Measuring and Managing Credit Risk in SMEs: a Quantitative and Qualitative Rating Model

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Abstract:

The main aim of this paper is to develop a qualitative and quantitative credit risk rating model for SMEs.
The scope of this model is to assign, through a discriminant function (see Altman,1969), a synthetic judgment of the firm management (Z).
First of all it must characterize n variables that multiplied for a weighted coefficient allow us to determine a score of the analyzed enterprises.
The classification is based on a discriminating function that maximize the variance of the variables among the firms of two groups and to minimize the variance among the firms of the same group.
An important aspect of the model is its ability to enclose in the judgment of rating also the qualitative part. The objective is to modify the quantitative score including the qualitative judgments that emerge from a qualitative questionnaire.
The final rating, therefore, is constructed assigning the final score (quantitative plus qualitative) to the class of rating that it includes such value. So a synthetic judgment of the solvency, the solidity and the forecasts is supplied about the firm analysis.
In conclusion we can say that the obtained results confirm the reliability of the model. The error percentage, in fact, is only of 13.65% for the performing firm and 8.91% for the non performing.
Further analyses have demonstrated that the model turns out reliable also in relation to possible distortions generated from dimensional (analysis for number of employers) and geographical (analysis for province) effects. Contrarily a surveying on industry does not give the same results. Various industry are characterize from different variability coefficients and it implies a meaningful sectorial effect.

1. INTRODUCTION

The recent finalization of the new minimum regulatory capital requirements drafted by the Basel Committee on Banking Supervision1 (henceforth known as Basel II) has generated significant debate among academics, policy makers and industry practitioners.

The Basel I Capital Accord, published in 1988, represented a major breakthrough in the international convergence of supervisory regulations concerning capital adequacy. Its main objectives were to promote the soundness and stability of the international banking system and to ensure a level playing field for internationally active banks. This would be achieved by the imposition of minimum capital requirements for credit risk, although individual supervisory authorities had discretion to build in other types of risk or apply stricter standards.

The framework defined the constituents of 'regulatory capital' (numerator of the solvency formula) and set the risk weights for different categories of on- and off-balance sheet exposures (denominator of the solvency formula). The risk weights, which were intentionally kept to a minimum (only five categories/buckets), reflected relative credit riskiness across different types of exposures. The minimum ratio of regulatory capital to total risk-weighted assets (RWA) was set at 8%, of which the 'core capital' element (a more restrictive definition of eligible capital known as Tier 1 capital) would be at least 4%. The most important amendment to the framework took place in 1996, when an additional capital charge was introduced to cover market risk in banks' trading books.

However, the basic credit risk capital measurement framework remained unchanged, although the definition of assets and capital has evolved over the years in response to financial innovation.

Following the publication of successive rounds of proposals between 1999 and 2003, active and broad consultations with all interested parties, and related quantitative impact studies, the Basel Committee members agreed in mid-2004 on a revised capital adequacy framework (Basel II). The framework will be implemented in most G-10 countries as of year-end 2006, although its most advanced approaches will require one further year of impact studies or "parallel running" and will therefore be available for implementation one year later8. For banks adopting the IRB approach for credit risk or the AMA for operational risk, there will be a capital floor following implementation of the framework as an interim prudential arrangement.

The main objective of the framework is to further strengthen the soundness and stability of the international banking system via better risk management, by bringing regulatory capital requirements more in line with (and thus codifying) current bank good practices.

This will be achieved by making credit capital requirements significantly more risk-sensitive and by introducing an operational risk capital charge. The intention is to broadly maintain the aggregate level of capital requirements, but provide incentives to adopt the more advanced risk-sensitive approaches of the revised framework. These changes are implemented by changing the definition of Risk Weighted Assets (i.e., the denominator of the CAR) while leaving most of the other elements of Basel I unchanged, such as the focus on accounting data, the definition of eligible capital, the 8% minimum CAR requirement and the 1996 market risk amendment to the Capital Accord.

Basel II consists of a broad set of supervisory standards to improve risk management practices, which are structured along three mutually reinforcing elements or pillars:

1. Pillar 1, which addresses minimum requirements for credit and operational risks
2. Pillar 2, which provides guidance on the supervisory oversight process
3. Pillar 3, which requires banks to publicly disclose key information on their risk profile and capitalization as a means of encouraging market discipline.

Financial institutions have traditionally attempted to minimize the incidence of credit risk primarily via a loan-by- loan analysis carried out during the credit underwriting process.
The foundations of a more analytical framework began in the early 1960s when the first "credit scoring" models were built to assist credit decisions for consumer loans. Although they initially classified debtors/counterparties on default potential based only on an ordinal ranking, they were the original precursors to numerical PD estimation. By the mid-1980s, particularly with the introduction of RAROC as a performance measure, leading financial institutions began calibrating each credit score to a particular PD to estimate EL and ultimately economic capital.

- The measurement of a PD pre-supposes the use of a definition of default that has tended to vary across credit institutions, thereby hindering comparisons. The definitions have started to converge in recent years, while Basel II adopts a reference default definition to facilitate comparability of capital results.

Several techniques have subsequently been developed to calculate PD, which can be divided into two broad categories: empirical and market-based (also known as structural or reduced-form) models. The former use historical default rates associated with each score to identify the characteristics of defaulting counterparties, while the latter use counterparty market data (e.g. bond or credit default swap spreads, volatility of equity market value) to infer the likelihood of default.
The empirical approach uses historical default data to characterize counterparties that default. This was originally done using discriminant analysis (Z scores) but more recently has been done with logit or probit regressions to define a score function *Z* of the form:

$$Z = a_1 X_1 + a_2 X_2 + \ldots + a_n X_n$$

The vector *x* contains the relevant risk factors, which in the case of commercial counterparties may be primarily financial statement ratios and non- financial information (e.g. management quality, years in operation); for retail customers, this might include income, work history and other demographic data.
The statistical model generates an ordinal score that ranks counterparties according to their likelihood of default, or it can directly provide an unadjusted PD. In both cases, the results of the model need to be calibrated to obtain a cycle-neutral cardinal scale.
This can be done in several different ways depending on how much historical data is available. For example, the cycle neutral central tendency of the entire portfolio can be identified and used as an anchor point to adjust the PDs calculated with data from a limited part of the economic cycle.

2. INTANGIBLE ASSETS

The concept of intangible assets has become an important theme of European policy for industrial competitiveness, as Europe increasingly becomes a knowledge driven economy.
Intangible assets are defined as those non-monetary assets that cannot be seen, touched or physically measured and which are created through time and/or effort. Intangible assets can be classified as follows:

_ Human capital is defined as the knowledge that employees take with them when they leave the firm at the end of the day. It includes the knowledge, skills, experience, and abilities of people. It might be either very unique or generic.
_ Structural capital is defined as the pool of knowledge that stays at the firm at the end of the working day. It comprises the organisational routines, procedures, systems, cultures, databases, etc. Some of them may be legally protected and thus become Intellectual Property Rights.

_ Relational capital is defined as all resources linked with the external relationships of the firm such as customers, suppliers, R&D partners, etc.

In increasing complexity of economic reality, the competitive advantage of firms lies in those business activities which the firm knows how to do well; more and more the "knowledge base" plays a key role in the survival, profitability and growth of the firms. Intangible assets are often indirect sources of value for most SMEs. Firms possess a number of different types of knowledge including scientific and technological knowledge, knowledge of their markets and customer base, knowledge of sources of supply of materials and components, the knowledge and skills of its employees, etc. Firms have learned how to organise various activities such as procurement, production, marketing, after sales service, innovation; how to combine these to secure the profitable delivery of competitive products to the market and how to recruit and develop skilled employees and managers, to motivate them to work effectively and to encourage them to co-operate in the best interests of the firm as a whole.
Moreover the increasing importance of human capital (proprietary knowledge and assembled workforces), reputation, customer relationships as well as formal intellectual property; the greater interdependence and communication among workers, firms, customers and suppliers and the increasing investments in intangible assets in many sectors are particularly relevant for small and mediums-sized enterprises (SMEs) considering it is estimated that 90% of SMEs are in the service sector, which typically generate income from their Intangible Assets.
Today an increasing share of the market value of young and innovative SMEs appears to be derived in many cases from their intellectual assets.
There are numerous reasons for conducting an intangible asset economic analysis; this reasons con be grouped into six general categories of client motivations:

1. Transaction pricing and structuring, for either the sale, purchase or license of intangible asset.
2. financing securitization and collateralization, for both cash flow-based financing and asset-based financing.
3. Taxation planning and compliance, with regard to intangible asset amortization deductions, abandonment loss deductions, substantiation of charitable contributions, and various other federal income taxation matters, as well as with regard to federal gift and estate tax compliance and estate planning.
4. Management information and planning, including business value enhancement analysis, identification of licensing and other commercialization opportunities, identification of spin-off opportunities, and other long-range strategic issues.
5. Bankruptcy and reorganization analysis.
6. Litigation support and dispute resolution, including marital dissolution, infringement, fraud, lender liability and a wide range of deprivation-related reasons (e.g., breach of contract, expropriation, etc.)

All these reasons highlight the crucial importance about the correct valuation of intangible assets for the financial sector. Basel II also supports the valuation of intangibles in credit analysis. The introduction of the new rules provided by the Basel II Committee will make it mandatory for businesses, in particular small/medium enterprises, to equip themselves with suitable tools able to enhance their intangible assets, their distinctive skills and to organise their activities according to management models more appropriate to communicate with the credit system. On the other hand banks will have to use standard approach or IRB (internal rating based approach) models to include qualitative information also on intangible assets in their assessment of the counterparty risk, in addition to balance sheet data.
In this paper a qualitative and quantitative scoring model is developed to explain the increasing role of intangible assets in the process of value creation.

3. THE MODEL FOR SMALL AND MEDIUM ENTERPRISES

This approach to a model of territorial benchmarking for SME is based on a research project developed by "CNA Emilia Romagna", "Ecipar" and "CNA Innovazione" with the scientific supervision of the University of Milan and the Association Benchmarking for Success (Italy) in the perspective to support competitiveness, innovation and development of SMEs' businesses.

This project is the result of a virtuous research project that, year by year, analyses, compares, selects and prizes the best practices at the origin of the SMEs' performances. The first purpose is to create a stable benchmarking tool that is able to support the innovation processes of SMEs improving their performances. This project has been started seven years ago and now it can present a big database with more than 6,500 enterprises analyzed through benchmarking approaches.

In 2006, driven by the culture of innovation and adoption of managerial practices, more than 760 enterprises have enjoyed to the benchmarking project for only the region Emilia Romagna.

This study has the merit to move the attention from the generic concept of excellent enterprise to the studying in depth of the practices at the base of the excellence.

Even if the difference quoted above looks small it has a sensible impact on the quality of the final results available to the SMEs' system and big repercussions on the core meaning of the research itself.

The idea to emphasize the practices as the source of the excellent results of enterprises means the recognition of the value hidden inside the operative function on the overall success of a firm comparing with the positive results on the short term. It's strategically important to analyze all the different steps to reach an excellent practice to make easier the comprehension and the application of it by the other organizations.

The value of the project is taking distance from the pure recognition of the business results of the firms to focus as much as possible on an action of support available to all the SMEs (not only the excellent ones) to help them during the path of improvement of their business.

The purpose of this project is to develop an integrated model of territorial benchmarking that allows estimating the value of the interaction processes that are developed in a specific territory and that help defining the potential business and the dynamic capability of a firm.

The database with all budget data of the SMEs is offered by CNA itself. This database includes more or less 30,000 enterprises divided by firms with ordinary accounting (with data about economic account and statement of assets and liability) and with simplified accounting (with data about economic account).

The process of selection of firms has allowed identifying 2 samples composed respectively by 3139 SMEs with ordinary accounting and 26218 with simplified accounting.

The model is built with the purpose of applying at each firm a specific score that once associated to a specific rating level, it give the possibility to evaluate simply and quickly the position of each single form respect to the whole sample. Moreover such model, differently from the similar projects, takes in consideration not only a ***quantitative analysis*** on accounting data, but also a ***qualitative analysis*** to evaluate intangible assets as the strategy, the planning, the relations and the percept value.

The last phase of the analysis project has been developed with the specific purpose to identify possible distortions derived by dimensional or geographical market effects on the solidity of the model.

3.1. QUANTITAVE ANALYSIS

In this section of the paper we are going to explain the procedure used to build the scoring model for the analysis of the quantitative data, model that belongs to the category of discriminant linear analysis.

The purpose of the model is to identify a discriminant function that, assigning a “score” to the SMEs in the database, is able to distinguish the performing enterprises (identified as “good”) to the not-performing ones (identified as “bad”). As a second step the model has to be able to give a higher score the “good” SMEs and a lower score to the “bad” ones, in this perspective it could be possible to indentify a threshold value that allows classifying with an error as small as possible a new different enterprise in the right group: “good” or “bad”.

The analysis is based on two main aspects:

1. Descriptive Aspect: building a classification rule that allows identifying the characteristics of the single statistical units that better discriminate among groups to determine the best indexes to build the discriminant function of the model;
2. Predictive Aspect: the capability of the model to classify an unknown new statistic unit in a specific group determined previously and the correlated classification error understood as the probability that the unit has been classified in a group different from the one the unit belongs to.

The different steps which lead to the realization of the model are:

- Definition of the right sample to use
- Identification of the variables that allow to discriminate between “good” and “bad” firms;
- Definition of the method of calculation of the discriminant coefficients to obtain the right score to assign to the single enterprise.

The quantitative analysis presumes the choice of n- variables that have to be multiplied by their weighted coefficients to determine a quick summary on the enterprise’s management (Z) as shown in the general equation below:

$$Z = a_1 X_1 + a_2 X_2 + ... + a_n X_n$$

Initially forty accounting indexes have been chosen to distinguish the “good” enterprise from the “bad” ones. Then these indexes have been divided into five categories: liquidity, profitability, financial lever, solvency and productivity.

The basic idea was to use the multi-collinear analysis in the perspective to select the most significant index for each one of the categories described above.

The multi-collinear approach concerns the structure of correlation among independent variables (X_n) and the influence of this structure on the dependence of *Z* from *X.* This approach is finalized to verify if among two or more indicators there could be situation of strong correlation that could influence the validity of the model.

If the dependent variables are strongly correlated they could be considered exchanged one with the other and so it would become difficult to separate the effect of an independent variable on the dependent one when all the other variables are kept constant. Moreover if we consider that it’s impossible to make unique estimation of the regression coefficients since the fact we have endless combinations that assure the same level of predictive efficacy to the model, high levels of collinear indexes increase the likelihood that a variable is statistically not significant and so rejected by the model.

Another contraindication is determined by the fact that collinear index increase the variance of the regression coefficients and so the coefficients estimated for different samples tend to be instable limiting the generalization of the results.

Therefore, through this investigation, the less reprehensive variables to determine the goodness of the model are eliminated. The purpose is to minimize the number of the indicators maintaining (whether possible increasing) the efficacy of the model.

Once the five referee indicators have been chosen, it's possible to proceed to divide the sample into "good" and "bad" sample. Such division has been determined by the study of the percentiles related to the five indicators selected as the most significant: it has been named as "bad" the SMEs that presented at least three indexes out of five in a critic situation. We have considered as a "critic situation" when, for the first four indications, the belonging to the first quartile (the twenty-fifth percentile) while, for the indebtedness index, the belonging to the last quartile (the sixty-firth percentile).

Once the variables that allow distinguishing between "good" and "bad" firms have been identified and as a consequence once the two samples are have been defined, the classification is based on a *discriminant function* that has the capability to maximize the variance of the identified variables among the firms of the two groups and to minimize the variance among the firms of the same group. Consequently the model is composed by a linear combination of variables where the coefficients (called *discrimination coefficients*) are chosen by a specific algorithm that guarantees these characteristic.

As presented before, the general equation of the model is: $Z = a_1 X_1 + a_2 X_2 + ... + a_n X_n$, where:

Z = Discriminant value per each firm

a_i = Discriminant coefficients

X_i = Variables

The coefficients' vector is given by $\overline{a} = (\overline{X}_s - \overline{X}_n)' S^{-1}$ where:

$\overline{X}_s$ = Vector of the mean of the variables for the "good" group

$\overline{X}_n$ = Vector of the mean of the variables for the "bad" group

S^{-1} = Inverse matrix of variance and covariance of the variables

In theory the coefficients should have the sign coherent with the expectation concerning the effect of the variable on the reliability of the firm: for instance, a coefficient with a positive sign for the profitability of the firm is concordant with the logical relation between the variable and the risk profile, while a coefficient with a positive sign for the indebtedness shouldn't be intuitive[1] (in out case the coherency of signs is a first indicator of the stability of the model).

At this step it becomes easy to use the discriminant function to calculate the score (Z) of each firm. This score gives us an indication regarding the level of risk of the observed firm. The heart of the linear analysis model is the determination of a cut-off point that separates the healthy firms from the rest. To determine the cut-off point is useful to use this easy trick: considering $\overline{Z}_s$ e $\overline{Z}_n$ (respectively the average of the scores of the healthy firms and of the insolvent firms) it can be possible to use as cut-off point the average of these two values ($\overline{Z}_c$) as discriminant.

$$\overline{Z}_c = \frac{\overline{Z}_s + \overline{Z}_n}{2}$$

Since generally in the scoring model as the one shown above the credit merit of the enterprises grows when the score grows[2], then it's possible to assume that $\overline{Z}_s > \overline{Z}_n$; as a consequence the classification rule will be the one that assigns the *j*-firm to the "good" firm group if $z_j > \overline{Z}_c$ or that, on the other hand, it assigns the firm to the "bad" group. Therefore

[1] Sometimes, the absence of coerence between coefficient and expectation is coming from the presence of high correlated variables.
[2] It depends from the used variables and from the coefficients.

it's the comparison between the score value and the cut-off value to determine the discrimination between sane and insolvent firms. Nevertheless, since the moment that the managerial profile of a firm healthy but closed to the cut-off point and the profile of a healthy and consolidated firm are very different, it's generally convenient to determine different rating classes inside the two "good" and "bad" macro-groups.
In this way it becomes easier to identify a classification of the firms inside the two groups.

To make this division it's necessary to determine previously the number of rating classes that we want to obtain and then to develop some analysis of the sample and on the distribution of the scores and of the firms themselves. An example it's presented on Table 2:

Tab. 1: Rating classes and Threshold

judgment	classes	Thresholds
Very good	A1	9
	A2	8,5
Good	A3	8
	A4	7
	A5	5,5
	A6	4
	B1	3
	B2	2,5
Sufficient	B3	2
	B4	1,5
Low risk	B5	0,5
	B6	0
Medium risk	C1	-1
	C2	-2
	C3	-3
	C4	-3,5
High risk	C5	-4,5
	C6	<-4,5

In the following chapters it has been illustrated the procedure to calculate the discriminant coefficient that allow to determine the quantitative score for both ordinary and simplified accounting firms.

3.1.1. QUANTITATIVE MODEL FOR ORDINARY ACCOUNTING FIRMS

The sample of ordinary accounting firms is composed by 3139 ordinary SMEs. Through the procedures explained previously it has been possible to define the five referee variables and the sub-division of the sample in "good" (2791) and "bad" (348) firms.
At this point the vector of coefficients has to be applied to use the discriminant function and to obtain the final scores. Later on the calculus related to the referred sample will be shown.
As a first step it has been shown the difference between the averages of the two groups related to the each single variable:

Tab. 1: Differences between the means of the tow groups per indicator $(\bar{X}_s - \bar{X}_n)$

	R5	*R10*	*R17*	*R23*	*R36*
Mean"good"	0,0254021	0,143995235	25066,41	1,2953009	0,011588
Mean "bad"	-0,126255	0,010447701	11610,037	0,6021759	0,026039
Differences	0,1516576	0,133547534	13456,373	0,693125	-0,01445

Then the inverse matrix S^{-1} was built. It has been required to define the variance and covariance matrix of the five indicators for each one of the two groups (good and bad);

Tab. 2: Variance – Covariance matrix ("good" firms)

	R5	*R10*	*R17*	*R23*	*R36*
R5	0,032562				
R10	-0,00242	0,013635			
R17	99,49162	149,699	1,16E+08		
R23	-0,01341	0,029284	723,8898	0,734099	
R36	4,75E-05	-0,00017	3,073485	-0,00347	0,000135

Tab3: Variance – Covariance matrix ("bad" firms)

	R5	*R10*	*R17*	*R23*	*R36*
R5	0,040141				
R10	0,000636	0,014663			
R17	-130,856	324,1225	78601050		
R23	-0,02834	-0,01409	-710,752	0,335797	
R36	0,000277	0,000187	33,08562	-0,00184	0,000222

then it was necessary to unify them creating a unique matrix created with the weighted average (for the number of firms in each group) of the two previous matrixes

Tab. 4: Variance – Covariance matrix of the mean of the two previous matrix

	R5	*R10*	*R17*	*R23*	*R36*
R5	0,033402178	-0,002082	73,95448787	-0,015063	7,298E-05
R10	-0,002082096	0,0137485	169,0361609	0,0244756	-0,000129
R17	73,95448787	169,03616	111988228,2	564,84058	6,4007294
R23	-0,015063062	0,0244756	564,8405786	0,6899421	-0,003287
R36	7,29759E-05	-0,000129	6,400729446	-0,003287	0,0001449

and finally to calculate the inverse matrix of the one here above.

Tab. 5: Inverse variance – covariance matrix (S^{-1})

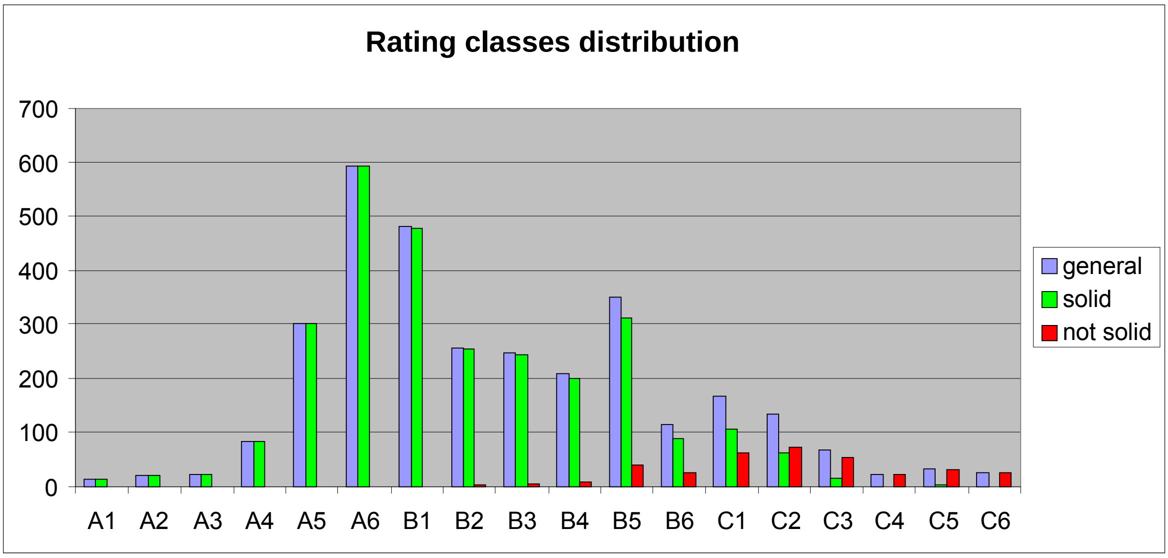
	R5	*R10*	*R17*	*R23*	*R36*
R5	30,49912617	4,003921	-2,91221E-05	0,5579574	2,1591439
R10	4,003920957	79,412885	-0,000110465	-2,564983	15,601027
R17	-2,91221E-05	-0,00011	9,19023E-09	-7,37E-06	-0,000657
R23	0,557957423	-2,564983	-7,37222E-06	1,735485	37,127209
R36	2,159143929	15,601027	-0,00065727	37,127209	7786,4087

So, applying the formula $\overline{a} = (\overline{X}_s - \overline{X}_n)' S^{-1}$ it has been possible to calculate the vector of the discriminant coefficients of the model:

R5	5,123792
R10	7,722858
R17	0,000109
R23	0,30926
R36	-93,2193

These coefficients allow calculating the score for each firm and subsequently to identify the rating class where the firm belongs to. The graph below shows the distribution of all the firms of the sample distinguishing between the performing and not performing ones.

Fig.1: Rating classes Distribution for ordinary accounting firms



Such a low value of the percentage error 13,65% for "good" firms and 8,91% for "bad" firms, shows a discreet efficacy on the assigning process of the firm to the right group.

3.1.2. QUANTITAVE MODEL FOR SIMPLIFIED ACCOUNTING FIRMS

The benchmarking model has been applied also to the simplified accounting firms, eliminating the variable referred to the liquidity (because we don't have the data related to the statement of assets and liability). The sample of simplified accounting firms is made by 26218 SMEs. The sub-division in performing and not-performing firms creates two sub-samples with respectively 24072 and 2146 SMEs. The procedure has been the same as presented for the ordinary accounting firms: the vector of coefficients has to be applied to use the discriminant function and to obtain the final scores.

Differences between of the means of the two groups per indicator $(\overline{X}_s - \overline{X}_n)$

	R5	*R10*	*R17*	*R36*
Mean"good"	0,067371008	0,43329	17808,5129	0,0048102
Mean "bad"	-0,1920733	0,020663	5825,03369	0,0149422
Differences	0,259444307	0,412627	11983,4792	-0,010132

Tab. 6: Variance – Covariance Matrix ("good firms")

	R5	*R10*	*R17*	*R36*
R5	0,096369			
R10	-0,00855	0,06232		
R17	355,9444	67,41848	1,07E+08	
R36	6,58E-06	-0,0003	18,80198	0,000115

Tab. 7: Variance – Covariance Matrix ("bad firms")

	R5	*R10*	*R17*	*R36*
R5	0,085885			
R10	0,002059	0,050279		
R17	69,08985	614,6551	42605321	
R36	0,000974	0,000548	27,34783	0,00034

Tab. 8: Variance – Covariance Matrix of the means of the two previous matrix

	R5	*R10*	*R17*	*R36*
R5	0,095511009	-0,007678972	332,464716	8,57E-05
R10	-0,007678972	0,061334817	112,210981	-0,000233
R17	332,4647163	112,2109813	101405093	19,50148
R36	8,57385E-05	-0,000232697	19,5014766	0,000133

Tab. 9: Inverse variance – covariance matrix (S^{-1})

	R5	*R10*	*R17*	*R36*
R5	10,71098573	1,412113492	-3,687E-05	0,969528
R10	1,412113492	16,65754919	-2,931E-05	32,4698
R17	-3,68659E-05	-2,93067E-05	1,031E-08	-0,001536
R36	0,969527701	32,46979993	-0,0015364	7785,6

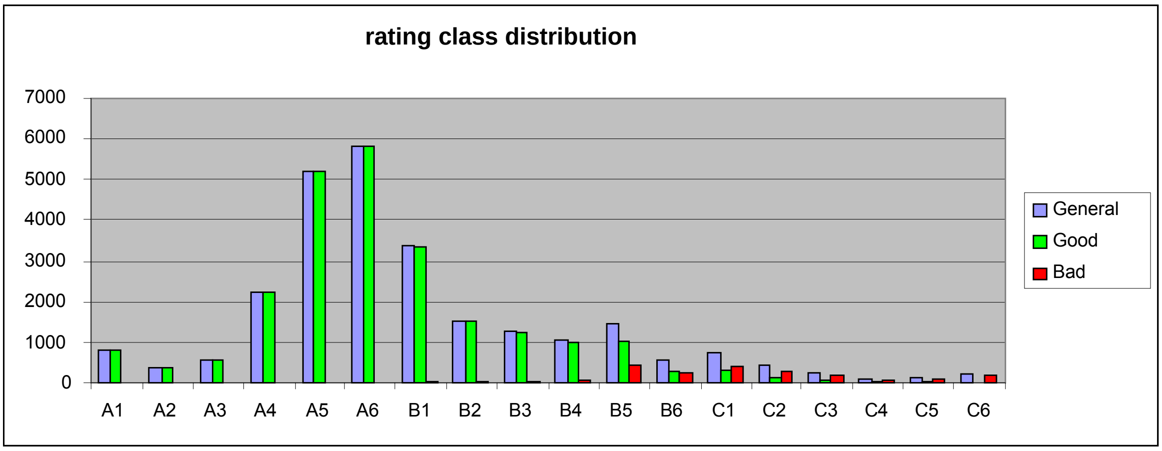
Calculation of the discriminant coefficients:

R5	2,909976
R10	6,559545
R17	0,000117
R36	-83,6452

These coefficients allow calculating the score for each firm and subsequently to identify the rating class where the firm belongs to.

The graph below shows the distribution of all the firms of the sample distinguishing between the performing and not performing ones. Such a low value of the percentage error 10,98% for "good" firms and 5,219% for "bad" firms, shows a discreet efficacy on the assigning process of the firm to the right group.

Fig.2: Rating class distribution for simplified accounting firms



3.2. QUALITATIVE ANALYSIS

The analysts have defined the assets in a reductive way, identifying only the resources that can be measured as in the case of plants and equipments. The intangible information as a specific technology, relevant information on consumers, brand, reputation, business culture, have an enormous value for the competitive position of the firm. As a matter of fact, the invisible resources are often the only sources of competitive advantage that can be maintained for a long time (H. Itami)

The qualitative analysis has been realized through a questionnaire named “Frame” that during the year gave us the opportunity to obtain a clear picture of the healthy status of all the attending firms.

“Frame” analyses 30 indicators (each indicator has a Liker scale from 1 to 5 with the possibility to indicate 0 when “I don’t know”), in particular 15 indicators of “practice” and 15 of “performances” have been analyzed. For “practice” we mean how a specific firm organizes its own business to operate respect to a single dimension) and for “performance” the result that a firms obtain respect to a single dimension). The measurement of the indicators is based on two main criteria: the transversity in more sectors and the measurability inside the small firm.

The main idea is to measure the variables which allow to explain the different level of success (performances) obtained by the SMEs inside their competitive arena, identifying the organizational model they depend on (practices).

The purpose of this analysis is to give qualitative judgments on some indicators that can help to create a general control board of the firm and of the competitive arena where the firm works. In this way these indicators result very important on the definition process of the managerial capability of the firm. On the contrary on what it has been done for the quantitative indicators, for the qualitative ones all the qualitative variables of “Frame” have been considered (excluding the variables that belong to the “results” category because they report the same information extrapolated from the quantitative data.

On the table below it’s possible to find all the qualitative variables used to build the model:

Table 10: Qualitative variables extrapolated from Frame

fm101	Business Strategy
fm102	Production strategy
fm103	Human resources
fm104	Labor

fm105	Market value
fm201	Customer Needs Analysis
fm202	Price
fm203	Interation with the customer
fm204	Interation with the production
fm205	Reliability of the Product/service
fm301	Governance Style
fm302	Learning
fm303	Decisional ability
fm304	Staff turnover
fm305	Days of absence
fm401	Production plannig
fm402	Technological Strategy
fm403	Phisical Environment
fm404	Delivery Punctuality
fm405	Production efficiency
fm501	R&D
fm502	Innovative Environment
fm503	Involvement in the production
fm504	Knowledge Management
fm505	Innovation and originalità

Every judgment (starting from the lowest level) helps to create the judgment of the step above (the one consequentially on the left) and, on its turn, it will make the same with the step respectively higher.

Tab. 11: Used qualitative weighted variables

Qualitative Score	20%	Planning and Strategy	25%	fm101	Business Strategy
			25%	fm102	Production strategy
			15%	fm103	Human resources
			15%	fm104	Labor
			20%	fm105	Market value
	20%	Customer Management	20%	fm201	Customer Needs Analysis
			20%	fm202	Price
			20%	fm203	Interation with the customer
			20%	fm204	Interation with the production
			20%	fm205	Reliability of the Product/service
	20%	Human Resource Management	20%	fm301	Governance Style
			20%	fm302	Learning
			20%	fm303	Decisional ability
			20%	fm304	Staff turnover
			20%	fm305	Days of absence
	20%	Production Organization	20%	fm401	Production plannig
			25%	fm402	Technological Strategy
			10%	fm403	Phisical Environment
			25%	fm404	Delivery Punctuality
			20%	fm405	Production efficiency

	20%	Innovation	15%	fm501	R&D
			25%	fm502	Innovative Environment
			15%	fm503	Involvement in the production
			20%	fm504	Knowledge Management
			25%	fm505	Innovation and originalità

From this series of weighted averages it's possible to reach a final mean that keep inside both a qualitative judgment on the sector the firm belong to and a specific judgment on the firm. This weighted average is called QWA (Qualitative Weighted Average) and it has the precise purpose of modifying the quantitative score reached through the model making it better or worse on the base of the score reached by the qualitative analysis.

To complete this task, the QWA has to be related to a range of points to add to the quantitative scoring: the limits of this range will be determined as the difference between the best and the worst value of the scoring of the rating class where the firm belong to thanks to the quantitative scoring. The intermediate values of this range will be determined based on the intervals where the weighted average will be collocated. The referee value assigned to the QWA is called "qualitative scoring".

From a mathematical point of view, if *w* is the qualitative scoring and *c* the rating class where the firm belongs to:

- if $0 \le QWA < 1$, then $w = \frac{-(\max(c) - \min(c))}{2}$
- if $1 \le QWA < 2$, then $w = \frac{-(\max(c) - \min(c))}{4}$
- if $2 \le QWA < 3$, then $w = 0$
- if $3 \le QWA < 4$, then $w = \frac{(\max(c) - \min(c))}{2}$
- if $4 \le QWA < 5$, then $w = \frac{(\max(c) - \min(c))}{4}$

In this way it's possible to define a qualitative scoring model that can integrate the quantitative scoring giving an extra synthetic measurement concerning the firm and the competitive arena where it operates on.

3.3. THE RESULTS OF THE MODEL

The final rating is built assigning the scoring obtained from the rating class that includes such value. In this way it's given a synthetic judgment on the performance of the prevision about the future of the analyzed firm.

> *Example*: the "Alfa" firm has 6,34 as quantitative scoring (z) that put it on the B2 class. From the qualitative analysis it's possible to define a good picture about the firm and its QWA is 3,6. Because the B2 class has 5,5 as lowest value and 7 as highest and QWA is between 3 and 4, then:

$$w = \frac{(\max(B2) - \min(B2))}{2} = \frac{7-5,5}{2} = 0,75$$

As a consequence, the final scoring S_f will be:

$$S_f = z + w = 6,34 + 0,75 = 7.09$$

Because 7,09 > 7, the firm Alfa has received an upgrading, passing now to the successive class B1, thanks to the support of the qualitative indicator.

3.4. DISTORSIVE EFFECTS

Further analyses have allowed identifying a series of heterogeneity of the sample that could create distortive effect more or less emphasized. The sample is composed by firms that belong to different geographic areas, to different market sector and with a dimension component very different one to the others.

All these diversities bring some critical elements in the attended results of the model; because of its generality the model is often unable to find specific aspects. The next notes and considerations don't have to discredit the efficacy of the model while they have to allow a better using of the tool and to support a better interpretation of the results.

Dimensional Effect

To analyze the behavior of the model concerning the dimensional aspect, the sample has been divided into three sub-samples:

- firms with less than 2 employees (sub-sample 1)
- firms with a number of employees included between 2 and 5 (sub-sample 2)
- firms with more than 5 employees (sub-sample 3)

For each sub-sample the discriminant coefficients have been calculated and consequently the new score attributed to the firms. The next step has been the comparison between the classes assigned to the firms by the model and the classes assigned by the model built on the sub-sample.

The basic idea foresees that gaps smaller than the two classes (positive or negative) should be considered as normal variation while bigger gaps should be weighted in a different way.

The below tables show the results obtained for each single sub-samples.

Tab. 12: Comparison between the general model and the dimensional model (less than 2 employees)

Deviation	cumulate frequency	Absolute frequency	relative frequency
-14	1	1	0%
-13	2	1	0%
-12	4	2	0%
-11	7	3	0%
-10	25	18	2%
-9	50	25	2%
-8	71	21	2%
-7	107	36	3%

-6	203	96	8%
-5	373	170	15%
-4	554	181	16%
-3	700	146	13%
-2	799	99	9%
-1	891	92	8%
0	980	89	8%
1	1037	57	5%
2	1069	32	3%
3	1115	46	4%
4	1136	21	2%
5	1143	7	1%
6	1146	3	0%
Sum		1146	100%
Deviation > 2 (in absolute value)			**68%**
Deviation <2 (in absolute value)			**32%**

Tab. 13: Comparison between the general model and the dimensional model (between 2 and 5 employees)

Deviation	Cumulate frequency	Absolute frequency	relative frequency
-6	2	2	**0%**
-5	17	15	**1%**
-4	62	45	**3%**
-3	122	60	**4%**
-2	338	216	**13%**
-1	901	563	**33%**
0	1257	356	**21%**
1	1442	185	**11%**
2	1568	126	**7%**
3	1641	73	**4%**
4	1678	37	**2%**
5	1684	6	**0%**
Sum		1684	100%
Deviation > 2 (in absolute value)			**14%**
Deviation <2 (in absolute value)			**86%**

Tab. 14: Comparison between the general model and the dimensional model (more than 5 employees)

Deviation	Cumulate frequency	Absolute frequency	relative frequency
-5	1	1	**0%**
-4	31	30	**2%**
-3	120	89	**6%**
-2	507	387	**26%**
-1	1088	581	**39%**
0	1425	337	**23%**
1	1466	41	**3%**
2	1471	5	**0%**
Sum		1471	100%
Deviation > 2 (in absolute value)			**8%**
Deviation <2 (in absolute value)			**92%**

The conclusions are heterogeneous. Among the three sub-samples, the second and the third presented a smaller percentage of gaps superior to the two classes and this percentage makes the dimensional effect not significant for the firms with more than three employees. On the other hand, 68% of the firms with less than two employees present a significant gap.

	General model	< 2 employees model		between 2 ande 5 employees model		> 5 employees model	
R5	5,123792	1,963706	3	1,743648	3	3,117759	2
R10	7,722858	6,265633	1	6,95153	1	8,808807	1
R17	0,000109	0,000011	10	0,000073	1	0,000073	1
R23	0,30926	0,005241	59	0,192519	2	0,140073	2
R36	-93,2193	-26,038221	4	-40,793087	2	-82,416969	1

Observing the discriminant coefficients obtained building the model with different sub-samples it's possible to identify that fir the firms with less than 2 employees the most different variables are the ones related to the liquidity and to the average value for each employee (R17 and R23). In the blue column is presented the report between coefficients of the general model for employee and the model related to the sub-sample.
As a conclusion it's natural to expect that in such small firms the capability to generate added value and to manage the liquidity have a smaller impact than the firm with a much bigger productive capability.

Sectorial Effect

The same analysis has been developed on a sectorial field. The firms of the sample belong to three main sectors: manufacturing (sector D), construction (sector F) and wholesale and retail commerce (sector G). The three sub-samples have been created to divide the firms on the basis of the sector of belonging, with the purpose to verify the presence of some distortive effects relatively to the sectorial belonging. As for the previous analysis the study has been realized determining ex novo the discriminant coefficients using the sub-samples previously described to analyze finally the diversions with the general main model.

Tab. 15: Comparison between general model and sectorial model (sector D)

Deviation	Cumulate frequency	Absolute frequency	Relative frequency
-2	1072	317	22%
-1	1234	162	11%
0	1402	168	11%
1	1454	52	4%
2	1461	7	0%
Total		1461	100%
Deviation > 2 (in absolute value)			**52%**
Deviation <2 (in absolute value)			**48%**

Tab. 16: Comparison between general model and sectorial model (sector F)

Deviation	Cumulate frequency	Absolute frequency	Relative frequency

-2	486	240	22%
-1	781	295	26%
0	973	192	17%
1	1053	80	7%
2	1089	36	3%
Total		1116	100%
Deviation > 2 (in absolute value)			**24%**
Deviation <2 (in absolute value)			**76%**

Tab. 17: Comparison between general model and sectorial model (sector G)

Deviation	Cumulate frequency	Absolute frequency	Relative frequency
-2	55	45	7%
-1	331	276	45%
0	604	273	44%
1	619	15	2%
2	619	0	0%
Total		619	100%
Deviation > 2 (in absolute value)			**2%**
Deviation <2 (in absolute value)			**98%**

The results are heterogeneous also in this case: while the F and G sectors don't present relevant gaps in term of percentages, different is the situation regarding the D sector where half of the firms present a gap bigger than the two classes.
It cannot be forget that different sectors are often structured in different ways, for example, Altman has highlighted as two samples different in terms of average and variance could give back very dissimilar results. This result let us conclude that firms of D sector diverge from the general model because of the fact they are different from the rest of the firms belonging to the general sample.
For the firms belonging to the debated sector these conclusions implicate that it's more adequate to classify the firms following the sectorial model than the general model. This assumption is based on the fact that the sectorial model is more indicated to catch differences with the other sectors.

Geografic Effect

As a last step it has been verified if the sample considered would present distortive effects generated by the geographical disposition of the firms. As a consequence the sample has been divided in provinces. Even if the initial intention was to proceed for each sub-sample with the same methodology used to analyze the previous distortive effects, the number of firms wasn't distributed in a uniform way among provinces and it yields the majority of the sub-samples obtained not so significant at a statistical level.
For each province a distribution graph has been realized with the objective to check if there was an homogeneous distribution in each sub-sample or better to verify the absence of not realistic situation.
The conclusions of the analysis would seem to preclude the presence of any geographic effects, highlighting a distribution almost homogeneous of the firms inside the different provinces and so conferring an ulterior consistence to the capability of classification of the model analyzed.

3.5. VALUTATION OF PRACTICES AND PERFORMANCES

The model of benchmarking analyzed foresees an important application: the possibility to evaluate the positioning to evaluate the positioning of practices/performances related to the growth, the profitability, the productivity, the liquidity and the financial structure of the firms belonging to the sample. What we have tried to identify is a micro-model of calculation able to give a position the firm not only in a macro-level respect to the other firms in their complex but for the single practices. The objective of this operation is to identify which practices should be improved and which practices can reach satisfactory levels and consequently the strength and the weakness of each firm considered.
So, summarizing the general macro-model establish the class of belonging of the firm (a possible development of the research is to associate the class to a determinate level of insolvency), the micro-level allow us to establish, using the analysis of the performances, which practices are farther or closer to an excellence level.

Later on it has been described an example concerning the firm XYZ; on the table below it has been represented the value of the single indexes that multiplied with the discriminant coefficient of the general model they allow to extract the partial score which added one to the others can determine the total Z-score (synthetic judgment). Finally this score allows associating a single firm to its specific class.

Tab. 18: Index values and score of XYZ firm

Index code	Index Value	Model coefficient	Z-index code	Score
R-5	-0,5833	5,123792	*Z-R5*	-2,9887079
R-10	-11,7324	7,722858	*Z-R10*	-90,607659
R-17	-179262	0,000109	*Z-R17*	-19,539558
R-23	0,9388	0,30926	*Z-R23*	0,29033329
R-36	0,1811	-93,2193	*Z-R36*	-16,882015
			Z-score total	-129,72761

To define a position for each firm concerning the practices analyzed it becomes necessary to identify for each field of analysis the percentiles of the distribution. These percentiles are calculated on the whole initial sample.

Tab. 19: Sample percentiles about the general model

	Percentiles						
	5	10	25	50	75	90	95
Z-R5	-1,5858138	-1,179	-0,528	0,0405	0,6118	1,2184	1,8225
Z-R10	-0,4301632	-0,02	0,3738	0,8572	1,5577	2,3578	2,8065
Z-R17	0,6355241	1,0449	1,7309	2,4836	3,3145	4,2028	4,9013
Z-R23	0,0546462	0,1003	0,1871	0,3034	0,5037	0,7785	0,9343
Z-R36	-3,8219896	-3,114	-1,808	-0,82	-0,27	-0,075	-0,037

At this point, every partial score of XYZ firm has been compared with the distribution of the percentiles of the general model to establish where, in term of business growing, profitability, productivity, liquidity and financial structure, the firm can be positioned.

In the table below it has been identified with "true" when this correspondence shows a positive sign.

Tab. 20: Positioning firm XYZ

	Score	Percentiles <5	5-10	10-25	25-50	50-75	75-90	90-95	>95
Z-R5 (growth)	-2,98870	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Z-R10 (profitability)	-90,6076	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Z-R17 (productivity)	-19,5395	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Z-R23 (liquidity)	0,290333	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE
Z-R36 (structure)	-16,8820	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

In this case the firm XYZ results to belong to the class C6 (see "the rating class" on the quantitative analysis chapter). The low score highlighted by the final Z-score shows the managerial inefficiency of the firm, the lack of results and the high risk of insolvency. The analysis of the positioning of the single firms, even if it doesn't avoid the truthiness of the reached conclusions, allows a more complex analysis of the business scenario and it highlights a very interesting aspect: the negativity of the results is not because of the management of the liquidity that is aligned with the average level of the sample.

Tab. 21: Strenght and weakness points of the XYZ firm

	Strenght points	in mean	Weakness points
Growth	*FALSE*	*FALSE*	*TRUE*
Profitability	*FALSE*	*FALSE*	*TRUE*
Productivity	*FALSE*	*FALSE*	*TRUE*
Liquidity	*FALSE*	*TRUE*	*FALSE*
Structure	*FALSE*	*FALSE*	*TRUE*

This tool is able to support and improve a consulting activity to identify performing processes for the firms and not with the purpose to improve at same time the inefficient practices and the to consolidate the ones that already present satisfactory levels.

4. CONCLUSION

To improve the efficiency of the model, the development and the using of quantitative and qualitative indicators (of performances) needs a vision of the business complex in a value creation perspective developed in contexts with different characteristics involved in a continuous cultural evolution. From the quantitative point of view it has to be analyzed the difficulty of the heterogeneity of the data for the creation's disposal of a model with an acceptable degree of goodness and generalization.
The usable data present firms that belong to different geographic zones, to different sectors and that present a dimensional component very different one from the others. Consequently

we have initially determined ex-novo the discriminant coefficients of the considered sub-sample with the purpose to analyze the divergent aspects with the general model allowing a more aware using of the tool and supporting a more rational interpretation of the results.
In a qualitative perspective, it's quite hard to conceptualize first and to concrete then the choice of the right variables that allow explaining different levels of success (performances) obtained by the firms inside their competitive arena and identifying the organizational model where they depend on (practices). In fact this process requires the capability to divide realistic and coherent targets with the productive and organizational contexts of reference.
Among the possible risks that this approach can present, it results evident the risk linked with the subjective of the qualitative evaluations but we can affirm that concerning the choice of using the tool "Frame" it has been reached a solid base both informative (allowing to evaluate the effective potential of the firm, and comparative among the different firms and samples.
In conclusion, after a long period of test and usage of the model, we can assume that the obtained results support the full reliability of the model itself.

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