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Critical Perspectives on Bankruptcy Prediction Models: an Alternative Approach.

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Critical Perspectives on Bankruptcy Prediction Models: an Alternative Approach♦

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Abstract

Understanding in time premonitory signals of a distress situation and taking actions to get out of these situations are financial management primary targets. Numerous contributions in accounting and finance have presented a plethora of studies about the Bankruptcy Prediction Models (BPMs) based on a statistical approach especially discriminant analysis, logit and probit techniques. The main issue sometimes seems to be that statistically meaning variables are not so meaningful in accounting.

The aim of this paper is to propose an BPM based on an alternative statistical approach to the discriminant analysis techniques. A specific model, based on accounting data, is developed to analyze the economic and financial conditions of the firms, using a new method called *Maps Positioning Approach* (MPA). The business distress is studied through financial ratios and through subsequent analysis of their statistical distributions. Two fundamental dimensions are taken into consideration: the economic one (like profitability and growth) and the financial one (liability, capital structure, liquidity).

The use of these two dimensions allows to develop a graphical positioning system in which it is possible to appreciate the situation of each firm considered and their economic and financial condition, in order to evaluate the changes in the financial risk and default likelihood. Moreover, trough MPA the effectiveness of accounting ratios to predict bankruptcy is compared.

Keywords: accounting data, financial ratios, bankruptcy prediction, positioning maps
JEL Classification: G43, M41

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1. - Introduction

Understanding in time premonitory signals of a distress situation and taking actions to get out of these situations are financial management primary targets and in this perspective scholars and practitioners have contributed with the definition of a plurality of bankruptcy prediction models (BPMs). These approaches incorporate several disciplines ranging from accounting (Beaver, 1966; 1968), to statistics (Goudie, 1987), to finance (Altman, 1968; 1983; 2000) and to banking management (Meyer-Pifer, 1970). These models are used in order to give a rating to the companies, to lend funds, to manage investor relationship activities.

The importance of BPMs was recently recalled in the content of the new Basel 2 agreements which, among numerous initiatives, turn greater attention to one more analytic determination of the default risk and its relative probability (Basel Commission on Banking Supervision, 2004, pp 15-112). This happened also through BPMs and the rating systems developed inside the credit institutions. Such a possibility represents therefore an important opportunity for scholars and practitioners, in order to elaborate approaches towards the local business, developing a series of *ad hoc* models accordingly to the different characteristics of the bank customers.

The aim of this paper is to propose a BPM based on an alternative statistical approach to the discriminant analysis techniques. In particular, using the accounting data and the financial ratios, a specific model is developed to analyze the economic and financial conditions of the firms studied. According to Mar Molinero and Serrano Cinca (2001) the approach here described consists in a graphical representation using positioning maps, although with a different statistical path to the multidimensional scaling (MDS). I called this method *Maps Positioning Approach* (MPA).

The use of maps has the further advantage that the results of the analysis can be graphically presented which have intuitive interpretation. Implementation does not make any sophisticated statistical background or hypothesis. What MPA offers is a different paradigm, a different way to look at the problem. The power of MPA lies in its accessibility. The results of MPA analysis can be interpreted without a deep understanding of the statistical underlying principles

The remainder of this paper is arranged as follows. In Section 2 I do a quick BPMs literature review, in Section 3 the MPA and the research hypothesis are explained. In Section 4 the MPA results are presented and discussed, while in Section 5 the main conclusions and future research agenda are exposed.

2. - Literature review

In the 1930s, 1940s and 1950s numerous contributions in accounting and finance have presented a plethora of studies about the BPMs based on a statistical approach (especially univariate and descriptive methods). These studies do not have predictive objectives; they want to identify a difference between "healthy" firms ratios (non bankrupt) and "anomalous" firms ratios (bankrupt). The main hypothesis of these studies is that you can research and see the preliminary aspects of an insolvency condition in the dynamics of ratios, through a financial statement analysis. Among the most famous works in this field the studies of Smith (1930), Fitz Patrik (1932), Ramser-Foster (1931), Merwin (1942), can be quoted, and, finally, Beaver's empirical study (1966), in which he shows evidence that healthy firms ratios and anomalous firms ratios were strongly different in the previous five years to the bankruptcy events. Moreover, this difference increases approaching the bankruptcy period.

From 1968, BPMs studies showed a notable evolution in terms of research methodology and scientific severity after the Altman's empirical researches (1968). The author uses, for the first time in accounting, the discriminant analysis technique applied to financial ratios implementing a scoring system to discriminate healthy firms from anomalous firms through a statistical function[1]. The Altman's model represents a milestone in BPMs researches and it is used nowadays by banks, firms and rating agencies, although probably with too confidence.

After 1968, the BPMs studies and researches developed in Altman's same direction, using the discriminant analysis technique. Some studies wanted to verify, improve and comment Altman's results (Deakin 1972, 1977; Edmister 1972; Blum, 1974) using a sophisticate approach and very analytical models (Elam, 1975; Libby, 1975; Altman-Haldeman-Narajanan, 1977; Taffler, 1982; Lincoln 1984)[2].

At the same time a new tendency of studies born in the international context, proposed non-parametric models, based on the causes analysis and on the symptoms explanation of the insolvency (Argenti, 1976). Argenti suggested the calculation of an indicator which summarizes a series of symptoms, mistakes and deficiencies in the firm under observation.

Other studies developed the Recursive Partitioning Algorithm (Frydman-Altman-Kao, 1985), the Neural Networks and the Genetic Algorithms methodology (Altman-Marco-Varetto, 1994).

During the 1970s and the 1980s there was a great debate about empirical financial research and bankruptcy prediction in terms of methodology (Joy-Tollefson, 1975; Eisembeis, 1977; Ball-Foster, 1982; Zmijewsky, 1984), financial ratios theories (Gordon, 1971; Wilcox, 1971) and results validity (Jhonson, 1970). A plethora of studies, contributes and comments was proposed in this two decades (Wilcox, 1973; Dambolena-Khoury, 1980; Ohlson, 1980; Houghton, 1984; Lau 1987). In the 1990s, instead, the main issues were focalised on the non-parametric approaches like Neural Networks and Genetic Algorithms[3].

In Italy the first study about BPMs was done by Alberici (1975) who applied the discriminant analysis technique corroborating Altman's and Beaver's same results for the Italian firms. However, the Alberici's model does not have a previsional validity because it has not been verified on a specific sample. Further Italian researches were produced by Appetiti (1984), Cascioli-Provasoli (1986), De Laurentis (1986), Forestieri (1986), Mantoan-Mantovan (1987), Falbo (1991), Barontini (2000), who developed a series of models accompanied by numerous empirical surveys using a prevalent statistical approach (discriminant analysis, logit analysis, principal components analysis, etc.)[4].

The main issue that has motivated this paper is that these models (Italian and foreign) are often built with a strong mathematical severity but sometimes statistically meaning variables are not so meaningful in accounting. In fact, a part of the accounting doctrine in Italy have studied the BPMs with a non statistical approach implementing conceptual framework based not only on the financial ratios analysis and their validity in a forecast way, but also on the qualitative aspects like environmental dynamics, strategic situations and business compositions. In this view the works of Brunetti-Coda-Bergamin Barbato (1974), Coda (1975; 1990), Cattaneo (1976), Cappelletto (1983), Gabrovec Mei (1984), Guatri (1986), Previti Flesca (1986), Brunetti-Coda-Favotto (1990) can be quoted.

3. - The Model: hypothesis and construction

The main objective of this research is to identify a specific set of ratios (brief but exhaustive) in term of profitability and financial structure and to find an opportune procedure of analyses able to completely expose the conditions of the analysed enterprises.

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[1] See Altman [1968, p. 590-598].
[2] For a description of these studies see Altman [1983, pp. 99-173], Comuzzi [1995, chapter 3].
[3] See Dimitras *et al*. [1996, pp. 506-509],. Varetto [1999, pp. 247-280].
[4] See Varetto [1999].

The research project presented here is a BPM based on a statistical approach as an alternative to the discriminant analysis techniques. The model has been estimated to a sample of 66 small local firms, mainly located in the province of Forlì-Cesena (Italy) and operating in the mechanical industry[5]. Specifically, in order to create the sample, it has been focused on two groups of firms:

- the first one is the "healthy" one (without any relevant problem, no bankrupt at the date of data collection, April 2004);
- the second one is the "anomalous" one (which will result bankrupt in the year 2000). The characteristic of "anomalous firm" was identified in the bankruptcy declaration.

Figure 1. – The economic and the financial conditions of the estimation sample (1998)

		Sales (in thousand)	Asset (in thousand)	Employees	ROI	S/TA	D/TA	D/S	IP/S	QR	SH
NB	*average*	€ 6.862	€ 6.073	44	9,9%	1,46	79%	0,61	2,6%	0,93	2,67
	median	€ 3.868	€ 2.884	28	8,3%	1,31	82%	0,62	2,2%	0,74	1,46
B	*average*	€ 4.610	€ 5.853	44	3,8%	0,84	88%	1,23	5,3%	0,63	1,11
	median	€ 3.226	€ 5.745	47	4,6%	0,78	90%	1,10	5,2%	0,55	0,82

NB	Non bankrupt firms
B	Bankrupt firms
ROI	Return on investment (EBIT[6]/ Total Assets)
S/TA	Turnover (Sales / Total assest)
D/TA	Debt ratio (Total Debt / Total Assets)
D/S	Debt intensity (Total Debt / Sales)
IP/S	Interest payments / Sales
QR	Quick Ratio (Current Assets - Inventory / Current Liabilities)
SH	Structural Hedge (Equity + Long term Debt – Fixed Assets)

The sample was composed of 49 healthy firms and 17 anomalous firms[7]. The two groups of firms have shown homogeneous features in terms of sales (revenues), capital and employees (see figure 1). At the same time, you can see relevant differences between the healthy firms (non bankrupt) and the anomalous firms (bankrupt) in the profitability ratios and in the financial structure indicators.

In order to carry out appraisals of the economic and financial situation of the firms, comparisons to the other members of the industry in which the firm operate should be completed. This because financial ratios are not totally meaningful if extirpated from the external context. The economic and financial problems that are reflected on the value of the ratios will be therefore visible also in their distribution of frequency. For instance, the firms with low profitability performances or patrimonial

[5] The data collection was done using the financial database AIDA™, powered by Bureau Vandjik. The research criteria were as follows:
- sampling joint stock companies and unlimited joint stock companies;
- located in the province of Forlì-Cesena (Italy);
- operating in the mechanical industry (ISTAT code definition);
- born before 1/1/1997.

[6] Earnings before interests and taxes.

[7] Pairing criteria were not realized between the two groups of firms. The sampling has been effectuated in this way:
- sampling of healthy firms;
- sampling of anomalous firms (control sample).

imbalances will show financial ratios smaller (with inferior value) than the other firms in the sample (e.g. best performer). Therefore these ratios will be placed in the inferior-quantils of their frequency distribution. On the contrary, the ratios of companies in good economic and patrimonial conditions will be placed in the superior quantils.

Consequently, reasoning in these terms, the values of bankrupt firms ratios compared with those of the non bankrupt firms, should rank, for the greater part, in the inferior-quantils of their distribution. These working hypotheses involve to the development of a scoring model based on a system of comparison between company and reference group, through a graphical analysis of positioning.

Having to estimate and to reduce the business complexity to a limited number of ratios I chose to consider the firm structure in its two fundamental dimensions: the economic one and the financial one. Therefore, the state of distress is not only appreciated by reference to the debt level but also considering profitability, growth, and cash flow ratios.

During the period 1997-2000 a set of financial ratios about all the firms included in the sample was analysed, in order to construct the model. A group of ratios has been selected to briefly but effectively describe the economic and financial condition of the firms through an approach which consists of these criteria:

- *relevance in literature*: many authors have shown that, in the previous years to the bankruptcy events, there are considerable differences between healthy firms ratios and anomalous firms ratios. Moreover, these differences increase approaching the bankruptcy period (Beaver, 1966, pp. 81-83). Literature review has indicated the more efficient ratios in several categories like profitability (Dambolena-Khoury, 1980, p. 1025), liquidity, cash flow (Casey-Bartczak, 1985; Gentry *et al*., 1985), and indebtedness (Alberici, 1975, p. 99 and fw.; Altman 1983 pp 109-110; Beaver, 1968, p. 121; Barontini, 2000, pp. 78-94).
- *No redundancy*: many ratios can be a linear transformation of other ratios. Therefore the model does not consider more ratios for the same phenomena.
- *Policy free financial statements*: the ratios in the model must not be (should not be) biased from windows dressing policy and management discretionality.

After these considerations, the variables of the models were:

a) Cash flow on Sales	= (Net income + Depreciation and Amortization) / Sales.
b) Revenues growth rate	= ($Sales_1 - Sales_0$) / $Sales_0$.
c) Coverage	= (EBITDA[8] / Financial interest).
d) Return on investment (ROI)	= (EBIT / Total assets).
e) ROI growth rate	= ($ROI_1 - ROI_0$) / $\lvert ROI_0 \rvert$.
f) Return on sales (ROS)	= EBIT / Sales.
g) Debt ratio	= Total debt / Total assets.
h) Debt intensity	= (Total debt / Sales.
i) Quick Ratio	= (Current assets - Inventory / Current liabilities).
J) Interests from liability on sales	= Interest payments / Sales.
k) Structural hedge	= (Long terms liability + Equity / Fixed assets).

[8] Earnings before interests, taxes, depreciations and amortizations.

To facilitate the comparison and the time and space investigation the ratios selected have been standardized as follows. Consider an indicator I for which M = max(I), m = min(I). In order to obtain an indicator (I^*) that:

- it assumes pertaining values belonging the range [0,1] in correspondence, respectively, to the min and the max of I;
- it maintains the order of the units determined from I and the relative distance with reference to I;

the following transformation is adopted:

$$I^* = \frac{I - m}{M - m} \tag{1}$$

for directed pointers, the higher is the ratio, the better are the economic and financial conditions of the firm (i.e. profitability), and

$$I^* = 1 - \left[\frac{I - m}{M - m}\right] \tag{2}$$

for inverse pointers, the higher is the ratio, the worse are the economic and financial conditions of the firm (i.e. debt ratio).

Subsequently, I proceeded constructing two distinguished levels of scoring about the economic and the financial dimension. In particular:

1. the first one including profitability, cash flows, coverage and growth ratios (SP, profitability score, with all the I_P standardized ratios);
2. the second one concerning variables of capital structure, liability and liquidity (SD, debt score, with all the I_D standardized ratios).

The analytical formulation is as follows:

$$SP = \sum_{i=1}^{n} I^*_{P_i} \cdot \omega(I^*_{P_i}) \tag{3}$$

$$SD = \sum_{i=1}^{n} I^*_{D_i} \cdot \omega(I^*_{D_i}) \tag{4}$$

where $\omega(I^*)$ is a function of I* that converts (categorizes) variable I* (continuous numeric data) in a discrete number of categories. The procedure creates new variables containing the categorical data.

Data are categorized based on percentile groups, with each group containing approximately the same number of cases. For instance, in this case a specification of 10 groups (deciles) would assign a value of 1 to cases below the 10th percentile, 2 to cases between the 10th and 20th percentile, 3 to cases between the 20th and 30th percentile, 4 to cases between the 30th and 40th percentile, until 10 to cases above the 90th percentile. These values represents the weights apply to the standardize ratios.

The logic of this approach is as follows:
standardized indicators, which assume a value next to 0 (lower performance), will be assess with inferior deciles (i.e. 1, 2 or 3) compared to the respective distribution. Consequently the multiplicative effect will be higher for standardized indicators with values next to 1 (better performance) that will be assess with the upper deciles (i.e. 8, 9 or 10). Basically, this procedure

increase the information of an indicator, stressing the difference between good performance ratios and bad performance ratios.

These two score indicators (standardized as above) were inserted in a system of Cartesian axes and created a position map based on two quantitative dimensions: profitability-growth and financial structure. In SP the ratios from a) to f) have been included (see the previous list in the text) while in SD the remaining indicators have been inserted.

SD and SP intercrossed in the map give a vision of every positioning of a single firm observed regarding the sample, prescinding however from average values. The positioning of the firms derives from the ratios values observed and standardized, using the method explained above.

The graphical presentation of the map identifies a system of scoring in which every firm receives two scores about the economic and the patrimonial-financial situation. The condition of the firms is evaluated using these two dimensions and appreciating the positioning regarding the others.

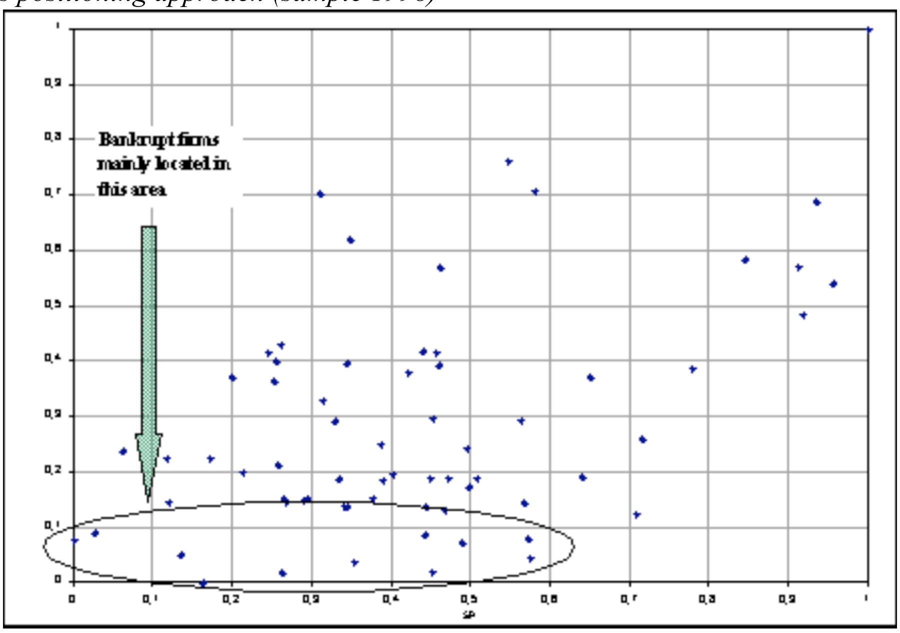
3. – The model: results

The classification model based on positioning maps system has been firstly tested for the year 1998 (two years before the bankruptcy events), then the results and the effectiveness have been tested during the period 1997-2000.

The map in figure 2 was obtained using the SD and SP coordinates for each firms, where each point represents a firm.

The appraisal carried out through the two score indicators has allowed to judge the financial and profitability situations of every single observed firms and therefore their position regarding the reference group. The map analysis has allowed to explain the economic and financial conditions of the firms studied and then the position as to the other firms in the sample. Bankruptcy risk was evaluated through a positioning approach. In fact, a different position in the map involves a different situation in the economic and financial variables and a different default risk.

Figure 2. – Maps positioning approach (sample 1998)



It was observed and verified that the anomalous firms were placed in the lower-left region of the map distinguishing themselves clearly from the healthy for all the years evaluated (1997-2000); vice versa good firms were placed in the upper-right region. A more sophisticated analysis would be to recognize that there is a region of space clearly associated with failure, a region of the space clearly associated with success, and a region of overlap, where anomalous and healthy firms coexist

Analyzing the graphical distribution of healthy and anomalous firms in the map in the two years previous to the failure (1998 and 1999), a threshold was searched which made it possible to classify correctly the two groups of firms (healthy *vs* anomalous) on the assumption of the empirical observations and to delimit a possible “safety zone” and a “distress zone”. Such a value, as a result of computing tests and experiments, has been characterized in which that it is able to maximize the total discriminatory effectiveness of the model (classifying healthy firms as healthy and anomalous firms as anomalous) and consequently minimizing the total allocation error. The analytical procedure is as follows:
let $\alpha(\gamma)$ and $\beta(\gamma)$ denote Type I and Type II error, induced by the choice of a given threshold $\gamma*$, the choice of $\gamma*$ is such that

$$\gamma^* = \arg\min\,[0{,}5\alpha(\gamma) + 0{,}5\beta(\gamma)] \tag{5}$$

The implicit assumption of this procedure is that both errors are equally important. In other words, the Type-I error (classifying a bankrupt firm as a healthy one) and Type II error (classifying a healthy firm as a bankrupt one) should be equal. Instead we now that for a credit institution the costs connected to these two errors are different: it is more onerous to grant a loan to a firm that later will become insolvent, rather than not granting it to one that later it will be discovered to be healthy. Consequently the Type I error is more expensive (and mainly critical) than the Type II error. However, it exists a trade-off between these two errors and it cannot be possible to minimize them both.

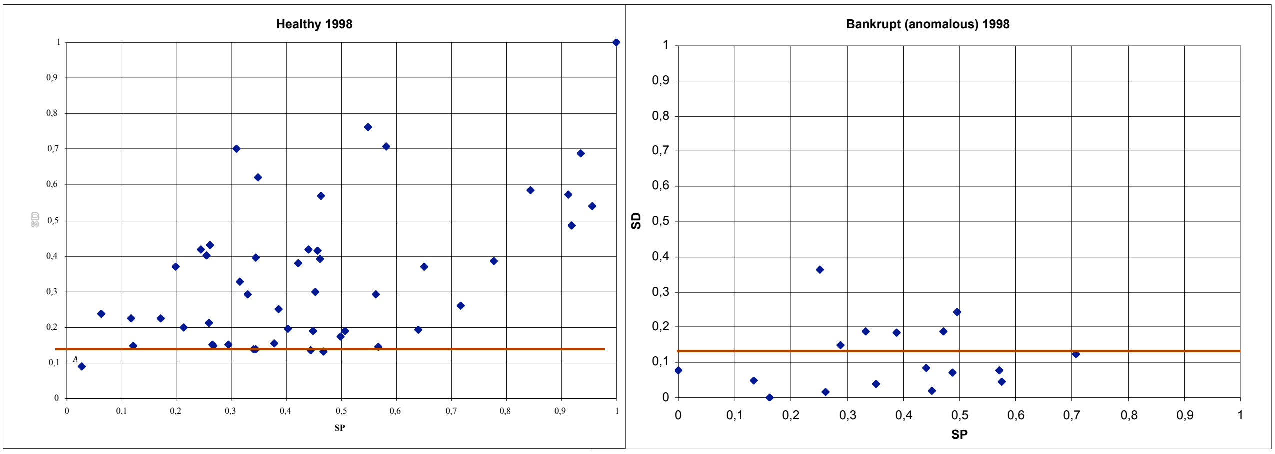
In analytical terms we can modify the previous algorithm as follows:
for any given $\delta \in [0, 1]$, the choice of $\gamma*$ is such that

$$\gamma^* = \arg\min\,[\delta\alpha(\gamma) + (1-\delta)\beta(\gamma)] \tag{6}$$

where δ represents a weight that the researcher can choose on the base on his/her Type I error preferences.

According to the algorithm (5), the threshold on SD axis in 0,131 has been determined. This cutoff maximizes the classification effectiveness and divides the cloud of the pointers in two areas: the higher ones where the healthy firms are placed, the inferior ones where the anomalous firms (bankrupt in 2000) are placed

Figure 3. – Cutoff level on the SD dimension and differences between healthy and anomalous firms (sample, 1998)



About 1998, using this threshold, the model has shown a 89% of total discriminatory effectiveness and a 11% of total error (see figure 4); a much satisfactory result also comparing it with the previous quoted studies. 98% of the healthy companies have been classified in the correct way, while, about the total of the bankrupt firms, the percentage of correct classification came down to 65%. Type-I error was equal to 35%, while Type-II error has shown a 2% value.

Discriminatory effectiveness during 1999, a year before the bankruptcy events, was equal to 89%, showing an identical value to one of the previous period (figure 4). In this case the algorithm has classified correctly 96% of the healthy companies and 71% of the bankrupt ones, consequently modifying the dimension of the Type I and Type II errors (respectively 29% and 4%).

In the year 2000, the bankruptcy period, the classification effectiveness is increased to 91% and the total error is consequently taken down to 9%. All the healthy firms have been classified in the correct mode, while the failed ones have been grouped correctly in 65% of the cases (figure 4). The increase of the discriminatory correctness is expected when we approach to the bankruptcy events.

Observing the diagrams it is shown that approaching the bankruptcy period, the distance (and the performance differences) between the healthy enterprises and the anomalous enterprises increases, and in the year 2000 Type II error was equal to zero. However, an analysis carried out in the moment in which the crisis is already manifest, does not supply important information for the estimation and for the model previsional ability.

Further verifications have been completed for the period 1997, three years before the bankrupt declarations. In this case the healthy firms have been grouped like in 92% of the cases, while the anomalous ones have been grouped in 71%. The total discriminatory effectiveness was equal to 86%, with a total error of 14%. It is clear, therefore, that going away from the date of financial trouble the ratios effectiveness decrease, as widely demonstrated by the studies proposed in literature and previously quoted. However, such a tendency informs to us also about the operation correctness of the implemented classification rule.

The observation of the empirical results using a threshold on SD shows that financial structure ratios are useful to discriminate healthy companies from anomalous ones. This suggests that the SD dimension could be a powerful failure indicator.

Figure 4. – Classification effectiveness using SD cutoff (0,131)

		Model response						Classification effectiveness	Total error
1997		**NB**	**B**	Total		**NB**	**B**		
Sample	**NB**	45	4	49	**NB**	92%	8%	**86%**	**14%**
	B	5	12	17	**B**	29%	71%		
				66					
1998		**NB**	**B**	Total		**NB**	**B**		
Sample	**NB**	48	1	49	**NB**	98%	2%	**89%**	**11%**
	B	6	11	17	**B**	35%	65%		
				66					
1999		**NB**	**B**			**NB**	**B**		
Sample	**NB**	47	2	49	**NB**	96%	4%	**89%**	**11%**
	B	5	12	17	**B**	29%	71%		
				66					
2000		**NB**	**B**			**NB**	**B**		
Sample	**NB**	49	0	49	**NB**	100%	0%	**91%**	**9%**
	B	6	11	17	**B**	35%	65%		
				66					

It is also possible to carry out the same analysis on SP dimension, and then to compare the classification effectiveness results.

Using the algorithm in (5) on SP dimension, I obtained a threshold of 0,02. This threshold maximizes the classification effectiveness using profitability and growth ratios. Now the map appears split trough a vertical line in two areas: the right-hand side one, where the healthy firms are positioned and the left-hand side one where the anomalous firms (bankrupt in 2000) are placed (figure 5).

About 1998, using this threshold, the model has shown a 76% of total discriminatory effectiveness and a 24% of total error (see figure 6); a more less result than using SD threshold. However, in this case 100% of the healthy firms have been classified in the correct way, while, about the total of the bankrupt firms, the percentage of correct classification came down to 6%. Type-I error was equal to 94%, while Type-II error has shown a null value.

Discriminatory effectiveness during 1999 was equal to 76% showing an identical value to one of the previous period (figure 6). In this case the algorithm has classified correctly the same number of firm like in 1998 and consequently also the Type I and Type II error are the same.

In the year 2000 (the bankrupt declaration period) the discriminatory effectiveness is increased to 77% and the total error is consequently taken down to 23%. All the healthy enterprises have been classified in the correct mode, while the failed ones have been grouped correctly in 12% of the cases (figure 6). The little increase of the discriminatory correctness seems to manifest the incorrect prediction ability of SP dimension. Observing the data, in fact, it is shown in some case that approaching the bankruptcy period there was not a relevance difference between healthy and anomalous firms in terms of profitability ratios.

Further verifications have been done for the year 1997. In this case the healthy firms have been grouped like in 98% of the cases, while the anomalous ones have been grouped in 6%. The total discriminatory effectiveness was equal to 74%, with a total error of 26%.

Figure 5. – Cutoff level on the SP dimension and differences between healthy and anomalous firms (sample, 1998)

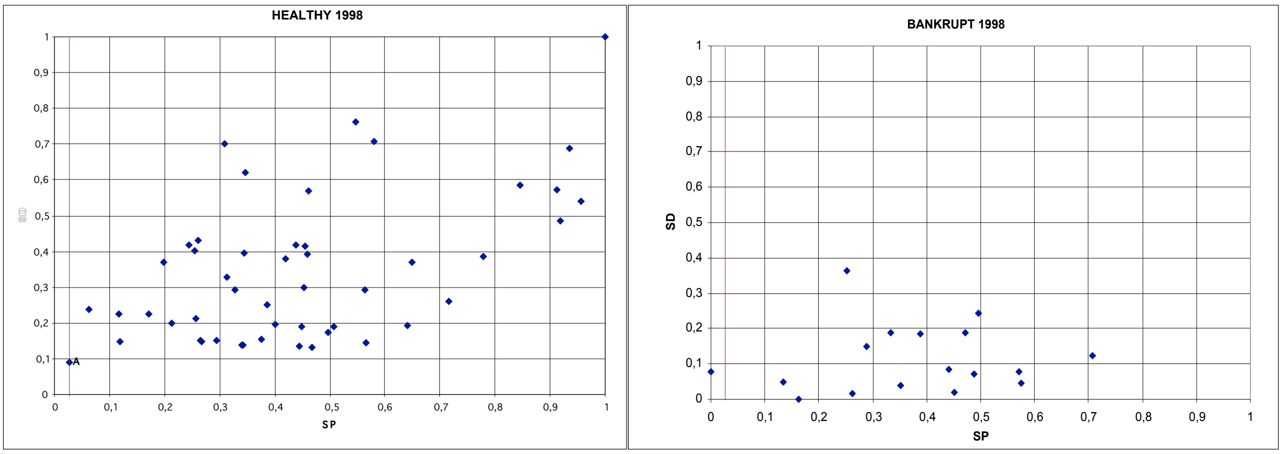


Figure 6. – Classification effectiveness using SP cutoff (0,02)

								Classification effectiveness	Total error
		Model response							
1997		**NB**	**B**	Total		**NB**	**B**		
Sample	**NB**	48	1	49	**NB**	98%	2%	**74%**	**26%**
	B	16	1	17	**B**	94%	6%		
				66					
		Model response							
1998		**NB**	**B**	Total		**NB**	**B**		
Sample	**NB**	49	0	49	**NB**	100%	0%	**76%**	**24%**
	B	16	1	17	**B**	94%	6%		
				66					
		Model response							
1999		**NB**	**B**			**NB**	**B**		
Sample	**NB**	49	0	49	**NB**	100%	0%	**76%**	**24%**
	B	16	1	17	**B**	94%	6%		
				66					
2000		Model response							
Sample		**NB**	**B**			**NB**	**B**		
	NB	49	0	49	**NB**	100%	0%	**77%**	**23%**
	B	15	2	17	**B**	88%	12%		
				66					

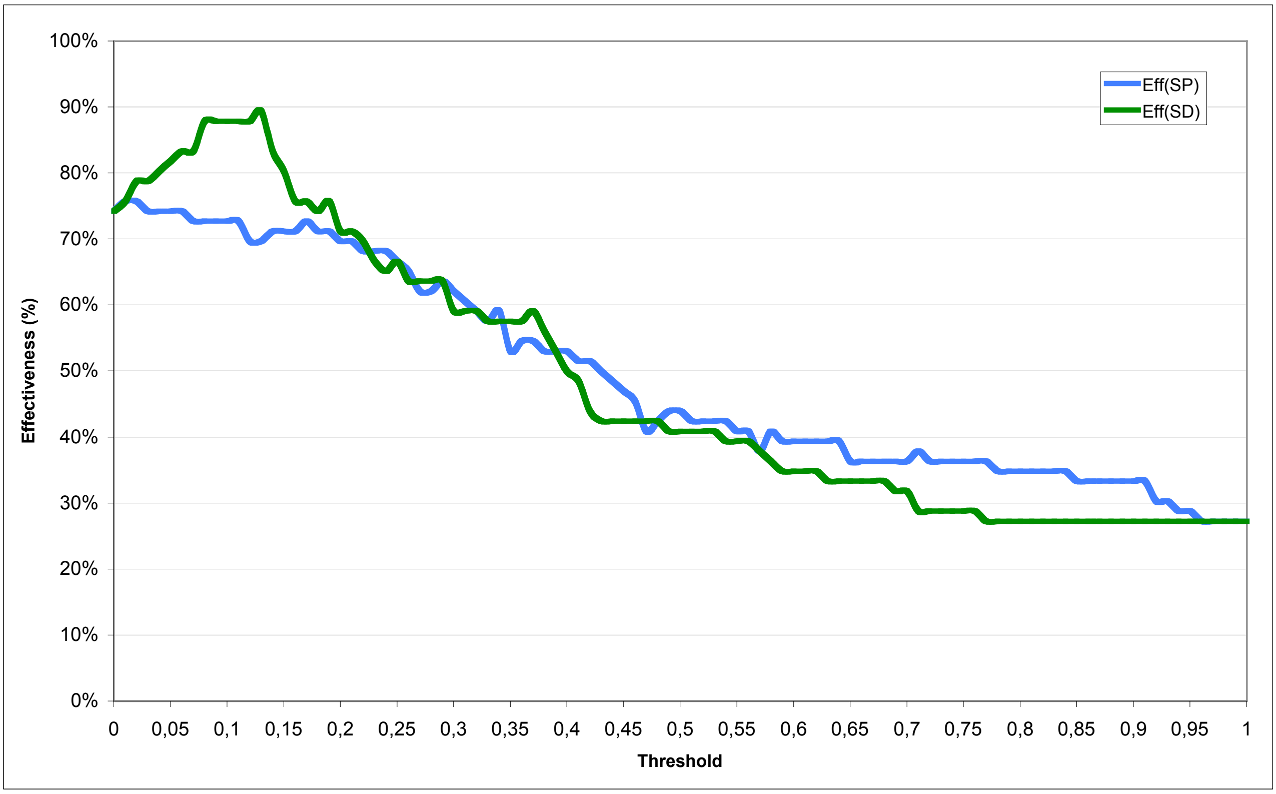
The observation of the classification results using a threshold on SP shows that profitability and growth indicators are not so useful to discriminate healthy firms from anomalous ones. The main motivations are as follows:

- the classification effectiveness is higher using a SD threshold than using a SP threshold;
- using SP threshold Type I error for each period is too high and unacceptable.

Figure 7 shows a comparison between SD an SP in terms of classification effectiveness and threshold choice.

These results need a further verification in order to test the predictive ability of different ratios combinations

Figure 7. – Classification effectiveness using different thresholds on the SD and the SP dimension (sample 1998)



4.1. – Testing ratios predictive ability trough ROC curves

As a further empirical test, ROC curves method was applied to the SD and SP classification algorithms in order to assess more accurately the ratios predictive ability.

ROC (Receiver Operating Characteristic) curves were developed in the 1950s as a by-product of research into making sense of radio signals contaminated by noise. More recently it is become clear that they are remarkably useful in medical decision-making and diagnostic tests.

A ROC curve is a graphical representation of the trade off between the Type I error (false negative rates) and Type II error (false positive rates) for every possible cut off. Equivalently, the ROC curve is the representation of the tradeoffs between sensitivity and specificity.

- The sensitivity is how good the test is at picking out bankrupt firms. It is simply the True Positive Fraction (TPF). In other words, sensitivity gives us the proportion of cases picked out by the test, relative to all firms who actually have financial problems (figure 8).
- Specificity is the ability of the test to pick out firms who do not have financial problems and It is synonymous with the True Negative Fraction (TNF).

Figure 8. – Sensitivity and Specificity in a classification test

		Model response	
		NB	**B**
Sample	**NB**	TNF	FPF (Type II error)
	B	FNF (Type I error)	TPF

From Figure 8 It appears clear that TNF + FPF = 1 and FNF + TPF = 1.

By tradition, the plot shows the false positive rate on the X axis and 1 - the false negative rate on the Y axis. You could also describe this as a plot with 1-Specificity on the X axis and Sensitivity on the Y axis.

A good diagnostic test is one that has small false positive and false negative rates across a reasonable range of cut off values. A bad diagnostic test is one where the only cut offs that make the false positive rate low have a high false negative rate and vice versa. It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).

We are usually happy when the ROC curve climbs rapidly towards upper left hand corner of the graph. This means that 1 - the false negative rate is high and the false positive rate is low. We are less happy when the ROC curve follows a diagonal path from the lower left hand corner to the upper right hand corner. This means that every improvement in false positive rate is matched by a corresponding decline in the false negative rate. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

The area under the curve is a measure of text accuracy. Accuracy is measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of 0,5 represents a worthless test. A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system:

- 0,90 - 1 = excellent (A);
- 0,80 - 0,90 = good (B);
- 0,70 – 0,80 = fair (C);
- 0,60- 0,70 = poor (D);
- 0,50 – 0,60 = fail (F);

The closer the area is to 0.5, the more lousy the test, and the closer it is to 1.0, the better the test[9]

Figures 9 and 10 show the ROC curves applied to the SD and SP dimension. The comparison between the plots shows that SD variable (the linear combination of ratios concerning liability,

[9] Computing the area is more difficult to explain and beyond the scope of this paper. Two methods are commonly used: a non-parametric method based on constructing trapeziods under the curve as an approximation of area and a parametric method using a maximum likelihood estimator to fit a smooth curve to the data points. Both methods are available as computer programs and give an estimate of area and standard error.

liquidity and capital structure) is more efficient to predict bankrupt than SP variable (the linear combination of ratios concerning profitability and growth). This is clearly visible in the different ROC curves structure.

Using the statistical software SPSS, the area under the SD and SP ROC curves was calculated and the results are as follows:

- SP ROC curve area = 0,5613 (fail, F);
- SD ROC curve area = 0,8637 (good, B).

These results confirm the main predictive ability of the SD dimension

Figure 9. – SD ROC curve

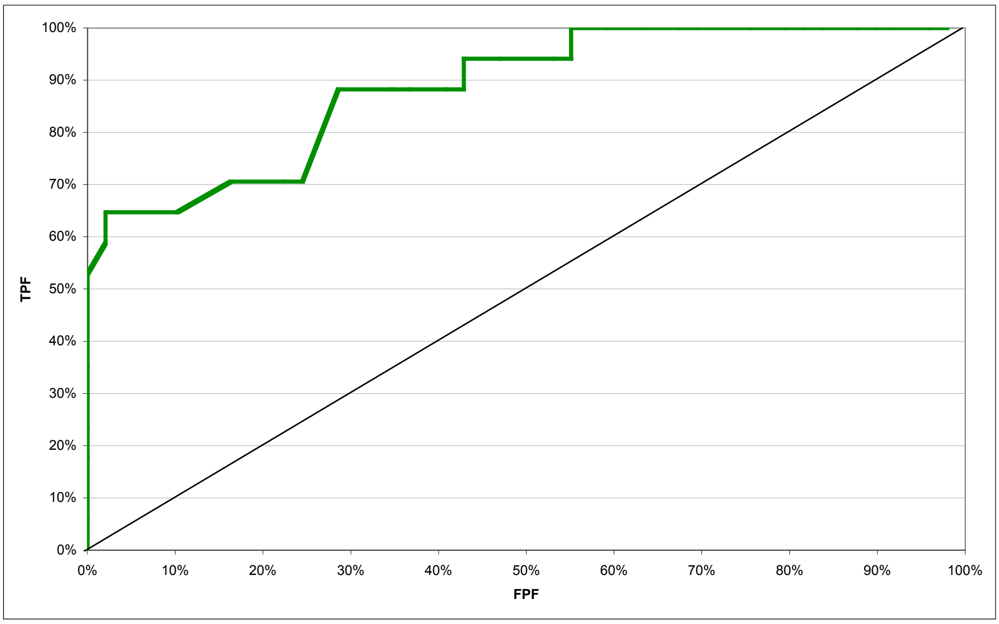
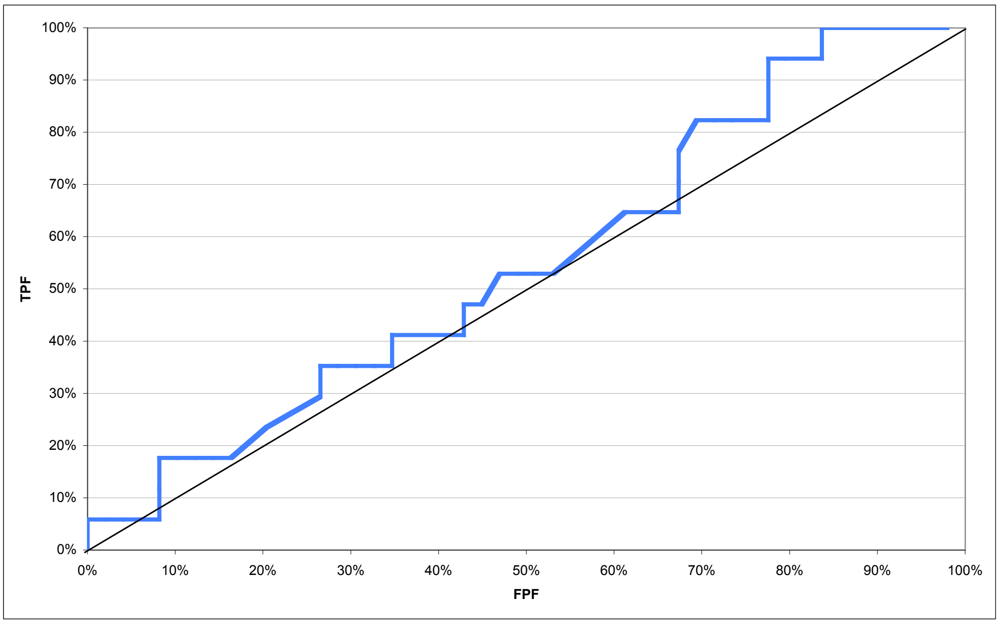


Figure 10. – SP ROC curve



5. – Summary and conclusions

In the present contribution I proposed a classification model based on accounting data (e.g. financial ratios), as an alternative to the multiple discriminant analysis and called *Maps Positioning Approach*. The business distress was studied through financial statement ratios and through subsequent analysis of their statistical distributions.

Two fundamental dimensions were taken into consideration:

- the economic one (like profitability and growth), called SP;
- and the financial one (liability, capital structure, liquidity), called SD.

The use of these two dimensions allowed to develop a graphical system in which it was possible to appreciate the positioning of every firm considered regarding the reference group.

The results seem to confirm the research hypotheses: the positioning of the firms is, in fact, indicative of their economic and financial condition and a different positioning in the map involves different managerial orders and financial risks. In particular it was observed that, during the data collection period (1997-2000), anomalous firms have always been placed in the inferior zone of the map, being characterized by low values of SD and SP. Therefore, a positioning in such area brings to light a problematic economic and financial situation and a main financial risk.

Using a specific mathematical algorithm it was possible to calculate a threshold on SD dimension and another threshold on SP dimension in order to maximize the classification effectiveness of the model proposed. The findings showed that a linear combination of ratios concerning financial and patrimonial dimension (SD) is more useful to discriminate healthy firms from anomalous one and consequently it is more accurate to predict bankruptcy. In fact, using a SD threshold the model showed an about 90% classification effectiveness for all the year explained.

Through each threshold determined (i.e. cut off point) the map was split in two potential areas (distress *vs* safety). Such a division could assume important reasoning in a comparative analysis. The trajectories of the firms could be drawn observing the shifts from one region to the other and the changes in the financial ratios value. Moreover, a comparison among the firms could be done in a static and dynamic context, examining the firms positions for a period of time and also for a time lag.

It must be observed, however, that the judgment expressed on the firms positioning is relative because it depends on the other firms' performances. The instrument introduced in this paper allows to estimate the firm situation (and its shifts in time) compared to a given group of other enterprises. The introduction of the same one in different reference group could change the positioning and, consequently, the final result.

The findings show that, in this empirical study and trough MPS, ratios concerning the financial and the patrimonial structure are more efficient to predict bankruptcy than ratios concerning profitability, cash flow and growth as confirmed by ROC curves.

In this paper the bankruptcy event seems to depend only on the financial structure with a strong link to the firm financial policy. In my opinion the main motivation of this finding could be as follows:

the bankruptcy events are often linked to convenience decisions of the owners (i.e. equity injection) and/or of the loaners (i.e. debt injection). Bankruptcy also concerning subjective aspects which prescind from quantitative measurements and deterministic aspects. For instance, personal guarantees (by management or owners) should be considered in BPMs. These guarantees, in fact, increase the firm credit ability to prescind from its accounting values.

Therefore, profitability and growth role remains to investigate for future researches in different samples.

References

Alberici A., (1975), *Analisi dei bilanci e previsione delle insolvenze*, Milano, ISEDI.

Altman E. I., (1968), *Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy*, Journal of Finance, n. 4, pp. 589-609.

Altman E. I., (1983), *Corporate Financial Distress and Bankruptcy*, New York, John Wiley & Sons.

Altman E. I., (2000), *Predicting Financial Distress of Companies: Revisiting the Z-Score and Z™ Model*, Working Paper available on www.stern.nyu.edu/.

Altman E. I., (2002), *Corporate Distress Prediction Models in a Turbolent Economic and Basel II Environment*, Working Paper available on www.stern.nyu.edu/.

Altman E. I., Haldeman R., Narajanan P., (1977), *Zeta Analysis: a New Model to Identify Bankruptcy Risk of Corporations*, Journal of Banking and Finance, n. 1, pp. 29-54.

Altman E. I., Marco G., Varetto F., (1994), *Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience)*, Journal of Banking and Finance, n. 3, pp. 505-529.

Appetiti S., (1984), *Identifying Unsound Firms in Italy. An Attempt to Use Trend Variables*, Journal of Banking and Finance, n. 2, pp. 269-279.

Argenti J., (1976), *Corporate Collapse. The Causes and Symptoms*, London, Mc Graw-Hill.

Ball R., Foster G., (1982), *Corporate Financial Reporting: a Methodological Review of Empirical Research*, Journal of Accounting Research, Studies on Current Research Methodologies in Accounting: a Critical Evaluation, pp. 161-234.

Barontini R., (2000), *La valutazione del rischio di credito. I modelli di previsione delle insolvenze*, Bologna, Il Mulino.

Basel Commission on Banking Supervision (2004), *International Convergence of Capital Measurement and Capital Standards*, Basel, Bank for International Settlements, available on www.bis.org.

Beaver, W. H., (1966), *Financial Ratios as Predictors of Failure*, Journal of Accounting Research, Empirical Research in Accounting: Selected Studies, pp. 71-111.

Beaver, W. H., (1968), *Alternative Accounting Measure as Predictors of Failure*, The Accounting Review, n. 1, pp. 113-122.

Blum M. P. (1974), *Failing Company Discriminant Analysis*, Journal of Accounting Research, n. 1, pp. 1-25.

Brunetti G., Coda V., Bergamin Barbato M., (1974), *Indici di bilancio e flussi finanziari: strumenti per l'analisi della gestione,* Milano, ETAS Libri.

Brunetti G., Coda V., Favotto F., (1990), *Analisi, previsioni, simulazioni economico-finanziarie d'impresa*, Milano, ETAS Libri.

Cappelletto R., (1983), *La previsione economico-finanziaria d'impresa e l'istruttoria del credito industriale*, Milano, Giuffrè editore.

Cascioli E., Provasoli A., (1986), *La previsione delle insolvenze aziendali. Un modello quantitativo*, in Cattaneo M., Cesarini F., Provasoli A., Quatraro B., (a cura di), *Crisi d'impresa e amministrazione controllata*, Milano, Giuffrè editore.

Casey C., Bartczak N., (1985), *Using Operating Cash Flow Data to Predict Financial Distress: Some Extension*, Journal of Accounting Research, n.1, pp. 384-401.

Cattaneo M., (1976), *Analisi finanziaria e di bilancio. Teoria e tecnica nella concessione del credito*, Milano, ETAS Libri.

Coda V., (1975), *L'analisi economico-finanziaria di un dissesto*, in Rivista dei dottori commercialisti, Milano, Giuffrè editore.

Coda V., (1990), *La valutazione della solvibilità a breve termine*, in Brunetti G., Coda V., Favotto F., (1990), *Analisi, previsioni, simulazioni economico-finanziarie d'impresa*, Milano, ETAS Libri, pp. 140-158.

Comuzzi E., (1995), *L'analisi degli squilibri finanziari d'impresa*, Torino, Giappichelli editore.

Dambolena I. G., Khoury S. J., (1980), *Ratio Stability and Corporate Failure*, Journal of Finance, n. 4, pp. 1017-1026.

De Laurentis G., (1986), *I principali approcci metodologici e le diverse applicazioni dei modelli di previsione delle insolvenze: una rassegna bibliografica*, in Forestieri G., (1986), (a cura di), *La previsione delle insolvenze aziendali. Profili teorici e analisi empiriche*, Milano, Giuffrè editore.

Deakin E. B., (1972), *A Discriminant Analysis of Predictors of Business Failure*, Journal of Accounting Research, n. 1, pp. 167-179.

Deakin E. B., (1977), *Business Failure Prediction: an Empirical Analysis*, in Altman E. I., (1977), *Financial Crises*, New York, John Wiley & Sons, pp. 72-88.

Dimitras A. I., Zanakis S. H., Zopounidis C., (1996), *A Survey of Business Failures with an Emphasis on Prediction Methods and Industrial Applications*, European Journal of Operational Research, n. 90, pp. 487-513.

Edmister R. O., (1972), *An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction*, Journal of Financial and Quantitative Analysis, n. 2, pp. 1477-1493.

Eisembeis R. A., (1977), *Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics*, Journal of Finance, n. 3, pp. 875-900.

Elam R., (1975), *The Effect of Lease Data in the Predictive Ability of Financial Ratios*, The Accounting Review, n. 1, pp. 1477-1493.

Falbo P., (1991), *Credit-Scoring by Enlarged Discriminant Models*, Omega, n. 4, pp. 275-289.

Fitz Patrik, P. J., (1932), *A Comparison of the Ratios of Successful Industrial Enterprises with Those of Failed Companies*, Washington, The Accounting Publishing Company.

Forestieri G., (a cura di), (1986), *La previsione delle insolvenze aziendali. Profili teorici e analisi empiriche*, Milano, Giuffrè editore.

Frydman H., Altman E. I., Kao D., (1985), *Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress*, Journal of Finance, n. 40, pp. 269-291.

Gabrovec Mei O., (1984), *La diagnosi della crisi d'impresa*, Rivista dei dottori commercialisti, Milano, Giuffrè editore, pp. 417-437.

Gentry J. A., Newbold P., Whitford D. T., (1985), *Classifying Bankrupt Firms with Funds Flow Components*, Journal of Accounting Research, n. 1, pp. 146-160.

Gordon M. J., (1971), *Towards a Theory of Financial Distress*, Journal of Finance, n. 2, pp. 347-356.

Goudie A. W., (1987), *Forecasting Corporate Failure: the Use of Discriminant Analysis within a Disaggregated Model of the Corporate Sector*, Journal of Royal Statistical Society (Series A), n. 1, pp. 69-81.

Guatri L., (1986), *Crisi e risanamento delle imprese*, Milano, Giuffrè editore.

Houghton K. A., (1984), *Accounting Data and the Prediction of Business Failure: the Setting of Priors and the Age of Data*, Journal of Accounting Research, n. 1, pp. 361-368.

Johnson C. G., (1970), *Ratio Analysis and the Prediction of Firms Failure*, Journal of Finance, n. 5, pp. 1166-1168.

Joy O. M., Tollefson J. O., (1975), *On The Financial Application of Discriminant Analysis*, Journal of Financial and Quantitative Analysis, n. 5, pp. 723-739.

Lau A. H., (1987), *A Five-State Financial Distress Prediction Model*, Journal of Accounting Research, n. 1, pp. 127-138.

Libby R., (1975), *Accounting Ratios and the Prediction of Failure: Some Behavioural Evidence*, Journal of Accounting Research, n. 1, pp. 150-161.

Lincoln M., (1984), *An Empirical Study of the Usefulness of Accounting Ratios to Describe Levels of Insolvency Risk*, Journal of Banking and Finance, pp. 321-340.

Mantoan M., Mantovan P., (1987), *Un modello di previsione del dissesto d'impresa*, Rivista dei dottori commercialisti, n. 1-2, Milano, Giuffrè editore, pp. 135-159.

Mar Molinero C., Serrano Cinca C., (2001), *Bank Failure: a Multidimensional Scaling Approach*, European Journal of Finance, n.7, pp. 165-183.

Merwin C. L., (1942), *Financing Small Corporations in Five Manufacturing Industries, 1926-1936*, National Bureau of Economic Research, vol. 22.

Meyer P. A., Pifer H. W., (1970), *Prediction of Bank Failures*, Journal of Finance, n.4, pp. 853-868.

Ohlson J. A., (1980), *Financial Ratios and the Probabilistic Prediction of Bankruptcy*, Journal of Accounting Research, n. 1, 109-131.

Previti Flesca G., (1986), *L'analisi di bilancio per la valutazione del merito di credito*, Rivista italiana di ragioneria e di economia aziendale, Roma, RIREA editore, pp. 442-488.

Ramser J. R., Foster L. O., (1931), *A Demonstration of Ratios Analysis*, Bureau of Business Research, University of Illinois, Bulletin n. 40.

Smith R. F., (1930), *A Test Analysis of Unsuccessful Industrial Companies*, Bureau of Business Research, University of Illinois, Bulletin n. 51.

Taffler R. J., (1982), *Forecasting Company Failure in the U.K. Using Discriminant Analysis and Financial Ratios Data*, Journal of Royal Statistical Society (Series A), n. 3, pp. 342-358.

Varetto F., (1999), *Metodi di previsione delle insolvenze: un'analisi comparata*, in Szego G., Varetto F., (a cura di), (1999), *Il rischio creditizio: misura e controllo*, Torino, UTET, pp. 178-301.

Wilcox J. W., (1971), *A Simple Theory of Financial Ratios as Predictors of Failure*, Journal of Accounting Research, n. 2, pp. 389-395.

Wilcox J. W., (1973), *A Prediction of Business Failure Using Accounting Data*, Journal of Accounting Research, Empirical Research in Accounting: Selected Studies, pp. 163-179.

Zmjewsky M. E., (1984), *Methodological Issues Related to the Estimation of Financial Distress Prediction Models*, Journal of Accounting Research, Studies on Current Econometric Issues in Accounting Research, pp. 59-82.