industrial sector. We distinguish two classes of annual reports: the class ‘nonbankrupt’ and the class ‘bankrupt’. An annual report of the first class is from a firm that did not go bankrupt in the

Table 1
Number of annual reports from the two classes

	Bankrupt					Nonbankrupt
	Year 1	Year 2	Year 3	Year 4	Year 5	
Old	556	476	424	370	322	1500
Young	732	492	342	234	132	1500
Total	1288	968	766	604	454	3000

period studied. An annual report of the second class belongs to a firm that went bankrupt[1] a specified number of years after the calendar year to which the annual report refers. If the number of years equals i (i=1, 2, 3, . . .), we say that the annual report is from year i. There are five sets of annual reports, with i=1, 2, 3, 4, 5. An annual report from year 1 is always the final annual report published before bankruptcy. Thus, the year after the calendar year of the final published annual report is considered to be the year of bankruptcy. Although the legal timing of the bankruptcy may not be in that year, we see the moment a firm stops publishing annual reports as the real moment of failure. The period between the closing date of the final published annual report and the legal moment of bankruptcy was between half a year and 2 years for 93% of the firms studied.

The last row in Table 1 lists the number of annual reports of class ‘bankrupt’ from each year. These annual reports belong to 1369 firms. In the table, it is evident that the number of reports decreases considerably as the years increase. There are two reasons, firstly, in the set of annual reports from year 5 there are naturally no annual reports from firms that existed for too short a period to have an annual report in this set. Secondly, we only have knowledge of bankruptcies that took place in the period studied (1986–1994). Therefore, an annual report from year 5 can refer to fewer calendar years than an annual report from year 1. For example, there cannot be an annual report from year 5 that refers to 1993 because, in the period studied, the latest bankruptcy took place in 1994. For the class ‘nonbankrupt’, we use 3000 annual reports taken from the following calendar years: 1988, 1989, 1990 and 1991 (750 reports from each year). Each annual report belongs to a different firm. The years 1992, 1993 and 1994 are not included because we want to ensure that for every annual report of class ‘nonbankrupt’ used in this study the corresponding firm did not go bankrupt within 3 years after the closing date of the annual report.[2]

In Table 1, a distinction is made between two groups: annual reports of old firms and annual reports of young firms. For the class ‘bankrupt’, we place in the first group annual reports of firms that had a life of more than 8 years, while the second group contains reports of firms whose life span was 8 years or less. The life is calculated as the time between the start of the firm and the deposit date of the final annual report published before bankruptcy. For example, there are 1288 annual reports from the first year before bankruptcy, of which 556 belong to old firms and 732 to young firms. For the class ‘nonbankrupt’, the first group

[1] At the time of the failure, the legal status of this firm was ‘bankrupt’. Firms with this legal status have suspended payments against creditors and have lost all credit.

[2] In a separate analysis, we found that using 3000 annual reports from 1988 to 1994 (instead of 1988–1991) did not significantly change the predictive values presented in Section 5.

Table 2
Percentiles of total assets, equity, added value and number of persons employed

		Total assets[a]			Equity[a]			Added value[a]			Employees		
		25%	50%	75%	25%	50%	75%	25%	50%	75%	25%	50%	75%
Old	Nonbankrupt	7.8	25.2	82.5	2.6	8.6	28.6	3.9	13.4	42.2	3	9	29
	Bankrupt (year 2)	9.4	25.7	69.6	0.9	3.4	13.6	5.1	15.4	39.9	4	12	34
Young	Nonbankrupt	3.5	8.6	27.6	0.7	2.0	7.3	1.5	4.4	13.2	1	3	9
	Bankrupt (year 2)	4.1	11.5	26.5	0.2	1.0	3.5	1.5	5.1	14.1	1	5	13

[a] In million BEF.

contains annual reports from firms that existed for more than 8 years at the deposit date of the annual report, while the second group consists of reports from firms that existed for 8 years or less at this date. Table 2 presents the percentiles (quartiles and median values) of total assets, equity, added value and number of persons employed for four samples of annual reports taken from Table 1. 1000 BEF is about 25 euros.

The 73 ratios selected are listed in Tables 5a and 5b. These ratios are divided into four categories: profitability ratios, activity ratios, liquidity ratios and solvency ratios. The division is somewhat arbitrary, since several ratios could be assigned to more than one category. Additional information about the ratios is provided in Appendix A.

4. Procedure

4.1. Model development

In order to derive the models, we apply the frequently used method of multiple discriminant analysis, MDA (e.g. Altman, 1968; Bilderbeek, 1979; Laitinen, 1992) and a more recent method known as neural networks, NN (e.g. Altman et al., 1994; O'Leary, 1998; Pompe and Feelders, 1997).[3] The neural network used is a feedforward one containing one hidden layer. All the analyses are completed using the software package S-Plus. We consider old and young firms separately and models are built for each year prior to failure. In this model building for a certain year, the annual reports of class 'bankrupt' from that year are used and, in addition, we always use the 1500 annual reports of class 'nonbankrupt'. For example, for old firms in year 2, we have 476 reports of class 'bankrupt' and 1500 reports of class 'nonbankrupt' (see Table 1). This set containing 1976 annual reports is randomly divided into two equal parts, a training set and a test set. We ensure that both parts contain the same number of reports from class 'nonbankrupt' and the same number of reports from class 'bankrupt'. Thus, each part consists of 750 annual reports of class 'nonbankrupt' and 238 annual reports of class 'bankrupt'. The training set is used for generating a model and the test set is used for estimating the predictive power of that model. Initially, the training set contains more annual

[3] There are other methods available for constructing models with a dichotomous dependent variable (in particular logistic regression and probit). Wilson and Sharda (1994) note that two statistical techniques appear to have been the most commonly used for deriving bankruptcy models, namely MDA and logistic regression, and that both techniques perform similarly.

reports of class 'nonbankrupt' than of class 'bankrupt'. However, before generating the models, we arrange it so that, in the training set, the number of reports of class 'bankrupt' equals the number of reports of class 'nonbankrupt' by duplicating reports of class 'bankrupt'. Before a method can be used, a number of parameters must be assigned values. The setting of the parameters influences the form of the model produced. The parameters should be assigned values such that the model achieves a good classification result for data that were not used in deriving the model. For example, in the case of MDA, there are two parameters in this research. The first parameter is the combination of prior probabilities, for which we try 11 combinations.[4] The second parameter is the degree of removal of annual reports with extreme ratio values from the training set; 12 degrees are tested. Thus, there are 11*12=132 different combinations of parameter values possible and each of these 132 settings are tried. An example of a neural network parameter for which several values are tried in this research is the number of hidden units. We apply 10-fold cross-validation to the training set to determine a good parameter setting for each method.[5] The parameter setting with the highest cross-validation result is selected. Using this setting, we derive a model from the training set, and use this model to classify the annual reports in the test set. The test result for the test set is calculated as (the percentage of reports of class 'nonbankrupt' in the test set that are classified correctly+the percentage of reports of class 'bankrupt' in the test set that are classified correctly)/2. Each experiment is always carried out 10 times and, in this way, we improve the reliability of the research results. The important change in each round of an experiment, compared to the other nine rounds, is that again the total data set is randomly divided into a training set and a test set. A test result in a table is always the average result based on the 10 rounds of the experiment.

The calculation of the test result shows that 1% misclassification of class 'nonbankrupt' has equal importance as 1% misclassification of class 'bankrupt'. This is a consequence of our assumption that $c(b)/c(n)=p(n)/p(b)$, where $c(i)$ equals the costs of incorrectly classifying an annual report of class i and $p(i)$ equals the prior probability of class i, i.e. the proportion of annual reports of class i in the population. The costs $c(b)$ are likely to be much higher than the costs $c(n)$ (Altman et al., 1977) and $p(n)$ is much higher than $p(b)$, so the assumption is not unreasonable. The performance of a model can be determined by calculating the total costs of misclassification, where

$$\text{total costs} = (100\% - \text{test}(b))*p(b)*c(b) + (100\% - \text{test}(n))*p(n)*c(n)$$

and test(i) equals the percentage of annual reports of class i in the test set that are classified correctly. If $c(b)/c(n)=p(n)/p(b)$, then total costs=((100%−test(b))+(100%−test(n)))* $p(b)*c(b)$, that is, a 1% misclassification of class 'nonbankrupt' increases the total costs by the same amount as a 1% misclassification of class 'bankrupt' (a 1% misclassification of each class has the same importance).

[4] Note that only this combination is varied, the actual ratio between the numbers of reports from the two classes in the training set (before removing reports with extreme ratio values) is always 0.5:0.5.

[5] In order to have a fair procedure, we ensure that, during cross-validation, the 10 parts $D_1, D_2, \ldots, D_{10}$ always contain the same annual reports regardless of the specific method and the specific parameter setting used. Furthermore, we arrange it so that an annual report of class 'bankrupt' that was duplicated and its duplicates are always in the same part D_i.

4.2. Variable selection

We have explored two methods in order to find good combinations of ratios for use in the models. With MDA, one often uses stepwise selection for identification of good predictor variables (Hand, 1981) and, therefore, we have applied this algorithm in the present study. The variables selected can also be included in models of neural networks. As the variable selection criterion, we used Wilks' λ and, for F-to-enter and F-to-remove, we chose the values 3.84 and 2.71. For the old firms, we used a set containing 500 of the 1500 annual reports of class 'nonbankrupt' and 500 annual reports of class 'bankrupt' (100 from each of the 5 years in order to give the same priority to each year). From this set, annual reports with extreme ratio values were removed, and then stepwise selection was applied. For the young firms, these numbers were 600 (class 'nonbankrupt') and 600 (class 'bankrupt'; 200 from each of the 3 years[6]). Not all 73 ratios were considered. After removing all ratios with a missing value in more than 1% of the annual reports, 45 ratios were left (see Appendix A). Stepwise selection was applied to these 45 ratios. To prevent the effects of multicollinearity, ratios with unacceptable variance inflation factors (Montgomery and Peck, 1992) were not permitted to enter the group of selected ratios.[7] Also, if entry of a ratio would lead to unacceptable variance inflation factors for ratios already in the group, the ratio was not entered. The selection process resulted in the following ratios: r_7, r_{31}, r_{35}, r_{52}, r_{59}, r_{62}, r_{64}, r_{68} (old firms), and r_9, r_{31}, r_{35}, r_{39}, r_{43}, r_{52}, r_{54}, r_{64}, r_{70} (young firms). In a separate analysis, the maximum VIF was set at 1000 (instead of 3 as before). As a result, the groups of selected ratios included some ratios with VIFs higher than 3 (the highest VIF was in fact 5.5). However, using these groups, instead of using the groups with a maximum VIF of 3, hardly changed the classification results of the models.

In some studies on bankruptcy prediction, factor analysis has been used to select combinations of ratios for use in the models (see for example Zavgren, 1985). With factor analysis, the object is to describe the covariance relationships among many variables in terms of a few underlying factors. In the present study, we have also applied factor analysis, using the same two sets as used with stepwise selection,[8] and considering the 45 ratios mentioned earlier. The criterion chosen for deciding how many factors to retain was that the factors should account for at least 70% of the total variance. With both old and young firms, eight factors were retained, accounting for 73% and 72% of the variance respectively (we used the principal factor estimate and the varimax rotation). Then, for each factor, the ratio most strongly related to this factor was selected for use in the models. This procedure resulted in the following ratios: r_2, r_8, r_{24}, r_{46}, r_{48}, r_{54}, r_{64}, r_{67} (old firms), and r_4, r_8, r_{24}, r_{44}, r_{46}, r_{50}, r_{64}, r_{67} (young firms). The corresponding loadings were 0.94, 0.89, 0.97, 0.89, 0.93, 0.75, 0.81, -0.89 (old firms), and 0.98, -0.85, 0.99, 0.94, 0.91, 0.89, 0.75, -0.82 (young firms). Table 3 presents values of all the ratios selected by stepwise selection and factor analysis (15

[6] In the next section, it is noted that, for young firms, we only look at years 1, 2 and 3.

[7] For each class, a separate variance inflation factor (VIF) was calculated. A ratio with unacceptable variance inflation factors was defined as a ratio for which at least either the VIF for class 'bankrupt', or the VIF for class 'nonbankrupt', was higher than 3.

[8] We used the two sets after removing reports with extreme ratio values.

Table 3
Percentiles of the ratios selected

	Old							Young					
	Nonbankrupt			Bankrupt (year 2)				Nonbankrupt			Bankrupt (year 2)		
	25%	50%	75%	25%	50%	75%		25%	50%	75%	25%	50%	75%
r_2	0.010	0.055	0.11	−0.065	0.019	0.064	r_4	0.011	0.067	0.15	−0.072	0.033	0.083
r_7	0.044	0.095	0.16	−0.032	0.024	0.068	r_8	0	0.12	0.33	−0.31	0.038	0.38
r_8	0.008	0.074	0.18	−0.23	0.003	0.16	r_9	0.16	0.42	0.82	0	0.38	0.92
r_{24}	0.005	0.054	0.15	−0.14	−0.012	0.022	r_{24}	−0.002	0.062	0.19	−0.18	0.002	0.068
r_{31}	0.34	0.53	0.78	0.31	0.52	0.81	r_{31}	0.27	0.48	0.75	0.25	0.45	0.75
r_{35}	0	0.009	0.047	0	0	0.003	r_{35}	0	0.003	0.046	0	0	0.002
r_{46}	0.32	0.48	0.66	0.26	0.38	0.54	r_{39}	170	189	249	175	197	263
r_{48}	0.67	1.1	1.9	0.40	0.60	0.86	r_{43}	0.40	0.62	0.83	0.48	0.68	0.85
r_{52}	−0.063	0.074	0.27	−0.29	−0.12	0.016	r_{44}	0.86	1.2	1.8	0.76	0.98	1.2
r_{54}	0.018	0.064	0.16	0.003	0.017	0.060	r_{46}	0.25	0.42	0.62	0.23	0.38	0.60
r_{59}	0.14	0.27	0.40	0.15	0.27	0.40	r_{50}	0.015	0.063	0.17	0.003	0.013	0.053
r_{62}	0.075	0.17	0.29	0.14	0.24	0.38	r_{52}	−0.044	0.091	0.30	−0.26	−0.060	0.041
r_{64}	0.22	0.39	0.62	0.059	0.16	0.29	r_{54}	0.024	0.093	0.25	0.004	0.021	0.083
r_{67}	0	0.054	0.19	0.017	0.10	0.24	r_{64}	0.13	0.28	0.49	0.036	0.13	0.26
r_{68}	0.064	0.21	0.41	−0.13	0.010	0.12	r_{67}	0	0.11	0.29	0.004	0.13	0.31
							r_{70}	0.061	0.18	0.37	−0.046	0.050	0.13

ratios in the case of old firms and 16 ratios in the case of young firms). For both classes, the percentiles (quartiles and median values) are given.

4.3. Dichotomous classification test

We determine the predictive values of the 73 individual ratios by means of the dichotomous classification test (see for example Beaver, 1966; Deakin, 1972; Laitinen, 1992). The procedure for the determination of a ratio's predictive value is as follows. First, the ratio values from the annual reports in the training set are put in a sorted row. For each pair of successive values in the row, we determine the value that is exactly midway. For example, if the sorted row is (0.2, 0.4, 0.5, 0.8, 0.9), then the 'in-between' values are (0.3, 0.45, 0.65, 0.85). For every 'in-between' value w, two scores are calculated.

$$\text{Score A} = (\text{lower}_{\text{bankr}}/\text{total}_{\text{bankr}} + \text{higher}_{\text{nonb}}/\text{total}_{\text{nonb}})/2*100\%$$

$$\text{Score B} = (\text{higher}_{\text{bankr}}/\text{total}_{\text{bankr}} + \text{lower}_{\text{nonb}}/\text{total}_{\text{nonb}})/2*100\%$$

Where lower_i (higher_i) equals the number of annual reports of class i in the set with a ratio value that is lower (higher) than value w. Furthermore, total_i is equal to the total number of annual reports of class i in the set. After the calculation of the scores for all 'in-between' values, we determine the 'in-between' value with the highest score (either score A or score B) and this is then the optimal cut-off value. If the highest score is a score A, the division between the classes is as follows: an annual report is classified as belonging to class 'bankrupt' if the ratio value in the annual report<the optimal cut-off value, and as belonging to class 'nonbankrupt' if the ratio value in the annual report>the optimal cut-off value. Then, score A represents the percentage of annual reports (the average percentage for both classes) in the training set that are classified correctly by this division. Naturally, where the highest score is a score B, the division is reversed (if ratio value<optimal cut-off value, then class 'nonbankrupt', else class 'bankrupt'). Finally, we make a division using this optimal cut-off value with the test set, and determine a new score A or B (depending on whether the highest score with the training set was a score A or B). This new score is the test result. As with the models, an experiment is always carried out 10 times. In each round of an experiment, we use the same training set and test set that are used with the models.

5. The predictive values of models and ratios

The test results of the models are given in Table 4. As an example, in each of the 10 rounds of the experiment in year 1 (old firms), an MDA model that uses the ratios selected by stepwise selection was derived, and then tested on the test set. The percentage (80%) in the left upper corner of Table 4 is the average of these 10 test results. It is important to note that a test result of a model (or an individual ratio) that equals 50% means that the model (or the ratio) is not able to produce a meaningful division between the two classes. A result of 50% could be achieved by simply guessing. With young firms, we only looked at years 1, 2 and 3,

Table 4
Predictive values of the models

		Stepwise selection					Factor analysis				
		1	2	3	4	5	1	2	3	4	5
Old	MDA	80	75	72	69	67	77	73	69	66	63
	NN	81	76	73	69	67	78	74	70	66	63
Young	MDA	76	72	68			74	68	66		
	NN	77	73	69			73	68	67		

since we considered less than 300 annual reports of class ‘bankrupt’ to be too few to analyse. The models that used ratios selected by factor analysis clearly performed least well. This finding can be explained. Using factor analysis, we were trying to find a few underlying factors that would describe the covariance relationships among the many ratios. However, there is no guarantee that every factor is a good predictive measure of bankruptcy. Note that the results using MDA and NN methods are almost equal. In Tables 5a and 5b, the test results for the ratios can be found. The test results are averages based on the 10 rounds of the experiment. In the tables, we present the difference between the test result of a MDA model and the test result of a ratio (we use the models that included ratios selected by stepwise selection; the test results are shown in the first row of each table). The information is presented in this way to provide a clear insight into the differences between the predictive values of the various ratios. The test result for a particular ratio can be easily deduced. For example, the test result of ratio r_1 in year 1 (old firms) is 69% (=80–11). In years 2, 3, 4 and 5, the test results are 63% (=75–12), 60%, 57% and 55%, respectively. With the young firms, the test results for this ratio are 68%, 62% and 59%. Thus, a high value in the tables reflects a low predictive value.[9] In Appendix B, the results of a significance test are provided and, further, we investigate the influence of the decreasing numbers of reports from class ‘bankrupt’ as the years increase.

Our hypothesis on ratio categories applies especially to established firms, since we assume that before bankruptcy a firm gradually runs into problems. This assumption is not applicable to young firms, because the life of a young failing firm is too short and, during its life, the performance of a young failing firm probably never rises above ‘poor’. After considering the results for the old firms, we must, however, conclude that there is no support for the hypothesis. Heading for bankruptcy, there is no fixed order in which the different categories of financial ratios start to be predictive. The solvency ratios appear to be the strongest category in the tables. However, certain of the profitability and activity ratios also performed

[9] Is it possible to compare the predictive values of the 23 ratios that use the item ‘turnover’ or the item ‘goods and services purchased’ with the predictive values of the remaining ratios? After all, in the case of the 23 ratios, the predictive values are determined with less data (see Appendix A). A comparison with the predictive value of ratio r_{70} proved to be very well possible. In each of the 5 years (old firms) and each of the 3 years (young firms), the predictive value of r_{70} was determined using the same annual reports as were used to determine the predictive values of the 23 ratios. The difference between this predictive value of r_{70} and the predictive value of r_{70} in Table 5b was always equal to 0% or 1%.

Table 5a
Predictive values of the profitability and activity ratios

	Old					Young		
	1	2	3	4	5	1	2	3
MDA model (stepwise selection)	80	75	72	69	67	76	72	68
Profitability:								
r_1 gross operating results/total assets	11	12	12	12	12	8	10	9
r_2 net operating results/total assets	11	16	14	14	13	11	13	13
r_3 gross results/total assets	10	11	12	10	10	8	10	9
r_4 net results/total assets	11	15	12	13	12	10	12	13
r_5 profit before taxes/total assets	3	6	8	7	6	5	9	8
r_6 profit after taxes/total assets	3	6	7	8	8	5	9	9
r_7 cash flow/total assets	5	6	8	8	7	5	6	6
r_8 profit after taxes/equity	17	11	12	11	10	17	15	14
r_9 cash flow/equity	18	16	14	15	15	20	16	15
r_{10} gross operating results/working assets	9	11	10	11	10	7	8	7
r_{11} net operating results/working assets	11	14	12	12	12	11	12	12
Activity:								
r_{12} gross operating results/turnover	13	12	12	11	9	10	9	9
r_{13} net operating results/turnover	10	14	15	12	12	9	13	10
r_{14} gross results/turnover	12	11	12	10	8	9	9	9
r_{15} net results/turnover	10	13	14	12	10	9	12	11
r_{16} profit before taxes/turnover	2	6	7	5	7	5	8	8
r_{17} profit after taxes/turnover	2	5	6	6	7	5	8	9
r_{18} cash flow/turnover	6	7	9	6	7	5	5	7
r_{19} gross operating results/added value	15	13	12	10	8	10	9	7
r_{20} net operating results/added value	14	13	14	12	10	12	13	13
r_{21} gross results/added value	14	12	10	10	9	10	9	7
r_{22} net results/added value	14	14	13	11	9	11	13	12
r_{23} profit before taxes/added value	6	5	6	7	5	7	8	9
r_{24} profit after taxes/added value	6	7	6	7	7	7	10	10
r_{25} cash flow/added value	9	8	7	6	6	6	7	4
r_{26} equity/turnover	11	12	11	7	9	7	9	7
r_{27} turnover/working assets	20	16	16	17	14	22	19	17
r_{28} turnover/fixed working assets	26	25	22	19	18	26	23	18
r_{29} turnover/current working assets	19	16	15	13	13	16	15	12
r_{30} turnover/total assets	23	22	22	19	18	26	21	18
r_{31} added value/total assets	24	23	19	14	12	23	22	19
r_{32} added value/turnover	28	22	22	17	14	23	21	14
r_{33} added value/fixed assets	26	24	20	16	15	26	21	17
r_{34} financial charges/added value	16	12	10	10	9	15	14	11
r_{35} income taxes/added value	11	9	9	6	5	10	9	9
r_{36} personnel charges/added value	15	13	12	10	8	11	10	8
r_{37} added value/number of persons employed	16	13	10	6	6	15	11	8
r_{38} fixed working assets/number of persons employed	25	22	18	13	12	21	17	14
r_{39} publication lag	22	20	22	18	18	19	20	15

Table 5b
Predictive values of the liquidity and solvency ratios

	Old					Young		
	1	2	3	4	5	1	2	3
MDA model (stepwise selection)	80	75	72	69	67	76	72	68
Liquidity:								
r_{40} working capital/turnover	11	12	12	11	10	11	12	10
r_{41} working capital/total assets	10	10	8	9	8	11	12	11
r_{42} current assets/turnover	25	22	20	20	18	22	21	17
r_{43} current assets/total assets	29	26	23	20	18	22	19	15
r_{44} current assets/short-term debt	10	7	7	8	8	9	10	9
r_{45} quick assets/turnover	25	20	18	13	10	26	22	18
r_{46} quick assets/total assets	22	18	16	15	13	24	20	19
r_{47} quick assets/short-term debt	9	7	6	7	5	9	10	9
r_{48} quick assets/amounts payable within 1 year	9	7	6	7	5	9	10	9
r_{49} (investments+cash)/turnover	15	12	11	9	8	10	9	7
r_{50} (investments+cash)/total assets	13	9	8	9	8	10	8	5
r_{51} (investments+cash)/amounts payable within 1 year	9	6	5	7	5	5	5	2
r_{52} (investments+cash−financial debts)/current assets	9	6	5	5	3	6	4	2
r_{53} cash/amounts payable within 1 year	11	8	9	9	8	7	6	4
r_{54} cash/current assets	16	11	11	10	10	8	7	6
r_{55} cost price of the production/stocks	19	14	14	11	11	21	17	14
r_{56} stocks/turnover	18	15	14	10	11	19	15	16
r_{57} stocks/total assets	23	17	15	12	13	19	16	12
r_{58} trade debtors/turnover	28	24	23	19	18	21	20	14
r_{59} trade debtors/total assets	30	25	21	19	16	21	18	13
r_{60} trade debts/goods and services purchased	18	14	13	12	9	12	15	11
r_{61} trade debts/turnover	18	15	13	12	10	13	14	11
r_{62} trade debts/total assets	23	17	14	13	10	12	11	9
r_{63} short-term debt/turnover	9	10	9	10	9	10	12	11
Solvency:								
r_{64} equity/total assets	4	5	4	5	5	5	7	7
r_{65} equity/permanent capital	21	16	14	13	10	18	17	12
r_{66} short-term debt/total assets	9	8	7	6	5	7	10	6
r_{67} long-term debt/total assets	25	20	17	14	12	23	20	16
r_{68} (reserves+accumulated profit or loss)/total assets	1	5	4	5	3	5	8	7
r_{69} profit after taxes/total debt	3	5	7	6	7	5	9	8
r_{70} cash flow/total debt	2	3	3	4	5	3	5	4
r_{71} cash flow/long-term debt	4	7	8	9	9	7	11	9
r_{72} net results/financial charges	2	3	5	4	4	4	7	6
r_{73} whether equity is positive or negative	15	19	18	16	15	13	16	15

well in all 5 years, see for example r_6 (profit after taxes/total assets) and r_{17} (profit after taxes/turnover). In contrast with our expectations, none of the liquidity ratios had a high predictive value just before bankruptcy. However, some liquidity ratios did predict well in years 4 and 5, for example r_{52} ((investments+cash−financial debts)/current assets). It would seem that ratios that evaluate different dimensions of a firm's financial position can have similar predictive powers many years before bankruptcy. In general, ratios that performed well with old firms also showed a good performance with young firms. However, the classification percentages for old firms are higher than for young firms. This means that our second hypothesis is confirmed: the bankruptcy of young firms is more difficult to predict than the bankruptcy of established firms.

The most famous study in which the dichotomous classification test has been used is the study by Beaver (1966). However, he examined only 79 industrial firms from each class and the firms were all large. Comparing Beaver's study with our research (insofar as similar ratios were used), we find a number of similarities. Ratios that use profit after taxes or cash flow in the numerator, in combination with total assets, turnover or total debt in the denominator are significant in both studies. Beaver found that the ability to predict failure was strongest using the ratio cash flow/total debt (r_{70}). This is also true in our research. As with our findings, Beaver did not find any liquidity ratios that had a high predictive value just before bankruptcy, and we further see that a number of ratios performed badly in both studies, such as turnover/total assets (r_{30}), current assets/total assets (r_{43}) and trade debtors/turnover (r_{58}). However, there are also differences. For example, profit after taxes/equity (r_8) and cash flow/equity (r_9) are more significant in Beaver's study. Also, we find that the significance of equity/total assets (r_{64}) is much less in Beaver's findings than in Table 5b.

A single cut-off value is nearly always sufficient for a good division of the classes. Just before bankruptcy, ratio r_8 (profit after taxes/equity) is an exception as shown by Table 6. The table concerns old firms and should be read as follows. For example, with 20% (5%+15%) of the annual reports of class 'nonbankrupt', the equity is positive and the profit after taxes is negative. 5% of the 'nonbankrupt' reports have a value of r_8 that is lower than, or equal to, -0.4. We can see that, in year 1 for class 'bankrupt', there is a large group of annual reports for which both the equity and the profit after taxes are negative. This group contains 5%+25%=30% of all annual reports from year 1. The majority of that group (25% of all reports from year 1) have large values for r_8 (greater than 0.4). Suppose that we define a division using two cut-off values: if the value of r_8 lies between 0 and 0.4, then the annual report is classified as belonging to class 'nonbankrupt'; else as belonging to class 'bankrupt'. Table 6 shows that this division classifies correctly 71% of the 'nonbankrupt' reports, 75% of the reports from year 1 and 46% of the reports from year

Table 6
Percentages of annual reports with specified values for equity, profit after taxes and ratio r_8

			Value for r_8				Value for r_8	
	Equity	Profit	$\langle -\infty, -0.4]$	$\langle -0.4, 0]$	Equity	Profit	$\langle 0, 0.4]$	$\langle 0.4, \infty\rangle$
Nonbankrupt	>0	<0	5	15	>0	≥0	70	7
	<0	≥0	0	1	<0	<0	1	1
Bankrupt (year 1)	>0	<0	24	21	>0	≥0	20	3
	<0	≥0	1	1	<0	<0	5	25
Bankrupt (year 4)	>0	<0	13	21	>0	≥0	52	5
	<0	≥0	1	1	<0	<0	2	5

4. The overall result in year 1 is thus 73% (=(71+75)/2), while Table 5a shows that the result achieved by r_8 amounts to 63% (=80–17). We see that a division using two cut-off values leads to a much better classification result. In years 2 and 3, the advantage of this division diminishes, and in year 4, the result using two cut-off values (59%=(71+46)/2) is similar to the result using r_8 (58%=69−11). A similar situation can be observed with the young firms.

The test results with a number of ratios are only slightly higher than 50%, for example ratio r_{58} (trade debtors/turnover). It seems plausible that firms in trouble try to collect money from trade debtors as quickly as possible in order to have more cash at their disposal (in that case a low value of r_{58} would reflect an unfavourable situation). Conversely, we could find that trade debtors postpone their payments if they suspect an impending bankruptcy (this time a high value of r_{58} would be a negative sign). Possibly, the two effects balance each other out. Other findings in Tables 5a and 5b are noteworthy. For example, consider ratios r_1, r_2, ..., r_7 and ratios r_{12}, r_{13}, ..., r_{25}, which use seven results from a firm: gross and net operating results, gross and net results, profit before and after taxes, and cash flow. Ratios using the three quantities mentioned last are considerably more predictive than ratios using the other four quantities. Apparently, it is important to use a result after subtracting financial charges. The good predictive value of ratio r_{72} (net results/financial charges) is another indication that financial charges are an important quantity. Furthermore, ratios that use the gross operating results (the gross results) seem to perform slightly better than ratios using the net operating results (the net results). Possibly, some firms that are approaching bankruptcy try to positively influence the results in the way fixed assets are depreciated. In doing so, the predictive values of ratios that use the net operating results or the net results decrease.

6. The predictive values of the stability of ratios

The predictive value of the stability of ratio r is determined in the same way as the predictive value of ratio r itself (as described in Section 4). However, in the latter case, an annual report a, in the training or the test set, is represented by the value of ratio r in report a, and in the former case an annual report a is represented by a value v. We use two definitions of a ratio's stability. In the first, the value v is equal to the standard deviation in the value of ratio r in annual report a, plus the values of ratio r in the annual reports published 1 year earlier and 2 years earlier (naturally, these three reports are from the same firm). In option 2, v equals the difference between the value of ratio r in annual report a and the value of ratio r in the annual report published 2 years earlier. We determine the predictive values of the stability of ratios in years 1 and 3 prior to failure for the old firms. For each of the 1500 annual reports of class 'nonbankrupt' in Table 1 (old firms), we tried to locate two earlier annual reports (published 1 and 2 years previously). In this way, we were able to create a series of 3 successive annual reports and for 1242 out of the 1500 annual reports, this proved to be possible (see Table 7). Table 7 also shows the numbers of series with respect to the class 'bankrupt'. For example, for 268 out of the 424 annual reports from year 3, we were able to create a series of three successive annual reports from years 3, 4

Table 7
Number of series to determine the predictive values of the stability of ratios

	Number in Table 1	Number of Series
Nonbankrupt	1500	1242
Bankrupt (year 1)	556	364
Bankrupt (year 3)	424	268

and 5. The predictive value using each definition of stability is determined from the annual reports in the right hand column of Table 7. In order to ensure a fair comparison, the data in this column (i.e. the first annual report of each series) are also used to redetermine the predictive values of the ratios.

The results are given in Table 8. For every ratio, there are three percentages for each year. For example, for ratio r_1, the percentages in year 1 are 70%, 9% and 10%. The 70% is the predictive value of r_1 in year 1 determined from the data in the last column of Table 7 (in Table 5a, the predictive value of r_1 in year 1 is 69%). The 9% indicates that, in year 1, the predictive value of the first definition of r_1's stability equals 61%, that is 9% less than 70%. Similarly, the predictive value of the second definition in year 1 is 60% (10% less than 70%). In Table 8, the predictive value of the stability of a ratio (regardless of the definition used) more often than not proves to be considerably worse than the predictive value of the ratio itself. In only a few cases, is the stability the better predictor. Regarding the two options, it seems that the standard deviations performed slightly better than the differences.

Next, we consider the multivariate importance of ratio stability (as defined in Section 2). Using the data in the right hand column of Table 7, and following the same procedure as before, we built models that included only ratios, and models that included ratios and standard deviations. Using stepwise selection, and considering the 45 ratios noted earlier and their standard deviations, the following groups were selected: r_7, r_9, r_{31}, r_{34}, r_{51}, r_{52}, r_{64}, r_{65} (year 1, ratios alone), r_7, r_9, r_{48}, r_{52}, r_{62}, r_{64}, r_{68}, s_8, s_{31}, s_{39} (year 1, ratios and standard deviations), r_7, r_{20}, r_{31}, r_{34}, r_{54}, r_{65}, r_{68} (year 3, ratios alone), and r_7, r_{31}, r_{34}, r_{51}, r_{52}, r_{64}, s_9, s_{54}, s_{65} (year 3, ratios and standard deviations). s_i is the standard deviation of ratio r_i. The MDA test results are: 79% (year 1, ratios alone), 79% (year 1, ratios and standard deviations), 72% (year 3, ratios alone) and 72% (year 3, ratios and standard deviations). Neural networks produced similar results. These percentages lead to the conclusion that the multivariate importance is limited. In contrast with our findings, Dambolena and Khoury (1980) report that the inclusion of standard deviations in a model considerably improved the predictive value of the model. However, the results of Dambolea and Khoury are statistically less reliable due to their very small data set of 23 bankrupt and 23 nonbankrupt firms. Furthermore, they examined a different population (large firms). In a separate analysis, we tested whether using standard deviations over 4 years would improve the univariate and multivariate results in year 1 prior to failure. To achieve this, we created series of four reports from years 1, 2, 3 and 4; and with class 'nonbankrupt', we tried to locate three earlier reports for each of the 1500 reports. However, the effects on the results were small.

Table 8
Predictive values of the stability of ratios

R=predictive value of the ratio
D_1=predictive value using the first definition of stability (standard deviation)
D_2=predictive value using the second definition of stability (difference)

	Year 1			Year 3		
	R	D_1	D_2	R	D_1	D_2
r_1	70	9	10	61	7	8
r_2	69	7	7	60	7	9
r_3	71	11	11	61	8	7
r_4	69	7	7	62	8	9
r_5	78	14	14	66	12	13
r_6	78	12	14	65	8	12
r_7	76	12	13	64	8	10
r_8	64	−9	4	62	1	7
r_9	62	−12	0	58	−3	3
r_{10}	71	15	12	63	14	12
r_{11}	69	11	9	63	14	14
r_{12}	68	5	5	61	10	10
r_{13}	70	5	6	59	7	10
r_{14}	69	7	8	59	8	10
r_{15}	71	7	8	59	8	9
r_{16}	79	15	16	65	14	16
r_{17}	79	13	15	66	12	15
r_{18}	75	11	11	62	12	12
r_{19}	66	4	6	60	6	8
r_{20}	67	4	8	59	7	9
r_{21}	67	5	6	61	9	8
r_{22}	67	4	7	61	11	11
r_{23}	75	12	15	67	15	17
r_{24}	75	11	13	68	16	18
r_{25}	73	8	10	64	10	10

	Year 1			Year 3		
	R	D_1	D_2	R	D_1	D_2
r_{26}	68	6	2	59	11	1
r_{27}	60	8	4	56	7	6
r_{28}	54	3	2	53	3	4
r_{29}	60	6	5	57	8	4
r_{30}	57	1	3	50	−3	−1
r_{31}	54	−5	−4	51	−4	−1
r_{32}	51	−10	−4	48	−4	−4
r_{33}	53	1	1	51	1	2
r_{34}	64	−4	0	63	6	9
r_{35}	68	3	8	64	−2	6
r_{36}	66	4	6	61	8	9
r_{37}	64	14	5	61	6	6
r_{38}	55	2	4	52	−3	0
r_{39}	57	−2	3	50	−2	−1
r_{40}	69	9	4	58	10	2
r_{41}	70	9	6	63	13	6
r_{42}	54	−8	−1	51	−5	−2
r_{43}	50	−4	−2	50	−2	−1
r_{44}	71	14	9	64	5	7
r_{45}	54	0	1	54	4	5
r_{46}	58	4	2	56	0	4
r_{47}	71	13	8	65	8	9
r_{48}	71	13	8	65	8	9
r_{49}	64	5	9	60	1	7
r_{50}	68	6	9	64	4	8

	Year 1			Year 3		
	R	D_1	D_2	R	D_1	D_2
r_{51}	73	6	11	67	3	8
r_{52}	73	16	13	68	18	17
r_{53}	71	6	11	63	0	6
r_{54}	66	4	11	61	1	6
r_{55}	60	8	4	56	1	3
r_{56}	61	−3	−2	58	0	4
r_{57}	57	−1	1	56	2	2
r_{58}	51	−7	−1	49	−6	−3
r_{59}	50	−3	−1	50	−1	0
r_{60}	63	6	7	58	6	3
r_{61}	60	2	1	57	3	1
r_{62}	56	−1	2	57	4	1
r_{63}	70	6	2	63	9	9
r_{64}	76	13	8	67	17	9
r_{65}	61	−3	1	59	0	2
r_{66}	72	8	5	63	11	3
r_{67}	56	2	3	58	3	5
r_{68}	77	12	10	69	16	10
r_{69}	79	24	20	66	14	17
r_{70}	79	26	19	68	15	14
r_{71}	78	29	17	63	12	9
r_{72}	79	22	20	68	7	15
r_{73}	64	2	3	54	2	2

7. Conclusions

This study has focused on the prediction of bankruptcy through the use of bankruptcy models and individual financial ratios. The four main findings of our study are as follows:

1. The hypothesis on the predictive power of different ratio categories during the successive phases before bankruptcy was not supported by the results. We expected that a downward trend would first be observed in the values of the activity ratios and the profitability ratios, followed by the values of the solvency ratios, and then in the liquidity ratios. We found, however, no fixed order in which the different categories of financial ratios started to be predictive. Ratios that evaluate different dimensions of a firm's financial position showed similar predictive efficacies 5 years before failure. We can suggest several reasons why the hypothesis was not supported. Possibly, a period of 5 years is too short, i.e. a longer period, for example 10 years, should be examined. It also may be that the hypothesis is simply incorrect and that we should come up with other propositions regarding the predictive efficacy of different ratio categories. Furthermore, the hypothesis may only be valid for some firms that go bankrupt. One can think of alternative scenarios; for example, a healthy firm undertakes a large investment using too much debt capital and runs into serious problems when the profitability of the investment is lower than expected. In this scenario, it seems that poor profitability and unfavourable solvency ratios will coincide. Still, with any scenario, one would expect highly predictive liquidity ratios just before bankruptcy and, in the present study, this is not the case. Future research could investigate the validity of the suggested reasons for the hypothesis not being supported.
2. The hypothesis that the bankruptcy of young firms is more difficult to predict than the bankruptcy of established firms was supported by the results. Young and old firms are not a homogeneous group; therefore, better classification results are probably achieved by having a separate model for each age category (as was the strategy in this study) rather than one general model for all firms.
3. The results indicate that virtually every ratio has some predictive power. Thus, an approaching bankruptcy is visible in almost every dimension of a firm's financial position. A few ratios, such as r_{70} (cash flow/total debt), achieved results that were close to the results of the models. In general, ratios that performed well with old firms also showed a good performance with young firms. It seems that certain ratios perform similarly with different populations, for example, cash-flow/total debt achieved the best overall accuracy with both old and young firms in our study, and also with large firms in Beaver's study (Beaver, 1966). However, studies on bankruptcy prediction nearly always focus on industrial firms. In future research, it would be interesting to apply the dichotomous classification test to large amounts of data from service industries and trading companies, and to see to what extent the predictive values of ratios are different.
4. It was found that the univariate and multivariate importance of ratio stability were not very high. This contradicts the results of Dambolena and Khoury (1980), who found a

high multivariate importance in the case of large firms. Possibly, the importance of ratio stability depends on the size of the firms studied. Future research could test whether this relationship really holds and, if so, try to identify the reasons for this relationship.

Early warnings of impending financial crisis are of interest to both practitioners and academics. Many studies have been devoted to assessing the ability to combine publicly available data with classification techniques in order to predict business failure. Numerous conclusions have been drawn from these studies. However, the reliability of the findings presented is often limited because so few data were used. This especially poses a problem when conclusions are based on small differences, for example, when classification results for two samples only differ slightly. We feel that, in future, research should put more effort into collecting larger data sets to avoid this problem.

Appendix A

This appendix lists the items, and the quantities, contained in the balance sheet, the profit-and-loss account, and the disclosure, that are required to calculate the ratios. Most annual reports are published using the so-called ‘abbreviated form’ and with these annual reports it is not possible to determine the exact values of a number of quantities used in the ratios. The values of these quantities are estimated as well as possible from the available data. Furthermore, in the abbreviated form, the debt charges are not given separately, and therefore the total financial charges have to be used.[10] Note that ratios r_{39} and r_{73} are not true ratios (i.e. having the form of numerator/denominator), but are referred to as ratios simply for convenience. Ratio r_{39} (publication lag) equals the number of days between the closing date and the deposit date. Ratio r_{73} reflects whether the equity is positive or negative; there are two values, if equity ≥ 0 then r_{73}=1, if equity <0 then r_{73}=0.

Sometimes, an annual report lacks a value for a certain ratio. There are two reasons for a missing ratio value. Firstly, the value of the denominator can be 0. Secondly, values for the item ‘turnover’ and the item ‘goods and services purchased’ are not given in about 40% of the annual reports since firms that publish using the ‘abbreviated form’ do not have to provide these values. Obviously, if the values are missing, the ratios that use these items cannot be calculated. For 28 of the 73 ratios, there is a missing ratio value in more than 1% of the annual reports. Twenty-three of these 28 ratios use ‘turnover’ or ‘goods and services purchased’, and for the other five ratios (r_{33}, r_{37}, r_{38}, r_{71}, r_{72}), the denominator equals 0 in more than 1% of the annual reports.

[10] The total financial charges include not only the debt charges but also other financial charges, such as additional expenses with respect to the acquisition of financial assets and investments, and the amount of the discount borne by the firm as a result of negotiating amounts receivable.

Quantities from the balance sheet used in Tables 5a and 5b. Total assets=1+7=total liabilities=15+22+23. Fixed working assets=2+3+4. Current working assets=8+9+14. Working assets=fixed working assets+current working assets. Working capital=7−25−28. Short-term debt=25+28. Long-term debt=22+24. Total debt=short-term debt+long-term debt. Permanent capital=15+22+24. Stocks=8. Cash=13. Quick assets=9+12+13.

Assets	Liabilities
Fixed assets (1)	Equity (15)
I. Formation expenses (2)	I. Capital (16)
II. Intangible assets (3)	II. Share premium account (17)
III. Tangible assets (4)	III. Revaluation surplus (18)
IV. Financial assets (5)	IV. Reserves (19)
V. Amounts receivable after one year (6)	V. Accumulated profit or loss (20)
Current assets (7)	VI. Investment grants (21)
I. Stocks and contracts in progress (8)	Provisions and postponed taxes (22)
II. Amounts receivable within 1 year (9)	Amounts payable (23)
A. Trade debtors (10)	I. Amounts payable after 1 year (24)
B. Other amounts receivable (11)	II. Amounts payable within 1 year (25), including:
III. Investments (12)	A. Financial debts (26)
IV. Cash at bank and in hand (13)	B. Trade debts (27)
V. Deferred charges and accrued income (14)	III. Accrued charges and deferred income (28)

Quantities from the profit-and-loss account and the disclosure used in Tables 5a and 5b. Operating income[11] (including the turnover). Added value=operating income−goods and services purchased. Gross operating results=added value−cash operating expenses. Net operating results=gross operating results−non-cash operating expenses. Gross results=profit before taxes+financial charges+all non-cash expenses. Net results=profit before taxes+financial charges. Profit before taxes. Profit after taxes=profit before taxes−income taxes. Cash flow=profit after taxes+all non-cash expenses. Cost price of the production=goods and services purchased+cash operating expenses+non-cash operating expenses. Personnel charges. Number of persons employed.

Appendix B

In this appendix, the results of a significance test are presented and, further, we investigate the influence of the decreasing numbers of reports from class 'bankrupt' as the years increase. In testing for significance, the non-parametric Wilcoxon rank sum test was used. With every ratio, we applied the test for each year. The null hypothesis is that the distributions of the ratio values are identical with both classes. The null hypothesis was almost always rejected. A test

[11] Operating income=turnover+increase/decrease in stocks of finished goods, work and contracts in progress+own construction of fixed assets+other operating income.

result of 55% or higher in Tables 5a and 5b always coincides with the rejection of the null hypothesis (with α=0.01, two-sided test). For example, for ratio r_1 (old firms), one can conclude that the null hypothesis was rejected in each of the 5 years since, in each year, the test result is 55% or higher.

Tables 4, 5a and 5b show that the percentage of correctly classified firms falls as one moves from year 1 to earlier years. The main reason is that it is increasingly difficult to predict bankruptcy as one moves further back in time prior to bankruptcy. Another reason seems to be that the number of annual reports of class 'bankrupt' decreases as the years increase, i.e. the training sets from earlier years contain less information. To estimate the importance of this second reason, we redetermined the predictive values of the models and ratios. The same procedure as before was followed, but this time the training set of each year contained an equal number of annual reports of class 'bankrupt'. With the old firms, this number was 161 (since there are 322 reports of class 'bankrupt' from year 5 and 322/2 is 161). For example, in year 1, 161 reports were in the training set and 395 (=556–161) reports were in the test set. With the young firms, the number of reports of class 'bankrupt' in each training set was 171 (=342/2). The results show that the importance of the second reason is limited. In most cases, the percentage of correctly classified firms did not change, or was only 1% lower. For example, the results for MDA models that used the ratios selected by stepwise selection were 78, 74, 72, 68, 67 (old firms) and 76, 71, 68 (young firms), compared with 80, 75, 72, 69, 67 and 76, 72, 68 as presented in Table 4. The results of ratio r_{70} amounted to 77, 71, 69, 65, 62 (old firms) and 72, 67, 64 (young firms), compared with 78, 72, 69, 65, 62 and 73, 67, 64 as given in Table 5b.

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