INSOLVENCY PREDICTION IN COMPANIES: AN EMPIRICAL STUDY IN ITALY

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Abstract

The study stems from the relevance of the global economic crisis which is affecting companies to an increasing extent. The objective of the paper is to test the degree of effectiveness of the insolvency prediction models, most widely used in the literature, including recent works (Jackson and Wood, 2013), with reference to Lombardy, the most important Italian region in terms of industrialization rate. The following models were used, selected according to their diffusion and the statistical technique used: 1) Discriminant analysis (Altman, 1983), (Taffler, 1983); 2) Logit Analysis (Ohlson, 1980). The study identifies the state of health of companies in 2012, using the financial reporting data of the three previous years. The research sample consists of 58,750 companies (58,367 non-failed and 383 failed). Among the main results, it is observed that, for all the models, a prediction of default is often erroneously made for companies which are solvent, whereas failed companies are classified with a lower degree of error. The objective of the paper is preparatory to the second part of the research in progress in which, on the basis of the results presented here, some modifications will be made to the insolvency prediction models selected, significant for the Italian context, with the aim of identifying a company insolvency "alert model" which can be used by the various stakeholders. The results are interpreted in the light of the Stakeholder Theory***.

Keywords: Prediction Models, Economic Crisis, Financial Reporting Data, Italian Companies, Stakeholder Theory

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1 Introduction

The study stems from the relevance of the global economic crisis which is affecting companies to an increasing extent. In particular, the frequency with which insolvency situations occur provides a stimulus for the development and analysis of themes concerning the prediction and prompt identification of situations considered to be at risk, in order to implement all the activities necessary to prevent them or to set up turnaround processes.

The success of a company turnaround obviously also depends, to a significant degree, on early identification of the insolvency symptoms with the creation, where possible, of reference categories; when these occur, the companies and the stakeholders most involved can take constructive steps to promptly identify lines of action. Once an insolvency situation has been identified, the companies must be able to deal with it effectively and with the correct timing, intervening on the causal factors which are often connected with management decisions that are not correct or are not coherent with the complexity of the competitive context.

In the light of this framework, the objective of the paper, which forms part of a wider research project, is to test the degree of effectiveness of the insolvency prediction models, selected on the basis of the main statistical techniques used and their citation index, employed also in recent literature (Jackson and Wood, 2013), with reference to Lombardy, the most important Italian region in terms of industrialization rate. The reference period is the global economic crisis from 2009 to 2012. The overall research sample consists of 58,750 companies comprising non-failed and failed companies.

In particular, the following models were used:

1) Discriminant analysis

1a) Altman (1983);

1b) Taffler (1983);

2) Logit Analysis

Ohlson (1980).

The objective of the paper is preparatory to the second part of the research in progress in which, on the basis of the results presented here, some modifications will be made to the insolvency prediction models selected, significant for the Italian context, with the aim of identifying a company insolvency "alert model" which can be used by all the stakeholders.

The results of this paper (and of the second part of the research in progress) are interpreted according to the Stakeholder Theory (Freeman, 1984; Donaldson and Preston, 1995) which recognises that organisations have many stakeholders to whom they relate and to whom they are accountable: primary stakeholders (shareholders, debt-holders, banks, customers, suppliers, employees) and secondary stakeholders (governments, society, community, charities). Each of these parties, in various ways, directly or indirectly undergoes the effects of the global economic crisis: therefore, the study of company insolvency and the possibility of forecasting it in advance to avoid worse consequences are of interest to civil society in general, i.e. the context in which the company operates. It happens firstly via the application of insolvency prediction models and, secondly, via the adaptation of these models to specific economic contexts, in our case Italy.

The paper continues in the following order: paragraph two recalls the Italian background in terms of legal instruments functional to overcoming the insolvency and used in the paper for the classification of companies into non-failed and failed; paragraph three offers a summary of the literature on the insolvency prediction models considered in the paper; paragraph four describes the sample of companies and the research method; paragraph five explains the results; the last paragraph presents the conclusions, implications, limitations and future evolution of the research.

2 The legal instruments for overcoming company insolvency in Italy

The occurrence of an insolvency situation entails a frequent process of erosion of the capacity to produce positive economic results, liquidity and self-financing by the company, in addition to a sudden loss of confidence of the main stakeholders. The company turnaround can be oriented to winding-up or to continuation in relation to its ability to resume operation with good economic and financial performance.

In terms of the legal instruments to support the turnaround, two scenarios can be identified (with different roles and impact on the turnaround) depending on whether the process is carried out through the courts or not.

The first case comprises turnaround processes based on debt restructuring agreements, composition with creditors, bankruptcy and the other procedures specifically established by the law which presuppose recourse to the courts, in various ways.

The second case (out of court restructuring) comprises turnaround processes for which no legal instrument is used or those in which the *certified recovery plans* established by art. 67 third paragraph letter d) of the Italian Bankruptcy Act, the so-called workouts, are used.

In the paper, explicit reference is made to the first type for the distinction between non-failed and failed companies in preparation of the sample. Debt restructuring agreements and composition with creditors are the instruments selected as they represent the most widespread ones, used and geared to enabling a company to make an effective turnaround, at least in theory. These two instruments are presented briefly below (Giacosa and Mazzoleni, 2012).

2.1 Debt restructuring agreements

The current law provides that «The entrepreneur in a state of insolvency can request, submitting the documentation specified in art. 161 of the Italian Bankruptcy Act, the approval of a debt restructuring agreement stipulated with the creditors representing at least sixty percent of the credits, together with a report drawn up by a professional, in possession of the legal requirements, on the truthfulness of the company data and the practicability of the agreement, with particular reference to its suitability to ensuring regular payment of the outside creditors in compliance with the following terms:

– within one hundred and twenty days from the approval, in the case of credits already past their due date at the date of approval;

– within one hundred and twenty days from the due date, in the case of credits not yet past their due date at the date of the approval».

The insolvent company can therefore reach agreements with its creditors (representing at least 60% of the overall indebtedness) aimed at rescheduling the debts, writing them off or identifying intermediate solutions. These agreements must be implemented to allow the company to resume operation with good economic and financial performance. The parties outside the agreement must be paid within the terms established by the law. The agreements with the creditors must be negotiated individually and each creditor may be treated differently.

2.2 Composition with creditors

Art. 160 of the Italian Bankruptcy Act establishes that «An entrepreneur in a state of insolvency can propose a composition with the creditors on the basis of a plan which can entail:

– restructuring of the debts and payment of the credits in various ways (…);

– attribution of the assets of the companies interested in the composition proposal to a third party (....);

– grouping of the creditors into classes according to similar legal positions and economic interests;

– different treatment of creditors belonging to different classes».

Under composition with creditors, the company can be wound up or can continue operating.

Via composition with creditors, the company's assets are "protected" in the sense that the creditors cannot take legal action to recover their credits either during preparation of the composition plan or during execution of the procedure.

The insolvent company proposes to its creditors a method for resolving its obligations via the composition plan (payment extensions, attribution to the creditors of company assets, write-off of the original credits, etc.). The proposal is voted by the creditors (only the non-secured creditors) and passed by a majority vote (51% of the nominal value of the credits).

The composition plan must also be certified by a professional expert in possession of the legal requirements.

3 Literature review

The models selected are those used most widely in the literature, also recently (Jackson and Wood, 2013); due to their widespread use, it is important to verify their effectiveness in the current economic context, also in the light of the fact that the authors have used their original model in more recent studies. For example, Agarwal and Taffler (2007) re-apply the model of Taffler (1983) to a sample of British companies; likewise, Altman, Danovi and Falini (2013) apply the Altman model (1983) to a sample of Italian companies.

All the models, regardless of the statistical technique used, can generate two types of errors; to each of these, a cost must be associated which varies according to the objectives pursued:

- First Type Error, when a failed company is classified as non-failed;
- Second Type Error, when a non-failed company is classified as failed.

3.1 Discriminant analysis

Discriminant analysis is a statistical technique which allows a company to be distinguished in the context of two or more pre-defined groups (Fisher, 1936; Teodori, 1989; Jackson and Wood, 2013), i.e. the group of non-failed companies and the group of failed companies. These groups, in the study, are defined *a priori* on the basis of the characteristics illustrated in par. 4.1. During the application of discriminant analysis, the linear form was chosen as it is the one most widely used in the literature up to 1980 and, also after this date, it represents a base model for the application of subsequent models (Balcaen and Ooghe, 2004; Altman and Narayanan, 1997; Aziz and Dar, 2006)[4].

The Z-score attributed to each company represents, in one single value, the information deriving from the m common variables referring to that company. Via this value, the company is classified as belonging to one of the two universes (group of non-failed companies or group of failed companies). The higher the Z-score of a company, the lower the possibility of the company being classified as a failed company.

For the purposes of this classification, a Z-score (cut-off point) is defined, which allows the two groups of companies (group of non-failed companies or group of failed companies) to be distinguished as clearly as possible. For application purposes, the cut-off points considered are those identified in the individual discriminant analysis models chosen in the study.

If the Z-score of a company is below the cut-off point, the company is classified as failed; if the Z-score of a company is higher than the cut-off point, it is classified as non-failed.

The choice of discriminant analysis in this study is due to the fact that this statistical technique underlies a series of authoritative studies in the literature on the subject, such as Altman (1968), Deakin (1972), Edmister (1972), Blum (1974), Libby (1975), Alberici (1975), Taffler (1976-1977), Altman, Haldeman and NaraYnan (1977), Deakin (1977), Lincoln (1984), Altman (1983), Mantoan and Mantovan (1987), (1987), Aziz et al (1988), Altman et al (1994), Back at al (1996), Booth (1983), Casey and Bartczak (1984), Coats and Fant (1993), Dimitras et al. (1999), El Hennawy and Morris (1983), Frydman et al. (1985), Gombola et al. (1987), Jo et al. (1997), Kahya and Theodossiou (1999), McGurr and DeVaney (1998), Moyer (1977), Piesse and Wood (1992), Pompe and Feelders (1997), Sung et al. (1999), Taffler and Tisshaw (1977), Theodossiou (1993), Yang et al. (1999). Other studies have also applied this methodology, thanks to the frequency of application in literature (Beyonon and Peel, 2001; Neophytou et al, 2001; Brockamn and Turtle, 2003; Agarwal and Taffler, 2007 and 2008; Jackson and Wood, 2013).

In the context of discriminant analysis, this study analyses the models of Altman (1983) and Taffler (1983), due both to their popularity in the literature (Balcaen and Ooghe, 2004 and 2006; Reisz and Purlich, 2007; Jackson and Wood, 2013) and the possibility of applying them to a sample of non-listed companies.

3.1.1 Altman (1983)

The model is as follows:

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[4] It is expressed as follows:

$$z_i = a + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_m X_{im}$$

where:
α = constant
i = identifies the i-th company (from 1 to n)
j = identifies the variables or the indexes which constitute the model (from 1 to m)
m = overall number of variables considered (in the ambit of the indexes considered)
z_i = Z-score attributed to the i-th company
X_{ij} = value assumed by the index j for the company i
B_j = discriminant coefficient for the j-th variable (weight attributed to the index j)

$$Z_i = a + \beta_1 \frac{WC}{TA} + \beta_2 \frac{RE}{TA} + \beta_3 \frac{EBIT}{TA} + \beta_4 \frac{BV_E}{TL} + \beta_5 \frac{S}{TA}$$

where:
α = constant
WC/TA = working capital/total assets
RE/TA = retained earnings/total assets
EBIT/TA = earning before interest and taxes/total assets
BV_E/TL = book value equity/total liabilities
S/TA = sales/total assets

For application purposes, the variables α, β_1, β_2, β_3, β_4 refer to Altman model (1983), as this study is geared to non-listed companies. The model applied is therefore as follows:

$$Z = 0.717 \frac{WC}{TA} + 0.847 \frac{RE}{TA} + 3.107 \frac{EBIT}{TA} + 0.420 \frac{BV_E}{TL} + 0.998 \frac{S}{TA}$$

3.1.2 Taffler (1983)

The proposed model is as follows:

$$z = a + \beta_1 \frac{PBT}{CL} + \beta_2 \frac{CA}{TL} + \beta_3 \frac{CL}{TA} + \beta_4 NCI$$

where:
α = constant
PBT/CL = profit before tax/current liabilities
CA/TL = current assets/total liabilities
CL/TA = current liabilities/total assets
NCI = (current asset-stock-current liabilities)/daily operating costs (excluding depreciation)

For application purposes, the variables α, β_1, β_2, β_3, β_4 refer to Taffler model (1983). The model applied is therefore as follows:

$$z = 3.2 + 12.18 \frac{PBT}{CL} + 2.5 \frac{CA}{TL} - 10.68 \frac{CL}{TA} + 0.029 NCI$$

3.2 Logit analysis

The models based on this analysis show the probability of a company belonging to the group of non-failed companies or the group of failed companies, defined *a priori* according to a series of characteristics[5].

Here again, the choice of the Logit model is due to the fact that this statistical technique underlies a series of authoritative studies in the literature, such as Ohlson (1980), Zavgren (1985), Forestieri (1986), Aziz et al (1988), Keasey and McGuiness (1990), Dimitras et al (1999), Aziz et al (1988), Keasey and McGuiness (1990), Dimitras et al (1999), Back et al. (1996), Kahya and Theodossiou (1999), Laitinen and Laitinen (1998), McGurr and DeVaney (1998), Platt and Platt (1990), Salchenberger et al. (1992), Theodossiou (1991), Ward (1994). More recent studies have also applied this methodology (Jackson and Wood 2013; Back et al,1996; Beyonon and Peel, 2001; Neophytou et al, 2001; Foreman, 2002; Brockamn and Turtle, 2003; Lin and Piesse, 2001; Westgaard and Wijst, 2001). In the ambit of the Logit

[5] The formula of the model used in the study is the following:

$$P_i = E\left(Y = 1 \mid X_i = \frac{1}{1+e^{-(a+\beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_m X_{im})}} = \frac{1}{1+e^{-Z}}\right)$$

where:
α = constant
i = identifies the i-th company (from 1 to n)
j = identifies the variables or the indexes that constitute the model (from 1 to m)
Y = variable which assumes value 1 (if the company is insolvent) or 0 (if the company is solvent)
P_i = the probability that the company i has failed observing the values assumed by the m indexes which define the model (given the values of the indexes, considered by the model for the company i, P_i identifies the probability that the company analysed has failed)
X_{ij} = value assumed by the index j for the company i
β_j = weight (or coefficient) attributed to the index X_j

model, we have chosen to adopt the Ohlson model (1980), in view of its popularity in the reference literature (Balcaen and Ooghe, 2004 and 2006; Jackson and Wood, 2013).

3.2.1 Ohlson (1980)

This model determines the probability of default of a company on the basis of a set of variables. It establishes three different operating modes:

– prediction of default within one year from application of the model;

– prediction of default within two years, if the company is not in default in the first year;

– prediction of default in one of the two years considered.

In the study, the first operating mode was chosen. This choice is justified by the fact that it is the one considered by the author of the model himself (Ohlson, 1980) as the most effective in predictive terms. The model is as follows:

$$z = a + \beta_1 SIZE + \beta_2 \frac{TL}{TA} + \beta_3 \frac{WC}{TA} + \beta_4 \frac{CL}{CA} + \beta_5 OENEG + \beta_6 \frac{NI}{TA} + \beta_7 FUTL + \beta_8 INTWO + \beta_9 CHIN$$

where:
α = constant
SIZE = natural logarithm of GDP-deflated total assets
TL/TA = total liabilities/total assets
WC/TA = working capital/total assets
CL/CA = current liabilities/current assets
OENEG = dummy variable equal to one if total liabilities exceed total assets, and zero otherwise
NI/TA = net income/total assets
FUTL = fund from operations (pretax income + depreciation + amortization)/total liabilities
INTWO = dummy variable equal to one if net income was negative over previous two years, and zero otherwise
CHIN = scaled change in net income calculated as $(NI_t – NI_{t-1})/(|NI_t| + |NI_{t-1}|)$ where NI_t is the net income for the most recent period

For application purposes, the variables α, β_1, β_2, β_3, β_4 refer to Ohlson model (1980). The model applied is therefore as follows:

$$z = -1.32 - 0.407 SIZE + 6.03 \frac{TL}{TA} - 1.43 \frac{WC}{TA} + 0.0757 \frac{CL}{CA} - 1.72 OENEG - 2.37 \frac{NI}{TA} - 1.83 FUTL + 0.285 INTWO - 0.521 CHIN$$

4 The sample and the research method

4.1 The sample

For development of the analysis, we referred to the economic fabric of Lombardy, a region in northern Italy. The area was considered suitable for the purposes of the study as it has the highest industrialization rate in Italy (Confindustria Study Centre, 2011): within the area, five courts were selected on the basis of their willingness to collaborate in the research[6]. Lombardy produces 21.3% of GNP, while the geographical areas under the jurisdiction of the courts involved contribute in the amount of 15.1% of GNP (processing of Eurostat data 2012). In 2012, the companies in Lombardy account for 19.1% of the overall turnover of the companies operating in Italy: those analysed represent 73.9% of the turnover of the entire region.

The companies[7] are classified according to business sector, adopting the Ateco classification of the National Institute of Statistics (Istat).

The study identifies the state of health of the companies in 2012: the forecast is made using the financial statement values of the three previous years (2009, 2010 and 2011). For this reason, the companies were identified with reference to the beginning of 2009, in order to ensure the availability of three years of financial reporting data (Table 1 in appendix).

[6] The courts are: Milan, Brescia, Bergamo, Mantua and Cremona. The first refers to the regional capital; the other four refer to the provinces of Eastern Lombardy bordering with Veneto, another important region for the Italian economy.

[7] The companies were identified using the Aida-Bureau van Dijk database, which contains economic-financial information on over one million Italian companies.

Table 1. Companies for industry (Ateco 2007)

Industry (first level)	Industry (second level)	Total companies
Agriculture, forestry and fishing	Crop and animal production, hunting and related service activities Forestry and logging Fishing and aquaculture	719
Accommodation, food and beverage	Accommodation Food and beverage service activities	2,803
Cultural activities	Creative, arts and entertainment activities Sports activities and amusement and recreation activities	1,172
Financial activities	Financial service activities, except insurance and pension funding Activities auxiliary to financial services and insurance activities	1,945
Professional activities	Legal and accounting activities Activities of head offices; management consultancy activities Architectural and engineering activities; technical testing and analysis Scientific research and development Advertising and market research Other professional, scientific and technical activities	9,510
Trade	Wholesale and retail trade and repair of motor vehicles and motorcycles Wholesale trade, except of motor vehicles and motorcycles Retail trade, except motor vehicles and motorcycles	15,003
Construction activities	Construction of buildings Civil engineering Specialised construction activities	11,728
ICT	Publishing activities Programming and broadcasting activities Computer programming, consultancy and related activities Information service activities	4,465
Real estate activities	Real estate activities	20,958
Manufacture	Manufacture of food products Manufacture of beverages Manufacture of textiles Manufacture of wearing apparel Manufacture of leather and related products Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials Manufacture of paper and paper products Printing and reproduction of recorded media Manufacture of coke and refined petroleum products Manufacture of chemicals and chemical products Manufacture of basic pharmaceutical products and pharmaceutical preparations Manufacture of rubber and plastic products Manufacture of other non-metallic mineral products Manufacture of basic metals Manufacture of fabricated metal products, except machinery and equipment Manufacture of computer, electronic and optical products Manufacture of electrical equipment Manufacture of machinery and equipment Manufacture of motor vehicles, trailers and semi-trailers Manufacture of other transport equipment Manufacture of furniture Other manufacturing Repair and installation of machinery and equipment	15,638
Business support activities	Rental and leasing activities Employment activities Travel agency, tour operator reservation service and related activities Office administrative, office support and other business support activities	2,602
Transport and warehousing	Land transport and transport via pipelines Warehousing and support activities for transportation	2,169
Utilities	Waste collection, treatment and disposal activities; materials recovery	301
	Total	**89,013**

Within the population (Table 1), two groups of companies, non-failed and failed, were identified with the criteria described below.

a) The non-failed companies are those in the following conditions:

– they were not subject, in the period examined, to any insolvency proceedings and did not present any application for admission to insolvency proceedings in 2012;

– they were operating (not failed) up to the end of 2012.

b) The failed companies are those which, in 2012, are in the following conditions:

– they have submitted to the court an application for admission to the insolvency proceedings considered in the study (debt restructuring agreements pursuant to art. 182-bis of the Italian Bankruptcy Act, and composition with creditors pursuant to art. 160 and following of the Italian Bankruptcy Act) or have been admitted to the above-mentioned insolvency proceedings by the end of 2012. The decision to consider even just an application for admission is due to the fact that the admission procedure requires a period of investigation and assessment by the court, which can last several months. We therefore wished to recognise the document in which, after an assessment of its state of health, the company formalizes the need to resort to insolvency proceedings. Companies undergoing other insolvency proceedings (administrative compulsory liquidation, extraordinary administration proceedings) which are not common or are intended for specific types of companies and are therefore of limited general interest, were excluded;

– have been declared bankrupt[8].

The companies that submitted to the court an application for admission to insolvency proceedings, considered in the study as failed, were identified using the information provided by the registrar's office of the courts[9] for the geographical reference area.

After defining the conditions for a company to be classified as non-failed or failed, the next step is verification that they possess all the information necessary for full application of the models.

The following were excluded from the non-failed companies initially identified:

– those in which the absence of detail in certain financial reporting data, the amount of which accounts for over 2.5%[10] of the total reference value, does not allow to calculate the variables of the company insolvency prediction models (17,608 companies);

– those whose financial statement contains a non-reconcilable balancing error, again accounting for over 2.5% of the total (660 companies);

– those in which the absence of some financial reporting data in the reference time horizon does not allow the calculation of one or more variables of the company insolvency prediction models (5,400 companies);

– those who submitted a request for voluntary winding up or cancellation from the business register, for reasons other than company insolvency (6,632);

– those who submitted an application for admission to insolvency proceedings prior to 2012[11] (50 companies);

– those who were admitted to other insolvency proceedings different from those examined (168 companies);

– those who have submitted an application for admission to the insolvency proceedings examined but who have not yet been admitted by the court (128 companies).

Overall, 58,367 non-failed companies were selected (Table 2).

Initially, 1,834 failed companies were identified (Table 2).

Here again, some exclusions had to be made, due to the difficulty of obtaining complete information. The following companies were excluded:

– those who do not have financial statements for the entire reference time horizon of the study (1.062 companies);

– those in which the absence of detail in certain financial reporting data, the amount of which accounts for over 2.5% of the total reference valur, does not allow to calculate the variables of the company insolvency prediction models (194 companies);

– the absence of some financial reporting data in the reference time horizon does not allow the calculation of one or more variables of the company insolvency prediction models (195 companies).

Overall, 383 failed companies were selected (Table 2).

The overall sample of the study therefore consists of 58,750 companies: 58,367 non-failed and 383 failed, 155 of which are bankrupt.

[8] 12,442 companies were declared bankrupt in 2012 in Italy (2.1% of the total number of operating companies), 1,899 (2.1%) of which in the courts examined and 2,817 (2.2%) in Lombardy as a whole.

[9] The registrar's office at the court is the office that receives the applications for admission to insolvency proceedings, and identifies the companies admitted to the insolvency proceedings and the bankrupt companies.

[10] There is no shared threshold for measuring the materiality connected with the financial statement values; many references are present only in operating practice. The figure of 2.5% was established considering the need for a full and expressive applicability of the models and is equivalent to the mean of the values generally taken as the reference in Italian practice.

[11] These companies cannot be considered non-failed given their insolvency in progress, neither are they considered among the failed companies, since the year of presentation of the application for insolvency proceedings does not comply with the time requirement of the study.

Table 2. Initial and selected companies per industry

Industry	Initial failed companies	Selected failed companies	Selected non-failed companies
Agriculture, forestry and fishing	5	2	489
Accommodation, food and beverage	70	6	1,083
Cultural activities	23	3	706
Financial activities	16	4	849
Professional activities	111	18	4,924
Trade	349	75	10,429
Construction activities	399	65	7,567
ICT	55	9	2,830
Real estate activities	144	23	14,032
Manufacture	486	150	11,546
Business support activities	42	6	1,546
Transport and warehousing	66	13	1,438
Utilities	4	1	208
Others	64	8	0
Total	**1,834**	**383**	**58,367**

4.2 The research method

The three models were applied to the financial statements of the companies in the sample in the period 2009-2011: the results of the models were then compared with the state of health of the companies in 2012, in order to measure the degree of effectiveness achieved[12].

The three company insolvency prediction models were applied in order to verify their effectiveness over a period of three years (2009-2011), two years (2010-2011) and one year (2011) prior to occurrence of the default situation. The models are applied in three modes:

a) use of all the companies available, without distinction. The validity of this mode is supported by the literature (Jackson and Wood, 2013). In particular, the numerousness of the reference sample has been considered positive also in other studies: of these, Ohlson (1980) applied the original model to groups containing a different number of companies, underlining the importance of the groups with the highest number of companies. This was also maintained in the study by Falkestein, Boral and Carty (2000), according to which the hazard model of Shumway (1999) shows a high effectiveness compared to other models due to the numerous sample examined;

b) use of reduced groups chosen at random, without recourse to further distinctions (sector and/or dimension). A sample of 60 failed companies was set against a sample of 60 non-failed companies, i.e. an overall number of 120 units for each sample. 2,000 samples were constructed on which the models were applied;

c) use of reduced groups chosen at random, this time using specific classification criteria, such as business sector and size. This method was used in the original work by Altman (1968). In this regard, some scholars, such as Beaver (1966), Libby (1975), Taffler (1983), Keasey and McGuinness (1990), Caritou et al. (2004) have maintained that the sample of non-failed companies and the sample of failed companies must contain the same number of companies and company composition in terms of sector and size. In particular, this number differs from model to model (for example, Altman (1968) uses samples of 33 companies; Altman, Haldeman, and Narayanan (1977) use a sample of 53 failed companies and 58 non-failed companies correlated in terms of size and sector); Taffler (1983) uses groups of 46 non-failed and failed companies. In this study, we used a sample of 53 failed companies (chosen at random), belonging to different sectors and having a given turnover, and another sample of 53 non-failed companies (chosen at random), having the same characteristics in terms of sector and size. For each sector, a maximum of two companies were identified (minimum one company) belonging to at least one turnover class[13], for a maximum total of 6 non-failed companies and 6 failed companies (minimum 1 non-failed and 1 failed). The sample of 53 companies therefore consists of companies belonging to the following sectors: Agriculture, forestry and fishing; Manufacture; Construction activities; Trade; Utilities; Transport and warehousing; Accommodation, food and beverage; ICT; Financial activities; Real estate activities; Professional activities; Business support activities and Cultural activities. The numerousness of the sample (i.e. 53 companies) is due to the fact that, considering the different observation criteria (sector

[12] For the purposes of application of the insolvency prediction models, the financial reporting data were obtained from the Aida-Bureau van Dijk database, while the GDP price-level index was obtained from the World Bank.

[13] Three sizes were identified for the companies analysed: micro-company (for turnover from 0 a 2 ml euro), small company (for turnover from 2 to 10 ml euro) and medium-sized company (10 to 50 ml euro).

and size), the threshold of 53 companies represents the maximum number possible for each sample.

In addition, the models were applied according to the above three modes to the sectors considered most significant in terms of failed companies. In particular, mode a) was applied to Manufacture, Construction activities, Trade, Real estate activities, Transport and warehousing, and Professional activities. Modes b) and c) were applied to the Manufacture sector, the only one characterised by a population of failed companies with the characteristics necessary for application of modes b) and c).

In order to ensure comparability of the results obtained from the above modes, the effectiveness of the individual models is tested using the ROC Curve constructed following Gönen (2006). Having chosen a cut-off point with which to compare the results obtained from the models, the companies are distinguished according to whether they belong to the group of non-failed companies or the group of failed companies.

To establish the effectiveness of the models, a contingency table was used (Table 3), which allows identification of the first and second type errors:

Table 3. Error types

Result prediction	Values observed	
	Non-failed	Failed
Non-failed	TP	FP
Failed	FN	TN

where:
TP (True Positive): a non-failed company is correctly classified;
FP (False Positive): represents a first type error;
FN (False Negative): represents a second type error;
TN (True Negative): a failed company is correctly classified.

The contingency table is also useful for calculating the sensitivity and 1-specificity parameters (the combination of which represents a point on the ROC Curve):

– sensitivity = TP/(TP+FN): represents the percentage of non-failed companies correctly identified by the model;

– specificity = (TN/(FP+TN): represents the percentage of failed companies correctly identified by the model.

To construct the curve, it was necessary to vary the cut-off point, create a new contingency table and then use various combinations of sensitivity and 1-specificity. Therefore, each cut-off point corresponds to a new contingency table, i.e. a new classification of the companies into non-failed and failed from which the new sensitivity and specificity values are deduced.

As the value of the cut-off point increases, the number of companies classified as non-failed decreases and the number of companies classified as failed increases and vice versa. The ROC Curve therefore graphically represents the sensitivity values (on the Y axis) and 1-specificity values (on the X axis), obtained by varying the cut-off point.

For the purposes of our analysis, the cut-off points used for construction of the ROC Curve correspond to the percentiles of the values in terms of Z-Score and probability obtained by applying the models. For the 101 cut-offs identified, the sensitivity and specificity values are deduced: the sensitivity and 1-specificity simultaneously assume the value 1 if the cut-off used is the absolute minimum value assumed by the z-Scores or by the probability (Logit model).

The effectiveness of the model is represented by the area below the ROC Curve, defined Theta, which is estimated using the Trapezoid Rule (Hanley and McNeil, 1982; Shi-Tao Yeh and GlaxoSmithKline, 2002). The Standard Error of Theta (Hanley and McNeil, 1982) represents an estimate of the variability of the model, i.e. a measurement of its inaccuracy: the lower the Standard Error, the more the sample is representative of the population[14].

The significance in statistical terms of the Theta estimated for each model is tested by means of the Z test (Jackson and Wood, 2013; Barniv, Agarwal and Leach, 2002)[15].

Another tool for evaluating the effectiveness of the models is the Accuracy Ratio (AR), calculated in

[14] The formula used in quantification of the Standard Error is the following:

$$SE(\hat{\theta}) = \sqrt{\frac{\hat{\theta}(1-\hat{\theta}) + (n_F - 1)(Q_1 - \hat{\theta}^2) + (n_N - 1)(Q_2 - \hat{\theta}^2)}{n_F n_N}}$$

where:

$$Q_1 = \frac{\hat{\theta}}{2-\hat{\theta}} = Theta$$

n_F = numerousness of failed companies
n_N = numerousness of non-failed companies
Q_1 = estimate of probability that two companies drawn at random from the group of failed companies both have higher values in terms of bankruptcy probability than a company drawn at random from the group of non-failed companies.

[15] The test is the following:

$$z = \frac{\theta - 0.5}{SE(\hat{\theta})}$$

where:
$\hat{\theta}$ = the area below the ROC Curve
$SE(\hat{\theta})$ = standard error of the estimate

relation to the study by Engelmann, Hayden and Tasche (2003) as $AR = 2(\hat{\theta} - 0.5)$. The perfect model reports an AR equal to 1.

In order to assess the effectiveness of each model, the distribution properties of the estimate of Theta were identified by applying mode b), previously illustrated, 2,000 times on random samples.

Following these applications, the values calculated with reference to Theta are the mean, the median, the standard error, the skewness and the excess kurtosis (more precisely the excess of kurtosis with respect to the value assumed by a normal distribution). On the basis of these last parameters, the Jarque and Bera test (1987) was used to assess whether the Thetas obtained have a normal distribution.

The threshold values corresponding to the significance levels of 1% and 5% are 9.21 and 5.99 respectively. The distribution is normal for limited values of the Jarque and Bera test: if the test assumes values greater than 9.21, the error committed by affirming that the distribution is not normal is less than 1%; if the values of the Jarque and Bera test are below 9.21, it means that the value of the test is part of the 99% of the observations characterising a Chi square with 2 degrees of freedom. If, corresponding to the values assumed by the skewness and the excess kurtosis, the value assumed by the test is below 5.99, the distribution analysed is not normal and an error greater than 5% is committed.

Having assessed the accuracy, the percentages of correct classification of the non-failed companies and the failed companies are drawn up applying the models, taking as cut-off point those used by the original authors (Table 4).

Table 4. Cut-off points

Models	Non-failed companies	Failed companies	Grey area
Altman (1983)	Z- Score > 2.9	Z- Score < 2.23	2.23 < Z-Score < 2.9
Taffler (2007)	Z- Score > 0	Z- Score < 0	
Ohlson (1980)	Probability < 0.5	Probability > 0.5	

5 Findings

Below, the results are distinguished according to the application mode.

5.1 Application mode a)

The models were applied to the entire sample, i.e. to all the companies available. The results are indicated in the following table (Table 5).

Table 5. Results of application mode a)

Models	Theta	SETheta	Z	AR
Altman prediction 3 years	67.73%	0.015	11.658	0.35
Taffler prediction 3 years	67.61%	0.015	11.572	0.35
Ohlson prediction 3 years	57.31%	0.015	4.779	0.15
Altman prediction 2 years	70.19%	0.015	13.428	0.40
Taffler prediction 2 years	69.40%	0.015	12.849	0.39
Ohlson prediction 2 years	61.62%	0.015	7.556	0.23
Altman prediction 1 year	79.11%	0.014	21.059	0.58
Taffler prediction 1 year	75.55%	0.014	17.704	0.51
Ohlson prediction 1 year	76.25%	0.014	18.327	0.53

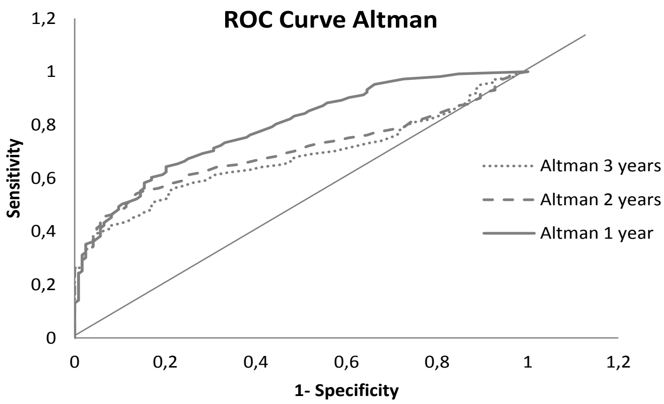
The Theta analysis shows that all the models are more effective in prediction roughly one year prior to manifestation of the insolvency. The discriminant analysis models, i.e. Altman (1983) and Taffler (1983), are more effective in prediction of company insolvency 3 and 2 years prior to occurrence of the event than the Logit model of Ohlson (1980). In the prediction of insolvency 1 year before the event, the effectiveness of the Logit model of Ohlson (1980) significantly increases with respect to the prediction of insolvency 3 and 2 years prior to the event: this confirms what the author himself says concerning the effectiveness of his model in prediction one year before the event.

Observing the Standard error of Theta, no differences emerge in relation to the effectiveness of the three models in the 3 and 2 year prediction. On the contrary, this parameter decreases in the prediction 1 year prior to the event, uniting all the models: it follows that the shorter the time period preceding manifestation of the company insolvency, the more accurate the prediction.

Observing the values of the Z test, it emerges that the models have a better prediction capacity than the random model (which has a mean effectiveness of 50%). The results obtained confirm that the prediction error decreases the closer it gets to manifestation of the company insolvency. Also analysing the information produced by the parameter AR, it emerges that the model of Altman (1983) has a better prediction capacity, with the exception of the 3-year prediction where the discriminant analysis models (Altman (1983) and Taffler (1983) are comparable.

The ROC Curves for the different models considered are given below. The following figure presents the ROC Curve for application of the Altman model (1983) (Figure 1).

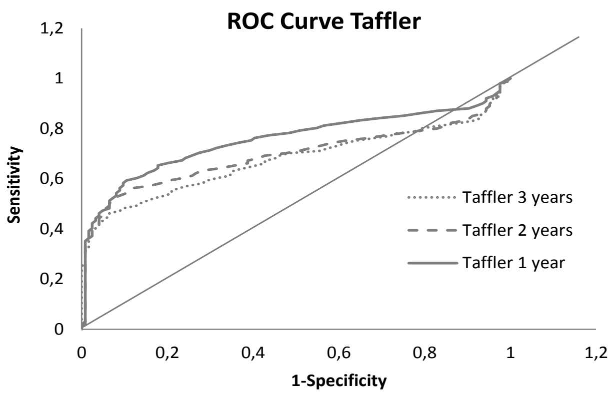
Figure 1. The ROC Curve of Altman (1983)



It can be seen that the highest Roc Curve (i.e. farthest from the straight line at 45°, which represents the line corresponding to the random model) is the one deriving from application of the model 1 year prior to manifestation of the event, demonstrating the greater accuracy of the model. The lowest one, on the other hand, is the one deriving from application of the model 3 years prior to manifestation of the event, demonstrating its lesser accuracy. In addition, it can be noted that the tendency of the ROC Curve at 3 years and 2 years, in its final part (i.e. approaching the 1-Specificity value of 1), shows a behaviour similar to the straight line at 45°, which is typical of the random prediction. In the 1-year prediction, on the other hand, the ROC Curve is evidently detached from the line at 45°, i.e. the prediction made by the model is not random.

The following figure presents the ROC Curve of application of the Taffler model (1983) (Figure 2).

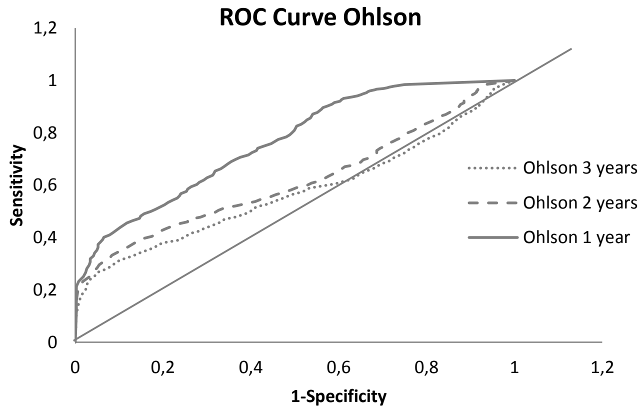
Figure 2. The ROC Curve of Taffler (1983)



As with the Altman model (1983), the greater effectiveness of the model in prediction 1 year prior to the event is confirmed, whereas the lowest effectiveness derives from application of the model 3 years prior to the event. An anomalous trend of the ROC Curve in the years considered can be seen: it is concave (i.e. normal) in the 3-year prediction, and convex (i.e. anomalous) in the 2 and 1 year prediction.

The following figure presents the ROC Curve of application of the Ohlson model (1980) (Figure 3).

Figure 3. The ROC Curve of Ohlson (1980)



As observed for the two previous models, the Ohlson model (1980) is more effective in the prediction 1 year prior to the event.

The percentages of companies correctly classified as non-failed or failed are given below, with reference both to the entire sample of non-failed companies and to the entire sample of failed companies.

The results deriving from the Altman model (1983) are given in Table 6.

Table 6. Results of the Altman model (1983)

Models	Sample of non-failed companies			Sample of failed companies		
	% non-failed correctly predicted	% non-failed grey area	Second Type Error	% failed correctly predicted	% failed grey area	First Type Error
Altman 3-year prediction	19.78%	40.06%	40.16%	64.49%	33.16%	2.35%
Altman 2-year prediction	20.11%	40.41%	39.48%	72.85%	24.54%	2.61%
Altman 1-year prediction	20.42%	40.02%	39.56%	84.07%	13.84%	2.09%

It emerges that both the first type error (i.e. a failed company classified as a non-failed company) and the second type error (i.e. a non-failed company classified as a failed company) decrease around 1 year prior to manifestation of the company insolvency. In particular, it emerges that the second type error decreases more than the first type error as the event approaches.

The results deriving from the Taffler model (1983) are given in Table 7.

Table 7. Results of the Taffler model (1983)

Models	Sample of non-failed companies		Sample of failed companies		Overall sample
	% non-failed correctly predicted	Second Type Error	% failed correctly predicted	First Type Error	% correct predictions
Taffler 3-year prediction	47.86%	52.14%	88.77%	11.23%	48.12%
Taffler 2-year prediction	49.33%	50.67%	90.08%	9.92%	49.60%
Taffler 1-year prediction	49.35%	50.65%	93.99%	6.01%	49.65%

Given that the Taffler model (1983), unlike the Altman model (1983), does not comprise a grey area (i.e. an area of uncertainty in the classification), the following emerges in the prediction 3, 2 and 1 years prior to the event: in the sample of non-failed companies, the second type error assumes higher values than the Altman model (1983) considering, however, that the latter comprises a grey area into which many of the non-failed companies fall; for the sample of failed companies, the first type error assumes higher values than the Altman model (1983). To summarise, both the second and first type error decrease as manifestation of the event approaches and, in particular, the first type error decreases more than the second type error.

With reference to the Ohlson model (1980), the following emerges (Table 8).

Table 8. Results of the Ohlson model (1980)

Models	Sample of non-failed companies		Sample of failed companies		Overall sample
	% non-failed correctly predicted	Second Type Error	% failed correctly predicted	First Type Error	% correct predictions
Ohlson 3-year prediction	64.87%	35.13%	34.46%	65.54%	64.67%
Ohlson 2-year prediction	67.87%	32.13%	36.03%	63.97%	67.67%
Ohlson 1-year prediction	67.14%	32.86%	66.06%	33.94%	67.14%

The Ohlson model (1980), like the Taffler model (1983) but unlike the Altman model (1983), does not comprise a grey area, i.e. an area of uncertainty in the classification. In the 3, 2 and 1 year prediction, the following emerges: for the sample of non-failed companies, the second type error assumes lower values than Taffler (1983); for the sample of failed companies, the first type error assumes much higher values than the Altman model (1983), since the latter does not comprise a grey area. With particular reference to the 1-year prediction, for the sample of failed companies, the first type error assumes higher values than the Altman model (1983), but approximately 50% lower than the 3 and 2-year prediction. In short, both the second and first type error decrease around 1 year prior to manifestation of the event. In addition, the first type error decreases more than the second type error. With respect to the Altman model (1983) (which benefits from the grey area, i.e. uncertainty in the estimate), the Taffler model (1983) is more frequently subject to first type error, whereas the Ohlson model (1980) is characterised by fewer second type errors.

Limiting the analysis to the most significant sectors in terms of failed companies (i.e. those that comprise a considerable number of failed companies), the following differences emerge with respect to the results obtained applying mode a) to the entire sample:

– in the Manufacture sector, an increase in the effectiveness of the models in the 3, 2 and 1 year prediction emerges;

– in the Construction activities, a reduction in the prediction effectiveness of the models emerges, with the exception of the 1-year prediction of the Altman model (1983);

– in the Trade sector, a greater effectiveness of the Altman model (1983) and Taffler model (1983) emerges and a lesser effectiveness of the Ohlson model (1980);

– in the Real estate activities, an increase in the prediction effectiveness of the models is observed, with the exception of the Taffler model (1983) at 1 year, which has a substantially identical effectiveness;

– in the Transport and warehousing sector, the Altman model (1983) highlights an increase in effectiveness of the 3, 2 and 1 year prediction, while for the Taffler model (1983) and Ohlson model (1980) there is an increase in effectiveness of the 2 and 1-year prediction and a reduction in the 3-year prediction. In particular, in the 3-year prediction, the Ohlson model (1980) does not show a good predictive capacity;

– in the sector of Professional activities, the effectiveness of all the models improves as the insolvency event approaches, with the exception of the Ohlson model (1980) in the 3-year prediction.

5.2 Application mode b)

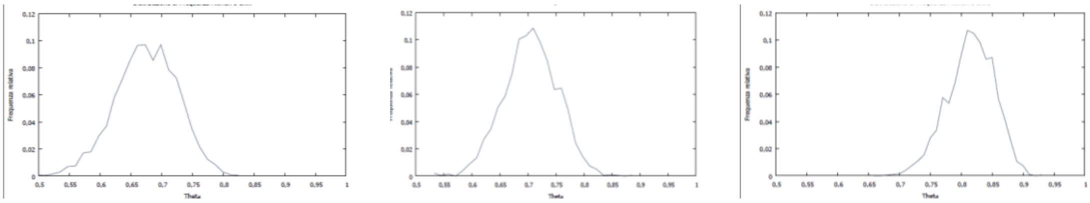
The following tables show the results of the individual models. The results for the three models are given in Table 9.

Table 9. Results of application mode b)

Model	Mean	Median	Std. Dev.	Skewness	Excess kurtosis	Jarque-Bera
Altman 3-year prediction	67.46%	67.57%	0.051	-0.267	0.121	23.574
Altman 2-year prediction	70.51%	70.60%	0.048	-0.114	0.082	4.641
Altman 1-year prediction	81.50%	81.77%	0.038	-0.343	0.018	45.936
Taffler 3-year prediction	67.80%	67.98%	0.051	-0.191	0.151	12.297
Taffler 2-year prediction	71.65%	71.86%	0.048	-0.116	-0.251	11.647
Taffler 1-year prediction	77.96%	78.01%	0.044	-0.122	0.100	5.347
Ohlson 3-year prediction	58.35%	58.31%	0.052	-0.049	-0.084	1.328
Ohlson 2-year prediction	62.58%	62.64%	0.051	-0.115	-0.049	4.922
Ohlson 1-year prediction	76.16%	76.27%	0.042	-0.208	0.127	14.276

With reference to the Altman model (1983), these results are in line with those obtained by applying mode a), confirmed by the mean of the results obtained from the different applications of the above model 3, 2 and 1 year prior to manifestation of the insolvency event (Figure 4).

Figure 4. Frequency distribution at 3, 2 and 1 years for Altman (1983)

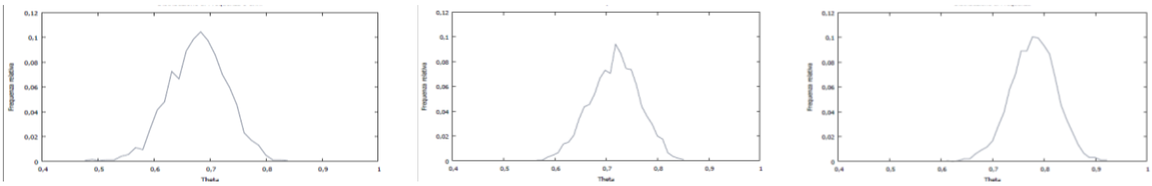


3 years 2 years 1 year

It emerges that the cases in which the effectiveness of the model is a long way from the mean behaviour occur less frequently in the 1-year prediction than in the 3 and 2-year prediction.

Also with reference to the Taffler model (1983), the results are in line with those obtained by applying mode a), confirmed by the mean of the results obtained from the different applications of the above model 3, 2 and 1 years prior to manifestation of the insolvency event (Figure 5).

Figure 5. Frequency distribution at 3, 2 and 1 years for Taffler (1983)

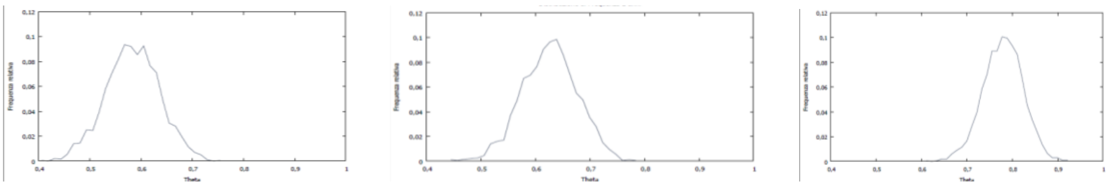


3 years 2 years 1 year

It emerges that the cases in which the effectiveness of the model is a long way from the mean behaviour occur less frequently in the 1-year prediction than in the 3 and 2-year prediction. The same considerations also apply to the cases in which the models' prediction capacity is higher than the mean.

Also with reference to the Ohlson model (1980), it emerges that the results are in line with those obtained by applying mode a), confirmed by the mean of the results obtained from the different applications of the above model 3, 2 and 1 years prior to manifestation of the insolvency event (Figure 6).

Figure 6. Frequency distribution at 3, 2 and 1 years for Ohlson (1983)



3 years 2 years 1 year

It emerges that the Ohlson model predicts fairly well 1 year from manifestation of the event and not as well over longer prediction horizons (2 and 3 years).

After individually observing the results of the above models, it emerges that the models are more accurate at around one year prior to the insolvency event.

Applying the models according to mode b) only to the firms operating in the Manufacture sector, for the Altman model (1983) and the Taffler model (1983) an increase in prediction effectiveness occurs both in the 1-year prediction and in the prediction 2 and 3 years prior to occurrence of the default, while for the Ohlson model (1980) there are no significant variations in terms of effectiveness.

5.3 Application mode c)

The results are shown in the following table (Table 10).

Table 10. Results of application mode c) for Altman (1983)

Models	Sample of non-failed companies			Sample of failed companies		
	% non-failed companies correctly predicted	% companies in grey area	Second Type Error	% failed companies correctly predicted	% companies in grey area	First Type Error
Altman 3-year prediction	20.75%	52.83%	26.42%	73.58%	24.53%	1.89%
Altman 2-year prediction	18.87%	41.51%	39.62%	73.58%	20.75%	5.67%
Altman 1-year prediction	20.75%	39.62%	39.63%	79.25%	16.98%	3.77%

With reference to the errors made, it emerges that both the first type error and second type error decrease around one year prior to manifestation of the event.

With reference to the Taffler model (1983), the following emerges (Table 11).

Table 11. Results of the Taffler model (1983)

Models	Sample of non-failed companies		Sample of failed companies		Overall sample
	% non-failed companies correctly predicted	Second Type Error	% failed companies correctly predicted	First Type Error	% correct predictions
Taffler 3-year prediction	47.17%	52.83%	88.68%	11.32%	67.92%
Taffler 2-year prediction	47.17%	52.83%	86.79%	13.21%	66.98%
Taffler 1-year prediction	47.17%	52.83%	94.34%	5.66%	70.75%

The Taffler model (1983), unlike the Altman model (1983), does not comprise a grey area (i.e. an area of uncertainty in the classification). The following emerges in the 3, 2 and 1-year prediction: for the sample of non-failed companies, the first type error assumes high values with respect to the Altman model (1983), since the latter does not comprise a grey area; for the sample of failed companies, the first type error assumes higher values than the Altman model (1983). In short, the first type error decreases around one year prior to manifestation of the event, while the second type error remains constant.

With reference to the Ohlson model (1980), the following emerges (Table 12).

Table 12. Results of the Ohlson model (1980)

Models	Sample of non-failed companies		Sample of failed companies		Overall sample
	% non-failed companies predicted correctly	Second Type Error	% failed companies predicted correctly	First Type Error	% correct predictions
Ohlson 3-year prediction	81.13%	18.87%	41.51%	58.49%	61.32%
Ohlson 2-year prediction	81.13%	18.87%	43.40%	56.60%	62.26%
Ohlson 1-year prediction	75.47%	24.53%	75.47%	24.53%	75.47%

The Ohlson model (1980), unlike the Altman model (1983). In the 3, 2 and 1-year prediction, the following emerges: for the sample of non-failed companies, the second type error assumes lower values than Taffler (1983); for the sample of failed companies, the first type error assumes much higher values than the Altman model (1983), since the latter does not comprise a grey area. In particular, in the 1-year prediction, for the sample of failed companies, the first type error assumes higher values than the Altman model (1983), but approximately 50% lower than the 3-year and 2-year prediction. In short, both the second type error and the first type error decrease around one year prior to manifestation of the event; in particular, the first type error decreases significantly.

Compared to the Altman model (1983), the Taffler model (1983) is more subject to first type error, while the Ohlson model (1980) is characterised by a more limited second type error.

Applying the models according to mode c) only to the firms operating in the manufacturing sector, for the Altman model (1983) a reduction occurs in the percentage of non-failed firms correctly predicted, while the percentage of failed firms correctly identified significantly increases. For the Taffler model (1983) an increase occurs in the percentage of non-failed companies correctly identified and failed companies correctly identified, with the exception of the percentage of correct identification of the failed companies one year prior to the default event which remains unchanged. For the Ohlson model (1980) an increase occurs in the percentage of non-failed firms correctly identified, but the percentage of correct identification of the failed firms decreases.

6 Conclusions, implications and limitations of the research

Application of the models of Altman (1983), Taffler (1983) and Ohlson (1980) repeated on the three sample sizes (mode a), mode b) and mode c)) enables us to reach the following conclusions for each individual mode.

As regards application mode a), the use of the ROC Curve highlights that the above models have a greater effectiveness around one year prior to manifestation of the insolvency event; furthermore, it emerges that the discriminant analysis models are more effective. One year prior to manifestation of the event, the Altman model (1983) is the one that performs best, followed by the Ohlson model (1980). In addition, using the points chosen by the same authors as cut-off points, the following emerges:

– the Altman model (1983) has two cut-off points for classification of the companies into non-failed companies, failed companies and companies belonging to the grey area (i.e. companies for which the model is not able to specify whether they are or are not in a situation of insolvency). However, with reference to the companies belonging to the grey area, Altman himself hypothesised that they may be companies (if non-failed) which are in a situation of insolvency which has not yet been manifested externally;

– the Taffler model (1983) and the Ohlson model (1980) only have one cut-off point for classification of the companies into non-failed companies and failed companies, i.e. these models do not comprise an area of uncertainty.

The Altman model (1983) shows a lower first type error (i.e. classification of a failed company as non-failed), comparing the results with the Taffler model (1983), which does not comprise a grey area. However, if we considered also the companies falling within the grey area, the Altman model (1983) would have a higher number of failed companies erroneously classified as non-failed, compared to the Taffler model (1983). The first type error in the Ohlson model (1980) significantly decreases the year prior to manifestation of the event, but remains higher than in the Taffler model (1983). With reference to the second type error (i.e. classification of a non-failed company as a failed company), the Ohlson model (1980) shows lower values than the multivariate discriminant analysis models. It should be reiterated that, although the Altman model (1983) comprises an area of uncertainty, the second type error is lower than the Taffler model (1983), but higher than the Ohlson model (1980).

In general, it emerges that the models of Altman (1983) and Taffler (1983) are more conservative, i.e. they predict the default of a higher number of companies than actually found. If the model is used to take decisions (for example, in the case of granting of a loan by a bank), it would entail a reduction in the "potentially" reliable companies, with a high degree of certainty concerning the probable solvency of the reliable companies.

As regards application mode b), the results obtained are coherent with the conclusions for mode a). In particular, each model is more effective in prediction at 1 year than in the prediction at 3 and 2 years prior to the event. Comparing the models, it can be seen that the discriminant analysis models are more effective than the Logit model in the 3 and 2 year prediction, while in the 1-year prediction the gap between the effectiveness of the models narrows significantly.

Generally speaking, the models are more effective the nearer the event gets; the Altman model (1983) is more effective than the other models taken into consideration.

As regards application mode c), the results obtained by mode a) are generally confirmed. The trend of the first and second type errors for the different models follows the general trend, i.e. these errors decrease in the prediction one year prior to manifestation of the event. Given that the two samples contain the same number of companies, it is observed that the discriminant analysis models commit fewer first type errors than second type errors in all three years observed. Furthermore, the Logit analysis model shows fewer second type errors than first type errors for the 3 and 2-year prediction, committing equivalent first and second type errors in the prediction 1 year prior to the event. It is also observed that, given the sample identified, the Altman model (1983) is more effective than the Taffler model (1983) and Ohlson model (1980). In the Altman model (1983), there are fewer first and second type errors than in the other models, due also to the provision of an area of uncertainty. What is noticeable, in accordance with the results obtained throughout the sample, is the lesser second type error in the Ohlson model (1980) when compared with the Taffler model (1983), neither of which have an area of uncertainty.

With reference to all the application modes, it is observed that, for all the models, the error committed in the prediction of default (classification of the company as failed) of a company which is solvent (and should therefore classified as non-failed) is high. On the other hand, the failed companies are classified with a lower degree of error (with the exception of the Ohlson model (1980)). Furthermore, the model could anticipate for some companies the occurrence of a state of insolvency in the years after 2012, emphasising its value as an indicator of an approaching insolvency situation.

The study has a number of theoretical and practical implications. The theoretical implications are connected with development of the research (currently in progress) in order to introduce correctives into the models aimed at increasing their effectiveness. These correctives could be:

a) an "update" of the traditional models (discriminants and Logit). This working hypothesis consists in using the original model, updating it (with reference to the weights of the variables and the cut-off points) in relation to the sample used in this research contribution. In fact, this sample is different from the authors' original one;

b) an "adaptation" of the traditional models (discriminants, logit and regressive). This working hypothesis consists in using the original model and integrating it with some variables that can make a significant contribution to improving their performance. In other words, the variables used by the authors are integrated/replaced by other variables.

As regards "updating" of the models:

i) in Altman (1983) and Taffler (1983), it is known that the weights of the variables, like the cut-off points, have been calculated by the authors on the basis of the samples used by them. The model according to its original configuration was applied to the sample used in this study, providing the results described in the previous pages. It is hypothesised that the performance of the model can be improved if its weights and cut-off points are modified, recalculating them with reference to the sample used in this study (update). This update will be developed as follows:

– using the sample of companies used in this research instead of the sample originally used by Altman and Taffler;

– starting from the original model (with reference to the variables that compose it), the use of a different sample involves recalculation of the weights which each variable assumes in the model. The model would be applied on the basis of the new weights;

– via application of the model with the new weights, the cut-off points for classification of the non-failed and failed companies would be recalculated;

– on the other hand, it would appear that the qualitative type variables appropriately transformed into quantitative variables cannot be used in these models (Knoke,1982); Tabachnick and Fidell, 2012);

ii) in the Logit models, the model will be updated using the sample of this study (different from the one used by the authors), via the same methodological steps as those used in the models of Altman (1983) and Taffler (1983).

As regards "adaptation" of the traditional models (discriminants, logit and regressive), the work programme is to add/modify some variables in the original configuration of the models. The objective is to test the influence of some non-accounting variables (quantitative or qualitative) on the performances of the models. The non-accounting variables considered could be those that are structured and available to parties outside the companies (such as the macroeconomic variables, the sector information, etc.). Other variables could be of a non-structured type and typically not known to parties outside the company (such as the management quality, the presence of independent directors, the presence of management control systems, the R&D activity, etc.).

The practical implications of the research derive from the fact that the ability to effectively predict the manifestation of a situation of company insolvency has emphasised the role of the prediction models for the parties who, in various ways, have or will have expectations in terms of the company's results (banks, suppliers of goods and services and other stakeholders). The new characteristics of company insolvency, on the one hand, and the general ineffectiveness of the prediction models (especially in relation to second type errors), on the other, are stimulating the scholars to identify a series of correctives to the traditional models in order to make them more performing.

The study has a number of limitations, namely:

– the difficulty of accurately identifying the failed companies, since there may be a large number of failed companies but without external evidence of an insolvency situation, hence they are not correctly placed in the sample;

– the number of failed companies has been considerably reduced due to non-availability of the financial statements for all the years involved in the analysis.

These research limits are balanced by a series of strengths of the analysis carried out, represented by the numerousness of the sample considered, and the identification of different application modes.

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