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Distinctiveness of Highly Risky Italian Firms That are Saved-A Logistic Approach

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Abstract

In our paper, we use a default mode approach in order to accurately classify a sample of 3,835 Italian manufacturing companies, and to gauge their health status on the basis of variables taken from the financial statement. The present study is oriented to test the potentiality of salvation for firms included within the worst classes of rating. The research aims to support the resolution of an elaborate theme: the identification of both highly risky companies designed to survive despite their own class of statistical rating, and firms that will move closer to a default status. In this way, the consequences of our examination could help to recognize, among firms considered "highly risky", the latent durability on the time.

Keywords: highly risky firms, credit rating, speculative ratings, risk alteration

1. Introduction

The present study is oriented to test the potentiality of salvation for firms included within the worst classes of rating. The research aims to support the resolution of an elaborate theme: the identification of both highly risky companies designed to survive despite their own class of statistical rating, and firms that will move closer to a default status. In this way, the consequences of our examination could help to recognize, among firms considered "highly risky", the latent durability on the time.

Highly risky companies are for banks the cluster of firms more unmanageable and expensive than other creditworthy companies. That is a serious problem for banks point of view. On the other side, this type of firms is more handy, available and reachable.

The study adopts as its starting point a ranking classification to forecast the probability of default built on a three-year period. This time-frame, longer than usual, is innovating compared to the prevalent literature on this matter. Unlike the more common statistical and regulated models to estimate the crisis, in fact, the present revision is intended to be much more forward looking.

The essential intention for this paper is to try to perceive latent factors of durability, among a group of firms included in highly risky classes of rating. This characteristic could give banks more information to read between the lines.

This study is split in three parts. The first part shows the construction of the rating model to forecast the probability of default and the resulting rating scale. The second part describes the designation of the sub-sample using the rating transition matrix over a period of three years after the first analysis. The sub-sample is composed by the firms with a high risk of default in 2007. The last part, finally, is the discernments of the analysis between the two groups of firms, highly risky in 2007, that have different prospects in 2010, after three years.

The subdivision into two sub-samples of analysis also stems from the aspiration to analyse the effects as errors of assessment.

In order to construct a prediction model of defaults, using the statistical technique of logistic regression, we test the accuracy of the prevision and we list companies within ten classes of risk. In this way the article focuses on the examination of the eventual distinctions, within the same risk category, among those firms that after three years are still healthy, and those firms that, vice versa, will have become insolvent. In other words, the present dissertation aims to search for the divergences among the companies that in 2007 marked a high level of risk, while three years later, in 2010, have evidently improved or worsened their own creditworthiness.

The essential plan of the logistic model is the connection between the probability of a company to become insolvent (latent variable) and a group of discernible quantities that are strictly related to the event with a statistical significance[1]. Rather than have a comprehensible separation between healthy and insolvent firms, logistic regression identifies a ranking in firm's classification.

We restricted the independent variables analyzed to those derivable from financial statements. Such statistics are quickly available for large numbers of companies.

On the basis of the foregoing, other sections of this paper are structured into four parts. The second paragraph gave a short literature review on past studies on bases of credit risk model. Paragraph three presents the motivations of research. The theoretical framework and methodology of the study was discussed under the fourth part. Paragraph five presents the empirical findings and discussion while, the last paragraph closes and proffers theoretical proposition to the analysis.

2. Review of Literature

The bank, today, must recognize the risks and must be able to grade both impact and probability. Most of the loss in value is attributable to reasons of risk that get overlooked or considered highly improbable. The rating models are very dissimilar, as they are built in order to answer to more than a few circumstances. The most classic type of rating models, aims to classify firms by default probabilities.

In order to be useful and working, the rating model must be transferrable, in time and space, and replicable on different subjects. It is basic that risk of default is estimated uniformly, quickly and accurately. The crucial aim of the credit risk-rating method is to exactly estimate the credit risk of a certain portfolio of companies and, in particular, to assess the expected and unexpected loss from investing in asset and the capital requisite to upkeep it.

Rating models can be differently built because of the disparate utilizable information, the quality of the records used, the types of firms analysed, the *time-frame* related to the timing of non-payment, the characterization of default, and the requirements of periodic maintenance.

Many empirical researches that assume the statistical approach intend to perfectly sort a sample of firms in healthy or default ones on the foundation of variables taken from financial statements. Forecasting bankruptcy has been an important goal of the financial analysis for several decades.

Starting from the original schoolwork of Altman (1968), several studies have been focussed on the theme of company default prediction modelling.

For almost thirty years univariate (Beaver, 1966) and multivariate discriminant analysis (Beaver, 1968, Blum, 1974 and Deakinn, 1972) have been the primary approaches to estimate the probability of bankruptcy. These processes, with some important specific assumptions, essay the different causes through which a firm can became insolvent.

These approaches demonstrate some weaknesses when the prediction variables used are not totally independent of one another (Ohlson, 1980 and Karels & Prakash 1987). In order to achieve better outcomes, in subsequent years, the authors apply the logistic regression analysis to classify the default probability. We remember Wiginton (1980), Grablowsky & Talley (1981), Altman, Marco & Varetto (1994), Laitinen & Laitinen (2000) and Friedman & Huang (2002).

This method, in order to gain a degree of insolvency for firms, recognizes either that the probability of default is logistically distributed and that the collective likelihood of bankruptcy assumes a logistic functional shape.

After the abovementioned researches, significant marks for this matter have been achieved by several authors: Edmister (1972), Lo (1986), Gentry, Newbold & Whitford (1987), Cantor & Packer (1994), Hosmer & Lemeshow (2000), Crouhy, Galai & Mark (2001), Shumway (2001), Carey & Hrycay (2001), Becchetti & Sierra (2003), Couderc & Renault (2005), Altman & Sabato (2007), Kayhan & Titman (2007), Muscettola & Pietrovito (2012 A), Muscettola (2015 A).

Regarding the cases of empirical analysis on Italian data we have made reference to numerous other studies: Appetiti (1984), Alberici & Forestieri (1986), Barontini (2000), Laviola & Trapanese (1997), Foglia, Laviola & Marullo Reedtz (1998), Lo Martire (2002), Muscettola & Gallo (2008), Muscettola & Pietrovito (2012 B), De Laurentis & Maino (2009), Muscettola (2014 A).

[1] Unlike discriminant analysis, this statistic method is constructive to gain a mathematic estimation of the probability of default.

As far as the developing of different statistical methods, the affiliation between simplification and specificity in these models is another extensively debated argument in literature. Some authors (Springate & Gordon (1978), Zmijewski (1984), Mossman, Bell, Swartz & Turtle (1998), Yu, Garside & Stoker (2001), Muscettola (2013), Muscettola (2015 B)) are discussing on require to expand specific models by restricting the analysis to specific sectors.

3. Motivation

The revision of risk migration is a central aspect in each rating model. It is important, for risk management, to calculate the prospect of ranking changes as exactly as possible. The reactions to this investigation contain the validity of the model to select - clearly and in permanent way - the risk of insolvency. The prospect is, therefore, that the majority of companies would remain at the same level of risk also for the following year. Downgrades to speculative-grade are features to consider with attention for banks.

The research purposes to support the resolution of an obscure theme: the identification of firms, included in the speculative grade ratings, intended to evolve to better classes, and firms that, on the other hand, will move closer to insolvency. In this way, the results of our study could help to identify, among firms measured "highly risky", the potential durability of firms and, in the same time, the fatal vulnerabilities that impact on company's solvency.

Why could firms overcome the deep crisis, even if they are rated highly risky?

Firms bounded in the same risk class can have different destinies. On the other hand, firms incorporated in the same risk class have an equal original judgment and, therefore, a comparable prospect of default after three years. If these companies have different destinies they still have different structures and different potentialities (Muscettola, 2014 D).

If a collection of explanatory factors (accounting ratios) is significant for the group of firms to increase their imminent standing we should detect these aspects more carefully and weigh better into a rating model.

The problems to solve in our study are two:

Within the class of firms classified into speculative grade ratings, are companies homogenous?;

Is it possible to recognize the chance of salvation, now, for firms included within the same high rating class?

4. Data and Methodology

From such introduction, we put under the magnifying glass a sample of 3,835 manufacturing SMEs using a set of ordinary and yearly financial statements[2] from 2007 to 2010. The sample contains 171 cases of defaults. In the sample we excluded financial firms, construction firms, farms, commercial, service and public firms.

The sample consists of Italian manufacturing firms with total revenues from sales between 5 and 50 million euro. In addition, we ignore firms that belong to financial and utility productions, as well as multi-segment firms that enclose sections in the financial or service industries.

As follows, on Table 1, there is a description of fundamental factors for the sample used in the examination.

Table 1. Characteristics of the sample used in the research

		Manufacturing firms	
		Healthy Firms	Insolvent Firms
Net Sales	More than 30 million €	707	28
	More than 15 million €	1,603	66
	More than 5 million €	1,354	77
Ages	more than 20 years	1,841	71
	more than 10 years	1,288	61
	more than 5 years	535	39
Total		3,664	171
		3,835	

In our study we use simply the quantitative analysis on the financial statements. The collection of ratios was selected on the basis of consistency in the research literature (Montrone, 2015) about bankruptcy estimate. Speculative grade, or sub-investment grade, allocates this rating to firms that are at this time highly vulnerable to non-payment. In our paper,

[2] The yearly statements are provided by "FourFinance Rating" collected from multiple databases as, above all, Cerved Group Spa and Crif Spa. As for the creation of the statistical model, the preliminary operations on the data, the choice of the outliers and the creation of financial ratios, the reader ought to refer exclusively to the authors.

speculative grade are the three worst clusters on the rating scale of model presented below.

In order to combine the particularities of firms to the prospect of default after three year, and to prove the hypothesis of this study we use a binomial logit model. This procedure is the logistic regression with a variable-reduction practice well-known as "forward stepwise". In this progression, we employ 67 accounting ratios like independent variables. In this way, our model consents a comprehensive utilizzation of all accounting quotients, starting from the ratio which can expose the most predictive power.

In order to shape the model to forecast defaults, we use yearly data from 2007, searching for the default event in 2010, after three years.

The logistic regression allows us to determine a default likelihood with a rating scale system. Through a binary response, the logistic model frameworks the subdivision of the whole sample into ten equally numerous clusters. The firms in the sample are branded into ten risk classes on a scale from 1 to 10, where 1 is the best, 10 is the worst. In order to shape the optimal cut-off between each class we use the technique of the median.

Table 2. Logistic Regression. Function calculated on firms in 2007 with the default event in 2008.

	B	S.E.	Wald[3]	Sig.	Exp(β)
Total fixed assets / Total assets	-0.01041	0.00444	5.48819	0,01915	0.98964
Intangible fix assets / Tot. assets	0.03396	0.00802	17.9289	0,00002	1.03454
Borrowings / Total assets	0.01000	0.00337	8.80799	0,00300	1.01005
Quick ratio	-0.00401	0.00189	4.51863	0,03353	0.99600
Net working capital / Tot. invest.	-0.03320	0.00588	31.8511	0,00000	0.96735
Interest expense / Total debt	0.21468	0.04513	22.6276	0,00000	1.23947
Interest expense / Sales	0.19411	0.04487	18.7131	0,00002	1.21423
Inventory turnover	-0.40928	0.10173	16.1875	0,00006	0.66413
Fixed assets turnover	-0.00470	0.00135	12.0651	0,00051	0.99531
Operating cash flow / Sales	0.03563	0.01224	8.47866	0,00359	1.03628
Ebitda / Total investment	-0.05886	0.01326	19.7140	0,00001	0.94284
Net working capital / Sales	0.01334	0.00434	9.43486	0,00213	1.01343
Costant	-3.89278	0.29352	175.889	0,00000	0.02039

After creating the rating model and then listing firms within ten classes of risk, this study focuses on the examination of the eventual divergences among the companies that in 2007 demonstrated a same extent of risk, a high risk of default, while three years later, in 2010, have a diametrically different future.

The next table shows the error matrix using a neutral approach. The table gives a sense of meticulousness to the level of sorting used, and particularly, displays the frequency of defaults within the ten classes of risk.

Table 3. Error matrix

	Neutral approach	
	No.	%
Error Type I	62	36.26
Error Type II	932	25.44
Hit (true default)	109	63.74
True (true positive)	2,732	74.56
Accuracy	74.08	

Specifically, the table depicts the calculation of the prediction errors of Type I[4] and Type II[5]. We use error matrix as a measure of the model's performance. It describes the frequency of firms classified correctly. As you can see, table measures more than 74% firms correctly estimated.

[3] The "Wald" statistic is the square of the ratio of the coefficient to its standard error.

[4] Type I errors refer to the predictions of false healthy.

[5] Type II errors refer to the predictions of false default.

A rating model is considered consistent if it is able to discriminate correctly firms. The assessment model is more proficient when the misclassifications of firms are less. At this stage, however, it is necessary to reiterate the substantial distinction between Type I Error (insolvent firm categorized as healthy firm) and Type II Error (healthy firm considered as insolvent). The first category of misclassification is evidently more expensive than the second one.

The interval between the reference time of analysed data and the hypothetical event under revision is three year. Beyond the more classical model for probability of default over one-year period[6] we suggest a more forward looking glance analyzing the firm features even for a longer time frame: over a three - year period.

At this phase, the analysis moves from the whole sample to a specific sub-sample of high risky firms. We have selected 244 companies within the three groups of firms called "A", "B" and "C" as expressed in the following table although our analysis focuses only on two groups of enterprises. We define "A-firms" the companies that are subject to Type I Error, "B-firms" are, on the other side, firms subject to Type II Error (after three years, migrated towards the better classes) and "C-firms" are true defaults. With regard to the group "B", for the number and for uniformity of data we catch only some companies included in the risk class number 8 and 9.

Table 4. Distribution of firms included into the sub-samples of analysis.

Rating Classes	Type I Errors False healthy	Type II Errors False default	Hit True default
1	1	0	0
2	0	0	0
3	4	0	0
4	4	0	0
5	6	0	0
6	6	0	0
7	20	0	0
8	21	30	3
9	0	43	42
10	0	0	64
Groups of Firms	62 A	73 B	109 C

In the second part of the paper we use the descriptive analysis to find the differences between the B-firms and the C-firms: false default firms and true default firms.

5. Results

All companies included in the worst classes of risk, by definition, share the same risk in 2007 and in terms of probability of default it is expressed with a similar cluster of rating. In order to get rated at a high degree of risk, consequently, they must have negative features. In financial investigation, it is ordinary to visualize a business company with a speculative grade rating as a firm that has negative ratios.

In next tables we determine the average values of some ratios for B-firms and C-firms in order to catch, by this descriptive analysis, some causes that distinguish the two sets of firms. For a better view of the tendencies we have chosen 3 explanatory variables for each collection of accounting index. At the end we use 24 ratios indicative of 8 different dimensions. We mean: Composition of assets, Capital structure, Liquidity, Debt coverage, Turnover, Net profitability, Operating profitability and Efficiency.

Now we search for the eventual differences between the two groups of firms. We analyzed companies in 2007, in the past, by the descriptive analysis. In order to check relationship, descriptive analysis is used after adjusting for heteroskedasticity of data to moderate the effect of extreme values (*outliers*). The distributions of ratios are winsorized at the 1% and 99% levels.

[6] In most of models used, the time-frame of rating models covers a typical period of one year even if, for several reasons linked to the publication of the financial statements or for more functionality, this time horizon should be projected surely lengthier than the usual twelve months (Muscettola, 2013).

Table 5. Averages of accounting ratios used for the two groups of firms

Accounting ratios	**false default B-firms**	**true default C-firms**	**Correlation**
Total fixed assets / Total assets %	32.48	32.87	-0,112338
Inventory / Total assets %	29.30	28.37	-0,000855
Trade receivables / Total assets %	29.59	29.14	0,003906
Long term liabilities/ Total assets %	13.45	16.95	0,026393
Total shareholders' equity / Short term debt %	29.51	26.62	0,273989
Financial leverage	4.95	5.39	0,235161
Quick ratio %	60.18	60.94	-0,162538
Current ratio %	110.95	113.17	0,047487
Equity / Fixed assets %	95.63	70.63	-0,113366
Interest expense / Total debt %	4.09	4.20	0,174343
Total debt / Sales %	99.33	104.05	-0,123539
Interest expense / Sales %	4.25	4.71	0,113505
Account receivable turnover	7.35	6.05	-0,043648
Inventory turnover	5.68	4.13	-0,050126
Fixed assets turnover	43.61	49.16	0,079253
Operating cash flow / Current liabilities %	5.01	4.90	-0,053281
Operating cash flow coverage %	1.35	0.98	0,019898
Operating cash flow / Sales %	3.43	3.37	-0,111344
Operating profit / Sales %	4.84	4.96	-0,114156
Gross profit / Sales %	21.75	23.19	0,048668
Ebit / Total liabilities %	4.01	3.84	-0,089093
Roi %	3.49	3.44	-0,120221
Total shareholders' equity / Sales %	22.57	19.74	0,166915
Gearing	0.75	0.73	-0,458290

Here, we analyse the average composition of the assets (Muscettola, 2014 B) of the two types of firms. Next picture shows that firms have an identical composition of assets.

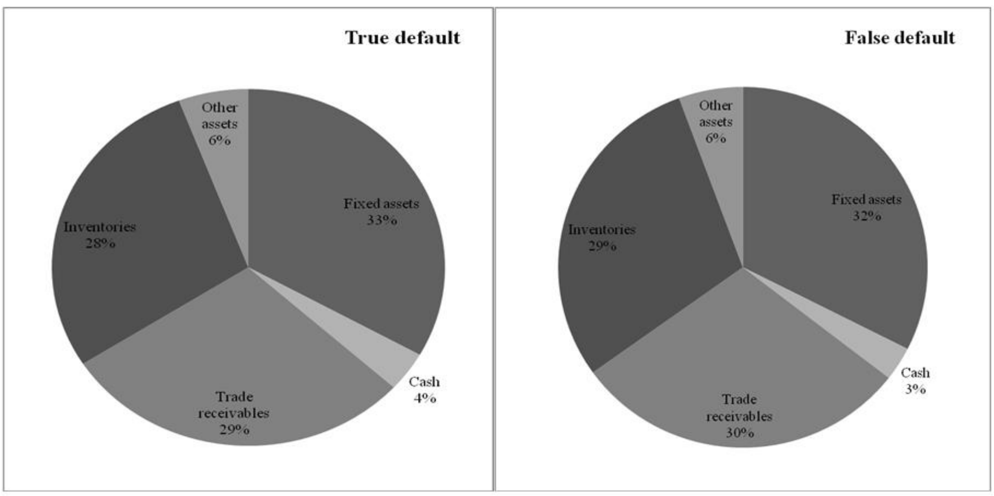

Figure 1. Average of the composition of assets inside the two subsamples

Next graph shows also the capital structure across the two groups. From this analysis, however, we note a barely perceptible lower borrowings and a consequently higher capitalization transpire in firms that will improve their creditworthiness after three years (false default firms).

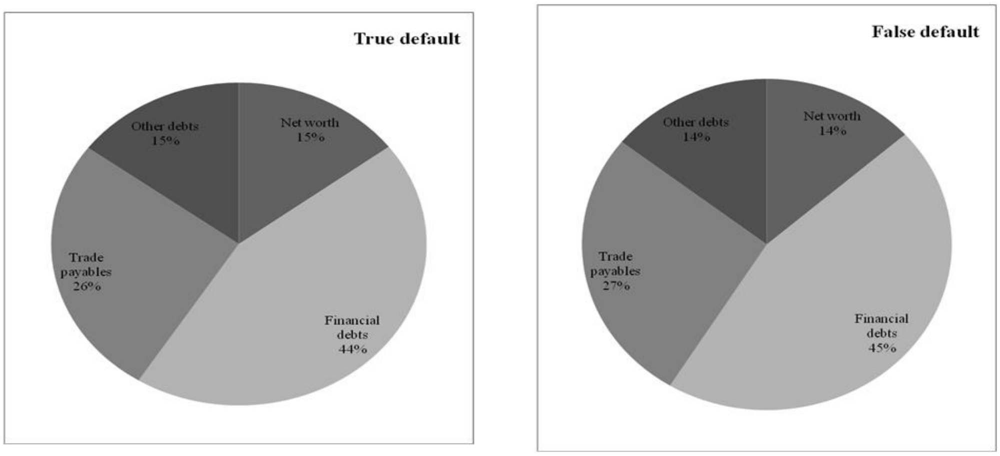

Figure 2: Average of capital structure inside the two subsamples

The two groups of firms have got capital structure and composition of assets perfectly identical. The true default firms have a better profitable position (operating profitability ratios) while, on the other side, they are slightly more indebted than the false default firms.

On a closer analysis, however, we note that the main differences can be read in the cash conversion cycle.

In management accounting, the cash conversion cycle is the most significant part in working capital management and it quantifies how long a company will be deprived of cash while it is waiting for the conclusion of the production cycle with the proceeds from sales[7]. Its depth is very important to calculate the financial needs when firm increases its investment in resources in order to expand customer sales (Muscettola, 2014 C).

In accountancy the cash conversion cycle is:

Number of days account receivable[8] + Number of day inventories[9] – Number days account payable[10].

Table 6. Cash Conversion Cycle for firms included into the two subsamples

	No. of Days Accounts Receivable	No. of Days Inventories	No. of Days Account Payable	Cash Conversion Cycle
	DIFFERENTIAL DAYS: YEAR 2007 - YEAR 2006			
True default	-36	+24	+13	1
False default	-27	+2	-21	-46
	TOTAL DAYS IN 2007			
True default	60	88	74	-75
False default	50	64	78	-35

In the examination of the cash conversion period we ascertain that companies that after three years are saved by default, in 2007 have a manufacturing cycle shorter than the insolvent firms. The difference is especially noticeable in average collection time of sales to customers and in the average time of material storage. The true default firms have a cash conversion cycle of 40 days longer than the false default firms. As regards the variation between 2007 and 2006, hence, we note that although the rotation of trade receivables improved for both groups of companies (even more emphatically for true default firms) this improvement is perfectly offset in true default firms by the worsening of inventory turnover and by the fact that suppliers require minor delays to its obligations. Conversely the other group of firms manages to get more extended terms from its suppliers[11].

With regard the healthy firms, we remember that all the indices formed by revenues (turnover ratios, efficiency ratios) don't have the same statistical significance. Probably because these ratios are more perishable in a medium time

[7] A firm could even realize a negative cash conversion cycle by collecting from customers before paying suppliers.

[8] No. of days accounts receivable: Account receivable / Sales x 365; Days sales outstanding is a calculation used to measure the average collection period and it measures the usual number of days that customers take to pay invoices.

[9] No. of days inventories: Inventories / Cost of sales x 365; Days in inventory is a financial ratio that measures the average number of days the company holds its inventory before selling it.

[10] No. of days account payable: Accounts payables / Purchases x 365; Days payable outstanding measures the average number of days a firm takes to pay its suppliers.

[11] The fact that suppliers restrict the average payment times could mean that their debtors are considered riskier.

(Muscettola & Naccarato, 2013). As regards the risky firms, conversely, these ratios are crucial to distinguish the companies that will be saved: false default firms.

6. Conclusions

The most important intention for this paper is to try to perceive latent factors of success also among a group of firms integrated in a high class of rating. This aspect could give banks more advises to be read between the lines.

Finding out some structural differences that lead towards statistically significant consequences, it is simpler to get an interpretation to find companies that are able to save themselves in spite of their position risk

The conclusion of the work is that among firms that have the same statistic risky class, it is possible to recognize firms that have, most likely, the potentialities to perk up, in the following years, and to identify the potentialities of notching-up their creditworthiness. This is most evident in the turnover ratios.

The main contribute of this study is the revelation that you can regulate a rating model to provide alternative responses about the possibility to remain healthy for firms highly risky. By this explanation, thus, the risk must be seen not only as an aspect to border, but also like opportunity.

Firms with a pronounced risk of bankruptcy can be judged in a better way if these firms have got positive efficiency ratios (turnover ratios). You can consider in a better way a firm that has a shorter cash conversion period to support even if it is a highly risky firm because that company has more potentialities to evolve and to exit from the risky area.

There are some boundaries intrinsic to this analysis: the data used were very restricted, with only accounting ratios as factors. Additionally, the study period included the financial crisis period that may have impacted on the trends of analysed firms. For a more perceptive examination, this study can be completed through more sources of information (qualitative data, behavioural data) or more categories of firm (commercial firms, service firms).

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