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PREDICTING CORPORATE BANKRUPTCY: AN APPLICATION TO ITALIAN MANUFACTURING FIRMS

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Abstract
Departing from a series of financial ratios analysis, we build up two indices which take into account both the firm's debt level and its sustainability. The construction of a composite over-indebtedness index is based on a Robust Principal Component Analysis (RPCA) for skewed data and it allows to classify firms according to their indebtedness degree and nature. This is a first, rather simple, tool to evaluate firms' default risk. Secondly, we propose a model aimed at investigating if and to what extent the proposed indices are able to correctly predict corporate bankruptcy. The econometric results are compared with those of the popular Altman Z-score for different lengths of the reference period. The empirical evidence would suggest a better performance of the proposed composite index which, therefore, could also be used as an *early warning signal*.

Keywords: Financial Ratios, Bankruptcy, Robust PCA, *Z*-Score, Early Warning signal.

1 INTRODUCTION

Due to the international financial crises, both the number and the average size of bankrupt firms has increased dramatically with the consequent greater interest from governments, financial institutions and regulatory agencies.
A correct measure of firms' insolvency risk is very important both for internal monitoring purpose and for the potential investors, stockholders, actual or potential firm's competitors. The purpose of this study is to construct, analyse and test a new bankruptcy prediction model which can extend and improve previous statistical models. The potential application of our model is in the spirit of

predicting bankruptcy and aiding companies' evaluation with respect to going-concern considerations, among others, since the early detection of financial distress facilitates the use of rehabilitation measures. Insolvency is mostly a consequence of a sharp decline in sales which can be caused by several and different factors like a recession, deficiencies of management, relevant changes in market dynamics, shortage of a row material, changes in lending conditions, etc. An early warning signal of probable bankruptcy is very important since it will allow to adopt preventive and corrective measures. Our study aims to contribute to the elaboration of efficient and effective corporate failure prediction instruments in order to prevent bankruptcy through the adoption of reorganization strategies. Failure, indeed, is not identifiable in a specific episode but in a process of progressive worsening of the financial health of a company. Given the dynamic nature of firms' financial crisis, it is necessary to build an early warning index for firms' insolvency which could signal a critical level of over-indebtedness behind which the financial status of the firm becomes pathological, therefore very difficult to rehabilitate.

Most of the past studies concentrated on specific industrial sectors and/or used a relatively small sample of firms. These studies include models for manufacturers by Beaver (1967), Altman (1968), Wilcox (1971, 1976), Deakin (1972, 1977) and Edmister (1972), among others, and models for specific industries such as Altman on railroads (1973), Sinkey on commercial banks (1975), Korobow and Stuhr (1975) and with Korobow et al. 1976 also on commercial banks, Altman and Lorris on broker/dealers (1976) and Altman on savings and loan associations (1977).

Beaver (1966), Altman (1968) and Van Frederikslust (1978), among others, argue that, although a failure may be caused by several circumstances, the development of some financial ratios can be a signal of the firm's financial health. Previous studies indicate that, with few financial ratios, corporate bankruptcy can be predicted with success for at least five years before failure. Important shortcomings, however, characterize previous works. First, financial ratios were chosen if they performed well, so without a specific reference to financial theory. Moreover, a very small sample of firms were considered in the empirical analysis. Therefore, the results obtained in these works cannot be generalized.

Our study contributes to the literature in several ways. First, since small sample size appears to be a limitation and "… any new model should be as relevant as possible to the population to which it will eventually be applied" (Altman et al., 1977, p.30), we consider the Italian manufacturing companies as a whole and include small, medium and large firms in a large industry sample. Secondly, we attempt to improve the research model by implementing a composite analysis based on both Principal Component Analysis (PCA) and logit model. We demonstrate that our combined method of PCA and logit estimation is promising in evaluating firms' financial conditions. Moreover, for a vast majority of the works, the country of origin of the dataset is USA followed by European countries. Few researches focus on Italian firms (Appetiti, 1984a; Appetiti, 1984b; Altman, Danovi and Falini, 2013; Amendola et al., 2011; Muscettola, 2013). Our study contributes to the international literature by explicitly analysing Italian manufacturing firms, whose financial structure is often characterised by a high indebtedness level. Furthermore, the effects of the recent international financial crises on firms' bankruptcy have been particularly relevant in Italy in comparison with the other European countries (European Central Bank (2013). Indeed, in spite of the economic recovery throughout Europe, the number of corporate insolvencies is still relatively high in Italy and has in fact increased since 2006. In 2014, only two countries posted year-on-year increases: Italy (+12.8 percent) and Norway (+5.2 percent) (Creditreform 2015 and 2012).

Finally, apart from effectiveness, we also attempt to evaluate the efficiency of our model, that is its economic and organizational sustainability in an operational context (Cestari et al., 2013). With reference to the actual usability of the model on the part of the potential users, our model proposes two steps/instruments in the analysis: 1) an accurate, but rather simple, bankruptcy prediction instrument which allows to classify firms in different categories with respect to their solvency status on the base of financial ratios; 2) a more complex logit model, based on both the first step computed indices and additional non-financial variables, which allows to compute specific bankruptcy scores

(predicted probabilities) for each firm included in the analysis. The logistic regression estimates are compared with those of the popular Altman Z-score for different lengths of the reference period.
In brief, we extend previous methodology by building a very large sample of firms and paying attention to both financial and non-financial firms' characteristics. Moreover, we examine how the model can be used in practice to analyze the risk of failure. In this context, we first derive a simple decision rule to classify firms as either at high risk of failure or at low risk of failure. We then propose a more complete model to predict the risk of failure as early warning signal of bankruptcy. In addition to several models that have been tested by the relatively short one-year prediction horizon, we test the predictive power of the index several years prior to bankruptcy.
The paper is organized as follows. Section 2 briefly summarizes the related literature, Section 3 describes our dataset, Section 4 defines the indebtedness indices and proposes a classification table, Section 5 illustrates the empirical findings and the reliability of the proposed index as early warning signal. Section 6 concludes.

2 A LITERATURE REVIEW

Bankruptcy has been the subject of numerous studies over the past years[2]. Researchers have investigated both the causes, the legislative and financial tools available to start a process of recovery/rehabilitation of the firm. Especially after the recent international financial crises, there has been a general need to predict insolvency and financial failure on-time in order to take corrective and remedial measures for protecting business from the problem of bankruptcy.
A broad international field of study has focused on predicting bankruptcy using statistics and economic-financial indicators. Prior to the development of quantitative measures of company performance, agencies were established to supply qualitative information assessing the creditworthiness of firms. During the 1930s many models were developed to help banks decide whether or not to approve credit requests (Smith, 1930; FitzPatrick, 1931, 1932; Ramser and Foster, 1931; Smith and Winakor, 1935; Wall, 1936). Bellovary et al. (2007) traces a brief historical summary of the early studies (1930 to 1965) concerning ratio analysis for bankruptcy prediction that laid the groundwork for the studies that followed.
At the end of the 1960s, several applications of univariate and multivariate statistical analysis were developed. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver (1967). His univariate analysis of a number of bankruptcy predictors set the stage for the multivariate attempts. Beaver found that a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure, but he completed a discriminant analysis on a single ratio (cash flow/total debt).
Altman (1968) and Deakin (1972) applied multivariate analysis, followed by several authors (Blum, 1974; Elam, 1975; Libby, 1975; Alberici, 1975; Taffler, 1976, 1982; Altman et. al., 1977, 1993; Wilcox, 1976; Argenti, 1976; Appetiti, 1984; Forestieri, 1986; Lawrence and Bear, 1986; Aziz, Emanuel and Lawson, 1988; Baldwin and Glezen, 1992; Flagg, Giroux and Wiggins, 1991; Bijnen and Wijn, 1994; Kern and Rudolph, 2001; Shumway, 2002; Hillegeist, et. al., 2004; Altman, Rijken, et. al., 2010). In his seminal study on bankruptcy detection, Altman (1968) improved research methodology by usage of multiple discriminate analysis (MDA) where the discrimination was determined by a score–the «*Z-score*»–calculated on the basis of five accounting ratios. Thus, only five financial ratios were enough to distinguish healthy from bankrupted companies. The first research on SME business failure was done by Edminister (1972) who also used MDA as statistical

[2] For recent and comprehensive reviews on predicting corporate bankruptcy methodologies, see Aziz and Dar (2006), Bellovary et al. (2007) and Ravi Kumar and Ravi (2007).

technique to discriminate among loss and non-loss SME borrowers. The empirical analysis, based on a MDA model with seven financial ratios, revealed that the models with industry relativized ratios were characterized by higher classification accuracy in comparison with models based on classical ratios.

After Altman's seminal study, the linear discriminant analysis has been intensively used in practice mainly because of the simplicity of its application. However, Johnson (1970) and Joy and Tollefson (1975) have criticized the excessive broadness of the so-called grey area and the difficulty of application in predicting bankruptcy *ex ante*. Guatri (1995) has stressed how predictions using multiple discriminant analysis could be a self-realizing prophecy since, if adopted by banks, it would be harder for a company with a low score to have access to external finance, causing it to be insolvent and to go bankrupt. Others have questioned that multiple discriminant analysis implies the respect of some strict statistical restrictions such as the normality of the distribution of the explanatory variables and requirement for the same variance-covariance matrices for both groups of bankrupt and non-bankrupt companies.

As a consequence, later studies have tried to upgrade the methodology and improve the predictive power of the models. Several authors have used logit and probit models - instead of MDA- depending on whether the residuals follow a logistic or normal distribution. Ohlson (1980) was the first one who used the logit model, followed by several authors (Mensah, 1984; Zavgren, 1985; Aziz, Emmanuel and Lawson, 1988; Bardos, 1989; Burgstahler, Jiambalvo and Noreen, 1989; Flagg, Giroux and Wiggins, 1991; Platt and Platt, 1991; Bardos and Zhu, 1997; Bell, Mossman, Swartz, and Turtle, 1998; Premachandra, Bhabra, and Sueyoshi, 2009; Bhargava et al., 1998; Nam and Jinn, 2000; Vuran, 2009; Pervan et al., 2011). In other studies, the probit models have been implemented (Zmijewsji, 1984; Gentry, Newblod, and Whiteford, 1985; Lennox, 1999). Similar methodologies – like duration models – have been developed in order to consider several periods in the analysis (Shumway, 2001; Duffie, Saita and Wang, 2007). But, apart from statistical methodology, almost all studies have been focused only on financial ratios, while nonfinancial variables (management, employees, clients, industry, etc.) have been excluded from the failure prediction models. The recent empirical evidence indicates that prediction of insolvency and credit risk management can be improved by incorporating nonfinancial information in prediction models. Nevertheless, only a few papers explicitly use non-financial variables to predict failure (Grunert et al., 2004; Berk et al., 2010, Pervan and Kuvek, 2013).

More recently, some authors have resorted to artificially intelligence expert system (AIES) models for bankruptcy prediction. Several types of AIES models have been implemented such as recursively partitioned decision trees, case-based reasoning models (Kolodner, 1993), neural networks (Odom and Sharda, 1990; Yang et al., 1999; Kim and Kang, 2010), genetic algorithms (Varetto, 1998; Shin and Lee, 2002) or rough sets model (Dimitras et al., 1999). Ravi Kumar and Ravi (2007) presents a comprehensive review of the work done in the application of intelligent techniques showing, for each technology, the basic idea, advantages and disadvantages. Note that, independently from the methodology applied, both statistical and AIES models focus on firms' symptoms of failure and are drawn mainly from company accounts.

Theoretical models, on the contrary, focus on the causes of bankruptcy and are drawn mainly from information that could satisfy the proposed theory. See Aziz and Dar (2006) for a clear description of the different types of theoretical models and their main characteristics.

On the whole, the above mentioned literature indicates that there have been many empirical applications of the bankruptcy prediction models. Despite the differences in the methodologies applied, they show high predictive ability. Further, despite the vast amount of literature and models that have been developed, researchers continue to look for "new and improved" models to predict bankruptcy. As argued by Bellovary et al. (2007) in their review of bankruptcy prediction studies, "… the focus of future research should be on the use of existing bankruptcy prediction models as opposed to the development of new models. Future research should consider how these models can be applied and, if necessary, refined" (Bellovary et al., 2007, pp.13-14). Our contribute to the

literature goes in this direction by applying an hybrid methodology based on both PCA and logit model. The review also suggests important insights and some areas for model improvement, incorporated in our analysis. First, much past research has employed relatively small samples of firms; recent evidence suggests that large samples are critically necessary to generalize empirical results. Second, financial ratios have been dominant explanatory variables in most research to date; it may be worthwhile to include nonfinancial variables and corporate governance structure in addition to financial variables. Third, several models have been tested by the relatively short one-year prediction horizon; it would be desirable to test the predictive power several years prior to bankruptcy. It is very important to consider how far ahead the model is able to accurately predict bankruptcy. Clearly, a model that is able to accurately predict bankruptcy earlier becomes more valuable for the investors and, at the same time, for the adoption of effective policies.
Moreover, previous studies have mainly focused on the development of models with high level of reliability. However, it is important to identify the parameters that can measure both effectiveness, in terms of reliability, and efficiency, in terms of organizational and economic sustainability, of prediction instruments (Cestari et al. 2013). For this reason, we also attempt to evaluate our model in terms of its practical implementation. The first part of the paper proposes a rather simple and efficient tool to evaluate firms' default risk. The second part of the paper illustrates a more complex model aimed at predicting default probabilities which can be used as early warning signals.

3 A DESCRIPTIVE ANALYSIS

The recent insolvency figures for Europe reflect the economic recovery after years of crisis. In Western Europe as a whole, in 2014 business failures fell by 5.37 percent compared with 2013. This is the first year-on-year decline since 2010/11, when the fall was only marginal, at 0.7 percent (Tab.1)
But despite the easing of the economic situation and the fall in the number of business failures in the Eurozone, the number of corporate insolvencies in Italy is still relatively high and characterized by a positive trend. Tab.1 and Tab.2 show respectively the absolute values of corporate insolvencies and the year-on year percentage variation in total bankruptcies in Western European countries over the 2006-2014 years. Italy is the only country always characterized by positive percent change in failures over previous year since the 2007-2008 international financial crises.
As it is illustrated in Fig.1, only Italy and Norway register year-on-year increases in 2014. Italy, in particular, shows the highest yearly percentage variation in corporate failures (+12.8 percent).
In 2010, Italy registers the largest proportion of firms with equity ratio less than ten percent in relation to the balance-sheet total. A low equity ratio indicates a weak capitalization of the firm which increases the insolvency risk.

Tab.1 Corporate insolvencies in Western Europe (2006-2014), absolute values

	2014	2013	2012	2011	2010	2009	2008	2007	2006
Austria	5600	5626	6266	6194	6657	7076	6500	6362	6854
Belgium	10736	11739	10587	10224	9570	9382	8476	7678	7617
Denmark	4049	4993	5456	5468	6461	5710	3709	2401	1987
Finland	2954	3131	2956	2944	2864	3275	2612	2254	2285
France	60548	60980	59556	49506	51060	53547	49723	42532	40360
Germany	24030	26120	28720	30120	32060	32930	29580	29150	34040
Greece	330	392	415	445	355	355	359	524	532
Ireland	1164	1365	1684	1638	1525	1406	773	363	304

Italy	16101	14272	12311	10844	10089	8354	6498	5518	8827
Luxembourg	845	1016	1033	961	918	698	590	680	634
Netherlands	6645	8375	7373	6176	7211	8040	4635	4602	5941
Norway	4803	4564	3814	4355	4435	5013	3637	2845	3032
Portugal	7200	8131	7763	6077	5144	4450	3267	2123	2400
Spain	6392	8934	7799	5910	4845	4984	2528	880	853
Sweden	7158	7701	7737	7229	7546	7892	6298	5791	5243
Switzerland	5867	6495	6841	6661	6255	5215	4222	4314	4528
United Kingdom	15240	16021	17765	18467	17468	19908	16268	12893	13686
Total	179662	189855	188076	173219	174463	178235	149675	130910	139123

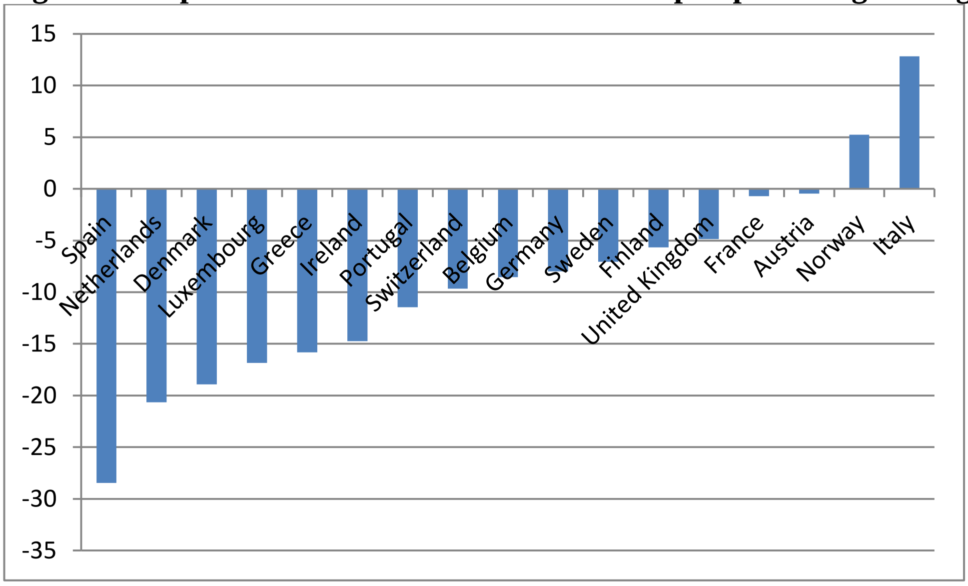
Source: own elaborations on Creditreform data

Tab.2 Corporate insolvencies in Western Europe (2006-2014), year-on-year % variation

	14/13	**13/12**	**12/11**	**11/10**	**10/09**	**09/08**	**08/07**	**07/06**
Austria	-0.46	-10.21	1.16	-6.96	-5.92	8.86	2.17	-7.18
Belgium	-8.54	10.88	3.55	6.83	2.00	10.69	10.39	0.80
Denmark	-18.91	-8.49	-0.22	-15.37	13.15	53.95	54.48	20.84
Finland	-5.65	5.92	0.41	2.79	-12.55	25.38	15.88	-1.36
France	-0.71	2.39	20.30	-3.04	-4.64	7.69	16.91	5.38
Germany	-8.00	-9.05	-4.65	-6.05	-2.64	11.33	1.48	-14.37
Greece	-15.82	-5.54	-6.74	25.35	0.00	-1.11	-31.49	-1.50
Ireland	-14.73	-18.94	2.81	7.41	8.46	81.89	112.95	19.41
Italy	12.82	15.93	13.53	7.48	20.77	28.56	17.76	-37.49
Luxembourg	-16.83	-1.65	7.49	4.68	31.52	18.31	-13.24	7.26
Netherlands	-20.66	13.59	19.38	-14.35	-10.31	73.46	0.72	-22.54
Norway	5.24	19.66	-12.42	-1.80	-11.53	37.83	27.84	-6.17
Portugal	-11.45	4.74	27.74	18.14	15.60	36.21	53.89	-11.54
Spain	-28.45	14.55	31.96	21.98	-2.79	97.15	187.27	3.17
Sweden	-7.05	-0.47	7.03	-4.20	-4.38	25.31	8.75	10.45
Switzerland	-9.67	-5.06	2.70	6.49	19.94	23.52	-2.13	-4.73
United Kingdom	-4.87	-9.82	-3.80	5.72	-12.26	22.38	26.18	-5.79
Total	-5.37	0.95	8.58	-0.71	-2.12	19.08	14.33	-5.90

Source: own elaborations on Creditreform data

Figure 1 Corporate insolvencies in Western Europe - percentage change 2014/2013



Source: Creditreform 2015

The international comparison highlights significant differences among countries in terms of corporate insolvencies and suggests some distinguishing features of Italian companies, which are worth to analyze. Policymakers have to take into consideration the heterogeneity existing among firms in order to adopt effective policies. Firm-level data provide critical information on firm's behavior that complements traditional macro analysis

The empirical analysis is based on accounting data of Italian manufacturing SMEs and large firms taken from the Aida Database, published by Bureau Van Dijk. After dealing with missing data, we build up an appropriate database including 31958 Italian manufacturing firms.

The work is carried out on the balance sheet and income statement over the 2006-2010 period in order to analyze the characteristics of firms affecting their probability of default after 5 years, that is, in 2011. We exclude microenterprises because of several missing and/or unreliable financial data.

An important issue concerns the definition of default. Business failure has been defined in many different ways in the empirical literature (Crutzen and Van Caillie, 2008), therefore it is important to clarify the meaning of bankruptcy adopted in this study. Specifically, we focus on companies that have undertaken the juridical procedure of bankruptcy because of permanent financial distress. Therefore, a firm is considered to have defaulted if it is under bankruptcy procedure, if it has filed for bankruptcy or it is in liquidation; we exclude firms with temporary financial problems or companies which have voluntary chosen liquidation for economic opportunity, mergers or acquisition. The information on the legal status of the firms with respect to bankrupt procedures has been collected from the AIDA database.

By applying the default definition provided, the work focuses on two groups of firms: defaulting firms, and non-defaulting firms. The composition of the sample is provided in Tab.3.

Tab.3 Sample Composition, 2010

	Defaulting Firms		Non-defaulting firms	
	Number	Percentage	Number	Percentage
Total Sample	1856	5.81	30102	94.19
Geographical Area				
North	1225	5.18	22419	94.82
Center	367	7.28	4671	92.72
South	260	7.98	2997	92.02
Turnover				
2-10 million euros	1207	5.68	20039	94.32
10-50 million euros	271	3.29	7955	96.71
>50 million euros	378	15.2	2108	84.8
Age				
<15	882	8.13	9967	91.87
16-24	371	4.91	7179	95.09
25-32	271	4.27	6071	95.73
>33	332	7.35	6685	92.65

Source: own elaborations on Aida database

The manufacturing firms included in the sample operate in different geographical areas, in different sectors and they significantly differ in size. Since we consider both large companies and SMEs, in order to mitigate the effect of firm size on selected variables, we first consider large, medium and small enterprises separately; we then divide each financial variable by the average turnover of the corresponding group and, finally, we build up the financial ratios.
The defaulting firms' group includes 1856 firms failed in 2011 and represents 5.81% of the firm population, while the non-failed group consists of 30102 companies representing 94.19% of the total. With reference to the geographical area in which the firms are located, the population includes 23644 firms in the North, 5038 in the Center and 3257 in the South of Italy. The distribution of failed firms among the different geographical areas mirrors the composition of the whole population. Most of defaulting firms, at least in absolute terms, are concentrated in the North (1225), while default firms in the Center and in the South of the country are 367 and 260 respectively. Looking at percentage values, the distribution of the two groups of firms shows a prevalence of default firms in the South of Italy.
Tab.3 also shows the composition of the sample with respect to firm size and age. As measure of size we consider the annual turnover [3], one of the parameters adopted by the Basel II Committee to define SMEs, while age is in terms of years of activity since firm foundation. Data show a higher concentration of bankruptcies among young firms.

In Europe, the distribution of insolvency among the different branches of the economy can vary considerably. Southern European countries usually register large numbers of defaulting firms in manufacturing sectors. In 2010, for example, Italy registers 24.1 percent of default firms belonging to manufacturing sectors, a value above the European average.

[3] In order to measure the size of a firm, different variables could be used like the number of employees, total assets and turnover. However, the accounting data on "turnover" are more reliable than those on total number of employees reported in the balance sheets, and there are less missing data. This is particularly true for small enterprises which represent a high percentage of Italian manufacturing firms and, as reported hereafter in the paper, a high percentage of our sample. Moreover, differently from total assets, the "turnover" variable allows to classify the firms and split the sample according to the European Union Classification reported in the Commission Recommendation 96/280/EC.

Tab.4 shows the percentage of corporate insolvencies across the manufacturing sectors, identified following the NACE Rev.2 classification and structured, for a descriptive purpose, following the Intermediate level SNA/ISIC-A*38 aggregation.
Within the manufacturing industry, the incidence of failure is relatively higher in the sectors of motor vehicles and transport equipment (8.44%), repair and installation of machinery and equipment (8.25%), followed by manufacture of wood, paper products and printing (7.42 %).
The manufacture of chemical and chemical products and the manufacture of pharmaceuticals, medicinal, chemical and botanical products show the lowest percentages of corporate failures, registering 2.70% and 2.91% of insolvencies respectively.

Tab.4 Percentage of corporate insolvencies by sector, year 2010

NACE Rev.2 code	Sector Description	N of defaulting firms	Total N of firms	% of corporate insolvencies
10, 11, 12	Manufacture of food products, beverage and tobacco products	117	2855	4.10
13, 14, 15	Manufacturing of textiles, apparel, leather and related products	265	3953	6.70
16, 17, 18	Manufacture of wood, paper products and printing	174	2345	7.42
19	Manufacture of coke and refined petroleum products	5	155	3.23
20	Manufacture of chemical and chemical products	38	1406	2.70
21	Manufacture of pharmaceuticals, medicinal, chemical and botanical products	9	309	2.91
22, 23	Manufacture of rubber and plastics products, and other non-metallic mineral products	234	3750	6.24
24, 25	Manufacture of basic metals and fabricated metal products, except machinery and equipment	408	6737	6.06
26	Manufacture of computer, electronic and optical products	60	1096	5.47
27	Manufacture of electrical equipment	70	1564	4.48
28	Manufacture of machinery and equipment n.e.c.	217	4670	4.65
29, 30	Manufacture of motor vehicles, trailers and semi-trailers Manufacture of transport equipment	83	983	8.44
31, 32	Manufacture of furniture Other manufacturing; repair and installation of machinery and equipment	176	2134	8.25

Source: own elaborations on Aida database

4 FINANCIAL HEALTH AND DEFAULT RISK: a simple classification tool

4.1 Indebtedness Indices

In this paragraph we propose a new over-indebtedness index by first defining a *Debt index* and then defining a *Sustainibility index* of such debt. These two indices are then combined in a synthetic one which can signal the financial health of the company.
The financial and accounting literature suggests that a firm's financial condition is better evaluated by considering several aspects of the indebtedness phenomenon (leverage, indebtedness capacity, form of the financial debt, net financial position, etc.). Following this approach (Bartoli, 2006; Costanzo et al., 2013), we build up a debt index which considers the *multifaceted* aspects of debt:

$$DEBT_{INDEX}=\alpha_1 \frac{FD}{N} + \alpha_2 \frac{CL}{FD} + \alpha_3 \frac{FD}{CF} + \alpha_4 \frac{CL}{CA} + \alpha_5 \frac{NFP}{TA} + \alpha_6 \frac{NTCA}{N} + \alpha_7 \frac{TFA}{LTD+N}$$

where **FD/N** is the inverse of the capitalization degree; **CL/FD** is the ratio between Current Liabilities and Total Financial Debt; **FD/CF** is the ratio between Total Financial Debt and Cash-Flow; **CL/CA** is Current Liabilities over Current Assets; **NFP/TA** measures the incidence of the net financial debt; **NTCA/N** is the ratio between Net Technical Assets and Shareholders Funds; **TFA/(LTD+N)** is Total Fixed Assets over the sum of Long-Term Debt and Shareholders Funds.

While a moderate level of debt can spur firm performance, an important element to consider when assessing firms' creditworthiness is the vulnerability of such debt. The maturity structure of assets and liabilities can provide valuable information about their vulnerability to changes in financing conditions. However, at the euro area level and in Italy in particular, short-term funding accounts for a small proportion of total funding, thus the maturity structure has a limited informative power (European Central Bank, 2013). Another important factor for an assessment of the sustainability of debt is the debt service burden of firms, which indicates the proportion of their income needed for servicing debt. For this reason, we define the following debt sustainability index:

$$NSD_{INDEX} = \delta_1 \frac{IP}{EBIT} + \delta_2 \frac{IP}{EBITDA} + \delta_3 \frac{IP}{CF}$$

where **IP** is the Interest Paid, **EBIT** the Earnings Before Interest and Taxes, **EBITDA** the Earnings Before Interest, Taxes, Depreciation and Amortization. **CF** indicates cash-flow.
Note that higher values of the NSD index indicate lower sustainability of debt, hence higher firms' debt vulnerability.

The accounting literature provides - for each financial ratio- specific threshold values which allow us to define when a firm is in a *good*, *normal* or *bad* financial condition, as shown in Tab.5.

Tab.5 Financial ratios and threshold values

Good financial status (<threshold 1)	*Normal financial status*	*Bad financial status (> threshold 2)*
Threshold 1		Threshold 2
1	$1 < \frac{FD}{N} < 1.6$	1.6
0.6	$0.6 < \frac{CL}{FD} < 0.8$	0.8
2.85	$2.85 < \frac{FD}{CF} < 6.7$	6.7
0.9	$0.9 < \frac{CL}{CA} < 1.1$	1.1
0.20	$0.20 < \frac{NFP}{TA} < 0.35$	0.35
1	$1 < \frac{NTCA}{N} < 2$	2
1.25	$1.25 < \frac{TFA}{LTD + N} < 3.33$	3.33
0.25	$0.25 < \frac{IP}{EBIT} < 0.58$	0.58
0.33	$0.33 < \frac{IP}{CF} < 0.5$	0.5
0.18	$0.18 < \frac{IP}{EBITDA} < 0.5$	0.5

Source: Bartoli (2006)

For example, a value of the financial ratio FD/N ranging between 1 and 1.6 denotes a normal financial status of the company. On the contrary, a value below 1 or over 1.6 denotes a good or a bad financial condition respectively.

Through the substitution of the threshold values for each financial ratio included in the $DEBT_{INDEX}$ and in the NSD_{INDEX} we will define the final threshold values for such two indices and classify the firms according to their degree of indebtedness.

More specifically, after estimating the $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ coefficients we are able to compute the $DEBT_{score}$ and NSD_{score} for every firm and make the classification based on the *indebtedness* and *sustainability* scores. By crossing these two dimensions we obtain the composite Indebtedness Index (I_{INDEX}), a classification tool that takes into account both a firm's indebtedness level and the sustainability of such debt at the same time.

Tab.6 reports the suggested classification. Specifically, when the composite I_{INDEX} takes value from 1 to 5, the firm can be considered in a good to normal health financial status; when the I_{INDEX} takes values from 6 to 8 the firm's financial status is fragile and it deteriorates as the I_{INDEX} index increases (I=9).

Tab.6 Indebtedness Index and Financial Status

	NSD< threshold1	thr. 1<NSD<thr. 2	NSD> threshold2
$DEBT$<threshold1	I_{Index}=1 (Optimal)	I_{Index}=2	I_{Index}=3
thr.1<$DEBT$<thr. 2	I_{Index}=4	I_{Index}=5 (Normal)	I_{Index}=6
$DEBT$>threshold 2	I_{Index}=7	I_{Index}=8	I_{Index}=9 (Bad)

We use a Robust Principal Component Analysis (RPCA) to obtain the values of the weights associated to each financial ratio, that is the coefficients α_i and δ_i. The next paragraph illustrates our methodology.

4.2 A Robust Principal Component Analysis (RPCA)

Financial data are often characterized by asymmetric distribution. For this reason we make use of Robust Principal Component Analysis (RPCA) approach to extract their principal components. PCA is one of the best known techniques of multivariate statistics. It is a dimension reduction technique which transforms the data into a smaller set of variables while retaining as much information as possible. These new variables, called the principal components (PCs), are uncorrelated and maximize variance (information). Classical PCA makes use of eigenvalues and eigenvectors of the classical sample covariance matrix, but it is well known that this technique is sensitive to outliers and asymmetric distribution of variables.
More specifically, in order to robustly estimate the α and δ coefficients of the DEBT and NSD indices, we apply the modified *ROBPCA algorithm for skewed data* suggested by Hubert et al. (2009). The algorithm is applied to average values of financial ratios 2006-2010.
Tab.7 shows the Robust Principal Components (RPC) produced by the ROBPCA with reference to $DEBT_{INDEX}$.

Tab.7 Robust Principal Components for $DEBT_{INDEX}$

Variable	***RPC1***	***RPC2***	***RPC3***	***RPC4***	***RPC5***	***RPC6***	***RPC7***
FD/N	0.9192	0.0252	-0.3911	-0.0352	0.0026	0.0021	-0.0141
CL/FD	0.0045	0.0086	-0.0246	0.0141	-0.0570	0.2103	0.9755
FD/CF	0.0885	0.9563	0.2607	0.0982	0.0112	-0.0042	-0.0022
CL/CA	0.0254	-0.0074	0.0810	-0.1113	-0.1599	0.9540	-0.2114
NFP/TA	0.0702	0.0238	0.2489	-0.9476	-0.1118	-0.1425	0.0436
NTCA/N	0.3706	-0.2861	0.8327	0.2203	0.1937	-0.0172	0.0337
TFA/LTD+N	0.0657	-0.0486	0.1291	0.1736	-0.9597	-0.1584	-0.0211

Source: own elaborations on Aida database

These new RPC variables are linear combination of original financial ratios, they are uncorrelated and maximize variance. In order to decide how many Robust Principal Components we need to represent the financial data, the percentages of total variances explained by each RCP have been estimated and shown in Tab.8. The percentage of variance explained by each RPC is computable from the robust eigenvalues given from ROBPCA algorithm[4].

Tab.8 Robust Eigenvalues for $DEBT_{INDEX}$

Robust Eigenvalues	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
	33.3526	5.9613	4.0668	1.6916	0.7494	0.1324	0.0296
Explained Cumulate Variance	0.725	0.855	0.943	0.980	0.996	0.999	1

Source: own elaborations on Aida database

RPC1 represents the most important dimension in explaining changes of financial conditions of firms and it explains 72.5% of the total variance of the financial ratios. We retain the first Robust Principal Component to estimate the coefficients α_i for $DEBT_{INDEX}$. The coefficients α_i are the weights given by RPC1, a linear combination of $DEBT_{INDEX}$ financial ratios:

$$\boldsymbol{DEBT_{INDEX}} = 0.9192\frac{FD}{N} + 0.0045\frac{CL}{FD} + 0.0885\frac{FD}{CF} + 0.0254\frac{CL}{CA} + 0.0702\frac{NFP}{TA} + 0.3706\frac{NTCA}{N} + 0.0657\frac{TFA}{LTD+N}$$

Tab.9 and Tab.10 show respectively the RPC and the robust eigenvalues with reference to NSD_{INDEX}.

Tab.9 Robust Principal Components for NSD_{INDEX}

Variable	***RCP1***	***RCP2***	***RCP3***
IP/EBIT	0.1572	-0.6957	0.7009
IP/EBITDA	0.2515	-0.6581	-0.7097
IP/CF	0.9550	0.2878	0.0715

Source: own elaborations on Aida database

Tab.10 Robust Eigenvalues for NSD_{INDEX}

Robust Eigenvalues	λ_1	λ_2	λ_3
	13.2803	5.9266	4.4327
Explained Cumulate Variance	0.562	0.812	1

Source: own elaborations on Aida database

[4] For example the variance explained by the first RPC is computable as $\frac{\lambda_1}{\lambda_1+\lambda_2+\cdots+\lambda_7}$.

RPC1 is the most important dimension in explaining changes of sustainability of firms debt. It explains 56.2% of the total variance of the financial ratios. As for $DEBT_{INDEX}$, by retaining only the first Robust Principal Component we estimate the coefficients δ_i for NSD_{INDEX}. The coefficients δ_i are the weights given by RPC1, a linear combination of NSD_{INDEX} financial ratios:

$$\boldsymbol{NSD_{INDEX}} = 0.1572\,\frac{IP}{EBIT} + 0.2515\,\frac{IP}{EBITDA} + 0.9550\,\frac{IP}{CF}$$

4.3 A Classification System

Through the substitution of the threshold values shown in Tab.5 for each financial ratio included in the $DEBT_{INDEX}$ and in the NSD_{INDEX} , we can define the final threshold values for the two indices, compose the I_{INDEX} and then classify the firms according to their degree of indebtedness:

$$Threshold1_{DEBTINDEX} = \sum_{i=1}^{7} \alpha_i \; Threshold1_i = 0.76$$
$$Threshold2_{DEBTINDEX} = \sum_{i=1}^{7} \alpha_i \; Threshold2_i = 1.63$$

$$Threshold1_{NSDINDEX} = \sum_{i=1}^{3} \delta_i \; Threshold1_i = 0.29$$
$$Threshold2_{NSDINDEX} = \sum_{i=1}^{3} \delta_i \; Threshold2_i = 0.69$$

Tab.11 illustrates the distribution of the Italian manufacturing firms in 2010 according to our classification method.

Tab.11 Distribution of firms by OI_{INDEX} – year 2010

$\boldsymbol{NSD_{INDEX}}$ / $\boldsymbol{DEBT_{INDEX}}$	**Good** NSD<0.29	**Normal** 0.69<NSD< 0.29	**Bad** NSD>0.69	**Total**
Good **DEBT**< 0.76	5929 *(18.6%)* ***1***	784 *(2.5%)* ***2***	761 *(2.4%)* ***3***	7474 *(23.4%)*
Normal 0.76<**DEBT**<1.63	3081 *(9.6%)* ***4***	1743 *(5.5%)* ***5***	3042 *(9.5%)* ***6***	7866 *(24.6%)*
Bad **DEBT**> 1.63	3422 *(10.7%)* ***7***	2123 *(6.6%)* ***8***	11073 *(21.9%)* ***9***	16618 *(52.0%)*
Total	12432 *(38.9%)*	4650 *(14.6%)*	14876 *(46.5%)*	31958 *(100%)*

Source: own elaborations on Aida database

According to our classification based on the OI_{INDEX}, the percentage of Italian manufacturing firms in a good financial status is 18.6%; these firms have a low level and a good sustainability of debt (OI= 1). The firm's financial status deteriorates as the OI_{INDEX} increases. 21.9% of firms are classified in the worst financial status (OI=9); these firms are both characterized by a high level of debt and a bad sustainability of the debt, therefore the risk to fail is high.
As it has been shown, the OI_{INDEX} is a rather simple instrument to classify firms according to their financial status.

5 THE ECONOMETRIC ANALYSIS : predicted probabilities as early warning signals

5.1 The Model

To evaluate the reliability of our indebtedness indices as early warning signal of financial bankruptcy, a logit analysis has been carried out over the period 2006-2011.
The logistic regression technique allows us to specify the probability of default as a function of a set of explanatory variables. Specifically, the dependent variable is a dichotomous variable that takes value 1 for defaulting firms (the firm is under bankruptcy procedure, it has filed for bankruptcy or it is subject to liquidation in 2011), 0 otherwise (the firm is still active in 2011). In formal terms:

$$p_i = \Pr(Y_i = 1) = F(x_i\beta) \tag{1}$$

where p_i is the probability that the dependent variable Y=1 for individual firm, F(_) is the logistic cumulative distribution function, x_i is the set of explanatory variables thought to affect p_i, and β are the regression coefficients. The explanatory variables, computed over the years 2006-2010, are expressed as follows:

$$\Pr(Y_i = 1) = F(\beta_0 + \beta_1 DEBT_i + \beta_2 NSD_i + \beta_3 SIZE_i + \beta_4 AGE_i + \beta_5 D\_own_i + \beta_6 D\_mult_i + \beta_7 PROD_i + \beta_8 X\_region_i + \beta_9 Y\_sector_i) \tag{2}$$

i = 1… n where i is the i*th* firm, n = 31958.

In accordance with the general literature on bankruptcy, the model considers the financial structure of the firm. The first two explanatory variables, given by the DEBT and NSD scores defined in section 4.1, take into account the financial health of the firm by measuring both the debt level and its vulnerability. Several works find a significant relation between the financial structure of the firms and their probability of default or exit from the market [5] (see, among others, Molina, 2005; Hovakimian et al. 2012; Graham et al. 2012; Bonaccorsi di Patti et al. 2014).
The model includes other regressors to control for additional non-financial characteristics of the firms, expected to be relevant in determining their probability of default. Both the theoretical and empirical literature suggest that age and size of the firms impact significantly on their performance (for a review, see Klepper and Thompson 2006). More recent studies also analyze the effects of productivity, industrial organization and ownership structure on firm performance (Beck et al. 2006 and 2008, Disney et al. 2003; Dunne et al. 1988 and 1989; Foster et al. 2006).
Therefore, equation (2) includes the variables reported hereafter.
The variable $SIZE_i$ is computed in terms of a firm's annual turnover[6], measured in hundred

[5] Note that the variable interest rate has not been included in the logit regression because the variable Interest Paid (IP) has been already included in the construction of the NSD index.
[6] See footnote 3 for our choice of turnover as measure of size.

thousands of Euros.
The variable AGEi is the age of a firm since its foundation.
D_own_i is a dummy variable equal to 1 for fully concentrated ownership (unique partner), 0 otherwise (fragmented ownership, several partners). It is a signal of corporate governance (since firms in countries with weaker investor protection also have more concentrated ownership (La Porta et al., 1998; La Porta et al., 1999).
D_mult_i is a dummy variable equal to 1 for multinational firms, 0 otherwise. Multinational firms have been identified through the analysis of ownership data, by selecting companies owning foreign subsidiaries (ownership share equals 51% by default).
The variable $PROD_i$ indicates labor productivity and it is given by value added per employee.
Finally, to take into account the characteristics of the institutional and financial environment in which the firms operate and the specificities of the industrial sectors, we consider both regional dummies and sector dummies as explanatory variables, included in the vectors X and Y respectively. The manufacturing sectors are defined to include firms in the NACE Rev.2 primary codes 10-32. Hence, the model includes 20 regional dummies and 23 sector dummies.

5.2 Empirical Results

Tab.12 shows the logistic regression estimates for different lengths of the reference period, in particular for 1, 2, 3, 4 and 5 years before failure [7].
It can be expected that the set of variables which performs well in the latest year before failure will not necessarily perform well in the other years prior to failure. Some variables, however, can play an important role in more than one regression since some factors leading to failure are of long run nature.
Given the non-linearity of the first-order conditions with respect to parameters, a solution of numerical approximation is adopted that reaches the convergence after five reiterations. Tab.12 reports the maximized value of the log-likelihood function for all the regressions.
LR Chi-square (49) is the asymptotic version of the F test for zero slopes. The p-value allows the rejection of the null hypothesis that all the model coefficients are simultaneously equal to zero. Therefore, the model as a whole is statistically significant. To avoid the risk of multicollinearity among variables, the computed bivariate correlation test has been carried out. It does not reveal any linear relation among variables. To further corroborate this result we computed two additional measures, namely the ‘‘tolerance’’ (an indicator of how much collinearity a regression analysis can tolerate) and the VIF (variance inflation factor-an indicator of how much of the inflation of the standard error could be caused by collinearity). Since both measures were close to 1 for the considered variables, we can exclude any multicollinearity.

Turning to the analysis of the estimates, our empirical findings show that both the DEBT score and the NSD score are statistically significant at 1% level with the expected positive sign. An increase in firm’s debt level and/or in its vulnerability significantly increases the probability of default.
Tab.12 also reports the odds ratio of the logistic regression, which coincides with the exponential value of estimated parameters. Considering one year prior to failure (2010), for a unit increase in the DEBT score, the odds of bankruptcy increases by 44%, holding the other variables constant. Likewise, a unit increase in the NSD score raises the odds by 67.9%. In other words, firms that are exposed to high debt are more than 1.44 times ($e^{0.365}$) likely to fail than the other firms; firms with an unsustainable debt are more than 1.68 times ($e^{0.518}$) likely to go to bankrupt than the other firms.

[7] Note that we have run a standard Logit, a Rare Events Logit and a Linear Probability Model and they produce similar results. We report the standard logistic regression estimates on the paper, while the other results are available upon request.

From these results it is clear that, as expected, the level of indebtedness and its vulnerability are important factors in explaining firms' default risk. Interestingly, both indebtedness indices enter with the highest coefficients in all the regressions, that is for different lengths of the reference period. Moreover, the coefficient associated to the vulnerability of debt is always greater than that related to the absolute level of debt. Hence, it is certainly true that total amount of debt and its composition signal the financial health of the company, but the capacity/potential of the firm to sustain such debt is a more important factor to consider in firms' creditworthiness evaluation. In this context, an early warning signal of over-indebtedness would assume a pivotal role in the adoption of effective reorganization procedures.

With reference to the other explanatory variables, firm size enter with negative sign at 10% level of significance, therefore larger companies would face lower probability of default. Age enters at 1% level with negative sign, suggesting that younger firms are more likely to go to bankruptcy than larger companies. These results confirm previous empirical findings on the impact of age and size on firm performance (European Central Bank, 2013; Hurst and Pugsley, 2011; Haltiwanger, 2013; Fort et al. 2013). In a recent work on Italian manufacturing firms, Ferretti et al. (2016) obtain similar results.

Ownership concentration would enter with negative sign in the first year prior to failure suggesting that alignment of interests in fully concentrated ownership firms reduces the probability of financial instability and default. The variable, however, is not significant in explaining the probability of default in the majority of regressions.

On the contrary, being a multinational firm would impact negatively on probability of bankruptcy maybe because it is possible to diversify risk among different market segments. Labour productivity, on the contrary, does not seem to influence the probability of default.

As it is expected, the pseudo R-square increases when the reference period before failure reduces.

Moreover, both the coefficients (thus the odds ratios) and, for some regressors, the significance levels decrease when an increasing number of years is considered before failure. However, the estimates suggest that while some variables (like the annual turnover) are strongly significant in the latest year before failure but less significant - or not significant - in the other years prior to failure, the indebtedness DEBT and NSD scores always enter at 1% level of significance with the expected positive sign. They play an important role in determining the probability of default for several years before bankruptcy, mainly due to their long run nature within the process leading to failure.

For a comparison, we have also estimated the model including the Altman (1983) Z-score (see the Appendix for a short description) instead of the DEBT and NSD scores. Empirical findings, reported in Tab.13, show that the Altman Z-score enters significantly with the expected negative sign. The rest of the results are quite similar both in sign and level of significance.

Tab.12 Probability of default: Logit estimates

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}
DEBT	0.365***	1.440***	0.338***	1.402***	0.286***	1.331***	0.373***	1.452***	0.275***	1.317***
	(0.057)	(0.083)	(0.047)	(0.067)	(0.037)	(0.049)	(0.040)	(0.058)	(0.042)	(0.055)
NSD	0.518***	1.679***	0.469***	1.599***	0.513***	1.671***	0.562***	1.755***	0.529***	1.698***
	(0.045)	(0.075)	(0.035)	(0.057)	(0.032)	(0.054)	(0.034)	(0.059)	(0.034)	(0.057)
SIZE	-0.134*	0.874*	-0.063	0.938	0.013	1.014	-0.001	0.999	0.075*	1.077*
	(0.065)	(0.057)	(0.053)	(0.050)	(0.044)	(0.045)	(0.042)	(0.041)	(0.041)	(0.044)
AGE	-0.262***	0.769***	-0.201***	0.817***	-0.186***	0.829***	-0.128***	0.879***	-0.060	0.940
	(0.066)	(0.050)	(0.052)	(0.043)	(0.044)	(0.037)	(0.043)	(0.038)	(0.044)	(0.042)
D_own	-0.034	0.965	0.144	1.155	0.157	1.170	0.232**	1.261**	0.244**	1.276**
	(0.150)	(0.145)	(0.123)	(0.142)	(0.104)	(0.122)	(0.096)	(0.121)	(0.097)	(0.124)
D_mult	-0.258*	0.772*	-0.297**	0.742**	-0.581***	0.559***	-0.403***	0.668***	-0.547***	0.578***
	(0.141)	(0.109)	(0.120)	(0.089)	(0.106)	(0.059)	(0.095)	(0.063)	(0.094)	(0.054)
PROD	0.074	1.077	0.139	1.149	-0.032	0.967	-0.087	0.915	-0.127	0.880
	(0.124)	(0.134)	(0.097)	(0.112)	(0.082)	(0.079)	(0.084)	(0.077)	(0.086)	(0.076)
Regional dummies	included	included	included	included	included	included	included	included	included	included
Sector dummies	included	included	included	included	included	included	included	included	included	included
Constant	-3.415**		-4.272***		-2.846***		-2.260***		-3.280***	
	(1.258)		(1.210)		(0.946)		(0.813)		(0.791)	
N of obs.	14486		14225		15466		16674		15809	
Log-likelihood	-1529.44		-2071.53		-2790.83		-3159.92		-3095.08	
Pseudo R^2	18.77		16.59		15.84		16.34		15.31	
LR Chi-square(49)	530.06		596.74		749.93		889.94		789.07	
Prob>Chi-square	0.000		0.000		0.000		0.000		0.000	

Notes: All variables in logs. Standard errors in parenthesis. Significance levels: *10%; **5%; ***1%.

Tab.13 Logit estimates, Z-score

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}	Coeff. β	Odds Ratio e^{β}
Z-score	-0.611***	0.542***	-0.470***	0.624***	-0.576***	0.561***	-0.687***	0.503***	-0.614***	1.698***
	(0.050)	(0.027)	(0.040)	(0.025)	(0.038)	(0.021)	(0.039)	(0.019)	(0.040)	(0.057)
SIZE	-0.124**	0.883**	-0.049	0.951	0.006	1.006	0.033	1.033	0.073*	1.077*
	(0.063)	(0.056)	(0.052)	(0.050)	(0.042)	(0.042)	(0.039)	(0.040)	(0.039)	(0.044)
AGE	-0.365***	0.693***	-0.353***	0.702***	-0.244***	0.783***	-0.156***	0.855***	-0.130***	0.940
	(0.063)	(0.043)	(0.048)	(0.034)	(0.041)	(0.032)	(0.039)	(0.033)	(0.041)	(0.042)
D_own	-0.018	0.981	0.054	1.056	0.115	1.122	0.215**	1.240**	0.136	1.276**
	(0.149)	(0.146)	(0.121)	(0.128)	(0.098)	(0.110)	(0.089)	(0.111)	(0.095)	(0.124)
D_mult	-0.580***	0.559***	-0.483***	0.616***	-0.739***	0.477***	-0.592***	0.553***	-0.677***	0.578***
	(0.140)	(0.078)	(0.116)	(0.072)	(0.100)	(0.048)	(0.088)	(0.048)	(0.090)	(0.054)
PROD	0.151	1.163	0.146	1.157	0.063	1.065	-0.145*	0.864*	-0.120	0.880
	(0.119)	(0.139)	(0.099)	(0.114)	(0.080)	(0.086)	(0.080)	(0.069)	(0.084)	(0.076)
Regional dummies	included	included	included	included	included	included	included	included	included	included
Sector dummies	included	included	included	included	included	included	included	included	included	included
Constant	-2.477*		-3.228***		-2.422***		-1.532***		-2.782***	
	(1.259)		(1.172)		(0.904)		(0.761)		(0.850)	
N of obs.	14491		14129		16165		17307		16342	
Log-likelihood	-1587.12		-2193.33		-3111.58		-3622.11		-3381.13	
Pseudo R^2	14.30		11.30		10.82		11.37		10.57	
LR Chi-square(49)	364.60		345.35		455.79		576.66		475.82	
Prob>Chi-square	0.000		0.000		0.000		0.000		0.000	

Notes: All variables in logs. Standard errors in parenthesis. Significance levels: *10%; **5%; ***1%.

5.3 Reliability of the model and comparison with the Z-score

To evaluate the model we compute the percentage of overall correct classifications, which gives us the percent of correct predictions of our model (Tab.14). In total, 97.24% of predicted probability is correctly classified in 2010. More specifically, with reference to the first year prior to failure, our data show that positive responses were predicted for 12 observations, of which 1 was correctly classified because the observed response was positive (y = 1), while the other 11 were incorrectly classified because the observed response was negative. Likewise, of the 14474 observations for which a negative response was predicted, 14085 were correctly classified and 389 were incorrectly classified. In brief, in 2010, 400 firms are misclassified, consisting of 389 non-failed firms, and 11 failed firms. Hence, the estimated chance of *misclassification* is 2.76 percent. Misclassification increases when the length of the reference period increases. For the second, third, fourth and fifth years prior to failure, the estimated chance of misclassification is 4.23 percent, 5.30 percent, 5.74 percent and 5.84 percent respectively.

Note that, in terms of classification accuracy, our model and the Altman Z-score perform similarly in the first two years before failure. However, a greater discrepancy occurs in the third, fourth and fifth years prior to failure with expected overall accuracy rates of 94.71 percent, 94.28 percent and 94.17 percent for DEBT-NSD scores *versus* 94.65 percent, 93.92 percent and 94.11 percent for the z-score.

At a deeper analysis, the empirical findings indicate that our model and the Altman Z-score show different percentages of first and second type errors. Type I errors refer to firms that are actually defaulting, but are classified as non-default firms. Type II errors refer to non-defaulting firms that are incorrectly classified by the model as default firms. As argued by Bottazzi et al. (2011) and Modina and Pietrovito (2014), it is standard to prefer prediction models that reduce the Type I error, that is models that maximize the percentage of correctly classified defaults. For a bank, and from a social point of view as well, it is more costly to fail to predict a default than to classify a non-default firm as a default firm.

Interestingly, our empirical findings show that the first type crucial error rates for misclassifying failed firms as non-failed firms for the first five years prior to failure are always lower in our model in comparison with the Altman Z-score.

We have further assessed the model's ability to accurately classify observations using a receiver operating characteristic (ROC) curve. A ROC curve is constructed by generating several classification tables for cutoff values ranging from 0 to 1 and calculating the sensitivity and specificity for each value. Sensitivity is plotted against 1, to make a ROC curve. The area under the ROC curve (AUC) is a measure of discrimination; a model with a high area under the ROC curve suggests that the model can accurately predict the value of an observation's response. Our model provides outstanding discrimination since the AUC for the first five years prior to failure is 0.83, 0.80, 0.79, 0.78, 0.77 respectively (Tab.14). Note that, as it is shown in Fig.2, the area under the ROC curve computed with the DEBT-NSD scores is always greater than the area computed with the Altman Z-score.

To test the model fit, Hosmer and Lemeshow's test was evaluated. A good fit will yield a large p-value. With a p-value of 0.42, our model fits the data well.

Finally, we have checked the presence of any specification error using the linktest. The idea behind linktest is that if the model is properly specified, one should not be able to find any statistically significant additional predictors, except by chance. The linktest uses the linear predicted value (_hat) and linear predicted value squared (_hatsq) as the predictors to rebuild the model. Since the variable _hat is a statistically significant predictor, the model is not misspecified. On the other hand, if our model is properly specified, variable _hatsq should not have much predictive power except by chance. Since, _hatsq is not significant, we have not omitted relevant variables and our equation is correctly specified. The empirical findings on the linktest are available upon request.

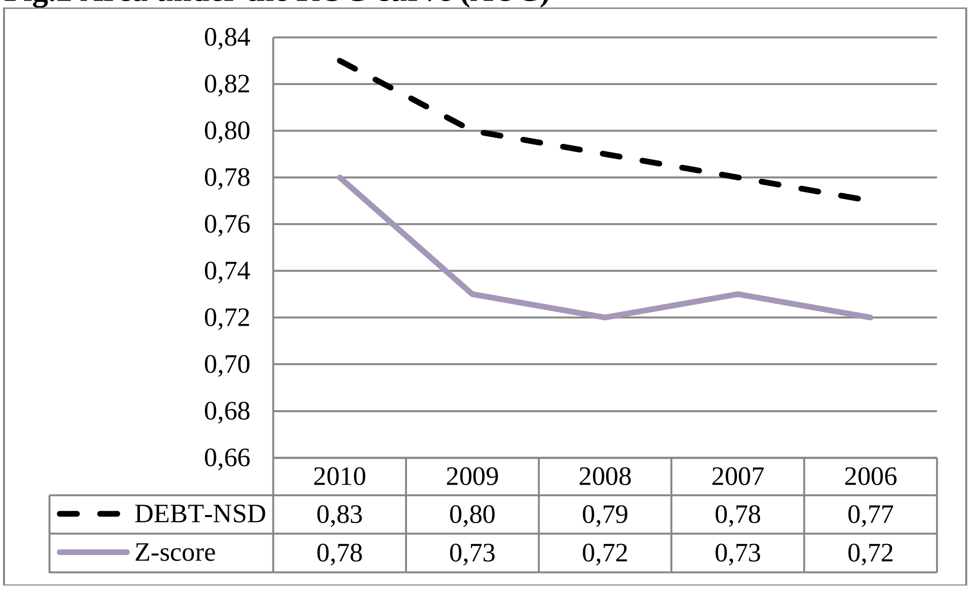
In brief, the overall evidence suggests that, in terms of classification accuracy and reliability, our model would outperform Altman Z-score and previous models for prediction of corporate failure (see Van Frederikslust 1978). This is especially true in the third, fourth and fifth years prior to failure indicating our DEBT-NSD indices to be good early warning signals of probable bankruptcy.

Tab.14 Model reliability

	Year -1 2010		Year -2 2009		Year -3 2008		Year -4 2007		Year -5 2006	
	DEBT-NSD	Z-score	DEBT-NSD	Z-score	DEBT-NSD	Z-score	DEBT-NSD	Z-score	DEBT-NSD	Z-score
Correctly classified	97.24%	97.22%	95.98%	96.00%	94.71%	94.65%	94.28%	93.92%	94.17%	94.11%
Type I error	2.69%	2.74%	3.94%	3.99%	5.18%	5.27%	5.58%	5.95%	5.72%	5.80%
Type II error	0.07%	0.04%	0.09%	0.02%	0.12%	0.09%	0.16%	0.15%	0.12%	0.10%
AUC	0.83	0.78	0.80	0.73	0.79	0.72	0.78	0.73	0.77	0.72

Notes: A firm is classified as default whenever its estimated probability of default (p_i) is higher than 0.5; it is classified as non-default otherwise. We refer to first type errors when the model classifies as healthy a critical firm. We refer to second type errors when the model classifies as critical a healthy firm.

Fig.2 Area under the ROC curve (AUC)



Source: own elaborations

6 CONCLUDING REMARK

Taking into account both the firms' debt level and its sustainability, we develop a new composite index based on financial ratios to identify over-indebted firms. We propose a Robust Principal Component Analysis for skewed data to estimate such new index.

We extend previous methodology by building a very large sample of firms and paying attention to both financial and non-financial firms' characteristics. Moreover, we examine how the model can be used in practice to analyze the risk of failure. In this context, we first derive a simple decision rule to classify firms as either at high risk of failure or at low risk of failure. We then propose a more complex model to predict the risk of failure as early warning signal of bankruptcy. In addition to several models that have been tested by the relatively short one-year prediction horizon, we test the predictive power of the index several years prior to bankruptcy.

The overall evidence suggests that, in terms of classification accuracy and reliability, our model would outperform Altman Z-score and previous models for prediction of corporate failure. This is especially true in the third, fourth and fifth years prior to failure indicating our indebtedness indices to be good *early warning signals* of probable bankruptcy.

The research can be developed following several directions. First, it would be interesting to compare the proposed index with other rating systems adopted, apart from the Z-score, to evaluate companies' financial stability and their creditworthiness. Second, it may be worthwhile developing a more general logit model of company default prediction including also management practices.

Finally, as the analysis as a whole would indicate that hybrid classifiers outperform individual techniques that constitute the ensemble classifiers, it would be worthwhile investigating new hybrid methodologies in order to amplify the advantages of the individual models and minimize their limitations.

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APPENDIX

A.1 Altman Z-score

The Altman *Z-Score* (1983) for Private Firms is defined as follows:

$$\boldsymbol{Z = 0,717X_1 + 0,847X_2 + 3,107X_3 + 0,420X_4 + 0,998X_5}$$

X1 is defined as Working Capital/Total Assets (WC/TA).
The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

X2 is defined as Retained Earnings/Total Assets (RE/TA).
Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. It should be noted that the retained earnings account is subject to "manipulation" via corporate quasi-reorganizations and stock dividend declarations. The age of a firm is implicitly considered in this ratio. For example, a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits.

X3 is defined as Earnings Before Interest and Taxes/Total Assets (EBIT/TA).
This ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure.

X4 is defined as Book Value of Equity/Book Value of Total Liabilities (MVE/TL).
The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. For example, a company with a value of its equity of $1,000 and debt of $500 could experience a two-thirds drop in asset value before insolvency. However, the same firm with $250 equity will be insolvent if assets drop only one-third in value.

X5 is defined as Sales/Total Assets (S/TA).
The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive conditions.