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Predictive Ability of Accounting Ratio for Bankruptcy

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Abstract

Among the most controversial issues in the literature, and empirical studies that have addressed the subject of bankruptcy prediction, there is certainly the understanding of what kind of indicators is most predictive in the report on time, and especially with fewer errors thorough a corporate crisis. In this regard, the present work contributes to the already vast literature that analyzes the determinants of the probability of firm default, with particular attention to the quantities contained in the accounting ratios. With the support of 9,390 Italian SMEs will occur the specific contribution of each ratio within each rating category considering, therefore, the predictive value of each explanatory variable. This survey's results can even prove the predictive ability of capital structure and debt coverage compared to the minor validity of some indicators of turnover, profitability, and cash conversion cycle.

JEL classification numbers: C13, C51, C53, G33
Keywords: Credit Rating, SME finance, Default risk estimation, model accuracy, accounting ratio, Discriminatory power

1 Introduction

The first aim of this study is to develop an empirical application of credit risk modelling for privately held corporate firms. The second main objective is to display what is the specific contribution of each explanatory variable in the model of bankruptcy prediction.
In recent decades many techniques occurred and many studies have been addressed by scholars throughout the world to clarify the most diverse aspects on the prediction of firms insolvencies. These models, despite their specificity, have in common the ability to select a subset of indicators that distinguish firms that become insolvent by healthy firms. So, regardless of the different methods used over time, it is possible to summarize this concept: talking about quality of the analytical techniques or functionality of the model means a successfully developed framework capable to predict the highest percentage of

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default and to commit, therefore, the fewer of forecast errors. In other words, it comes to detect the predictive ability of some indicators taking in a certain account the phenomenon of insolvency.

Although many researchers developed failure prediction models using a variety of statistical techniques, an extensive volume of the corporate failure literature has mainly employed US data to extend Beaver’s (1966) early univariate methodology and Altman’s (1968) successive linear multiple discriminant analysis model (MDA).

For manifest restrictions of the linear discriminant analysis approach, Ohlson (1980) employed logistic regression [2] to calculate the probability of default. The logistic regression is a procedure that eludes some of the problems of the MDA method. Since then, logistic regression has been extensively used for the development of failure firm models. A logit analysis of the use of accounting ratios for predicting corporate failure was performed by indeed many authors: Platt e Platt (1990), Ooghe *et al.* (1995), Mossman *et al.* (1998), Becchetti e Sierra (2003), Altman e Sabato (2007), Pierri *et al.* (2011), Muscettola e Naccarato (2013), Muscettola (2014a).

Many empirical studies that adopt the statistical approach usually aim to correctly classify a sample of firms in healthy or default ones on the basis of variables taken from financial statement. Prediction of default rates has been a target of the financial analysis for decades. After the research made by mentioned pioneers, important results for this branch, executing the criteria for explanatory variables used in this research[3], have been achieved by Edmister (1972), Springate and Gordon (1978), Zmijewsky (1984), Lo (1986), Gentry et al (1987), Cantor and Packer (1994), Laitinen and Laitinen (2000), Hosmer and Lemeshow (2000), Crouhy et al (2001), Shumway, (2001), Carey and Hrycay (2001), Grice and Ingram (2001), Couderc and Renault (2005), Altman and Sabato (2007), Kayhan and Titman (2007), Muscettola (2013).

In addition to the aforementioned works, this paper refers to important examples of empirical analysis on Italian data. In this context, the references are for the studies of Appetiti (1984), Alberici and Forestieri (1986), Barontini (1992), Altman et al (1994), Laviola and Trapanese (1997), Foglia et al (1998), Lo Martire (2002), Montrone (2005), Muscettola and Gallo (2008), De Laurentis and Maino (2009), Muscettola and Pietrovito (2012a), Muscettola (2014c).

With the advantage of a rich literature on the matter, there will be a good selection of accounting ratios most widely used in the quantitative rating models and they will build a predictive archetypal. Considering that, this paper deals with a very large sample of Italian SMEs. To seek peculiarities of firms that became insolvents after three year - after constructing a function that can separate the good firms from insolvent companies employing the technique of logistic regression, with an excellent accuracy of the model - the final goal of the essay will be, furthermore, to highlight the predictive power of individual financial variables.

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[2]The logistic exploration is classically used when the dependent variable is dichotomous, and one is interested in approximating the probability of one of the two possibilities as a function of some firm’s quantitative appearances.

[3]The initial set of ratios was selected on the basis of frequency in the research literature on bankruptcy prediction.

2 Dataset and Accounting Ratios

The firms analyzed in the research are Italian companies with minimum revenues of sales of € 5 million and maximum of 50 million euro. Small and medium sized enterprises (SMEs[4]) are the predominant type of firms in several countries, and particularly in Italy. The research was conducted acquiring the accounting data of firms from 2007 to 2010. Sample firms engaged in production, trade and services sector. Financial companies, farms and construction companies have been excluded from the analysis. This study does not take in no account neither holding companies, or enterprises with public participation and firms established after year 2002.

In order to test the propositions and to build a valid scoring model, the whole sample of firms has been divided into two sub-samples evenly distributed: experimental sample and control sample.

An organized research often matches the results obtained from investigational sample against a testing sample, which is essentially a duplicate of the first sample with this exception: an alteration of the independent variables and the consequent connection between cause and effect.

The final sample is a composition of 37,560 firm-year observations[5] that span 9,390 individual companies. The reference year for the analysis is 2007. All the firms (9,068 firms) which have not been insolvent at least until the year 2010 are reasonably considered “good firms”. Concerning those firms turned insolvent (bad firms), not to spoil the time frame, the analysis does not cover all the firms which got insolvent in 2007, in 2008 and in 2009, but only the firms that became insolvent in 2010. In this way the time frame has been set as three consecutive years. Among the selected ones, firms got insolvent after three years are 322 whose 95 commercial, 171 manufacturing and 56 services businesses. As a percentage of total number of companies analyzed, therefore, the incidence will be 3.43%.

Table 1: Characteristics of the sample used in our research

	Whole Sample		Bad Firms		Good Firms	
	Nr	**%**	**Nr**	**%**	**Nr**	**%**
Manufacturing Firms	4,321	100.00	171	3.96	4,150	96.04
Commercial Firms	3,512	100.00	95	2.71	3,417	97.29
Service Firms	1,557	100.00	56	3.60	1,501	96.40
Whole Sample	**9,390**	**100.00**	**322**	**3.43**	**9,068**	**96.57**

[4]In the European Union are considered SME firms with less than 250 employees or less than 50 million euro of yearly sales.

[5]The yearly statements are provided by Crif Spa. As for the creation of the statistical model, the preliminary operations on the data, the choice of the outliers and the creation of financial ratios, the reader ought to refer exclusively to the author.

In our research, a firm has been considered as default - grade during year 2010 (bad firms) if in that year the Central Credit Register of the Bank of Italy reports the existence of credit overdue for more than three months[6] (Muscettola & Pietrovito, 2012b) like the standardised definition formulated by the Basel Committee. Those firms have initiated bankruptcy proceedings, have a serious negative act report (judicial or legal mortgage ...) or have a credit overdue. In other words, a firm is defined insolvent exclusively via objective sources.

Table 2: Summary statistics

		Quartile 1	Median	Mean	Quartile 3	Standard Deviation
Composition of assets	Total fixed assets / Total assets %	8,18	18,71	23,58	34,13	19,43
	Inventory / Total assets %	5,31	16,54	20,20	29,92	18,07
	Trade receivables / Total assets %	25,60	41,21	42,02	57,73	22,31
	Intangible fixed assets / Total assets %	0,14	0,68	2,64	2,54	5,16
Capital structure	Long term liabilities/ Total assets %	0,00	4,16	8,83	13,57	12,04
	Borrowings / Total assets %	5,17	21,48	23,16	37,42	18,98
	Trade payables / Total assets %	20,44	32,82	34,94	47,12	19,55
	Leverage	-0,08	0,78	2,00	2,55	4,96
Liquidity	Quick ratio %	65,38	89,30	101,20	117,07	64,20
	Long term debts and equity/Fixed assets %	106,82	179,81	449,44	379,70	920,49
	Current ratio %	102,78	120,40	140,04	152,30	72,37
	Net working capital / Total investment %	0,80	13,39	16,33	29,49	26,12
Debt coverage	Interest expense / Total debt %	0,95	1,96	2,16	3,01	1,57
	Total debt / Sales %	32,23	47,43	59,00	67,59	54,37
	Current liabilities / Total debt %	80,91	94,16	87,70	100,00	16,03
	Interest expense / Sales %	0,33	0,88	1,32	1,72	1,57
Turnover	Account receivable turnover	2,45	3,30	11,78	5,57	42,38
	Investment turnover	1,06	1,44	1,74	2,03	1,14
	Trade payables turnover	1,56	2,41	7,77	4,05	36,98
	Fixed assets turnover	4,34	12,34	28,24	27,71	60,67
Net profitability	Operating cash flow/Current liabilities %	2,78	6,68	12,40	14,95	18,25
	Operating cash flow coverage %	1,06	3,00	67,60	10,40	303,97
	Operating cash flow / Sales %	1,15	2,80	4,22	5,73	5,58
	Roe %	0,70	6,06	7,04	17,26	36,70
Operating profitability	Operating profit / Sales %	1,54	3,30	4,31	6,03	6,33
	Ebitda / Interest expense %	2,58	5,43	223,65	16,07	1.302,99
	Ebit / Total liabilities %	3,32	6,38	10,29	12,71	14,16
	Ebitda / Net financial position %	-0,25	0,18	-0,37	0,45	5,54
Efficiency	Roi %	2,84	5,29	7,29	9,59	9,35
	Net working capital / Sales %	0,42	7,37	10,13	19,09	21,86
	Total shareholders' equity / Sales %	5,21	12,43	21,80	26,37	29,89
	Gearing	0,08	0,54	0,39	0,78	1,19

The financial ratios, which formed the explanatory variables of model, were determined by yearly statements belonging to 9,390 unique firms from 2007 to 2010, as mentioned

[6]This definition is narrower than the one generally applied in bank rating models, as these consider default to be the onset of serious financial distress which borrowers cannot solve if unaided, and through which the credit and loans granted may be lost.

above.
Before we start describing the impact of specific ratio on rating scale, however, it is necessary to highlight the heterogeneity of the sample used and the linearity of trend variables.
For a better view of the trends we have selected 4 accounting ratios for each type of variable. At the end the indices used were 32 representing 8 different dimensions: Composition of assets, Capital structure, Liquidity, Debt coverage, Turnover, Net profitability, Operating profitability and Efficiency.
Table 2 reports summary statistics. It shows the distribution of the average values, median, standard deviation and first and third quartile for each ratio that formed the list of explanatory variables of the study.

3 Scoring Model

The explanatory variables designated were combined together in order to achieve a model that is statistically significant. The model has the higher discriminating power according to the dealings of model validation measured by the accuracy ratio and, although a smaller time-frame would be more suitable[7], it predicts principally a default likelihood over a time horizon of three years following the prevision. To calculate the relation beetwen variables and default and to prove the hypothesis of this paper, in this research, consistent with other recent academic examinations, we utilize logistic regression with a variable-reduction process known as “forward stepwise”[8]. In this way the model allows a totality use of 32 variables starting from the indicator which can reveal the most predictive power.
The logistic regression consents to approximate a default probability instead of a credit score with an easier statement of the rating scales. On the other side, however, the logistic method has a substantial difficulty: the logistic distribution function does not expose the relationship of cause – effect among the explanatory variables and risk of default.
For this reason, the present study aims to clarify the explanatory power of each variable within each rating class constructed through logistic regression model.
The results of the logistic regression through the forward stepwise procedure are descripeted in belove table.

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[7]The effective accuracy of the model estimation increases as rapidly as the horizon of the analysis is shortened and it is also clear that the estimated coefficients of the logistic regression change markedly when the timeframe is lengthened.
[8]In this procedure, each of the 32 variables (financial ratios) is tried, one at a time, and 32 one-variable regression models are produced. The sequence is repeated until no new indicator makes any considerable contribution to the model.

Table 3: Stepwise logistic regression - Functions calculated on firms in 2008 - Event: default during 2010.

	β	***S.E.***	***Wald***	***Exp(β)***
Total fixed assets / Total asset	-0,01041	0,00444	5,48819	0,98964
Intangible fixed assets / Total assets	0,03396	0,00802	17,92895	1,03454
Borrowings / Total assets	0,01000	0,00337	8,80799	1,01005
Quick ratio	-0,00401	0,00189	4,51863	0,99600
Net working capital / Total investment	-0,03320	0,00588	31,85112	0,96735
Interest expense / Total debt	0,21468	0,04513	22,62762	1,23947
Interest expense / Sales	0,19411	0,04487	18,71316	1,21423
Investment turnover	-0,40928	0,10173	16,18754	0,66413
Fixed assets turnover	-0,00470	0,00135	12,06515	0,99531
Operating cash flow / Sales	0,03563	0,01224	8,47866	1,03628
Ebitda / Total investment	-0,05886	0,01326	19,71408	0,94284
Net working capital / Sales	0,01334	0,00434	9,43486	1,01343
Constant	-3,89278	0,29352	175,88962	0,02039

4 Results and Model Validation

To test the performance measures of model accuracy in this research it is used a method based on error matrix. This is a tool for evaluating a model’s aptitude to correctly ex-post rank the default risk, in order to even confirm the predictive performance of the prototype per se.

In this study the contingency table is the percentage of firms correctly classified. The error matrix gives a sense of the classification accuracy and what type of misclassification is more frequent. From the error matrix and error rates in table 4 it is absolutely visible the strong accuracy of the model.

Table 4: Error matrix

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Estimated</td></tr>
<tr><td>Good firms</td><td>Bad firms</td></tr>
<tr><td rowspan="2">Observed</td><td>Good firms</td><td>True good
78,27 %</td><td>Type II error
False default
21,73 %</td></tr>
<tr><td>Bad firms</td><td>Type I error
False good
29,82 %</td><td>True default
70,18 %</td></tr>
<tr><td colspan="3">Accuracy</td><td>77,95</td></tr>
</table>

The construction of the rating scale is a consequence of the logistic function mentioned in previous paragraph. Given the values for a set of predictors like the coefficients of regression, it is possible to foresee the probability that each observation may belong to a class of rating. Through a binary reaction, the logit model defines the division of the analysis sample into ten evenly numerous classes. Rating scale is composed by ten classes from 1 to 10, where 1 is best and 10 is worst, and each number corresponds to an increment of 10 percentage points[9].

In order to determine the position of the cut-off value between each class, in this paper is accustomed the technique of the median (Muscettola & Gallo, 2008)[10]. Table 5 specifies the frequency of 322 cases of insolvent firms within the ten classes of rating. It is easily seen that most of the defaults were judged already at high risk three years before the event.

Table 5: Distribution of cases of bankruptcy within the rating classes

Rating classes	**Insolvent firms**	**Frequency on total defaults**	**Frequency on population of each class**
1	1	0.31	0.11
2	7	2.17	0.75
3	5	1.55	0.53
4	9	2.80	0.96
5	19	5.90	2.02
6	12	3.73	1.28
7	20	6.21	2.13
8	42	13.04	4.47
9	70	21.74	7.45
10	137	42.55	14.59

Using the probability of default there are 137 cases found in the worst class of rating. The performance of the model calibrated to the logistic regression is optimal in order to mark the insolvent firms. One sole bad firm has been incorrectly classified into the first class of ranking and over 77% of the subset has got the lowest rating (within worst three classes of rating). In the third column there is the default frequency estimated for each class, dividing the number of default observations by the total number of observations for each rating class.

These default frequencies denote the probability of default valuations of the statistical rating model for each rating class. The frequencies in third column can be understood as an estimate to the long-run averages of three-years approximated default rates for the companies in each rating class.

The following table 6 sets out the average data for the accounting ratios used in this exploration by identifying the analysis sample by status: good firm or insolvent firm.

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[9]There is a 10% probability that each observation may belong to each of the ten ordinal classes.

[10]Cut-off value for a two-class instance is 0.5. This is done by setting a cut-off value, so that remarks with probabilities above the mean of the specific decile can be branded as belonging to upper cluster, and moreover explanations with probabilities below this mean are categorized as belonging to lower class.

Table 6: Averages of financial data by status of firms after three year.

	Accounting ratios	Means	
		Insolvent firms	Good firms
Composition of assets	Total fixed assets / Total assets %	27,46	23,44
	Inventory / Total assets %	25,40	20,01
	Trade receivables / Total assets %	36,72	42,21
	Intangible fixed assets / Total assets %	4,12	2,59
Capital structure	Long term liabilities/ Total assets %	13,66	8,65
	Borrowings / Total assets %	36,95	22,67
	Trade payables / Total assets %	32,05	35,04
	Leverage	4,61	1,91
Liquidity	Quick ratio %	73,59	102,18
	L.T. debts and equity / Fixed assets %	289,47	455,12
	Current ratio %	118,07	140,82
	Net working capital / Total investment	5,92	16,70
Debt coverage	Interest expense / Total debt %	3,25	2,12
	Total debt / Sales %	86,49	58,03
	Current liabilities / Total debt %	82,81	87,87
	Interest expense / Sales %	2,61	1,27
Turnover	Account receivable turnover	11,11	11,80
	Investment turnover	1,38	1,75
	Trade payables turnover	7,49	7,78
	Fixed assets turnover	39,14	27,85
Net profitability	Operating cash flow / Current liabilities %	7,29	12,58
	Operating cash flow coverage %	2,35	69,92
	Operating cash flow / Sales %	3,51	4,24
	Roe %	-0,02	7,29
Operating profitability	Operating profit / Sales %	4,12	4,32
	Ebitda / Interest expense %	4,24	231,44
	Ebit / Total liabilities %	5,46	10,46
	Ebitda / Net financial position %	0,11	-0,39
Efficiency	Roi %	4,50	7,39
	Net working capital / Sales %	5,42	10,29
	Total shareholders' equity / Sales %	19,20	21,89
	Gearing	0,69	0,38

Results of means are consistent with the literature on the statistical significance of accounting ratios (Muscettola & Pietrovito, 2012b). Using the univariate analysis, through the study of difference of means, it is possible to select the most intuitive and powerful variables (Fernandes, 2005). The groups of variables that – taken individually – are able to better discriminate the sample of good firms from the ones that will become insolvent after three years are the capital structure ratios and the debt coverage ratios. The difference between the means of the two sub-samples, presented in Table 6, is objectively

manifest even three years before the corporate crisis.
In order to better observe the relative detachments between the means of the two samples, the analysis of standardized averages defined below is used.
The diagrammes below (*Figure 1 and Figure 2*) visibly show how the standardised variables referred to insolvent firms are detached from the averages of good firms.

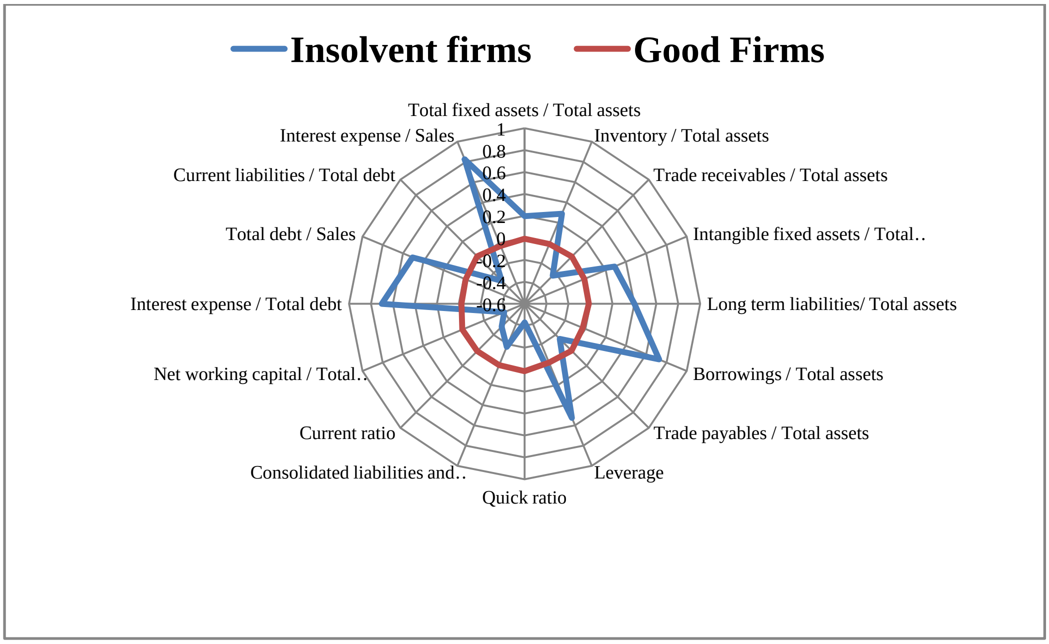

Figure 1: Trend of averages of accounting ratios.

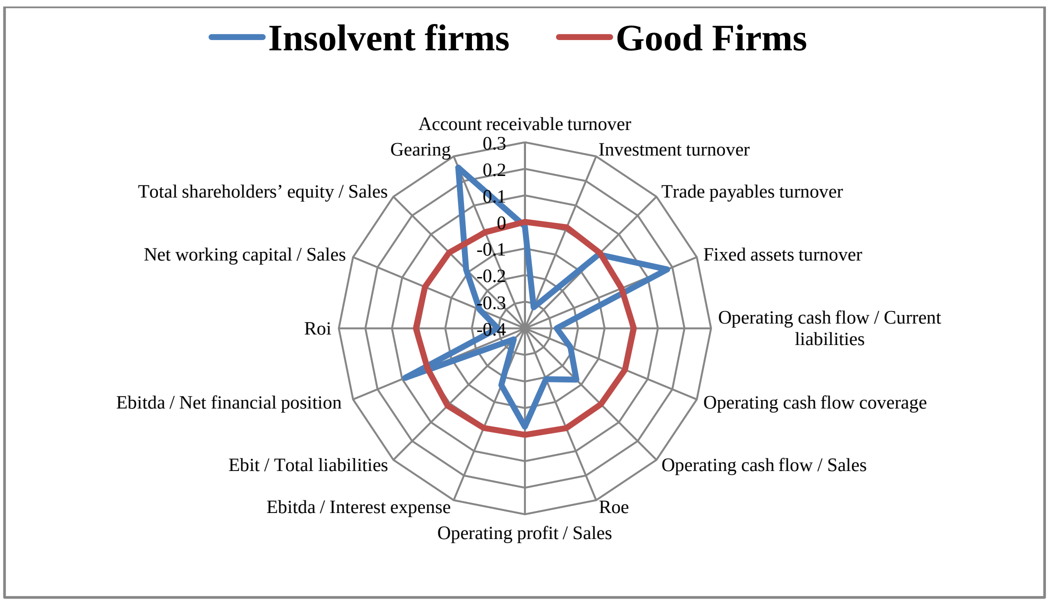

Figure 2: Trend of averages of accounting ratios.

Standard scores[11] allow to analyze ratios, taken from different assessments and referred to the different area sectors, and to compare they on a common scale. This research uses as a descriptive analysis the standardized averages aiming to compare the distributions of the insolvent firms and good firms of the sample. With this intention it is easier to get a quick glance towards the distinctiveness of firms in a unique chart like figure 1 and figure 2.

5 Most Predictive Variables

The scoring output offers a quantitative calculation of the creditworthiness of each firm. What is interesting in this step is to test the predictive power of each accounting ratio given that the rating model has a time horizon of three years and considering that it is functioning, as seen in the previous section about the model validation.

Next table 7 labels the averages of each indicator for each rating class population. This will make it possible to establish the performance of the means at different risk classes. In other words, the table explains how vary the accounting ratio when the risk of insolvency increases.

Looking carefully at the table you can make interesting thoughts on the matter. To make more readable the prospectus, cells in which the average of the population present in the specific rating class had a worse value than the average of the insolvent firms were stained grey. On the other side, cells that contain a value that is placed in an intermediate way between the average of the good firms and the average of insolvent firms were stained orange. Finally cells relative to values better than the averages of healthy companies, for each specific ratio, remain white.

First, it is possible to judge not able to discriminate the sample firms that become insolvent those ratios that have several orange cells. In this sense it is possible to attribute to these indicators a wide "gray zone" in which coexist insolvent firms and healthy firms without a clear distinction. The averages overlap especially as regards profitability ratios such as, for example, “Ebitda / Interest Expense”, “Ebitda / Net financial position” or “Operating cash flow coverage”. Even accounting ratios which form part of the indices of liquidity and efficiency have a large number of white cells, confirming that also on these indicators there is an excessive proportion of the population that are not perfectly distinguishable. In this regard we note the “Net working capital / Total investments” and “ROI”.

[11]This transformation process is named standardizing or normalizing of average. With such modeling technique each raw score (original datum that has not been converted) may be given an equivalent “z-score”. In statistics, the standard score is the number of standard deviations a datum is above the mean. A score that is exactly on the mean of polulation corresponds to a z of 0. Positive scores are above average, and negative scores are below average. Mathematically, a standard score is dimensionless quantity achieved by subtracting the whole sample mean from an individual raw score and then dividing the difference by the whole sample standard deviation. Explicitly it is a consequential point that expresses how far a raw score is from some reference point such as the mean in terms of standard deviation units.

Table 7: Averages matrix with the class boundaries determined by the logistic regression methodology

Accounting ratios	Rating scales									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Total fixed assets / Total assets	18.11	20.70	21.40	22.99	21.92	23.02	24.50	25.35	28.04	29.71
Inventory / Total assets	11.16	14.12	15.19	17.35	19.47	21.76	23.47	24.52	26.17	28.78
Trade receivables/Total assets	38.80	44.69	46.76	46.29	46.67	44.53	42.83	41.10	36.91	31.66
Intangible fixed assets / Total ass.	1.46	1.70	1.94	2.18	2.07	2.66	2.74	2.81	3.56	5.27
Long term liabilities/ Total assets	2.77	4.26	5.56	6.77	7.98	8.83	10.08	12.76	14.04	15.21
Borrowings/Total assets	2.74	6.88	11.49	16.23	20.99	25.73	29.95	35.38	39.26	42.95
Trade payables / Total assets	27.48	35.69	37.93	37.85	38.95	38,.8	36.74	34.24	32.46	29.46
Leverage	-0.99	-0.46	0.13	0.56	1.33	2.24	3.08	3.66	4.83	5.61
Quick ratio	1.2	136	118	102	93.36	84.96	77.55	75.93	68.14	61.70
LT debts and equity / Fixed ass.	1.044	637	491	464	392	353	271	314	225	297
Current ratio	230	172	152	137	129	123	116	116	111	110
Net working capital / Total inv.	50.63	30.34	21.96	16.19	13.69	10.18	7.53	7.14	3.84	1.80
Interest expense/Total debt	0.70	1.04	1.39	1.69	1.97	2.14	2.51	2.85	3.27	3.99
Total debt / Sales	33.04	37.79	42.59	47.80	50.87	58.38	63.53	69.12	80.37	106
Current liabilities/Total debt	94.80	92.42	90.66	89.19	88.36	87.69	86.46	83.38	82.42	81.59
Interest expense / Sales	0.24	0.36	0.57	0.76	0.94	1.12	1.47	1.84	2.36	3.53
Account receivable turnover	20.47	9.87	9.82	10.58	10.43	10.82	9.17	9.53	10.33	16.76
Investment turnover	2.38	2.09	1.99	1.87	1.84	1.66	1.58	1.48	1.34	1.16
Trade payables turnover	13.74	6.49	6.76	6.57	8.35	4.18	6.19	6.52	7.52	11.35
Fixed assets turnover	24.69	21.92	22.32	25.24	22.62	24.18	26.29	30.30	35.49	49.34
Operating cash flow/ Current liab	31.13	20.32	15.23	13.07	10.14	8.35	7.41	6.96	5.79	5.59
Operating cash flow coverage	394	136	63.56	29.14	17.21	12.15	10.51	2.96	1.76	7.25
Operating cash flow/ Sales	7.01	5.69	4.63	4.42	3.78	3.42	3.30	3.26	3.10	3.54
Roe	16.72	13.73	9.68	9.35	9.69	5.34	4.77	3.89	-0.66	-2.10
Operating profit / Sales	7.41	5.79	4.39	4.16	3.78	3.20	3.48	3.32	3.50	4.08
Ebitda / Interest expense	1.443	398	177	79.14	38.10	35.82	30.95	5.62	3.57	24.04
Ebit / Total liabilities	26.14	17.84	12.63	10.28	8.51	6.49	6.31	5.33	4.99	4.39
Ebitda / Net financial position	-1.58	-1.90	-0.34	-0.14	-0.18	0.15	0.09	0.08	0.07	0.02
Roi	17.02	11.26	8.22	7.18	6.25	5.12	5.12	4.60	4.22	3.93
Net Working capital/ Sales	26.42	18.21	13.89	10.37	9.49	7.43	5.17	5.53	3.34	1.39
Total stakeholders' equity / Sales	38.52	28.43	23.93	22.33	18.79	17.64	16.81	16.42	15.98	19.17
Gearing	-0.13	-0.07	0.14	0.32	0.40	0.50	0.60	0.65	0.73	0.76

Turnover ratios have the problem of having the means of the two groups of firms too close. This gear generates, especially, a phenomenon in which the average of the bad

firms has mesh too loose. Deepening the analysis, in fact, we note that “accounting receivables turnover” and “trade payables turnover” have most of rating classes marked with an average worse than the average of the insolvent firms even if the bad firms are only 322 and each class contains 939 firms.
Likewise “Operating profit / Sales”, “Total shareholder’s equity/Sales” and “Current ratio” have a too high frequency of cases in which, into a rating class, the average is worse than the average of insolvent firms.
Another problem that is described in the table is the not linearity of the distribution of the averages within the rating categories. An irregular trend, in fact, is reflected, in addition to the indices of rotation, also for “Trade receivables/Total assets” and for “Trade payables/Total assets” confirming that the indices of the cash conversion cycle have a slight power to predict the corporate crisis (Muscettola, 2014b).
On the contrary, among the most predictive indicators there are certainly the explanatory variables that haven’t the defects mentioned above. These indicators have regular distributions, but do not show too many orange or grey cells. With the exception of the excellent performance of “Fixed assets turnover”, the lower numbers of stained cells are attributed to composition of assets ratios, capital structure ratios and debt coverage ratios, whereas the largest number is assigned to the group of ratios of operating profit.
Besides the aforementioned accounting ratio "fixed assets turnover" are characterized by having very good performance and, therefore, a reasonable predictive power, “Total fixed assets / Total assets”, “Long term liabilities/ Total assets” and “Interest expense/Sales”. They can also be used alone and still get a high level of accuracy in separating the two samples of companies.

6 Conclusions

In summary, this empirical research extends prior studies through a predictive model of business failure, via logit analysis, using a recent large sample of Italian SMEs that went bankrupt after three years and it is an attempt to extend the analysis of the links between rating class and the discriminating power of accounting ratios. Therefore, the research develops a corporate failure prediction models using a parsimonious logit model with 32 financial ratios. The explanatory variables were subsequently used to build an alternative model using the specific averages of each accounting ratio in order to explore the incremental information content of individual ratios in predicting the probability of business failure.
The results delineated in this paper contribute to the existing literature substantially in two ways. First, the investigation has shown that the business failure can be forecast on the basis of some accounting ratios, even if it is made with an anticipated period of three years. The logit model achieved overall a good correct classification. Second, the obtained results displayed the statistical significance of debt coverage ratios, capital structure ratios and composition of assets ratios. Relatively to individual indicators, specifically, above all were classified as best indicators to predict the bankruptcy “Interest expense / Sales” and “Fixed assets turnover”, also present in the regression function. A good predictive ability is also attributed to the ratios “Total fixed assets / Total Assets”, “Intangible assets / Total assets”, “Borrowings / Total assets”, Interest expense / Total debt” and “Investment turnover”. They all also present in the logit model. Despite having the average of the explanatory variables significantly separated among groups, statistically poorly predictive

are the ratios about “Efficiency”, “Net profitability” and, above all and contrary to prior studies, “operating profitability”.

For all matters shown, in this particular economic downturn, it is good not only focus attention on aspects of profitability of firms which, as we have seen, lead to a large number of misclassifications. On the other hand it is advisable to overestimate the structural and financial ratios such as debt coverage ratios and, in general, the capital structure of firms that always manage to be excellent for bankruptcy prediction. Hence, results suggest furthermore that Italian firms that became insolvents after three year, on average, are characterized by heavily rely on external debt.

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