CORPORATE
OWNERSHIP & CONTROL

Postal Address:

Postal Box 136
Sumy 40000
Ukraine

Tel: +380-542-610360
e-mail: info@virtusinterpress.org
www.virtusinterpress.org

Journal Corporate Ownership & Control is published four times a year, in September-November, December-February, March-May and June-August, by Publishing House “Virtus Interpress”, Gagarina Str. 9, office 311, Sumy, 40000, Ukraine.

Information for subscribers: New orders requests should be addressed to the Editor by e-mail. See the section "Subscription details".

Back issues: Single issues are available from the Editor. Details, including prices, are available upon request.

Advertising: For details, please, contact the Editor of the journal.

Corporate Ownership & Control

ISSN 1727-9232 (printed version)
1810-0368 (CD version)
1810-3057 (online version)

CORPORATE OWNERSHIP & CONTROL

VOLUME 14, ISSUE 1, FALL 2016, CONTINUED - 1

CONTENTS

RE-ESTIMATION OF COMPANY INSOLVENCY PREDICTION MODELS: SURVEY ON ITALIAN MANUFACTURING COMPANIES

Elisa Giacosa*, Estela Halili**, Alberto Mazzoleni**, Claudio Teodori**, Monica Veneziani**

*University of Turin, Italy
**University of Brescia, Italy

Abstract

The global research stems from the relevance of the global economic crisis.
The research has several objectives: 1) 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 Italian manufacturing companies; 2) to modify the insolvency prediction models selected with the aim of identifying a company insolvency “alert model” which can be used by the various stakeholders; 3) to compare the effectiveness of the re-estimated models vis-à-vis the original ones. 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 was carried out on a population of Italian companies (27,982 non-failed and 478 failed) with financial statements available for the years 2007-2012. It emerged that, the overall error of the original models, using the original cut-off points, is significant. The error is reduced for cut-off points different from those identified by the original authors. Furthermore, the new re-estimated models have an improved or identical effectiveness vis-à-vis the original models. In particular, the Ohlson re-estimated model is the one that improves most compared to the original model; however, the effectiveness of the Ohlson re-estimated model is lower than the Altman re-estimated model.

Keywords: Insolvency Prediction Models, Economic Crisis, Italian Companies, Financial Alert model

1. INTRODUCTION

The global research 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 objectives of the paper are three: first of all, 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 Italian manufacturing companies; secondly, to modify the insolvency prediction models selected with the aim of identifying a company insolvency “alert model” which can be used by the various stakeholders; lastly, to compare the effectiveness of the re-estimated models with the original ones.

The study was carried out on a population of Italian companies, with financial statements available for the years 2007-2012. The sample consisted of 28,460 companies (27,982 non-failed and 478 failed). The analysis was performed with reference to the state of health of the companies in 2014. The original models of the authors and the re-estimated models in the 3 previous years starting from the second year prior to manifestation of the crisis (i.e. 2012, 2011, 2010) were applied.

In particular, the following models were used:
1) Discriminant analysis
1a) Altman (1983);
1b) Taffler (1983);
2) Logit Analysis
Ohlson (1980).

The results of this paper 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. This 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 study is also coherent with the need for an "alert model" to avert company insolvency, the importance of which has been recently highlighted in Italy by the reforms to the Bankruptcy Law (R.D. 267/42) and ongoing amendments .

The paper continues in the following order: paragraph two offers a summary of the literature on the insolvency prediction models considered in the paper; paragraph three describes the sample of companies and the research method; paragraphs four explains the results and discussion; the last paragraph presents the conclusions, implications, limitations and future evolution of the research.

2. 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 Taffler model (1983) to a sample of British companies; likewise, Altman, Danovi and Falini (2013) apply the Altman model (1983) to a sample of Italian companies.

The literature divides the models used for insolvency prediction into two main types:

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. 3.1. 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).

The Z-score attributed to each company represents, in one single value, the information deriving from the 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; Brockman 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.

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.

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), 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; Brockman and Turtle, 2003; Lin and Piesse, 2001; Westgaard and Wijst, 2001). In the ambit of the Logit 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).

The literature has studied not only the theme of use of an appropriate model for the prediction of insolvency, but also the composition of the sample on which to verify the effectiveness of the models. In particular the size of the sample is important, with particular reference to the incidence of the failed companies on the total number of companies. On this specific point the main sources of literature are cited, summarised in table 1 below.

Table 1. Bankruptcy Rate in literature

Authors	Sample analysis time period	No. Failed	No. non-failed	Bankruptcy Rate
Mario Hernandez Tinoco & Nick Wilson (2013)	1980-2011	1,254	21,964	5.40%
Jackson & Wood (2013)	2000-2009	101	6,494	1.53%
Chih-Ying Christidis & Alan Gregory (2010)	1978-2006	589	49,063	1.19%
Altman, Sabato & Wilson (2010)	2000-2007	66,833	5,749,188	1.15%
Alfaro, Garzia & Elizondo (2008)	2000-2003	590	590	50.00%
Vineet Agarwal & Richard Taffler (2007)	1980-2005	232	27,011	0.85%
Altman & Sabato (2007)	1994-2002	120	1,890	5.97%
Beaver, McNichols & Rhie (2005)	1962-2002	544	74,823	0.72%
Tyler Shumway (1999)	1962-1992	300	28,226	1.05%

Source: Personal processing

It emerges that the percentage impact of the failed companies on the total number of companies analysed is lower than 1.20%, with the exception of the cases in which:

- in addition to the failed companies, the companies in financial difficulty are also classified among the failed companies (Hernandez Tinoco & Wilson). This introduces elements of a subjective nature into the evaluation of the state of health of the company;
- the choice of the number of non-failed companies is guided by the actual bankruptcy rate at national level (Altman & Sabato – model for the SMEs US). In this case, given the national bankruptcy rate and the number of failed companies that can be analysed, a sample is chosen at random from among the non-failed companies with size such that the bankruptcy rate actually encountered at national level is reflected within the research sample;
- groups of non-failed and failed companies with the same size are considered (Alfaro et al). In the latter case, the size of the sample is limited, as it is guided by the number of failed companies actually analysed.

3. THE SAMPLE AND THE RESEARCH METHOD

3.1. The Sample

As already said, the paper has three objectives. With reference to the first objective (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), the original models were applied to a sample of Italian small-medium sized enterprises , operating in the manufacturing sector , whose status (failed/non-failed) was verified at 31/12/2014. Companies that provide financial statement information not sufficient for the purposes of application of the models are not considered in the final sample.

Table 2. Sample for verification of effectiveness of original models

Region	Non-failed companies		Failed companies	
	NR	**%**	**NR**	**%**
Lombardy	8,941	31.95%	138	28.87%
Veneto	4,448	15.90%	65	13.60%
Emilia-Romagna	3,217	11.50%	43	9.00%
Piedmont	2,488	8.89%	57	11.92%
Tuscany	2,074	7.41%	34	7.11%
Campania	1,176	4.20%	20	4.18%
Lazio	914	3.27%	20	4.18%
Marches	841	3.01%	19	3.97%
Friuli-Venezia Giulia	803	2.87%	19	3.97%
Puglia	693	2.48%	21	4.39%
Sicily	474	1.69%	8	1.67%
Abruzzo	416	1.49%	5	1.05%
Trentino-Alto Adige	358	1.28%	1	0.21%
Liguria	329	1.18%	12	2.51%
Umbria	312	1.12%	6	1.26%
Sardinia	210	0.75%	6	1.26%
Calabria	158	0.56%	3	0.63%
Basilicata	55	0.20%	1	0.21%
Molise	48	0.17%	0	0.00%
Valle d'Aosta	27	0.10%	0	0.00%
General total for Italy	**27,982**	**100.00%**	**478**	**100.00%**

Source: Personal processing

The non-failed companies, identified using the Aida Bureau van Dijk database, are companies which have not been admitted to any insolvency or bankruptcy proceedings as of 31/12/2014. The failed companies were identified using the same database and are those that failed during 2014.

The sample composed as above consists of non-failed and failed companies in different numbers, in order to guarantee a sizeable sample. The validity of this method is supported by the literature (Jackson and Wood, 2013). In particular, the large size of the reference sample was supported by other studies: of these, Ohlson (1980) applied the original model to groups of companies having different numbers, commending the "size" variable of the sample; Stein (2002) maintained that the accuracy of the predictive models depends largely on the number of failed companies rather than on the number of the observations. This was supported also by the study of 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 large size of the sample examined. The sample is illustrated in table 2.

The second objective (to modify the insolvency prediction models selected with the aim of identifying a company insolvency "alert model" which can be used by the various stakeholders, in order to obtain the so-called "re-estimated models") requires the use of two samples. The first, also called training sample, is used to obtain the new formulation of the model (changing the weights of the variables with respect to the original models). To determine the training sample, a sample of small to medium sized Italian enterprises operating in the manufacturing sector is used as a starting base, whose status (failed/non-failed) is verified at 31/12/2013. The sample is composed of failed companies, identified from among those failed in 2013, and non-failed companies, i.e. those who have not resorted to insolvency proceedings by 31/12/2013 (Table 3).

Table 3 – Sample for reformulation of models

Region	Non-failed companies		Failed companies	
	NR	%	NR	%
Lombardy	9,240	32.21%	128	26.02%
Veneto	4,586	15.99%	90	18.29%
Emilia-Romagna	3,336	11.63%	45	9.14%
Piedmont	2,540	8.85%	43	8.74%
Tuscany	2,114	7.37%	43	8.74%
Campania	1,112	3.88%	18	3.66%
Marches	1,036	3.61%	24	4.88%
Lazio	936	3.26%	14	2.85%
Friuli-Venezia Giulia	769	2.68%	31	6.30%
Puglia	685	2.39%	12	2.44%
Sicily	469	1.64%	9	1.83%
Abruzzo	405	1.41%	8	1.63%
Trentino-Alto Adige	349	1.22%	5	1.01%
Umbria	320	1.12%	6	1.22%
Liguria	311	1.08%	3	0.61%
Sardinia	212	0.74%	4	0.81%
Calabria	138	0.48%	5	1.02%
Basilicata	60	0.21%	-	0.00%
Molise	43	0.15%	4	0.81%
Valle d'Aosta/Vallée d'Aoste	24	0.08%	-	0.00%
General total for Italy	**28,685**	**100.00%**	**492**	**100.00%**

Source: Personal processing

The second sample, also called verification sample, has the objective of verifying the effectiveness of the re-estimated models; it is the same sample as the one used to meet the first objective (illustrated in table 2). The re-estimated models are applied to this sample.

With reference to the third objective (comparison of the effectiveness of the re-estimated models vis-à-vis the original ones), the verification sample is used, illustrated in table 2.

3.2. The Research Method

The research method is illustrated by distinguishing the three stages of the research, aimed at achieving the study objectives.

First stage: verification of effectiveness of the original company insolvency prediction models

The three company insolvency prediction models were applied verifying their effectiveness over a time horizon of four years (2010-2014), three years

(2011-2014) and two years (2012-2014) prior to the default situation observed in 2014.

In order to make the results deriving from the above methods comparable, the effectiveness of the individual models is tested using the ROC Curve constructed following Gönen (2006). The cut-off points used for construction of the ROC Curve are probabilities of failure and vary from 0 to 1, with step equal to 0.01. For this purpose, the z-Scores for the Altman and Taffler model are converted into probability, actuating a logit transformation of the score following the formula: 1/(1+exp(z-score)).

The effectiveness of the model is represented by the area below the ROC Curve, defined Theta, which is estimated using the trapezium method (Hanley and McNeil, 1982). The Standard Error of Theta (Hanley and McNeil, 1982) represents an estimate of the variability of the model, or a measurement of its imprecision: the lower the Standard Error, the more the sample is representative of the population.

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

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

where:
$Q_1 = \hat{\theta}/(2-\hat{\theta})$ = Theta
n_F = number of failed companies
n_N = number of non-failed companies
Q_1 = estimation of probability that two companies drawn at random from the group of failed companies both have higher values in terms of probability of failure than a company drawn at random from the group of non-failed companies.

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

The test is the following:

$$z = \frac{\hat{\theta}-0.5}{SE(\hat{\theta})} \quad (2)$$

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

Another tool for evaluating the effectiveness of the models is the Accuracy Ratio (AR), calculated in relation to the study by Engelmann, Hayden and Tasche (2003) as AR=$2(\hat{\theta}-0.5)$. The perfect model gives an AR equal to 1.

Having evaluated 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 5). For this purpose, a contingency table was used (Table 4), which allows identification of type I and II errors:

Table 4. Type of errors

Prediction of result	Values observed	
	Non-failed	Failed
Non-failed	TP	FP
Failed	FN	TN

Source: Personal processing

where:

TP (True Positive): a non-failed company is correctly classified;

FP (False Positive): represents a first type error, a failed company is erroneously classified by the model as non-failed;

FN (False Negative): represents a second type error, a non-failed company is erroneously classified by the model as failed;

TN (True Negative): a failed company is correctly classified.

Table 5. Cut-off points

Models	Non-failed companies	Failed companies	Grey area
Altman (1983)	Z- Score > 2.9	Z- Score < 1.23	2.13 < Z-Score < 2.9
Taffler (2007)	Z- Score > 0	Z- Score < 0	
Ohlson (1980)	Probability < 0.5	Probability > 0.5	

Source: Personal processing

Second phase "Re-estimation of company insolvency prediction models and verification of their effectiveness"

The second part of the research entails re-estimation of both the weights of the variables of the individual models and of the cut-off point. The models are estimated using Logit analysis as the statistical technique. This choice was considered appropriate, since:

- Logit analysis does not require the persistence of the following conditions: the multivariate normal distribution of the variables forming part of the model; the equivalence of the variance and covariance matrices of the variables for the non-failed and failed companies;

- there is an absence of significant differences in the effectiveness of the models constructed by the same variables, the weights of which are determined following the multivariate discriminant analysis and the Logit analysis. In other words, the effectiveness of the Altman model (re-estimated using multivariate discriminant analysis as the statistical technique for redetermination of the weights) is very similar to the effectiveness of the same Altman model re-estimated using Logit analysis as the statistical technique for redetermination of the weights (Altman et al. 2014).

However, also the Logit models are characterised by drawbacks concerning the presence of a series of phenomena that can distort the validity of the results obtained (Balcaen & Ooghe, 2004). In particular, the phenomena are characterised by:

- multicollinearity[1], which is not easy to avoid since the financial ratios are correlated with one another (Tucker, 1996);

1 Multicollinearity is a statistical term used to describe situations in which the independent variables, i.e. the variables used in the model, are highly correlated with one another. In these cases, several variables give the same information and the model is not able to determine their contribution to explanation of the phenomenon in question, consequently providing

- "extreme non-normality" of the data, since the distribution of the values of a given indicator is very far from a normal distribution (non-normality is not a problem for the Logit models, but becomes a problem when the distribution is characterised by a marked non-normality, a distribution very far from the normal distribution). In these cases a transformation of the data is advisable to improve the normality of the data (McLeay & Omar, 2000);

- outliers and missing values, making revisitation of the sample necessary, i.e. the outliers and missing values must be eliminated with the appropriate techniques described in the statistical literature (Joos et al., 1998).

In order to make the estimate sample reliable, the estimate of the models via the Logit analysis required the identification of the extreme values (outliers) and the cases in which the individual variables are markedly non-normal. In the case of the outliers, after their identification, the Winsorizing method was followed, while the variables characterised by the presence of marked non-normality were transformed following the approach of Box & Cox. Subsequently, the parameters of the model were estimated using the statistical software Gretl.

In the second phase, two different methods were used to re-estimate the models:

a) method 1: aims to create re-estimated models that return as output the probability of default at 4 years, 3 years and 2 years. In this case, the re-estimated models at 4 years, 3 years and 2 years are characterised by different parameters for each year. This is the method used by Ohlson (1980);

b) method 2: aims to create re-estimated models that return as output the probability of default within the time horizon of 4 years. The model used is unique and is applied to different years to test its predictive capacity in the long term; from an *ex ante* viewpoint, however, it does not provide an estimate of the time horizon within which the event occurs. This is the method used by Altman (1983) and Taffler (1984).

The models estimated as above are first applied to the estimation reference samples, corresponding to which the cut-off point is calculated[2]. Subsequently, they are evaluated on the sample of companies used, to evaluate the predictive effectiveness on the sample on which the original models are also tested.

Third phase "Comparison of effectiveness of the re-estimated models vis-à-vis the original ones"

The effectiveness of the re-estimated models compared to the original ones was assessed using the Roc Curve. In particular, the significance of the differences encountered between the models is tested via the use of statistical tests.

The test implemented (Hanley & McNeil, 1983) has the following form:

$$test\ t = \frac{Theta_1 - Theta_2}{\sqrt{\text{SETheta}_1{}^2 + \text{SETheta}_2{}^2 - r * \text{SETheta}_1 * \text{SETheta}_2}} \quad (3)$$

where:

Theta = area below the ROC curve

SETheta = standard error of the area below the ROC curve

r = correlation between the two ROC areas tested

The correlation between the ROC Curves is indicated by r, determined following the formulation of Hanley & McNeil (1983).

4. FINDINGS AND DISCUSSION

The findings are illustrated below, discussing the individual phases and objectives of the research.

First phase – Verification of effectiveness of the original company insolvency prediction models

The objective of the first phase of the research is to test the degree of effectiveness of the company insolvency prediction models developed in the original version of the authors, applying them to the sample identified in this study. In order to perform a comparative analysis, the T test is used to investigate (Table 6):

- the differences that emerged in the Theta of the models in different years;

- the differences that emerged in the Theta of the different models.

Table 6. Comparison of effectiveness of the different models

Model	T test		Model	T test		
	2-3 years	3-4 years		2 years	3 years	4 years
Altman model	4.938	3.590	Altman - Taffler	7.343	8.639	6.639
Taffler model	2.536	2.096	Altman - Ohlson	6.702	4.858	3.201
Ohlson model	6.375	1.892	Ohlson - Taffler	-0.569	-4.668	-4.030

Note: The values in the reference table were calculated using the results illustrated in the appendix in Panel A table a1

The results of the tests conducted enable us to affirm that, at a significance level $\alpha = 0.05$, the models show an increase in prediction effectiveness the nearer the year of manifestation of the company insolvency, with the exception of the Ohlson model which, in the 3 and 4 year prediction, highlights a statistically equivalent effectiveness. These results are confirmed also at graphic level, see figure a1 in Panel A illustrated in the appendix.

The Altman model is the one that shows the greatest discriminant capacity. In general, the discriminant analysis models, i.e. Altman (1983) and Taffler (1983), have greater effectiveness in the prediction of company insolvency than the Logit model of Ohlson (1980) in the 3 and 4 year prediction. In the 2 year insolvency prediction, the effectiveness of the Logit model of Ohlson (1980) increases significantly compared to the same at 4 and 3 years and is equivalent to the performance of

unreliable parameters (Doumpos & Zopoudinis, 1999; Joos et al., 1998a; Ooghe et al., 1993; Ooghe et al., 1994a).

2 The cut-off point is calculated, following Ohlson, as the point that minimises the overall classification error in the construction sample. In particular, initially attributing an equal weight to both errors (50% and 50%) and then attributing a greater weight to the first type error (67% e 33%).

the Taffler model. The Altman model is considered more performing than the other two models examined in this research.

Evaluating the models via the use of different cut-off points, it emerged that the first and second type errors decrease as the insolvency event approaches, therefore the probability of default assigned to the failed companies increases and the probability of default assigned to the non-failed companies decreases as the evaluation time horizon is reduced (Panel A tables a2, a3 and a4 of the appendix). It can also be affirmed that the cut-off points selected by the authors are not the ones that minimise the overall prediction error (1st type error + 2nd type error). Observing the various models, it is deduced that at the cut-off points selected by the authors, the Ohlson model (2 year prediction) shows more balanced first and second type errors; in addition, at the cut-off points that minimise the error, the Altman model is the one with the lowest error. In general, the Altman model attributes to the companies a lower probability of failure than the Taffler and Ohlson models, whereas the Taffler model is the one that attributes to the companies a significant probability of failure (Table 7).

Table 7. First and second type errors of the models

	Original cut-off points				**Cut-off points with minimum error**			
	Second Type Error		**First Type Error**		**Second Type Error**		**First Type Error**	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
4 year prediction								
Altman model	23,365	83.50%	6	1.26%	4,605	26.39%	101	21.13%
Taffler model	13,473	48.15%	54	11.30%	9,354	33.43%	111	23.22%
Ohlson model	7,136	25.50%	225	47.07%	11,819	42.24%	124	25.94%
3 year prediction								
Altman model	23,062	82.42%	8	1.67%	4,466	20.76%	81	16.95%
Taffler model	13,700	48.96%	48	8.79%	6,523	23.31%	118	24.69%
Ohlson model	6,884	24.60%	277	42.05%	12,650	45.21%	90	18.83%
2 year prediction								
Altman model	23,217	82.97%	5	1.05%	3,896	13.92%	71	14.85%
Taffler model	13,524	48.33%	29	6.07%	3,354	11.99%	112	23.43%
Ohlson model	7,116	25.43%	125	26.15%	8,113	21.76%	104	28.99%

Second phase - "Re-estimation of company insolvency prediction models and verification of their effectiveness"

The objective of the second phase of the research is re-estimation of the models, aimed at increasing their effectiveness with reference to the sample of Italian companies.

In particular, the two methods illustrated in the methodology were used (method 1, method 2).

In order to perform a comparative analysis, the T test was used to investigate the performance of the adapted models compared to the original models (Table 8).

Table 8. Comparison of effectiveness of the different models

Model for estimation of PD within 4 years	**T test**			**Model for estimation of PD within 2, 3, 4 years**	**T test**		
	2 years	**3 years**	**4 years**		**2 years**	**3 years**	**4 years**
Altman -Altman New	-0.436	-0.483	-0.406	Altman -Altman New	1.080	-0.281	-0.696
Taffler - Taffler New	-4.395	-1.578	-0.318	Taffler - Taffler New	-4.211	-1.722	-0.188
Ohlson - Ohlson New	0.840	-0.269	-0.314	Ohlson - Ohlson New	-4.785	-6.207	-2.667

Note: The values in the reference table were calculated using the results illustrated in the appendix in Panel B tables b1, b3, b5, b7, b9 and b11

Method 1.

With reference to the adapted Altman model for estimation of the probability at 4 years, 3 years and 2 years, it is observed that, with the exception of the 2 year prediction, the new models have a higher Theta than the original model. However, in all three cases, the differences between the Thetas are statistically non-significant at a significance level of 0.05, indicating that the effectiveness of the re-estimated and original models is substantially equivalent. For the Taffler model, it is observed that the effectiveness with respect to the original model increases significantly in the 2-year prediction, whereas it remains unchanged in the 3 and 4 year prediction. With reference to the adapted Ohlson model for estimation of the probability at 4 years, 3 years and 2 years, it is observed that the new models have a higher Theta than the original model. These differences are significant at a significance level of

0.05, indicating that the new model has a greater predictive effectiveness than the original model.

The same results are confirmed if we compare the first type and second type errors of the original models with those that occurred in the re-estimated models (Table 9).

Table 9. Comparison of first type and second type errors of the models re-estimated according to method 1 with the original models

	Original cut-off points				**Cut-off points with minimum error**				**Cut-off points with minimum error in re-estimated model**			
	Second Type Error		**First Type Error**		**Second Type Error**		**First Type Error**		**Second Type Error**		**First Type Error**	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
4 year prediction												
Altman model	23,365	83.50%	6	1.26%	7,384	26.39%	101	21.13%	5,549	19.83%	127	26.57%
Taffler model	13,473	48.15%	54	11.30%	9,354	33.43%	111	23.22%	7,572	27.06%	143	29.92%
Ohlson model	7,136	25.50%	225	47.07%	11,819	42.24%	124	25.94%	10,902	38.96%	81	16.95%
3 year prediction												
Altman model	23,062	82.42%	8	1.67%	5,809	20.76%	81	16.95%	5,255	18.78%	96	20.08%
Taffler model	13,700	48.96%	48	8.79%	6,523	23.31%	118	24.69%	8,770	31.34%	86	17.99%
Ohlson model	6,884	24.60%	277	42.05%	12,650	45.21%	90	18.83%	6,268	22.40%	133	27.82%
2 year prediction												
Altman model	23,217	82.97%	5	1.05%	3,896	13.92%	71	14.85%	4,659	16.65%	55	11.51%
Taffler model	13,524	48.33%	29	6.07%	3,354	11.99%	112	23.43%	5,442	19,45%	84	17,57%
Ohlson model	7,116	25.43%	125	26.15%	8,113	21.76%	104	28.99%	5,764	20.60%	82	17.15%

In general, it is observed that the adapted models exhibit second type errors which are markedly lower than the original models, if compared with the errors shown by the latter at the cut-off points originally highlighted by the authors. However, an increase in first type error is observed for the Altman and Taffler models; for the Ohlson model, on the other hand, a reduction in first type error is highlighted in the prediction of PD over a 2 and 3 year time horizon (Panel B table b2, b6 and b10 of the appendix).

Comparing the original models with the re-estimated models, using the cut-off points that minimise the errors in the reference sample, it is observed that the overall errors committed by the re-estimated models are slightly lower than those emerging from application of the original models at the cut-off point that minimises the error.

Method 2.

With reference to the re-estimated Altman model, although the new model has a higher Theta than the original model, this difference is not significant at a significance level of 0.05: substantially, there is no significant variation in effectiveness between original models and re-estimated models. For the Taffler model, the effectiveness with respect to the original model significantly increases in the 2 year prediction, whereas it remains unchanged in the 3 and 4 year prediction. The results that emerge from Table 22 for the Ohlson model indicate that the adapted model has an effectiveness substantially equivalent to the original model in the prediction of insolvency within the 4 year horizon.

The same results are confirmed if we compare the first type and second type errors of the original models with those that occurred in the re-estimated models (Table 10).

The adapted models highlight second type errors clearly lower than those of the original models, if compared with the errors exhibited by the latter at the cut-off points originally highlighted by the authors. However, an increase in first type error is observed (Panel B tables b4, b8 and b12 of the appendix).

Comparing the originals models with the re-estimated models, and using the cut-off points that minimise the errors in the reference sample, the overall errors committed by the adapted models are slightly lower than those emerging from application of the original models at the cut-off point that minimises the error.

To conclude, the new re-estimated models formulated for estimation of the probability of failure at 2, 3 and 4 years have an effectiveness better than or equal to the original models. The model that improves most is the Ohlson model; however, the effectiveness of the latter is lower than the Altman model, which is the best performing one.

Table 10. Comparison of first type and second type errors of the models re-estimated according to method 2 with the original models

	Original cut-off points				Cut-off points with minimum error				Cut-off points with minimum error in re-estimated model			
	Second Type Error		First Type Error		Second Type Error		First Type Error		Second Type Error		First Type Error	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
4 year prediction												
Altman model	23,365	83.50%	6	1.26%	7,384	26.39%	101	21.13%	5,188	18,54%	125	26.15%
Taffler model	13,473	48.15%	54	11.30%	9,354	33.43%	111	23.22%	7,600	27.16%	140	29.29%
Ohlson model	7,136	25.50%	225	47.07%	11,819	42.24%	124	25.94%	8,260	29.52%	187	39.12%
3 year prediction												
Altman model	23,062	82.42%	8	1.67%	5,809	20.76%	81	16.95%	5,042	18.02%	88	18.41%
Taffler model	13,700	48.96%	48	8.79%	6,523	23.31%	118	24.69%	7,966	28.47%	99	20.71%
Ohlson model	6,884	24.60%	277	42.05%	12,650	45.21%	90	18.83%	7,390	26.41%	179	37.45%
2 year prediction												
Altman model	23,217	82.97%	5	1.05%	3,896	13.92%	71	14.85%	5,683	20.31%	36	7.53%
Taffler model	13,524	48.33%	29	6.07%	3,354	11.99%	112	23.43%	8,260	29.52%	52	10,88%
Ohlson model	7,116	25.43%	125	26.15%	8,113	21.76%	104	28.99%	4,029	14.40%	165	34.52%

In addition, the new re-estimated models determine the probability of failure of a company over a horizon of 4, 3 and 2 years. This aspect does not emerge from the original models; in fact, Altman (1983) and Taffler (1984) do not determine the probability of failure of a company, whereas Ohlson (1980) determines the probability of failure of a company only up to the two years prior to manifestation of the crisis.

5. CONCLUSIONS, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

The research has several objectives: firstly, 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 Italian manufacturing companies; secondly, to modify the insolvency prediction models selected with the aim of identifying a company insolvency “alert model” which can be used by the various stakeholders; lastly, to compare the effectiveness of the re-estimated models with the original models.

The empirical analysis highlighted that the original models of Altman (1983) and Taffler (1984) have a high percentage of effectiveness in identification of the failed companies, but are characterised by the following aspects:

- Altman (1983) highlights a high second type error, if one single cut-off point is assumed[3]. In fact, a significant number of non-failed companies are identified as failed;

- according to Taffler (1984), one non-failed company out of two is considered a failed company.

These results suggest that, if the models are used to take decisions (for example, the granting of a loan by a bank), they would entail a reduction in the number of “potentially” reliable companies and, conversely, a high safety level concerning the probable lack of insolvency on the part of the companies granted the loan. The models therefore exhibit a very prudent and conservative approach in terms of their predictions.

With reference to the Ohlson model (1980) in the prediction of insolvencies at 2 years from the year of manifestation of the crisis, the error committed in identification of a non-failed company is roughly similar to the error committed in identification of a failed company. Furthermore, correct identification of the non-failed companies is higher than the models previously analysed, with a lower ability to predict the defaults (high first type error).

The results obtained from the empirical investigation suggest that the original models are not suited to the Italian economic context; in fact, the overall prediction error of said models significantly decreases if the cut-off point is varied with respect to the one used in the original model[4]. This may be due to different reasons:

- firstly, the original models were created in a period characterised by a different economic context from the current one, in terms of both number of companies and characteristics of their financial structure;

- the Italian economic context differs from the context (British and American) on which the original models were defined. The sample used by this study, representing the entire population of Italian manufacturing companies having the requirements illustrated in par. 3.1, is composed mostly of small to medium-sized enterprises. In fact, 99.9% of the companies in the sample have a turnover lower than 50 million Euro and 61.5% have a turnover lower than 5 million Euro.

The original models of the authors are therefore significantly improved by applying to them (with the original weights of the variables) cut-off

3 Between the two cut-off points established by the original model, 2.91 was prudently chosen to make it comparable with the others.

4 The new cut-off points are calculated with reference to the sample of Italian companies used in this study.

points different from the original ones recalculated with reference to the Italian context.

Lastly, after re-estimation of the above models, a slight improvement emerges in the percentages of correct prediction of the crisis. The re-estimation of the models was obtained by calculating new weights of the variables and applying the same models to the new cut-off points.

The improvement obtained with respect to the original models nevertheless still highlights the existence of significant errors concerning the ability to correctly classify the companies among the "non-failed companies" and the "failed" companies. It is therefore necessary to include new variables in the models or modify some of those already present.

This study makes a series of contributions to the literature:

- firstly, the effectiveness of the company insolvency prediction models is evaluated in the Italian economic context of the manufacturing companies, which have been badly affected by the crisis; therefore, it constitutes an important field of observation;
- secondly, the study highlighted a significant improvement in the models with respect to the original versions;
- thirdly, the new re-estimated models also determine the probability of failure of a company over a horizon of 4, 3 and 2 years. This aspect does not emerge from the original models: Altman (1983) and Taffler (1984) do not determine the probability of failure of a company, while Ohlson (1980) determines the probability of failure of a company only as far as the two years preceding manifestation of the crisis;
- this study has not concentrated on the effectiveness of the company insolvency prediction models one year prior to manifestation of the crisis. In the opinion of the authors, this prediction is not useful as the time span is too short to make a series of useful corrective interventions aimed at company turnaround. Consequently, an alert model one year prior to manifestation of the crisis would have no significance;
- lastly, interpreting this study in the context of the Stakeholder Theory (Freeman, 1984; Donaldson and Preston, 1995), the different stakeholder categories can better understand the company situation, i.e. to what extent the company is likely to undergo a crisis. In fact, 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.

The study is characterised by a series of theoretical and practical implications. The theoretical implications are also connected with the possible developments of the research via an "adaptation" of the traditional models (discriminant, logit and regressive) with some variables able to significantly contribute to improvement of their performances. This aspect derives from the awareness that, with a view to improving the first and second type errors, one choice could be that of reformulating the variables of the models, adding new variables or removing some of those already present. This activity will be the subject of future research. As regards "adaptation" of the traditional models (discriminant, 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 improve their performance and to create new alert model.

The study has a number of limitations, namely:

- the difficulty of accurately identifying the companies in financial difficulty. The failed companies are only a part of the companies in financial difficulty. While the failed companies (or those that resort to procedures established by the Bankruptcy Law) appear in official and public documents (registration with the Chamber of Commerce), the other companies in financial difficulty are not recorded in any official source. For this reason the number of companies in financial difficulty is certainly higher than the number of failed companies;
- 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.

REFERENCES:

1. Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? Accounting and Business Research, 37 (4), 285-300.
2. Agarwal, V., & Taffler, R. J. (2008). Comparing the performance of market-based and accounting-based bankruptcy. Journal of Banking and Finance, 32 (8), 1541-1551.
3. Alberici, A. (1975). Analisi dei bilanci e previsione delle insolvence. Milano: ISEDI.
4. Alfaro, E., García, N., Gámez, M., Elizondo, D. (2008). Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks. Decision Support Systems, 45(1), 110-122.
5. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4), 589-609.

6. Altman, E. I. (1983). Corporate financial distress: A complete guide to predicting avoiding and dealing with bankruptcy. New York: John Wiley and Sons.
7. Altman, E. I., Danovi, A., Falini, A. (2013). Z-Score Models' application to Italian companies subject to extraordinary administration. Journal of Applied Finance, 23(1), 128-137.
8. Altman, E. I., Haldeman, R. C., Narayanan, P. (1977). Zeta analysis: a new model to identify bankruptcy risk of corporations. Journal of Banking and Finance, 1(1), 25-54.
9. Altman, E. I., Sabato, G. (2007). Modelling Credit Risk for SMEs: Evidence from the U.S. Market. A Journal Accounting, Finance and Business Studies, 43(3), 332-357.
10. Altman, E. I., Sabato, G., Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. The Journal of Credit Risk,6(2), 1-33.
11. Aziz, A., Emanuel, D. C., & Lawson, G. H. (1988). Bankruptcy prediction – an investigation of cash flow based models. Journal of Management Studies, 25(5), 419-437.
12. Aziz, M., & Dar, H. (2006). Predicting corporate bankruptcy: Where we satnd. Coorporate Governance, 6(1), 18-33.
13. Back, B., Laitinen, T., Sere, K., & Wezel, M. V. (1996). Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms. In Technical Report No. 40. Turku: Turku Centre for Computer Science.
14. Balcaen, S., & Ooghe, H. (2004). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. Working paper, Ghent University, 2004/248.
15. Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic methodologies and their related problems. The British Accounting Review, 38(1), 69-93.
16. Barniv, R., Agarwal, A., Leach, R. (2002). Predicting bankruptcy resolution. Journal of Business Finance & Accounting, 29(3 & 4), 497-520.
17. Beaver, W. (1966). Financial ratios as predictors of failures. Journal of Accounting Research, 4(3), 71-102.
18. Beaver, W. (1968). Market prices, financial ratios and prediction of failures. Journal of Accounting Research, 6(2), 179-192.
19. Beaver, W. H., McNichols, M., Rhie, J. (2005). Management of the loss reserve accrual and the distribution of earnings in the property-casualty insurance industry. Review of Accounting Studies,10(1), 93-122.
20. Beynon, M. J., Peel, M. J. (2001). Variable precision rough set theory and data discretisation: an application to corporate failure prediction. Omega, 29(6), 561-76.
21. Blum, M. (1974). Failing company discriminant analysis. Journal of Accounting Research, 12(1), 1-25.
22. Booth, P. J. (1983). Decomposition measure and the prediction of financial failure. Journal of Business Finance & Accounting, 10(1), 67-82.
23. Brockman, P., Turtle, H. J. (2003). A barrier option framework for corporate security valuation. Journal of Financial Economics, 67(3), 511-29.
24. Casey, C. J., Bartczak, N. J. (1984). Cash flow – it's not the bottom line. Harvard Business Review, 62(4), 61-66.
25. Charitou, A., Neophytou, E., Charalambous, C. (2004). Predicting corporate failure: empirical evidence for the UK. European Accounting Review, 13(3), 465-497.
26. Christidis, C.Y., Gregory, A. (2010). Some New Models for Financial Distress Prediction in the UK. Centre for Finance and Investment, Discussion Paper no: 10/04.
27. Coats, P. K., Fant, L. F. (1993). Recognizing financial distress patterns using a neural network tool. Financial Management, 22(3), 142-155.
28. Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. Journal of Accounting Research, 10(1), 167-179.
29. Deakin, E. B. (1977). Business failure prediction: an empirical analysis. In E. I. Altman, A.W: Sametz (Eds.). In Financial crises: Institutions and markets in a fragile environment (66-88). New York: John Wiley & Sons.
30. Dimitras, A. I., Zanakis, S. H., Zopounidis, C. (1999). A survey of business failure with an emphasis on prediction methods and industrial applications. European Journal of Operational Research, 90(3), 487-513.
31. Donaldson, T., Preston, L. E. (1995). The Stakeholder Theory of the Corporation: Concepts, Evidence, and Implications. Academy of Management Review, 20(1), 65-91.
32. Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. Journal of Financial and Quantitative Analysis, 7(2), 1477-1493.
33. El Hennawy, R. H., Morris, R. C. (1983). The significance of base year in developing failure prediction models. Journal of Business Finance and Accounting, 10(2), 209-223.
34. Engelmann, B., Boral, A., & Tasche, D. (2003). Testing rating accuracy. Risk, 16(1), 82-86.
35. Falkestein, E., Boral, A., Carty, L. (2000). RiskCalc for private companies: Moody's default model. Moody's KMV.
36. Fisher, R. A. (1963). The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenics, 7(2), 179-188.
37. Foreman, R. D. (2002). A logistic analysis of bankruptcy within the US local telecommunications industry. Journal of Economics and Business, 6(1), 1-32.
38. Forestieri, G. (1977). La previsone delle insolvenze aziendali. Milano: Giuffrè Editore.
39. Freeman, R. E. (2010). Strategic Management A Stakeholder Approach. Cambrige: Cambrige University press.
40. Frydman, H., Altman, E. I., Kao, D. (1985). Introducing recursive partitioning for financial classification: the case of financial distress. The Journal of Finance, 40(1), 269-291.
41. Gombola, M. J., Haskins, M. E., Ketz, J. E., & Williams, D. D. (1987). Cash flow in bankruptcy prediction. Financial Management, 16(4), 55-65.
42. Gönen, M. (2006). Receiver operating characteristic (ROC) curves. In proceedings of the SAS users Group international 31 conference. San Francisco, CA: Available on the internet at http://www2.sas.com/proceedings/sugi31/210-31.pdf.
43. Hanley, J., & McNeil, B. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143(1), 29-36.
44. Hanley, J., & McNeil, B. (1983). A Method of Comparing the Areas under Receiver Operating Characteristic Curves Derived from the Same Cases. Radiology, 148(3), 839-843.
45. Hernandez Tinoco, M., Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and

macroeconomic variables. International Review of Financial Analysis, 30, 394-419
46. Jackson, R., Wood, A. (2013). The performance of insolvency prediction and credit risk models in the UK: A comperative study. The British Accounting Review, 45(3), 183-202.
47. Jo, H., Han, I., Lee, H. (1997). Bankruptcy prediction using casebased reasoning, neural networks, and discriminant analysis. Expert Systems with Applications, 13(2), 97-108.
48. Joos, P., Vanhoof, K., Ooghe, H., Sierens, N. (1998), Credit classification: A comparison of logit models and decision trees, Proceedings Notes of the Workshop on Application of Machine Learning and Data 49 Mining in Finance, 10th European Conference on Machine Learning, April 24, Chemnitz (Germany), 59-72.
49. Kahya, E., Theodossiou, P. (1999). Predicting corporate financial distress: a time-series CUSUM methodology, Review of Quantitative Finance and Accounting. Review of Quantitative Finance and Accounting, 13(4), 323-345.
50. Keasey, K., McGuinness, P. (1990). The failure of UK industrial firms for the period 1976-1984: logistic analysis and entropy measures. Journal of Business Finance and Accounting, 17(1), 119-35.
51. Laitinen, E. K., Laitinen, T. (1998). Cash management behaviour and failure prediction. Journal of Business Finance and Accounting, 25(7 & 8), 893-919.
52. Libby, R. (1975). Accounting ratios and the prediction of failure: some behavioural evidence. Journal of Accounting Research, 13(1), 150-161.
53. Lin, L., Piesse, J. (2001). The Identification of Corporate Distress: A Conditional Probability Analysis Approach. Documents, Department of Management, Birbeck, University of London, London.
54. Lincoln, M. (1984). An empirical study of the usefulness of accounting ratios to describe levels of insolvency risk. Journal of Banking and Finance, 8(2), 321-340.
55. Mantoan, M., Mantovan, P. (1987). Un modello di previsione del dissesto s'impresa. Rivista Dottori Commercialisti,. Rivista Dottori Commercialisti, 135-159.
56. McGurr, P. T., DeVaney, S. A. (1998). Predicting business failure of retail firms: an analysis using mixed industry models. Journal of Business Research, 43(3), 169-176.
57. McLeay, S., Omar, A., (2000). The sensitivity of prediction models to the non-normality of bounded an unbounded financial ratios. British Accounting Review, 32(2), pp. 213-230.
58. Moyer, R. C. (1977). Forecasting financial failure: a re-examination. Financial Management, 6(1), 11-17.
59. Neophytou, E., Charitou, A., Charalambous, C. (2001). Predicting corporate failure: emprical evidence for the UK. School of Management, University of Southampton, Southampton.
60. Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 18(1), 109-131.
61. Piesse, J., Wood, D. (1992). Issues in assessing MDA models of corporate failure: a research note. British Accounting Review, 24(1), 33-42.
62. Platt, H. D., Platt, M. B. (1990). Development of a class of stable predictive variables: the case of bankruptcy prediction. Journal of Banking, Finance and Accounting, 17(1), 31-51.
63. Pompe, P., Feelders, A. (1997). Using machine learning, neural networks, and statistics to predict corporate bankruptcy. Microcomputers in Civil Engineering, 12(4), 267-276.
64. Reisz, A., Purlich, C. (2007). A market based framework for bankruptcy prediction. Journal of Financial Stability, 3(2), 85-131.
65. Salchenberger, L. M., Cinar, E. M., Lash, N. A. (1992). Neural networks: a new tool for predicting thrift failures. Decision Sciences, 23(4), 899-916.
66. Shumway, T. (1999). Forecasting bankruptcy more accurately: A simple hazard model. University of Michigan : Available on the internet at http://www-personal.umich.edu/~shumway/papers.dir/forcbank.pdf.
67. Stein, R. (2007). Benchmarking default prediction models: pitfalls and remedies in model validation. Journal of Risk Model Validation, 1(1), 77-113.
68. Sung, T. K., Chang, N., Lee, G. (1999). Dynamics of modelling in data mining: interpretive approach to bankruptcy prediction. Journal of Management Information Systems, 16(1), 63-85.
69. Taffler, R. J. (1982). Forecasting company failure in the U.K: using discriminant analysis and financial ratio data. Journal of Royal Statistical Sociaty, 145(3), 342-358.
70. Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model. Accounting and Business Research, 15(52), 295-308.
71. Taffler, R. J., Tisshaw, H. (1977). Going, going, gone – four factors which predict. Accountancy, 88(1003), 50-54.
72. Teodori, C. (1989). Modelli di previsione nell'analisi economico-aziendale. Torino : G. Giappichelli Editore.
73. Theodossiou, P. T. (1991). Alternative models for assessing the financial condition of business in Greece. Journal of Business Finance and Accounting, 18(5), 697-720.
74. Theodossiou, P. T. (1993). Predicting shifts in the mean of a multivariate time series process: an application in predicting business failures. Journal of the American Statistical Association, 88(422), 441-449.
75. Tucker, J. (1996). Neural networks versus logistic regression in financial modelling: a methodological comparison. Paper published in Proceedings of the 1996 World First Online Workshop on Soft Computing (WSC1), Nagoya University, Japan, August 19-30, 1996.
76. Ward, T. J. (1994). An empirical study of the incremental predictive ability of Beaver's naive operating flow measure using four-state-ordinal models of financial distress. Journal of Business Finance and Accounting, 21(4), 547-561.
77. Westgaard, S., Wijst, N. (2001). Default probabilities in a corporate bank portfolio: a logistic model approach. European Journal of Operational Research, 135(2), 338-349.
78. Yang, Z. R., Platt, M. B., Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. Journal of Business Research, 44(2).
79. Yeh, S.-T. (2002). Using trapezoidal rule for the area under a curve calculation. In proceedings of the SAS users Group international 27 conference. San Francisco, CA: Available on the internet at http://www2.sas.com/proceedings/sugi31/210-31.pdf.
80. Zavgren, C. V. (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. Journal of Banking and Finance, 12(1), 19-45.

APPENDIX

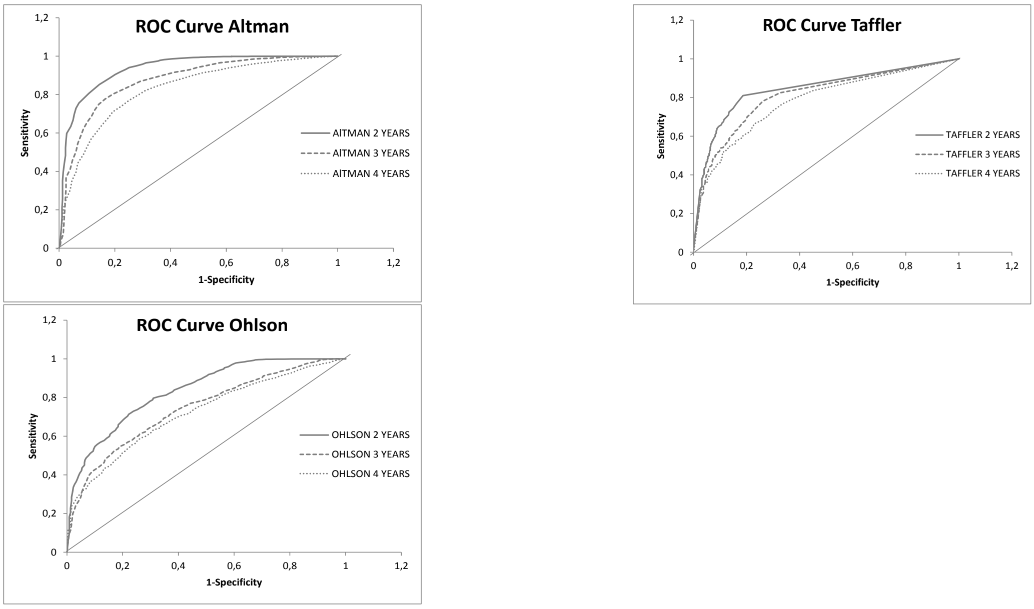
Below, the results are distinguished according to the research objectives that were achieved via the first two phases of the research, while the third phase of the research is included under the discussion.

Panel A. Verification of effectiveness of the original company insolvency prediction models

Table A.1. Effectiveness of original models estimated via Theta

Models	Theta	SETheta	Z	AR
Altman 4 year prediction	82.87%	0.012	28.260	0.66
Taffler 4 year prediction	77.92%	0.013	22.154	0.56
Ohlson 4 year prediction	71.39%	0.013	15.957	0.43
Altman 3 year prediction	87.38%	0.010	35.960	0.75
Taffler 3 year prediction	80.83%	0.012	25.533	0.62
Ohlson 3 year prediction	74.22%	0.013	18.475	0.48
Altman 2 year prediction	92.86%	0.008	52.368	0.86
Taffler 2 year prediction	84.28%	0.011	30.364	0.69
Ohlson 2 year prediction	83.47%	0.011	29.135	0.67

Figure A.1. ROC Curve of original models



The results of the application of the original individual prediction models are shown below.

A) Altman model

Table A.2. First and second type errors for the Altman model

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
0.05	*17.03%*	*82.97%*	*98.95%*	*1.05%*	*17.58%*	*82.42%*	*98.33%*	*1.67%*	*16.50%*	*83.50%*	*98.74%*	*1.26%*
0.1	39.69%	60.31%	98.54%	1.46%	41.18%	58.82%	96.03%	3.97%	39.60%	60.40%	93.93%	6.07%
0.2	75.59%	24.41%	92.89%	7.11%	77.74%	22.26%	83.47%	16.53%	77.02%	22.98%	74.90%	25.10%
0.3	94.10%	5.90%	74.90%	25.10%	95.06%	4.94%	47.28%	52.72%	94.86%	5.14%	35.15%	64.85%
0,4	98.75%	1.25%	57.95%	42.05%	99.10%	0.90%	23.22%	76.78%	99.11%	0.89%	9.83%	90.17%
0,5	99.67%	0.33%	45.19%	54.81%	99.73%	0.27%	14.02%	85.98%	99.77%	0.23%	3.77%	96.23%
0,6	99.87%	0.13%	36.82%	63.18%	99.90%	0.10%	6.69%	93.31%	99.94%	0.06%	1.88%	98.12%
0,7	99.94%	0.06%	28.66%	71.34%	99.97%	0.03%	3.97%	96.03%	99.97%	0.03%	1.26%	98.74%
0,8	99.96%	0.04%	21.13%	78.87%	99.98%	0.02%	2.30%	97.70%	99.99%	0.01%	0.84%	99.16%
0,9	99.97%	0.03%	15.48%	84.52%	99.99%	0.01%	2.09%	97.91%	100.00%	0.00%	0.42%	99.58%

The percentages of correct prediction and the first and second type errors at the various cut-off points used for construction of the curve are illustrated in the table. The cut-off points analysed vary from 0.1 to 0.9 with step 0.1. They also comprise one of the cut-off points identified by the author, the 2.91 cut-off point, which indicates a probability of default equal to 1/(1+exp(2.9)) = 0.05166.

B) Taffler model

Table A.3. First and second type errors for the Taffler model

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
0.1	39.94%	60.06%	96.23%	3.77%	38.55%	61.45%	95.40%	4.60%	39.01%	60.99%	94.35%	5.65%
0.2	43.96%	56.04%	95.40%	4.60%	42.76%	57.24%	94.35%	5.65%	43.33%	56.67%	92.26%	7.74%
0.3	46.79%	53.21%	94.77%	5.23%	45.91%	54.09%	92.89%	7.11%	46.69%	53.31%	89.75%	10.25%
0.4	49.29%	50.71%	94.56%	5.44%	48.54%	51.46%	92.68%	7.32%	49.20%	50.80%	89.12%	10.88%
0.5	*51.67%*	*48.33%*	*93.93%*	*6.07%*	*51.04%*	*48.96%*	*91.21%*	*8.79%*	*51.85%*	*48.15%*	*88.70%*	*11.30%*
0.6	54.22%	45.78%	93.72%	6.28%	53.63%	46.37%	89.75%	10.25%	54.50%	45.50%	86.40%	13.60%
0.7	56.92%	43.08%	93.10%	6.90%	56.43%	43.57%	87.45%	12.55%	57.54%	42.46%	84.10%	15.90%
0.8	60.35%	39.65%	91.84%	8.16%	60.18%	39.82%	85.98%	14.02%	61.44%	38.56%	79.71%	20.29%
0.9	65.87%	34.13%	89.54%	10.46%	66.27%	33.73%	82.01%	17.99%	67.51%	32.49%	75.31%	24.69%

The cut-off point identified by the Author is equal to zero which, converted into probability, corresponds to 0.5 (1/(1+exp(0))=0.5).

C) Ohlson model

Table A.4. First and second type errors for the Ohlson model

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
0.1	28.51%	71.49%	98.33%	1.67%	27.87%	72.13%	95.19%	4.81%	26.74%	73.26%	95.40%	4.60%
0.2	43.64%	56.36%	94.56%	5.44%	43.71%	56.29%	88.91%	11.09%	41.94%	58.06%	85.77%	14.23%
0.3	55.73%	44.27%	89.12%	10.88%	55.73%	44.27%	79.29%	20.71%	54.29%	45.71%	76.78%	23.22%
0.4	65.89%	34.11%	81.59%	18.41%	66.38%	33.62%	67.57%	32.43%	64.79%	35.21%	66.11%	33.89%
0.5	*74.57%*	*25.43%*	*73.85%*	*26.15%*	*75.40%*	*24.60%*	*57.95%*	*42.05%*	*74.50%*	*25.50%*	*52.93%*	*47.07%*
0.6	82.97%	17.03%	62.13%	37.87%	83.60%	16.40%	42.68%	57.32%	83.32%	16.68%	40.17%	59.83%
0.7	91.23%	8.77%	49.79%	50.21%	92.01%	7.99%	27.20%	72.80%	91.52%	8.48%	21.97%	78.03%
0.8	97.50%	2.50%	39.96%	60.04%	98.01%	1.99%	12.55%	87.45%	97.53%	2.47%	7.53%	92.47%
0.9	99.65%	0.35%	29.92%	70.08%	99.82%	0.18%	6.07%	93.93%	99.84%	0.16%	1.46%	98.54%

The cut-off point identified by the Author is equal to 0.5.

Panel B. Re-estimation of company insolvency models and verification of their effectiveness

A) Altman model

Table B.1. Effectiveness of the adapted Altman model estimated via Theta following method 1

Models	Theta	SETheta	Z	AR
Altman 4 year prediction training	80.68%	0.012	25.718	0.61
Altman 4 year prediction validation	83.75%	0.011	29.546	0.67
Altman 3 year prediction training	87.39%	0.010	36.441	0.75
Altman 3 year prediction validation	87.70%	0.010	36.636	0.75
Altman 2 year prediction training	91.88%	0.009	48.308	0.84
Altman 2 year prediction validation	91.82%	0.009	48.172	0.84

Table B.2. First and second type errors for the Altman model following method 1

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	83.35%	16.65%	88.49%	11.51%	81.22%	18.78%	79.92%	20.08%	80.17%	19.83%	73.43%	26.57%
p. 2	72.42%	27.58%	93.72%	6.28%	60.28%	39.72%	92.47%	7.53%	58.39%	41.61%	88.08%	11.92%

The table illustrates the first and second type errors at the point p. 1 which minimizes the overall error (1st type error + 2nd type error) giving equal weight to both the errors. The cut-off point p. 2 corresponds to the point that minimizes the classification error, attributing 2/3 weight to the first type error (i.e. incorrect classification of a failed company) and 1/3 weight to the second type error (i.e. incorrect classification of a non-failed company).

Table B.3. Effectiveness of the adapted Altman model estimated via Theta following method 2

Models	Theta	SETheta	Z	AR
Altman prediction training	87.31%	0.006	62.810	0.75
Altman 2 year prediction validation	93.24%	0.008	54.144	0.86
Altman 3 year prediction validation	87.92%	0.010	37.120	0.76
Altman 4 year prediction validation	83.39%	0.012	29.003	0.67

Table B.4. First and second type errors for the Altman model following method 2

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	79.69%	20.31%	92.47%	7.53%	81.98%	18.02%	81.59%	18.41%	81.46%	18.54%	73.85%	26.15%
p. 2	65.35%	34.65%	96.03%	3.97%	67.46%	32.54%	89.33%	10.67%	66.71%	33.29%	84.10%	15.90%

B) Taffler model

Table B.5. Effectiveness of adapted Taffler model estimated via Theta following method 1

Models	Theta	SETheta	Z	AR
Taffler 4 year prediction training	81.20%	0.012	25.933	0.62
Taffler 4 year prediction validation	78.22%	0.013	22.489	0.56
Taffler 3 year prediction training	84.48%	0.011	31.054	0.69
Taffler 3 year prediction validation	83.50%	0.011	29.172	0.67
Taffler 2 year prediction training	91.06%	0.009	45.429	0.82
Taffler 2 year prediction validation	90.05%	0.009	42.418	0.80

Table B.6. First and second type errors for the Taffler model following method 1

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	80.55%	19.45%	82.43%	17.57%	68.66%	31.34%	82.01%	17.99%	72.94%	27.06%	70.08%	29.92%
p. 2	71.96%	28.04%	88.08%	11.92%	47.88%	52.12%	94.77%	5.23%	50.43%	49.57%	88.28%	11.72%

Table B.7. Effectiveness of adapted Taffler model estimated via Theta following method 2

Models	Theta	SETheta	Z	AR
Taffler prediction training	85.36%	0.006	56.353	0.71
Taffler 2 year prediction validation	90.21%	0.009	42.899	0.80
Taffler 3 year prediction validation	83.25%	0.012	28.810	0.67
Taffler 4 year prediction validation	78.44%	0.013	22.729	0.57

Table B.8. First and second type errors for the Taffler model following method 2

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	70.48%	29.52%	89.12%	10.88%	71.53%	28.47%	79.29%	20.71%	72.84%	27.16%	70.71%	29.29%
p. 2	51.92%	48.08%	94.98%	5.02%	51.84%	48.16%	92.47%	7.53%	52.73%	47.27%	87.45%	12.55%

C) Ohlson model

Table B.9. Effectiveness of adapted Ohlson model estimated via Theta following method 1

Models	Theta	SETheta	Z	AR
Ohlson 4 year prediction training	81.69%	0.012	26.941	0.63
Ohlson 4 year prediction validation	78.60%	0.012	22.902	0.57
Ohlson 3 year prediction training	90.42%	0.009	44.063	0.81
Ohlson 3 year prediction validation	84.12%	0.011	30.120	0.68
Ohlson 2 year prediction training	89.42%	0.010	41.233	0.79
Ohlson 2 year prediction validation	89.91%	0.009	42.024	0.80

Table B.10. First and second type errors for the Ohlson model following method 1

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	79.40%	20.60%	82.85%	17.15%	77.60%	22.40%	72.18%	27.82%	61.04%	38.96%	83.05%	16.95%
p. 2	68.26%	31.74%	90.79%	9.21%	73.59%	26.41%	77.41%	22.59%	50.93%	49.07%	89.75%	10.25%

Table B.11. Effectiveness of adapted Ohlson model estimated via Theta following method 2

Models	Theta	SETheta	Z	AR
Ohlson prediction training	73.57%	0.008	31.275	0.47
Ohlson 4 year prediction validation	71.93%	0.013	16.422	0.44
Ohlson 3 year prediction validation	74.68%	0.013	18.900	0.49
Ohlson 2 year prediction validation	82.27%	0.012	27.418	0.65

Table B.12. First and second type errors for the Ohlson model following method 2

	2 year prediction				3 year prediction				4 year prediction			
	Non-Failed		Failed		Non-Failed		Failed		Non-Failed		Failed	
Cut-off	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error	% Non-Failed	2nd Type Error	% Failed	1st Type Error
p. 1	85.60%	14.40%	65.48%	34.52%	73.59%	26.41%	62.55%	37.45%	70.48%	29.52%	60.88%	39.12%
p. 2	58.84%	41.16%	89.33%	10.67%	42.07%	57.93%	92.05%	7.95%	41.22%	58.78%	92.26%	7.74%