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Medium Risk Companies: The Probability of Notching-Up (Note 1)

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Abstract

The probability of default and risk-rating class is studied for 9,390 Italian SMEs using a set of ordinary and yearly financial statements (not abbreviated) from 2007 to 2010. After constructing the rating model and then listing companies within ten classes of risk, this paper aims to support the resolution of an intricate topic: the identification of 713 firms included in the median classes of rating designed to evolve to better classes, and firms that, instead, will move closer to high risk of default. In this way, the results of our research could help to identify, for similar firms in 2007, two different destinies after three years (in 2010). The most interesting result emerging from our analysis is related to the presence of a positive relationship between some financial ratios (capital structure and fewer inventories) and the probability of notching-up. The overall evidence is supportive of the hypothesis that the benefits gain up by profitability ratios cannot give to the firms a solid class of rating guaranteed for the future.

Keywords: credit rating, medium risk, risk alteration, notching-up

1. Introduction

Credit activity of banks builds on certain defining elements. The intermediation function ultimately deals with the different needs of the community. Either changing the maturities or shaping the expected profitability with the supported risks, all is contained inside the definition of theoretical typicalness of banks. Banks are at the service of the capital markets and stands, therefore, in the middle between investors and users. The grand feature of banks is the risk management.

If, on the one hand, it is clear the number of benefits descending from a strategic and integrated managing of risk, on the other hand it is a remarkable fact that the risk is not to be addressed only reactively. The handling of the risk means also to ensure the achievement of targets. Risk is the probability that the future event does not identify with what expected (Note 2). By this definition, thus, the risk must be seen not only as a factor to control and limit, but also like opportunity.

Model ratings, whether they are attributed by either public rating agencies or some internal rating procedures, play a significant role in both credit risk management and defaultable debt estimation. Rating, now more than ever, is a long-term investment, a delicate tool to handle with care and attention and to improve with careful daily work to achieve a continuously improved its reliability.

The bank, today, must identify the risks and must be able to classify both impact and likelihood. The key issue is the distinction between acceptable risks and unacceptable ones, which must be treated in the most appropriate method. Banks' leaders must have in mind what are the inherent risks, such as residual risks and what risks target maximizing the probabilities of positive outcomes and minimizing the risk of losses (Note 3).

The rating models are very different, as they are built in order to respond to several scenarios. Inter alia, however, every single rating model contains just one specific response related to the rules and the methods of construction (Muscettola, 2013). Among the most common mistakes that can be committed, therefore, there is the supposition that managing only one statistical model, you can draw more types of responses.

The most classic type of rating models, aims to classify firms by default probabilities; it may be differently built because of the dissimilar usable information, the quality of the same data used, the types of company analyzed, the *time-frame* (Note 4) respect to the timing of default, the definition of default, and the needs of periodic maintenance. Besides all these variables, the rating model, in order to be useful and working, has to respond to a couple of particular features, as the transferability in time and space, and the replicability on different subjects. Different ratings for firms that seem to be comparable damage the reliability of the risk-rating system. On the other side, it is indispensable that risk of default is estimated uniformly, quickly and accurately.

The essential aim of the credit risk-rating system is to correctly approximate the credit risk of a detailed transaction or portfolio of assets. The final goal, therefore, is to measure the expected and unexpected loss from investing in an asset and the capital required to upkeep it.

A rating model is considered reliable if it depends only on its own ability to correctly select firms. The evaluation and selection model is more efficient when the wrong classification of firms is less, but with a reminder, a steady distinction between Type I Error (insolvent firm classified as healthy firm) and Type II Error (healthy firm judged insolvent). Type I Errors, in effect, are clearly more expensive than the latter ones (Note 5).

Most risk-rating models, especially used by banks, reflect both quantitative and qualitative elements to judge the risk of default. Furthermore, the information employed in creating risk-rating models is often centred on accounting data that are updated intermittently and at tardy points in time and do not effusively reproduce the dynamics of risks.

Without a chance to include elements taken from qualitative survey and behavioural analysis, in this argumentation we will analyse our sample of firms under a quantitative point of view. The explanatory variables of the model are taken exclusively from the analysis of the available financial statements. Our analysis is completed on many attributes of the borrower including financial, earnings and cash-flow, quality of assets, and liquidity of the firm. Unlike rating models of banks, in this model will tend to rely more heavily on repayment capacity, solvency, profitability and efficiency than on the quality of management, history of firm, sectorial analysis and corporate projects, even if, like many risk-rating systems, this model is founded on historical financial statistics produced under circumstances that may not be applicable in the future.

From such premises, we put under the magnifying glass a sample of 9,390 Italian SMEs (Note 6) using a set of ordinary and yearly financial statements (not abbreviated) belonging to 9,390 unique firms, from 2007 to 2010 in order to first construct a prediction model of defaults with a consequent risk scale. After constructing the rating model and then listing companies within ten classes of risk, this paper focuses on the analysis of the eventual differences, inside the same median class of risk, among those firms that after three years will have migrated towards the three major risk classes (notching-up), and those firms that, vice versa, will have migrated towards the three minor risk classes (downgrading). In other terms, the present study aims to seek the differences among the firms that in 2007 manifested a same level of risk, while three years later, in 2010, have clearly enhanced or worsened their own creditworthiness.

The research aims to support the resolution of an intricate topic: the identification of firms included in the median classes designed to evolve to better classes, and firms that, instead, will move closer to speculative grade ratings. In this way, the results of our research could help to identify, among firms considered "medium-risk", on the one hand, the potential growth and durability, while on the other hand, the latent dangers that could impact the company's solvency.

The study takes as its starting point a rating system built on one-year period; these rating systems are prevalent among Italian banks. Although there is a same initial judgment and, therefore, a similar probability of default after one year, companies still have different structures and different potentialities. The rating assigned to the company, for that reason, should not be interpreted through overly myopic perspective, helping to create incomprehensible and unjustifiable barriers to access to credit. The rating is a statistical tool prone to different interpretations.

According to an exquisitely empirical point of view, we built our research on an observable factor that would eventually confer an improvement about the predictive accuracy of credit rating changes. This seems relevant in order to investigate what the latent factory really is.

The rest of the paper is structured as follows. Next section presents the literature bases of credit risk model. Section 3 presents the motivations of research. Section 4 describes the model data and the modelling approach used to estimate the probability of default. Section 5 explains the credit rating transition. Section 6 defines the particular sub-sample of analysis. Companies defined as "medium-risk" will be analyzed in depth with descriptive analysis distinguishing between these companies that after three years have improved its rating by companies, instead, that have worsened their creditworthiness. An estimation result of credit risk model is presented in Section 7. Section 8 concludes the paper.

2. Literature Review

A variety of analytical techniques have been used for credit-risk assessment. Default mode and mark-to-market are two central methodologies to quantifying credit risks. The default mode approach converges in a straight line on the characteristic of firms. The mark-to-market approach efforts to calculate how potential alterations in the credit risk features of a loan or a group of loans will influence the firm market value, as well as potential repayment capacity of firm. The default mode, used in this paper, is more conventional and generally applied.

The default mode includes statistical methods, such as linear, multivariate or quadratic discriminant analysis, logistic and probit regression analysis. Furthermore, under this approach to the issue can be listed also models based on contingent claims and asset value coverage of debt obligations or more complex methodologies such as neural networks. Among default mode there are also operational research methods such as linear or quadratic programming and data envelopment analysis.

The largeness of literature about the default mode approach has concentrated on the use of accounting ratios of firms such as composition of assets, capital structure, indebtedness ratios, cash flow ratios, profitability ratios, efficiency or liquidity. The firm's financial ratios are key inputs to PD models. They capture firm specific effects and reflect the riskiness of firms.

These models, despite their specificity, have in common the aptitude to select a subset of indicators (accounting ratios) that discriminate firms that become insolvent by healthy firms. So, regardless of the different approaches used over time, it is possible to recapitulate this conception: talking about value of the analytical methodologies or functionality of the model means a successfully developed framework able to forecast the highest percentage of insolvencies and to perform, therefore, the fewer of predict errors.

Many experimental studies that assume the default mode approach usually aim to accurately classify a sample of companies in healthy or default ones on the foundation of variables taken from financial statement. Forecasting of default rates has been a goal of the financial analysis for decades. An extensive quantity of the company bankruptcy literature has largely employed financial data of firms to extend Beaver's (1966) early univariate methodology and Altman's (1968) successive linear multiple discriminant analysis model. After the research made by first pathfinders, important results for this branch have been achieved by Edmister (1972), Springate and Gordon (1978), Zmijewsky (1984), Lo (1986), Gentry et al. (1987), Platt and Platt (1990), Cantor and Packer (1994), Ooghe et al. (1995), Mossman et al. (1998), Laitinen and Laitinen (2000), Hosmer and Lemeshow (2000), Crouhy et al. (2001), Shumway (2001), Carey and Hrycay (2001), Grice and Ingram (2001), Couderc and Renault (2005), Altman and Sabato (2007), Kayhan and Titman (2007), Muscettola and Pietrovito (2012), Muscettola (2015 A).

The default mode approach, therefore, takes advantage of historical data of firms to construct a predict model to forecast the insolvencies. Historical data shall be analyzed with objectivity, detachment and mathematical approach. The main goal of these models is to measure the expected loss, unexpected loss and recovery rates.

While an ambition of risk-rating classifications is to generate accurate and reliable ratings, qualified decision, personal evaluations and experience must also be part of the rating procedure. Many financial institutions make use of some category of mathematical modelling to support in the rating procedure but, nevertheless, judgmental rating systems produce a great weight to the final result (Note 7). Qualitative judgment, or behavioural analysis, is indispensable and provides greater accuracy, confidence, and flexibility to the rating model. On the other hand, textbook handlings of rating variables suggest the ordered probit and the ordered logistic models to forecast the probability of default of firms. These mathematical model approaches are more used because it is much easier for the researcher to interpret the latent linear model with standard normally distributed errors where a detachment of the borders is used to produce the pragmatic discrete distribution of ordered results. The most important achievement of ordered models is the unspoken conventionality to the scaling of the dependent ranking variable.

As banks appraise and develop their risk-rating models, portfolio managers are moving from judgmental consideration toward greater dependence on quantitative estimation of default risk. Quantitative estimation speeds up the risk-rating method and can guide to some more harmonized outcomes (Yu et al., 2001). In order to develop the effectiveness of the quantitative rating models, banks need to ascertain that they are employing adequately the granularity into the design of the risk classes.

With the advantage of a very rich literature on the matter, we take a large selection of accounting ratios, most widely used in the quantitative rating models, and we will build a predictive model of ranking. Considering that, this paper deals with a very large sample of Italian SMEs, to seek peculiarities of firms that became insolvents we will use the technique of logistic regression to separate the good firms from insolvent companies. The initial set of ratios was selected on the basis of frequency in the research literature on bankruptcy prediction.

3. Motivations

Whilst normative theories attempt to describe, by some deductive analysis, why a certain section of firms might allegedly come to a fail, we instead maintain a propensity to a positive approach. In our research, supported by empirical results, we effort to explicate by inductive interpretation why firms are able to overcome the crisis even if they are judged averagely risky. To achieve this purpose we construct a rating scale starting from a simple statistical and mathematical approach. By means of logistic regression, with the forward stepwise method, we build a regression functions capable of distinguishing good firms from bad firms (Note 8). After that, we will have one rating scale to be associated with our test sample.

Finally, we have explored the potential impact of some accounting ratios for different future ratings of firms. Building on the literature on financial constraints and classical banking model to evaluate the firms, we have chosen to approximate the extent of potential probability of success faced in the normal sample of regular companies by means of the matrix of migration. In particular, we have considered the companies that are positioned within a medium class of risk searching for the peculiarities that involves a significant alteration of risk, for good or for bad.

Firms enclosed in the same risk class (Note 9) can have different fates. If a group of variables (accounting ratios) is decisive for the cluster of companies to improve their future standing, even if judged averagely risky, we should observe these features more carefully and weigh better into the rating model.

The major purpose of this work is the clear identification, within a group of firms judged to medium risk by means of an ordinary statistical method, of latent factors of success and latent factors of vulnerability. This could give banks more data, supported by studies, to interpret, as well as to read between the lines and remould, in the essential function of credit risk management.

The problems to solve in this research are three as follows:

1) Within a class of rating, are always companies homogenous?
2) Is it possible to identify the probability of migration of risk, from one class to another of rating and is it possible to identify the direction of the alteration of risk?
3) Is it possible to forecast different destinies, for firms included within the same rating category?

4. Data and Methodology

The functionality of the evaluation model is directly and positively dependent on the quality and quantity of data input available and on the information summarized and analyzed. In order to obtain a working model, the present study has examined a scheme of analysis that is transferable, in time and space, to other samples of firms and that is empirically verifiable in time. For these reasons, it synthesizes the sources of information avoiding phenomena of overfitting and problems of multicollinearity of variables (Note 10).

A deeper reflection, however, deserves the arrangement and cleaning of the sample analysis. Before starting to work on the data, it is essential to clean the dataset removing firms that seem to have irrational data or that may have been caused by exceptional situations from the analysis sample. It is a crucial step, therefore, to verify the impact of outliers (Note 11). As regards the treatment of outliers we have chosen to follow a fairly wide acceptance. This is in order to don’t lose significant data and because, in a sufficiently large and specific sample such as our dataset, the anomalous cases are not detected numerically excessive. The sample excludes firms with significant outlier in some of their explanatory variables so that all the observations in the 1st and the 100th percentile are dropped.

In this article was deemed necessary to restrict the definition of “default”. In addition to the failure to fulfil a bank obligation, appearing in a law court, also some other events of insolvency arising from the imperfect payment of debts (especially to repay a loan) were included in the definition. Default, in fact, is defined as a payment being ninety days or more past due at least once since origination. Ninety days or more is a typical definition of default in the market (Note 12). This limited definition was chosen because we cannot have access to the behavioural analysis of the firms. Data about insolvencies, credit overdue, bankruptcies are gathered in Credit register at Crif Spa (Note 13). In this way sub-sample of insolvent firms will not be limited to a critical and closed definition, even if the allocation of a company into the default class is fundamentally rooted in objective definition.

The final sample is a composition of 37,560 firm-year observations (Note 14) that span 9,390 individual companies. The companies analyzed are small and medium sized enterprises with not less than 5 million euro of total revenues from sales and not more than 50 million euro of total sales on the yearly statements under examination.

The firms included in the sample are operating in Italy for at least 5 years. Off the analysis sample also are all those firms that have shown significant shareholdings in other companies or, on the other hand, are dependent by a parent company. We excluded financial firms, public firms, farms and construction firms.

Table 1. Characteristics of the sample used in the research

Sector	Net Sales			Ages			Default	Total
	More than 30 million €	More than 15 million €	more than 5 million €	more than 20 years	more than 10 years	more than 5 years		
Manufacturing	849	1,904	1,568	2,134	1,577	610	241	4,321
Trading	572	1,451	1,489	1,230	1,871	411	197	3,512
Services	35	409	1,113	613	567	377	66	1,557
Total	1,456	3,764	4,170	3,977	4,015	1,398	504	9,390

The reference year for the rating model is 2007. All the firms (504 firms) which have been insolvent until the year 2008 are reasonably considered "default firms".

In order to associate the peculiarities of companies to the probability of default after one year (to estimate the PD), and to verify the hypothesis of this paper, in this research, consistent with other recent academic studies, we use a binomial logit model: logistic regression (Note 15) with a variable-reduction process known as "forward stepwise". In this process, each of the 56 independent variables (accounting ratios) is strained, one at a time, and 56 one-variable regression models are fashioned. The sequence is repeated until no new indicator makes any improvement in the performance of the risk-rating systems. In this way, the model allows a complete use of all variables, asymptotically efficient, starting from the indicator which can expose the most predictive power.

The logistic regression allows to approximate a default probability (Note 16), instead of a credit score with an easier statement of the rating scales. The results of the logistic regression through the forward stepwise procedure are descripted in Table 2. In order to model the probability of default, we use yearly data from 2007, searching for the default event in 2008.

The results of the logistic regression expresses a function of separation of firms, which will become insolvent after one year, from firms that, instead, will remain solvent throughout the period under our analysis. Considering the estimated parameters, you can formulate the prediction model of corporates' insolvencies in the following way:

z = -6.790037 + (Cash and bank deposits / Total assets %) x -0.023432 + (Prepaid expenses and current fin. / Total assets %) x 0.033183 + (Long term liabilities/ Total assets %) x 0.025517 + (Net working capital / Total investment %) x -0.022165 + (Interest expense / Total debt %) x 0.125711 + (Total debt / Sales %) x -0.018684 + (Interest expense / Sales %) x 0.174580 + (Intercompany and shareholder debt / Assets %) x -0.028434 + (Debt ratio %) x 0.016256 + (Current liabilities / Sales %) x 0.031290 + (Operating cash flow / Sales %) x -0.067719 + (Operating profit / Sales %) x 0.054522 + (Ebit / Total liabilities %) x 0.041460 + (Roa %) x -0.122865 + (Net working capital / Sales %) x 0.015279

Table 2. Logistic regression: function calculated on firms in 2007 with the default event in 2008

	β	*S.E.*	*Wald*	*Sig.*	*Exp(β)*
Cash and bank deposits / Total assets %	-0.0234	0.0084	7.770	0.005311	0.976840
Prepaid expenses and current fin. / Total assets %	0.0331	0.0090	13.329	0.000261	1.033740
Long term liabilities/ Total assets %	0.02551	0.0053	23.056	0.000002	1.025845
Net working capital / Total investment %	-0.0221	0.0045	23.645	0.000001	0.978079
Interest expense / Total debt %	0.12571	0,0447	7.9061	0.004927	1.133955
Total debt / Sales %	-0.0186	0.0024	58.928	0.000000	0.981490
Interest expense / Sales %	0.17458	0.0425	16.855	0.000040	1.190746
Intercompany and shareholder debt / Assets %	-0.0284	0.0054	27.159	0.000000	0.971966
Debt ratio %	0.01625	0.0038	17.722	0.000026	1.016389

Current liabilities / Sales %	0.03129	0.0033	87.750	0.000000	1.031785
Operating cash flow / Sales %	-0.0677	0.0124	29.414	0.000000	0.934523
Operating profit / Sales %	0.05452	0.0109	24.978	0.000001	1.056036
Ebit / Total liabilities %	0.04146	0.0128	10,331	0.001308	1.042332
Roa %	-0.1228	0.0190	41.520	0.000000	0.884383
Net working capital / Sales %	0.01527	0.0034	19.404	0.000011	1.015396
Constant	-6.790	0.3413	395.67	0.000000	0.001125

The construction of the rating scales occurs in connection with the logistic functions remarked. Once the factors for a set of predictors are supposed, it is possible to foresee the odds that each observation may belong to a class of risk of default.

Through a binary response, the logistic model outlines the subdivision of the sample of 9,390 firms into ten equally numerous clusters. A rating on a scale of 1 to 10 where 1 is best, 10 is worst, and each number corresponds to an increment of 10 percentage points: The firms in the sample are categorized into ten risk classes. In order to shape the optimal cut-off between each class, and to perceive the class in which its probability of membership is highest, we have been making use of the technique of the median: cut-off value for a two-class case is 0.5. Once the mapping has been completed, the characteristics of the firms in each risk-rating class are known and we can use these characteristics in providing benchmarks for each risk-rating class.

Table 3 shows the model validation. Specifically, in the table were counted the prediction errors of Type I and Type II. As anticipated, the Type I Errors refer to the provision of false healthy while Type II errors refer to the forecasts of false default (Note 17).

We use error matrix as measure of performance of the model. It describes the amount (percentage) of firms classified correctly. As you can see, table 3 measures more than 78% firms have been correctly evaluated. The error matrix (Table 3), gives a sense of precision to the level of classification used, and especially, shows the type of misclassification most frequently observed.

Table 3. Error matrix

	Neutral approach	
	No.	%
Error Type I	97	19.25
Error Type II	1,966	22.12
Hit (true default)	407	80.75
True (true positive)	6,920	77.88
Accuracy	78.03 %	

Establishing a demarcation point between the two sets (healthy firms and default firms) it is possible to estimate the performance of the model by quantifying the number of errors that occur. With a neutral methodology (Note 18), cut-off value for the two groups of firms instance is 0.5, 97 firms (on 504 defaults) were incorrectly assessed and 1,966 firms (on 8,886 healthy firms) were mistakenly judged insolvent.

Finally, Table 4 describes the distributions of 504 cases of default within the risk classes in order to have a visually stunning on the functioning of the model. It is effortlessly seen that most of the defaults were already judged at high risk one year before the insolvency.

Table 4. Distribution of insolvency cases within the classes of ranking built using logistic regression

Rating classes		Default cases	Frequency
Probability of default	Description		
1 - None	Remote: failure is unlikely	5	0.99
2 - Very minor	Low: failures are few and far between	5	0.99
3 - Minor	Low: relatively few failures	8	1.59
4 - Very low	Moderately low: infrequent failures	18	3.57
5 - Low	Moderate: occasional failures	18	3.57
6 - Moderate	Moderately high: frequent failures	30	5.95
7 - High	High: failures occur often	32	6.35

8 - Very high	High: repeated failures	34	6.75
9 - Extremely high	High: failures occur almost as often as not	81	16.07
10 - Dangerously high	Failure is almost inevitable	273	54.17
	Total	504	100.00

Table 4 highlights that the most of insolvent firms stands inside the higher risk zones. Over 75% of firms, about to be insolvent, are included in the three worst risk classes, and more than 50% of *default* cases even inside the last cluster of the ranking scale.

On the other side, there are only 54 cases of insolvent firms inside the first five classes of risk with an overall frequency measuring approximately a good 10% of the total defaults. Remembering that the ten classes include the same number of firms, it is permissible to declare reliable the predictive ability of this model (Note 19).

5. Credit Rating Transition

It is important for risk management, to calculate the possibility of rating changes as well as defaults in the future as precisely as plausible. The study of class migration is an important factor in each rating model. The responses to this analysis include the validity of the model to select - unmistakably and in permanent way - the risks of firms. The expectation is, therefore, that the majority of companies would remain with the same level of risk also for the following year.

Credit rating transition is the migration of a risk of default from one rating class to another rating class over a certain period. This relocation is either an upgrade or a downgrade from an existing class of rating. Upgrades and downgrades, particularly from investment to speculative-grade, can be very important for banks, as credit transitions are interrelated with the economic cycle. This rating changes as and when new information is obtainable about the financial health of firms and, in such a way assembled, indicates the alteration in the credit quality of the portfolio.

Nevertheless, as some pragmatic academic papers already showed, it seems correct to presume that the rating transition probabilities change as time passes because of uneven economic cycles and so forth. Consequently, it is logical to consider an evaluation difficulty of rating transition probabilities under the postulation that such prospects are not invariable in time but dependent on some dynamics and factors linked to both firms and economy.

Common practice is to assemble average transition probabilities in a matrix, as shown in Table 5, and use them as projections.

Through the transition matrices, we can define the sub-sample to analyze. Our sub-sample consists of the companies that during the year 2007 were classified within the median classes of risk (5 or 6) while, in 2010, they migrated to the three best classes of risk or to the three worst classes of risk.

Percentages of credit rating transitions are calculated on three-year horizons and it is evident that changes are more likely followed by downgrades, rather than upgrades: the stock of non-fulfilling firms significantly increased during the crisis (Muscettola, 2014 B).

Table 5 displays credit rating transitions, which are computed on three-year horizons from 2007 to 2010. The Three-Year transition matrix explains the alteration of rating class expressed in percentage. The sum of each row is equal to 100%.

Table 5. Three-Year transition matrix: percent

%	Rating class in 2010									
Rating class in 2007	1	2	3	4	5	6	7	8	9	10
1	63.55	19.70	7.52	2.62	1.82	1.48	1.14	0.80	0.80	0.57
2	27.96	30.58	19.16	9.53	4.71	2.30	1.68	1.26	1.05	1.78
3	9.93	23.56	26.19	17.23	9.93	4.97	2.92	2.53	1.36	1.36
4	3.99	13.09	18.30	22.39	16.16	9.20	6.65	4.40	2.76	3.07
5	3.42	6.56	11.55	17.61	20.45	14.87	10.96	7.05	3.91	3.62
6	1.14	2.46	5.30	11.55	16.38	20.83	15.15	12.31	8.24	6.63
7	1.00	1.50	3.70	6.60	11.80	17.40	18.10	19.90	10.90	9.10
8	0.33	1.77	1.99	3.21	6.75	12.39	15.93	21.90	19.14	16.59
9	0.56	1.00	1.67	1.56	3.79	6.35	10.36	18.49	26.28	29.96
10	2.08	1.49	1.79	2.38	2.53	4.17	5.51	9.08	17.86	53.13

The Table 6 denotes the same aspect but with numbers of firms. The sum of all these numbers is 9,390 that is the whole sample used.

Table 6. Three-year transition matrix: number of firms

No.	Rating class in 2010									
Rating class in 2007	1	2	3	4	5	6	7	8	9	10
1	558	173	66	23	16	13	10	7	7	5
2	267	292	183	91	45	22	16	12	10	17
3	102	242	269	177	102	51	30	26	14	14
4	39	128	179	219	158	90	65	43	27	30
5	35	67	118	180	209	152	112	72	40	37
6	12	26	56	122	173	220	160	130	87	70
7	10	15	37	66	118	174	181	199	109	91
8	3	16	18	29	61	112	144	198	173	150
9	5	9	15	14	34	57	93	166	236	269
10	14	10	12	16	17	28	37	61	120	357

The fact that the transition matrix is based on a time span longer than the classic period of one year, does not affect the results. In facts, the method of assessment in 2010 is the same rating model as for 2007. The firms, therefore, are catalogued with the identical tool during the all period of analysis. On the other side are off the sub-sample the firms in default. This choice is motivated to avoid extreme behaviour of firms: companies without business continuity.

6. Subsample of Analysis

At this phase, the analysis moves from the entire sample to a specific sub-sample of averagely risky firms in 2007. 713 companies have been identified within the risk classes 5 and 6 that, after three years, migrated in the first three merit classes (defined A-firms), and in the worst of the three classes of risk (defined B-firms). It is recalled that insolvent firms were excluded by analysis (Note 20). The two sub-samples so identified are shown in the following table:

Table 7. Analysis sub-sample

Rating class in 2007	Best three rating classes in 2010	Latter three rating classes in 2010
5	218	142
6	90	263
	308	405

The companies analysed, however, in 2007 are judged similarly and with a medium risk of default. After only three years, firms of subsample will have a future horizon looking diametrically opposed.

Medium risk companies are manageable and accessible for financiers and investors. This is a key - cluster for banks. They are handy, available, and reachable in a larger way than other types of risky firms.

Companies included in the medium classes of risk, by definition, share the same risk in 2007 and in terms of probability of default it is expressed with a similar class of rating. To be rated with a middle level of risk, therefore, firms must have both positive and negative characteristics, which are normally netted. They have positive aspects opposed to downsides. In financial analysis, it is normal to imagine a firm with a moderate risk of default as a firm that has some positive indices balanced by other negative ratios. For these reasons, it is significant to understand the eventual differences among this crucial group of companies.

In the Table 8, we calculated the average values of some indicators (Note 21) for A-firms and B-firms in order to capture, by this descriptive analysis, some factors that differentiate the two sets of firms.

At this phase we analyze companies in 2007, in the past, by the descriptive analysis searching for the eventual differences between the two groups of firms (Muscettola, 2014 A (Note 22)). Below we analyse the average composition of the assets of the two types of firms.

Table 8. Averages of accounting ratios used for the two groups of firms

	Accounting ratios	A-Firms	B-Firms
Composition of assets	Total fixed assets / Total assets %	25.23	20.50
	Inventory / Total assets %	17.67	23.86
	Trade receivables / Total assets %	44.90	42.45
	Intangible fixed assets / Total assets %	3.23	2.56
Capital structure	Long term liabilities/ Total assets %	7.30	7.88
	Borrowings / Total assets %	20.81	25.85
	Trade payables / Total assets %	37.32	38.58
	Leverage	0.96	1.73
Liquidity	Quick ratio %	92.44	82.67
	Long term debts and equity / Fixed assets %	348.90	397.35
	Current ratio %	125.13	122.05
	Net working capital / Total investment %	9.24	10.85
Debt coverage	Interest expense / Total debt %	2.02	2.29
	Total debt / Sales %	59.15	54.99
	Current liabilities / Total debt %	89.28	88.90
	Interest expense / Sales %	1.14	1.15
Turnover	Account receivable turnover	8.42	13.44
	Investment turnover	1.79	1.84
	Trade payables turnover	8.42	13.44
	Fixed assets turnover	3.02	4.84
Net profitability	Operating cash flow / Current liabilities %	9.46	6.83
	Operating cash flow coverage %	10.51	3.49
	Operating cash flow / Sales %	3.72	3.07
	Roe %	2.06	8.91
Operating profitability	Operating profit / Sales %	6.41	5.44
	Ebitda / Interest expense %	20.17	25.52
	Ebit / Total liabilities %	6.79	6.37
	Ebitda / Net financial position %	-0.03	0.56
Efficiency	Roi %	4.66	5.44
	Net working capital / Sales %	7.68	7.88
	Total shareholders' equity / Sales %	24.98	14.98
	Gearing	0.47	0.44

The next picture shows that firms, which after three years will have improved their own standings, have lower inventories, 18% compared to 24%, and higher portion of fixed assets, 25% compared to 21% of B-firms.

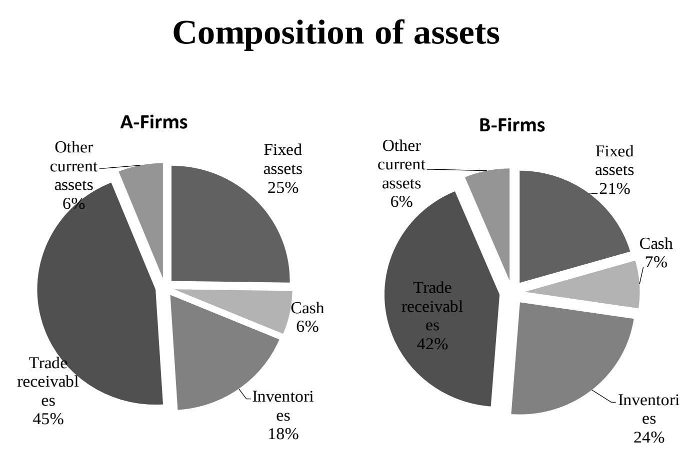

Figure 1. Average of the composition of assets inside the two subsamples

Figure 2 shows also the capital structure across the two groups. However, from this analysis lower borrowings and a consequently higher capitalization transpire in firms that will improve their creditworthiness after three years.

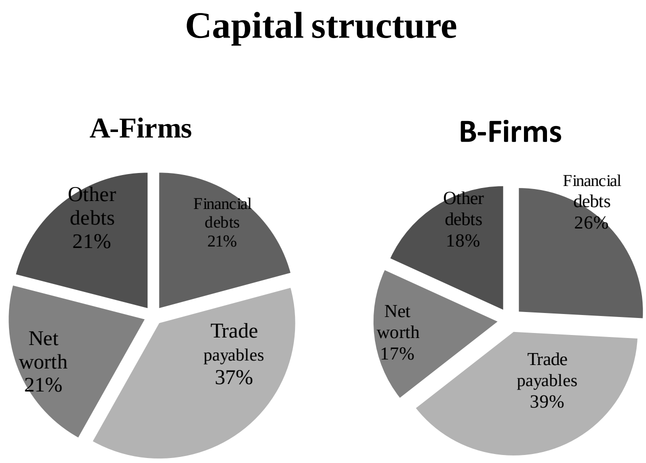

Figure 2. Average of capital structure inside the two subsamples

7. Results

Within the group of firms that during 2007 had the same statistic risks, and therefore the same rating, it is possible to distinguish a sub-sample of companies, most likely, that will have the potential to evolve in the following years and migrate to best classes of rating. In contrast, there are firms whose structure involves a higher probability of weakening toward the worst classes of rating.

Evidently A-firms and B-firms share the same risk in 2007 but they have different structures and different potentialities. So if the A-firms have a more solid capital structure they will highlight more deficient profitable position than the B firms.

A-firms have lower financial debts (Borrowings/Total Assets = 20.81% against 25.85% of B-firms) and a lower debt burden compared to the operating cash flow (Operating cash flow coverage = 10.51% against 3.49% of B-firms). They have a better quick ratio (92.44% against 82.67% of B-firms).

On the other side, B-firms can be judged in a better way than A-firms with regard to the indices of rotation, for ROE, for ROI and for a lower intensity of fixed assets. More specifically, it would seem that the higher level of debt is offset by higher revenues from sales. In this logic, you can read as the index debt / sales is equal to 55% for B-firms against over 59% for A-firms.

Although some operating profit ratios are increased by the higher sales, this one implies also that a discrete profitability may be linked to a greater vulnerability. Trusting in purely economic (as the volume of sales) phaenomena generates greater defencelessness to this type of company, especially during a time of economic downturn. When consumption is reduced for the crisis and, therefore, the productions fall down, and at the end the B-firms have the worst impact.

The results of our study are intended to highlight the importance for firms to have substance in assets, a solid capital structure and a better coverage of short-term debt through activities readily convertible into cash (cash and trade receivables, Muscettola, 2014 C). The three indices that best represent the differentiation between the two groups of firms are: Inventory / Total Assets, borrowings / Total Assets and Quick ratio. Profitability ratios and, however, all the indices formed by revenues (turnover ratios, efficiency ratios) do not have the same statistical significance because they are perishable in a medium time (Muscettola, 2014 D).

8. Conclusions

A reliable and solid rating is a primary target.

Without a common and objective risk assessment, you cannot raise steady relationships, operative opportunities as well as conditions for a good assistance and support, which make flourish the relationship between banks and firms (Muscettola, 2015 B).

This study introduce a new trail for analysis with which may contribute to start a modern approach towards rating models.

The biggest contribution of this study is the demonstration that you can calibrate a rating model to supply alternative responses to the conventional forecasting of the probability of default. The rating class, for that reason, could be prone to different interpretations and alternative discernments.

Results shown in Table 8 indicate that firms whose credit rating is downgraded to speculative (Note 23) from medium rating classes have got incrementally more debt relative to equity than other firms. The distance of the averages suggests that the overall results a downgrade to speculative implies approximately a higher level of inventory and borrowings and a minor level of fixed assets and capitalization. In our analysis a downgrade from fifth or sixth class of rating to eighth, ninth or tenth ones implies greater subsequent turnover ratios increasing versus firms that notch-up on rating scale. Underscoring the importance of these factors, firms particularly target the investment grade credit rating level have a greater level of net worth on sales and a lesser grade of profitability on the revenues.

The most important purpose for this work is to try to detect latent factors of success and latent factors of risk, among a group of firms included in a medium class of rating. This aspect could give banks more data to be read between the lines.

The conclusions of the study are three:

1) Among firms that have the same statistic rating, it is possible to identify firms that have, most likely, the potentialities to improve their creditworthiness, in the following years, and to identify the potentialities of notching-up on a rating scale.

2) Among firms that have the same statistic rating it's possible to identify firms whose structure implicates a higher probability of deterioration and the potentialities of notching-down on a rating scale.

3) It's possible to discover a group of "solid" accounting ratios that are the essential basis for the notching-up while, on the other side, it's possible identify another group of ratios that we can define as "vulnerable" ratios that don't consent firms to evolve.

Firms with a moderate risk of default can be judged in a better way if these firms have got positive solid ratios (composition of assets and capital structure, for example). You can assess in a better way a firm that has solid ratios even though it is averagely risky, because that firm has more chances to evolve and reach a certain notching-up.

There are some limitations inherent in the study. The data used for the study was very limited, with only accounting ratio as explanatory variables. Moreover, the study period included the global financial crisis, which may have adversely impacted on the health of the companies under analysis. These have repercussions in the coefficients of 2007-08 year dummy variable inside the fixed effects regressions. Thus, the results of our study may not be generalizable.

The study can be extended to consider more disaggregated measures for a most sensitive analysis of its impact on future of firms. Furthermore, a proper temporal perspective can be captured by taking another time-frame for data, so that the accounting ratio may be properly estimated and modelled, and forecasting model may also be applicable, in order to estimate lagged impacts.

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Notes

Note 1. An early version of this paper was presented orally at IRMC 2015, 8th Annual Meeting of "The Risk Banking and Finance Society" in Luxembourg. There isn't an original version of article which premiered in Luxembourg for the international conference.

Note 2. *"It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all.* (Frank. H. Knight, 1921 - Risk, Uncertainty, and Profit).

Note 3. It is recalled that most of the loss in value is attributable to sources of risk ignored or considered highly improbable.

Note 4. Time lapse between the reference time for analysed data, and the hypothetical event under study. In most of cases, the time-frame of rating models covers a standard period of one year. By the judgement, so, you may understand how many chances a firm has to get insolvent within a year, even tough, for reasons related to the approval and release of the financial statements, these time-frames should be intended certainly longer than the standard twelve months (Muscettola & Naccarato, 2013).

Note 5. In this regard, imagine a bank that wrongly lends money to a firm looking solvent (Type I Error) compared to the case of a bank that does not lend money to a firm, which is really able to repay the loan. The difference between the error types is simplistically to quantify in approximately twenty times: the cost of the *false positive* will exceed twenty times the cost of the *false negative*.

Note 6. The sample contains 516 cases of defaults. As above, such numerosity is supposed acceptable not to be included in any case of defect of the aforementioned sample.

Note 7. Above all small banks are inclined to have a relative advantage in using soft information technologies (Berger & Udell, 2002). All the same, in a new revision, Berger and Black (2011) demonstrate that bank will usually choose a hard information technology over a soft information technology if satisfactory hard information is obtainable.

Note 8. The logit regression is calculated by relying exclusively on the accounting ratios (independent variables) and dividing the analysis sample by type of activity carried out by the firms.

Note 9. Firms included in the same risk class have an identical original judgment and, therefore, a similar probability of default after one year.

Note 10. To this particular goal, we have chosen the variables to get data always available through the time and measurable by quality. In order to grant such a long-term quality for this model, thus, we must carry out our analysis with a clear and simple distinction for each segment of our sample. It requires a not too heavy series of variables, to which we may add hereafter more reachable, and enough numerous, data.

Note 11. It is better to estimate the frequency and the origin of any anomalous values, in order to fully limit their manipulation.

Note 12. A loan is called "past-due" if the firm missed a principal or interest payment for more than 90 days.

Note 13. CRIF is the leading provider in Italy of banking credit information. CRIF is an independent company of credit bureau services, business information systems, and credit and risk management solutions to support banks and financial institutions.

Note 14. The yearly statements are provided by 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.

Note 15. This technique uses maximum likelihood estimation to select coefficient dimensions that maximize the likelihood of the sample dataset being observed. The maximum likelihood process is reliable with large samples of firms. It normally generates distributed coefficient estimates which consent the handler to assume archetypal hypothesis testing methods.

Note 16. This variable takes the value of “1” if default has occurred and “0” otherwise.

Note 17. A false positive, in a particular test, may actually not to take advantage of those pretty conditions it supposedly got. Conversely, a false negative does not reveal any of the bad conditions it supposedly got.

Note 18. It is fairly clear that there is a non-symmetric cost structure in the event of Error of Type I or Error Type II, evidently skewed towards the higher costs caused by misclassification of firms that will become insolvents. It isn’t economically acceptable to treat the two categories of error in the same way. The neutral approach contemplates in the same way the two types of costs moving the cut-off exclusively in consideration of the computation, a priori, of the for probability of error. It is noted that banking models generally move forward the cut-off of separation, in order to obtain fewer cases of Type I Error (false positive error). The probability to find an insolvent firm in the macro-sample of companies, the focus of our analysis, it is taken by the statistical default: 5.37%. With the aforementioned statistics we will be able to move forward with the criterion of the cut-off separation in order to have a smaller number of cases of error.

Note 19. The ten rating classes are populated by the same number of companies. This means that in each class there are 939 firms. In the first five classes, therefore, there are 4,695 firms including 54 insolvent firms and 4,641 healthy firms. 54 defaults correspond to 10.7% of insolvent companies and 4,641 healthy correspond to 98.8% of healthy companies.

Note 20. In some cases a firm is downgraded from medium rating class to a significantly worse rating within the speculative grade category which may contaminate the results, in particular, if the firm is in default.

Note 21. For a better view of the trends we have selected 4 explanatory variables for each group of accounting ratio. At the end the ratios used were 32 representing 8 different dimensions: Composition of assets, Capital structure, Liquidity, Debt coverage, Turnover, Net profitability, Operating profitability and Efficiency. This choice of indicators solves the problem of statistical correlation avoiding, thus, redundant indicators or duplicates in the dataset. In the selection of ratios we found that each of the variables used to answer positively to the principles of monotonicity test and sensitivity or specificity check (*Roc curve*). The whole set is going to be essential for the validation of the results formed by the logit model. The explanatory variables employed may be placed, by a corresponding examination carried out with the factor analysis, in eight macro-groups of ratios.

Note 22. For other specification about the distinction and composition of assets and capital structure see Muscettola (2014 A).

Note 23. Speculative grade, or sub-investment grade issues, assigns this rating to obligations, or firms, that are currently highly vulnerable to non-payment. In our paper, speculative grade are the three worst classes on the ranking scale.