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Evaluating intellectual capital for supporting credit risk assessment: an empirical study

Abstract

The aim of this work is to propose a new methodology for credit risk assessment, by considering *not only* financial indicators, but *also* variables concerning the intellectual capital (IC) of the firm. Two credit scoring models based on Multi Discriminant Analysis (MDA) have been developed: (1) a model which takes into account only financial data and (2) a model which takes into account also intellectual capital variables, divided in the three traditional dimensions, human, structural and relational capital. The two models have been applied on a sample of large firms and the obtained results have been compared. The study highlights that the model which integrates IC and financial variables is more accurate than the model developed using only financial data. Intellectual capital reduces, and in some cases eliminates, both type I and type II errors. The result shows the importance of taking into account some aspects of intangible assets into the credit risk evaluation. Intellectual capital variables can help provide a better understanding of the firm's value (financial and intangible).

Keywords: credit risk assessment, Multi Discriminant Analysis (MDA), credit scoring, intellectual capital, financial reports.
JEL Classification: C53, G32, G33.

Introduction

Many economists consider the current financial crisis as the most severe since 1929. One of the reasons that have led to the financial crisis is a lack of ability in credit risk assessment. Therefore, during the last few years, the evaluation of credit risk has become essential for many scholars and practitioners (Abdou et al., 2008).

The definition and quantification of credit risk is very complex. In the literature, there are many approaches which attempt to measure credit risk (Iazzolino and Fortino, 2012). In general, credit risk evaluation is based on financial data, obtainable through financial reports. As in Alwert et al. (2009), financial data is not sufficient to assess risk, because in an organization there are intangible assets and other resources. Financial reports are not able to cover intangible information, which can generate information asymmetry, whereby the managers of the firm know the true value of the firm but outside investors do not. Intellectual capital reports are useful to provide higher transparency in order to explain the hidden value of an organization (Edvinsson and Malone, 1997). Intellectual capital can help to better understand the role of intangible assets in credit risk analysis (Guimon et al., 2005).

The aim of the paper is to propose a new model for credit risk assessment, in which the variables related to intellectual capital are included into a Multi Discriminant Analysis (MDA) model, together with financial variables. MDA is a statistical approach commonly used to find effective linear transformations in particular contexts. Furthermore, it is a simple and very useful tool (as demonstrated by results in literature) for separating, in a data space, two classes of objects having the following characteristics: (1) the average distance between the objects within the class is the smallest; and (2) the average distance between the classes is the largest. In section 1 the literature analysis on both credit risk evaluation and intellectual capital (and impact on financial performance) is presented. Section 2 describes the research methodology, section 3 describes the dataset. In section 4 the empirical research is illustrated; section 5 is devoted to the description of results and to discussions. In the final section the conclusions and future works are presented.

1. Theoretical background: literature review on credit risk assessment and intellectual capital

1.1. Methodologies for credit risk assessment: the MDA models. There are many definitions of credit risk. In general it could be defined as the possibility for the borrower not to meet the financial obligation previously assumed in an agreement, thereby causing a loss for the creditor counterparty (Ammann, 2001).

Models for credit risk evaluation can be divided in three groups: (1) structural models (Black and Scholes, 1973; Merton, 1974; Black and Cox, 1976); (2) reduced form models (Jarrow and Turnbull, 2000); (3) hybrid models (Beaver, 1966; Altman, 1968; Altman and Sabato, 2007). In this section the models belonging to the third group only are analyzed, that are those more strictly linked to the research described in this paper. In particular the analysis is concentrated on the discriminant analysis methodologies.

Hybrid approaches in credit risk assessment use several models such as statistical methods, including regression, multivariate discriminant analysis, probit and logit models, artificial neural network and other methods (Altman, 1968; Altman and Katz, 1976; Ang and Patel, 1975; Baran, Lakonishok, and Ofer, 1980; Gu, 2002; Yim and Mitchell, 2005; Chijoriga, 2011; Vaziri et al., 2012).

As regard the discriminant analysis, Beaver (1966) was the first to employ univariate models, in which risk is considered function of cash flows the firm is able to generate. In order to identify firms with a higher probability of going bankrupt, the most effective indicators are those related to cash flow dynamics and to relation between cash flow and debt.

The univariate models try to evaluate the significance of an indicator (or more than one indicators connected with each other) to determine which score has to be assigned to a firm. Univariate models often overlap with qualitative models. Many models have been generated using the Interest Coverage Ratio that put into relation Ebit and Interest Expenses. The most known is the model by Damodaran (2002).

The multivariate models, among which the first contribution was given by Altman (1968), are based on the concept that the identification of the point of possible insolvency (cut-off) depends on the weighting of different indicators, selected within the set of the most significant financial risk indicators.

Many versions of Altman's model have been developed (Eisenbeis, 1977; Grice and Ingram, 2001) and a very large debate has been carried out. Altman (2000) uses MDA and a model he called ZETA (Z) (Altman et al., 1977) to evaluate characteristics of business failures in order to specify and quantify the variables which are effective indicators and predictors of corporate distress. Another combination of quantifiable financial indicators of firm performance and additional variables are described in Altman (2002). Altman and Sabato (2007) developed a new model (using a logit technique) for predicting default in Small and Medium Enterprises (SMEs). The discriminant function has been defined in different ways, by changing the selected indicators and their weights.

MDA is used in many studies to develop credit scoring models for loan evaluation purpose. Thus, Reichert et al. (1983) examined the theoretical requirements of the MDA model in the context of realistic lending situations and described the extent of bias when these theoretical assumptions are not fully met. Taffer and Tisshaw (1977) developed a bankruptcy prediction model using linear discriminant analysis based on UK manufacturing companies; in particular, they analyzed a sample of 46 failed firms matched by 46 non-failed manufacturing companies. Therefore, in order to discriminate these set of firms, they investigated 80 different ratios and then they defined four variables: profit after tax to current liabilities, current assets to current liabilities, current liabilities to total assets, and no-credit interval. The latter variable measures the time for which the firm could finance its continuing operations from its immediate assets if all other sources of finance were cut off. Kwansa and Parsa (1991) and Gu (2002) carried out analyses on bankruptcy into restaurant industry. The first mentioned authors have developed an event approach for identifying events into the failure process of the restaurant companies. This model is not a prediction model, but it is an explanatory model. Hence, this model do not discriminate between two or more classes but it compares the groups (failed and non-failed firms) basing on the characteristics common to failing firms, which are absent in the non-failing set. Instead, the model developed by Gu (2002) may be considered as a prediction model (with a 92-percent accuracy rate 1 year prior to bankruptcy); this MDA model was constructed starting from the analysis of 12 financial ratios, commonly used into previous works regarding business failure prediction such Gardiner et al. (1996) who conducted similar analyses on hospital sector. They carried out discriminant models, separately for both non-profit and proprietary hospitals; hence, they developed MDA models containing variables linked to the main aspects of financial health: liquidity, solvency, profitability, and efficiency. Doumpos et al. (2002) developed a Multi-group Hierarchical Discrimination (M.H.DIS), an alternative approach originating from MCDA (Multi Criteria Decision Aid). This method was used to develop a credit risk assessment model using a large sample of firms derived from the loan portfolio of a leading Greek commercial bank. To investigate the performance of M.H.DIS the authors compared their model with discriminant, logit and probit analysis. Also in this case, for measuring all aspects of financial performances, the authors have used ratios similar to those used in previous works. Hence, MDA models could be compared with other methodologies as done by Lee (2007) compares his Support Vector Machine (SVM) methods (using 10 financial variables belonging to the categories cited above) with MDA, Case-based Reasoning (CBR) and Back-propagation Neural Nets (BPNs) for evaluating the performance of his methodology; Abdou and Pointon (2009) study how decisions are made within the Egyptian public sector environment and determined whether the decision making can be significantly improved through the use of credit scoring models. In this study, authors have put beside Probabilistic Neural Net (PNN) and Multi Discriminant Analysis (MDA); Chijoriga (2011) investigated whether the inclusion of risk assessment variables in MDA model improves banks' ability in making correct customer classification, predicting firm's performance and credit risk assessment.

Furthermore, in the literature there exist some models that put beside discriminant analysis with other evaluation methodologies such as SVM, CBR, and neural networks.

1.2. Intellectual capital and financial performance. The growth of new economy, driven by information and knowledge, has led to an increased interest in intellectual capital (Stewart, 1997; Thurow, 1999; Petty and Guthrie, 2000; Bontis, 2001). Nowadays, in organizations it has become essential to assess knowledge and to evaluate intangibles and innovation (Corvello et al., 2013). Iazzolino and Pietrantonio (2005) proposed a knowledge audit methodology (KAM) based on a Balanced Scorecard-based scheme. Although there are various definitions of intellectual capital (IC), many scholars and practitioners identify three main components of IC: human capital, structural capital, relational capital (Edvinsson, 1997; Sveiby, 1997; Stewart, 1997; Bontis, 1998; Mavridis and Kyrmizoglou, 2005; Tayles et al., 2007; Wall, 2007; Walsh et al., 2008; Ruta, 2009). Human capital includes experience, knowledge, intellect, behavior, relationship, attitude and special skills of the personnel of a business entity employed in order to create economic value (Cohen and Kaimenakis, 2007; Schiuma et al., 2008). Structural capital includes non-human storehouses of knowledge in organizations (Watson and Stanworth, 2006). Structural capital is defined as a general system for solving problem and innovation (Chu et al., 2006). Relational capital concerns the value created through the relations between organizations and with suppliers, customers, shareholders and other institutions and/or individuals (Grasenik and Low, 2004; Chu et al., 2006). Intellectual capital is an extremely important component in organizations. Pulic (2000) argued that in modern age, investment in knowledge to create value has become the main competitive strategy. He proposed a measure of Intellectual Capital Efficiency (ICE) based on the Value Added of Intellectual Coefficient (VAIC). In this context the use of a multicriteria algorithm has been proposed (Iazzolino et al., 2012).

Intellectual capital has a positive impact on market value and financial performance and may be considered as an indicator for future financial performance (Chen et al., 2005). There are some applications that attempt to understand the role of intellectual capital on financial performance: Guo et al. (2012) provided a framework in which the relationship between intellectual capital and financial performance of listed biotech firms are analyzed. Tan et al. (2007) studied the association between IC of firms (using Pulic's approach) and financial returns. Razafindrambinina and Anggreni (2011) investigated the link between IC and financial performance on listed firms in Indonesia. Wang (2011) studied IC and its effect on financial performance in companies in Taiwan and China. Alipour (2012) analyzed the role of IC and its relationship with financial performance on Iran insurance companies. Maditinos et al. (2011) examined the impact of IC on market firm's value and financial performance considering a sample of Greek listed firms. Murthy and Mouritsen (2011) discussed how Intellectual Capital is related to human, organizational, relational and financial capital. Alwert et al. (2009) investigated how Intellectual Capital Reports (IC Report) of SMEs impact on the evaluation behavior of analysts. The authors argue that IC Reports allow a more homogeneous rating assessment to be implemented.

Guimón (2005) argues that IC Reports are relevant for credit risk analysts and could have a positive impact on credit decisions, as they facilitate the evaluation of the relative competitiveness of the firm and provide a good image of firm's management team. Although researches in intellectual capital have been carried out to better understand the impact that IC has on the credit risk assessment (Alwert et al., 2009; Guimón, 2005), there aren't many authors who put intellectual capital variables within credit risk models. In our research we propose a new model that integrates IC-based variables within the traditional financial indicators.

2. Research methodology

The research is based on an experimental study design, in order to figure out a new framework in which intellectual capital variables are included within a credit scoring model. In our methodology, intellectual capital is divided in three dimensions: human capital, structural capital and relational capital (Edvinsonn, 1997). As in Alwert et al. (2009), intellectual capital can help to better understand economic evaluations; therefore, we have used intellectual capital-based indicators within our credit scoring model. We propose a model for credit risk evaluation in which the traditional financial ratios are integrated by indicators based on intellectual capital.

2.1. The selected financial indicators. By considering the indicators proposed in Z-score models (Altman, 1968; Altman and Hotchkiss, 2005; Altman and Sabato, 2007), we selected five financial ratios belonging to the following categories:

♦ Solvency: These ratios are able to assess a company's ability to meet its long-term obligations and explain how the company has been financed (debt or equity). In this category we have, for example, the Debt ratio and the Leverage ratio.

- Liquidity: They are used to determine whether a company is able to pay off its short-term debt obligations. They are: Quick ratio and Current ratio.
- Profitability: They depend not only on the margins generated, but also on the assets, i.e. ROE, ROI, etc.
- Interest coverage: They are used to determine how easily a company can pay interest on outstanding debt. There are the EBIT/Interest expenses and the EBITDA/Interest expenses.
- Efficiency: They are the different kind of income and include Net Income, EBIT, EBITDA, also in percentage on Sales. The five selected ratios are the following: Short-term debt/Equity book value; Cash/Total assets; EBITDA/Total assets; Retained earnings/Total assets; EBITDA/Internet expenses.

2.2. The selected IC-based indicators. Ten indexes based on the concept of intellectual capital have been selected. They are grouped in three categories, describing the main three components of IC:

1. Human capital.
2. Structural capital.
3. Relational capital.

Human capital is composed by three indicators: (1) employee satisfaction, that regards personnel motivation; (2) personnel training, that regards the activities that the firm finalizes to the professional growth of employees; (3) educational level, which is related to the educational qualification of employees.

For structural capital four indicators have been selected: (1) investments in R&D, that are linked to investments the company claims for innovations (product, process, organizational, business innovations); (2) organizational processes, regarding organizational and business process; (3) information systems, related to the applications of information systems to obtain greater efficiency; (4) intellectual property, i.e. patents, trademarks, etc.

Relational capital is made up of three indicators: (1) customer relationships, that regard relationships firm has with its customers; (2) relationships with research centers and universities; (3) relationships with other partners, i.e. other firms, institutions, other groups, etc. The IC-based indicators are shown in Figure 1.

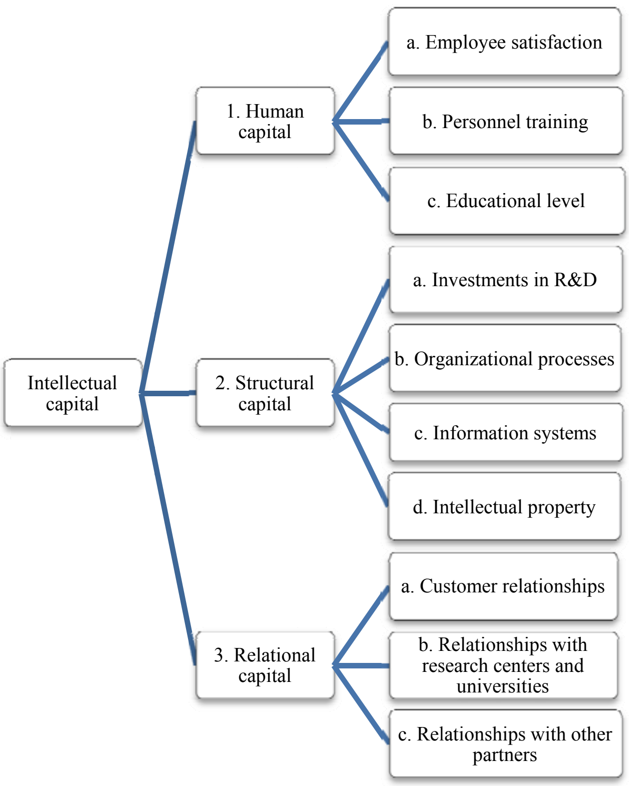

Fig. 1. Intellectual capital indicators

2.3. Methodology steps. This paper proposes to integrate variables concerning intellectual capital and financial factors into a single model. Our research methodology has been conducted according to the following steps:

1. The MDA (Multi-Discriminant Analysis) model, using financial indexes *only*, has been applied (Model 1):

$$Z = \mu_1 X_1 + \mu_2 X_2 + \mu_3 X_3 + \mu_4 X_4 + \mu_5 X_5, \quad (1)$$

where

$$X_1 = \frac{Short\ term\ debt}{Equity\ book\ value};\ X_2 = \frac{Cash}{Total\ assets};$$

$$X_3 = \frac{EBITDA}{Total\ assets};\ X_4 = \frac{Retained\ earnings}{Total\ assets};$$

$$X_5 = \frac{EBITDA}{Interest\ expenses}.$$

2. The MDA model, using also intellectual capital variables, together with financial indexes, has been applied (Model 2):

$$Z = \mu_1 X_1 + \mu_2 X_2 + \mu_3 X_3 + \mu_4 X_4 + \mu_5 X_5 + \\ + \mu_6 X_6 + \mu_7 X_7 + \mu_8 X_8, \qquad (2)$$

where

$$X_1 = \frac{Short\ term\ debt}{Equity\ book\ value};\ X_2 = \frac{Cash}{Total\ Assets};$$

$$X_3 = \frac{EBITDA}{Total\ Assets};\ X_4 = \frac{Retained\ earnings}{Total\ Assets};$$

$$X_5 = \frac{EBITDA}{Interest\ expenses}$$

and X_6 = Human capital indicator; X_7 = Structural capital indicator; X_8 = Relational capital indicator.

3. A comparison between the application of the MDA model using financial indicators only (Model 1) and the application of MDA model using both intellectual capital variables and financial ratios (Model 2) has been carried out.

3. Dataset

Data were extracted from the AMADEUS Bureau van Dijk Database. We have selected a sample of Italian very large firms, with the following characteristics:

- Operating revenue ≥ 100 mln Euro (140 mln USD).
- OR Total assets ≥ 200 mln Euro (280 mln USD).
- OR employees ≥ 1000.
- OR Listed.

We selected firms belonging to NACE Rev. 2 sector (from 10 to 33) (Manufacturing sector) and NACE Rev. 2 sector (58, 60, 61, 62, 63, Quaternary sector). We selected 100 firms for the first sector (Manufacturing) and 100 firms belonging to the latter (Quaternary). Then, we analyzed the reports, containing financial and non-financial information, of the 200 firms.

After evaluating the reports, 40 firms (20 for each of the two sectors) have been chosen, on the basis of the level of disclosure concerning intellectual capital within the reports. The more the level of disclosure (and then the abundance and completeness of information on intellectual capital), the more the firm has been included in the sample. A firm has been entered in the sample if it can be obtained enough information from its report to make it possible to assign a score to the IC-based indicators, as defined in Figure 1. Regarding the way of assigning the score see next section 4. Furthermore, we have considered for the analysis an additional sample of *default* firms, composed by 4 firms[1]. Table 1 shows the 20 manufacturing firms; Table 2 shows the 20 quaternary sector firms; Table 3 shows the 4 default firms selected.

Table 1. An additional sample of *default* firms

Manufacturing firms		Quaternary sector firms		Default firms	
Number	Firm name	Number	Firm name	Number	Firm name
1	Saras	21	Engineering	41	Sitindustrie
2	ERG	22	Zambon	42	ElsagDatamat
3	Italcementi	23	Tiscali	43	TexFer
4	Parmalat	24	Snai	44	Comau
5	Danieli	25	Telecom Italia		
6	Indesit	26	Wind		
7	DeLonghi	27	IKF		
8	Piaggio	28	NoemaLife		
9	Campari	29	Newron		
10	Brembo	30	TasGroup		
11	Geox	31	MolMed		
12	Tod's	32	Reply		
13	Carraro	33	Bee Team		
14	Recordati	34	Exprivia		
15	SOL	35	Buongiorno		
16	Natuzzi	36	ComData		
17	IMA	37	Fullsix		
18	LaDoria	38	MutuiOnline		
19	Interpump	39	AccentureItalia		
20	IRCE	40	H3G		

Firms that we have selected have been divided according to their operating revenue as shown in Figure 2.

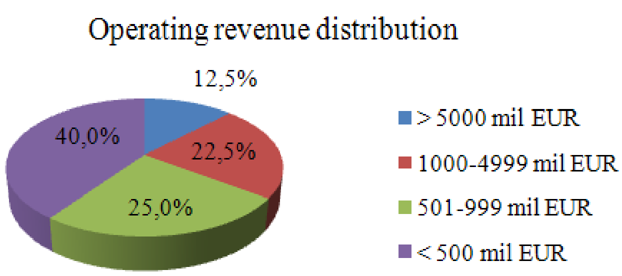

Fig. 2. Operating revenue distribution

[1] This choice is based on the Italian failure rate that is the 4%, as confirmed by AMADEUS and the Cerved Group report (2010) (then we should have been 2 firms). Two additional *default* firms have been selected in order to better understand the model behavior, given the low extention of the sample. Then the overall considered *default* firms are four.

4. Empirical research: the application of the models

In order to develop our credit scoring model, we have calculated the values of financial and IC variables for the sample. Other researches have been carried out that assign a score to the intellectual capital variables (Mangena et al., 2010).

As regard the evaluation of IC variables, we have to say that it is very difficult to calculate them objectively. A score has been assigned to the IC disclosure on the basis of a subjective assessment. Every item in Figure 1 has been evaluated through a score from 1 to 5 (1 = low, 5 = top) and the items were grouped into the three main components of intellectual capital: human, structural and relational capital. A weighted average value has been calculated for obtaining a score for each of the three components (the detailed values are not included in the paper for space reasons. For further details you can contact the corresponding author, G. Iazzolino). Tables 2a and 2b show the overall financial and IC indicators calculated for non-default (Table 2a) and default firms (Table 2b). Firms are considered non-default or default on the basis of the classification provided by AMADEUS.

Table 2a. Financial and IC's indicators for non-default firms

Firm name	Financial indexes					IC variables		
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Saras	1.70	0.02	0.05	0.02	4.0	9	6	10
ERG	0.90	0.24	0.03	0.008	2.59	9	9	12
Italcementi	0.35	0.05	0.08	0.019	4.76	10	12	9
Parmalat	0.20	0.16	0.10	0.06	19.85	7	7.5	8
Danieli	2.57	0.28	0.084	0.04	5.76	8	8.25	6
Indesit	2.12	0.09	0.13	0.04	8.55	6	11.25	11
DeLonghi	0.76	0.12	0.13	0.058	9.71	9	6.75	6
Piaggio	1.35	0.10	0.127	0.03	5.55	12	9	11
Campari	0.29	0.097	0.113	0.059	7.18	3	6	7
Brembo	1.15	0.078	0.18	0.079	15.13	9	8.25	8
Geox	0.42	0.18	0.21	0.093	26.62	8	9.75	6
Tod's	0.23	0.18	0.20	0.12	114.5	5	9	9
Carraro	4.98	0.059	0.067	-0.014	-1.32	5	7.5	8
Recordati	0.31	0.16	0.20	0.12	47.53	12	9.75	9
SOL	0.39	0.049	0.18	0.049	16.00	9	9.75	7
Natuzzi	0.33	0.12	0.04	-0.021	45.77	9	9.75	8
IMA	3.18	0.17	0.09	0.029	7.48	9	8.25	9
LaDoria	1.27	0.027	0.11	0.04	5.39	5	4.5	8
Interpump	0.77	0.19	0.10	0.03	2.68	5	5.25	3
IRCE	1.053	0.016	0.10	0.034	6.09	4	6.75	3
Engineering	1.28	0.086	0.15	0.089	29.59	14	11.25	12
Zambon	0.39	0.16	0.15	0.079	25.32	13	12.75	13
Tiscali	2.73	0.028	0.18	-0.066	4.67	7	9.75	9
Snai	1.61	0.014	0.077	-0.042	1.92	6	8.25	9
Telecom Italia	0.56	0.061	0.13	0.04	2.80	12	14.25	12
Wind	1.74	0.028	0.160	-0.017	2.54	8	9.75	9
IKF	4.21	0.002	0.009	0	0.49	8	7.5	8
NoemaLife	2.07	0.11	0.11	0.015	6.10	9	11.25	13
Newron	0.32	0.21	-0.87	0.089	-4.40	9	10.5	10
TasGroup	0.72	0.050	0.037	0.015	0.71	9	10.5	11
MolMed	0.093	0.49	-0.22	-0.23	-51.04	10	12	9
Reply	1.10	0.13	0.13	0.056	27.38	11	12	10
Bee Team	1.43	0.029	0.073	0.0073	5.50	10	10.5	9
Exprivia	1.062	0.04	0.087	0.028	7.75	14	12	10
Buongiorno	0.69	0.10	0.108	0.032	13.42	9	8.25	6
ComData	8.91	0.12	0.044	-0.073	1.91	11	8.25	9
Fullsix	2.205	0.46	0.015	-0.016	1.018	9	6.75	8
MutuiOnline	0.29	0.23	0.52	0.342	88.03	7	9.75	7
AccentureItalia	10.62	0.026	0.10	0.050	102.77	12	11.25	11
H3G	0.40	0.023	0.075	0.0206	7.76	6	9	8

Table 2b. Financial and IC's indicators for default firms

Firm name	Financial indexes					IC variables		
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Sitindustrie	5.53	0.015	-0.056	-0.14	-1.29	5	4.5	3
ElsagDatamat	7.60	0.019	-0.10	-0.10	-5.43	6	5.25	5
Texfer	80.60	0.004	-0.064	-0.17	-2.51	4	4.5	5
Comau	2.92	0.0001	-0.041	-0.05	-0.60	4	5.25	3

4.1. Application of the models: Model 1. The μ coefficients referred to the sample for the first model (Model 1, with only financial data) have been calculated. In Table 3 the results are exhibited.

Table 3. μ coefficients for Model 1

μ	Value
μ_1	-0.763
μ_2	8.954
μ_3	3.647
μ_4	23.827
μ_5	-0.016

Note: For further details on the computations of μ coefficients for Model 1 please contact the corresponding author, G. Iazzolino.

The resulting model is the following:

Model 1:

$$Z_i = -0{,}763X_{1i} + 8{,}954X_{2i} + 3{,}647X_{3i} + \\ + 23{,}827X_{4i} - 0{,}016X_{5i},$$

where Z_i is the score of firm i.

4.2. Application of the models: Model 2. Similarly to the first model, the μ coefficients for Model 2 (including 8 variables, among which three are referred to intellectual capital) have been calculated. In Table 4 the results are illustrated.

Table 4. μ coefficients for Model 2

μ	Value
μ_1	-0.760
μ_2	11.470
μ_3	6.392
μ_4	29.689
μ_5	-0.038
μ_6	-0.154
μ_7	0.401
μ_8	1.100

Note: Also in this case you can contact the corresponding author, G. Iazzolino, for further details on the computations of μ coefficients for Model 1.

The resulting model is the following:

Model 2:

$$Z_i = -0{,}760X_{1i} + 11{,}470X_{2i} + 6{,}392X_{3i} + \\ + 29{,}689X_{4i} - 0{,}038X_{5i} - 0{,}154X_{6i} + \\ + 0{,}401X_{7i} + 1{,}100X_{8i},$$

where Z_i is the score of firm i.

5. Results and discussions

5.1. Results for Model 1. In order to verify the reliability of the model and to understand model's discriminatory ability, we have determined the critical value, named cut-off point (Z_c):

$$Z_c = \frac{(Z_1' + Z_2')}{2},$$

where Z_1' is the average value of Z_i for non-default firms of the selected sample and Z_2' is the average value of Z_i for default firms of the selected sample. If a firm is below the cut-off point, it is considered abnormal (default firm). For Model 1, $Z_c = -3{,}686$. Then, it has been compared the classification obtained through our model with the classification provided by the AMADEUS Database (considered to be reliable); differences between the two classifications have been considered as errors of our model. The models (Model 1 and Model 2), based on Multi Discriminant Analysis (MDA) are able to classify non-default and default firms and furthermore they provide the Probability of Default (PD), defined as follows (Resti and Sironi, 2008):

$$PD = P(B|x_i) = \frac{1}{1 + \frac{1-\pi_B}{\pi_B} \times e^{z_i - \alpha}},$$

where $P(B \mid x_i)$ is the probability of belonging to group B (default firms), given a vector x_i of independent variables (financial and/or IC indicators); π_B is the default probability defined "a priori", a measure of the "average quality" of the loan portfolio of the bank depending on the general market; α is the cut-off point; z_i is the score of the generic firm i.

The calculated score and the PD, together with the errors, are shown in Table 5a and in Table 5b.

Table 5a. Results for non-default firms

Number	Firm name	Score (Z_i)	PD	Error
1	Saras	-0.46458	0.1990%	No
2	ERG	1.795057	0.0208%	No
3	Italcementi	0.945496	0.0487%	No
4	Parmalat	2.819934	0.0075%	No
5	Danieli	1.802045	0.0207%	No
6	Indesit	0.597848	0.0689%	No
7	DeLonghi	2.263812	0.0130%	No
8	Piaggio	0.971801	0.0474%	No

Table 5a (cont.). Results for non-default firms

Number	Firm name	Score (Z_i)	PD	Error
9	Campari	2.354792	0.0119%	No
10	Brembo	2.133111	0.0148%	No
11	Geox	3.883528	0.0026%	No
12	Tod's	3.315637	0.0045%	No
13	Carraro	-3.349	3.4451%	No
14	Recordati	4.093894	0.0021%	No
15	SOL	1.750164	0.0218%	No
16	Natuzzi	-0.24713	0.1602%	No
17	IMA	0.076769	0.1159%	No
18	LaDoria	0.581902	0.0700%	No
19	Interpump	2.433962	0.0110%	No
20	IRCE	0.43948	0.0807%	No
21	Engineering	2.021454	0.0166%	No
22	Zambon	3.221097	0.0050%	No
23	Tiscali	-2.80775	2.0344%	No
24	Snai	-1.85112	0.7915%	No
25	Telecom Italia	1.522774	0.0273%	No
26	Wind	-0.95564	0.3248%	No
27	IKF	-3.17075	2.8989%	No
28	NoemaLife	0.131156	0.1098%	No
29	Newron	0.711066	0.0615%	No
30	TasGroup	0.399701	0.0840%	No
31	MolMed	-1.26592	0.4424%	No
32	Reply	1.811029	0.0205%	No
33	Bee Team	-0.47944	0.2020%	No
34	Exprivia	0.431642	0.0813%	No
35	Buongiorno	1.35725	0.0322%	No
36	ComData	-7.32108	65.4508%	Type II error
37	Fullsix	2.114933	0.0151%	No
38	MutuiOnline	10.54492	0.0000%	No
39	AccentureItalia	-7.93978	77.8616%	Type II error
40	H3G	0.547805	0.0724%	No

Table 5b. Results for default firms

Number	Firm name	Score (Z_i)	PD	Error
41	Sitindustrie	-7.68808	73.2222%	No
42	ElsagDatamat	-8.41704	85.0036%	No
43	TexFer	-65.8252	100.0000%	No
44	Comau	-3.58722	4.3316%	Type I error

As regard the non-default firms, by this analysis it can be seen that there are two incorrect evaluations: Com Data and Accenture Italia. These two firms are considered non-default by AMADEUS Database, but our model gives them a low score, below the cut-off (and a high PD). This is a "type II" error (non-default firms classified as default). In this case the percentage for the error is 5% (2 firms out of 40).

As regard the default firms, there is one incorrect evaluation: Comau, a default firm (by AMADEUS) but classified as non default by our model (score upon the cut-off). This is a "type I" error. The percentage for the error is 25% (1 firm out of 4).

5.2. Results for Model 2. We have verified the reliability of the second model. The cut-off point, i.e. the discriminatory value between default and non-default firms, is Z_c = 4,877. Results of the application of Model 2 for non-default firms are shown in the following tables.

Table 6a. Results for non-default firms (Model 2)

Number	Firm name	Score (Z_i)	PD	Error
1	Saras	11.80547	0.0049%	No
2	ERG	17.92179	0.0000%	No
3	Italcementi	14.50626	0.0003%	No
4	Parmalat	14.1659	0.0005%	No
5	Danieli	11.55439	0.0063%	No
6	Indesit	16.97072	0.0000%	No
7	DeLonghi	10.99588	0.0110%	No
8	Piaggio	15.49562	0.0001%	No
9	Campari	12.74479	0.0019%	No
10	Brembo	13.68697	0.0007%	No
11	Geox	14.16882	0.0005%	No
12	Tod's	15.2919	0.0001%	No
13	Carraro	7.983543	0.2232%	No
14	Recordati	16.6888	0.0000%	No
15	SOL	12.55193	0.0023%	No
16	Natuzzi	10.37954	0.0204%	No
17	IMA	12.62764	0.0022%	No
18	LaDoria	10.93018	0.0117%	No
19	Interpump	8.021082	0.2150%	No
20	IRCE	6.227942	1.2782%	No
21	Engineering	18.10484	0.0000%	No
22	Zambon	21.38751	0.0000%	No
23	Tiscali	10.0256	0.0290%	No
24	Snai	10.40007	0.0200%	No
25	Telecom Italia	19.2862	0.0000%	No
26	Wind	11.97935	0.0041%	No
27	IKF	7.438866	0.3842%	No
28	NoemaLife	18.11951	0.0000%	No
29	Newron	13.29579	0.0011%	No
30	TasGroup	15.63311	0.0001%	No
31	MolMed	12.27766	0.0031%	No
32	Reply	16.38419	0.0001%	No
33	Bee Team	12.29278	0.0030%	No
34	Exprivia	14.43096	0.0004%	No
35	Buongiorno	10.33637	0.0213%	No
36	ComData	4.178652	9.1324%	Type II error
37	Fullsix	13.33103	0.0011%	No
38	MutuiOnline	23.17395	0.0000%	No
39	AccentureItalia	5.238282	3.3660%	No
40	H3G	12.25042	0.0031%	No

Table 6b. Results for default firms, Model 2

Number	Firm name	Score (Z_i)	PD	Error
41	Sitindustrie	-4.26437	99.7861%	No
42	ElsagDatamat	-2.44095	98.6901%	No
43	TexFer	-60.0315	100.0000%	No
44	Comau	0.8125	74.4326%	No

As regard the non-default firms, it can be seen that there is one incorrect evaluation: ComData. This firm is considered non-default by AMADEUS

Database, but our model gives it a low score, below the cut-off (and a high PD). This is a “type II” error. In this case the percentage for the error is 2.5% (1 firm out of 40). As regard the default firms, there are no incorrect evaluations. Then there are no “type I” errors. The percentage of this error is 0%. Through Model 2 (including extra variables “IC-based”), the error is halved or dissolved.

5.3. Comparison between Model 1 and Model 2. Two matrixes can be constructed for better showing results of Model 1 and Model 2. On the axes we have the Real Situation, as provided by AMADEUS, and the Obtained Situation, as obtained by the application of our models.

Table 7a. Matrix for Model 1

Real situation		Obtained situation			
		Non-default	Default	Total	Percentage error
	Non-default	38	2	40	5% (Type II)
	Default	1	3	4	25% (Type I)

Tab. 7b. Matrix for Model 2

Real situation		Obtained situation			
		Non-default	Default	Total	Percentage error
	Non-default	39	1	40	2.5% (Type II)
	Default	0	4	4	0% (Type I)

The first aspect that it could be seen by comparing the two models is the reduction of errors: by applying Model 1, two non-default firms have been classified as default and one default firm has been classified as non-default, whereas in Model 2 only one non-default firm has been classified as default and no default firms have been classified incorrectly. Then in Model 2 there are no Type I errors, while Type II errors have been halved. This result highlights the importance that intellectual capital evaluation can have in supporting credit risk analysis. Financial indicators are the basic data, very important in credit risk analysis, but, comparing the two models, we can say that for a better understanding, it could be useful to evaluate non-financial data. In our case the non-financial variables are “IC-based”. Model 2, which integrates financial and intellectual capital variables, clears Type I errors. A particular case is ComData that has been classified incorrectly by both models; but while in Model 1 PD is 65%, in Model 2 PD is 9%. Despite the not correct evaluation, by considering also intellectual capital variables, the PD of ComData has decreased significantly.

Conclusions and further works

Risk evaluation has become essential for organizations in general (Iazzolino et al., 2013; Pantano et al., 2013). In this historical period, characterized by a severe financial crisis, credit risk assessment emerges as one of the most important risk evaluation areas. Therefore, in this study we have applied two models based on Multi Discriminant Analysis (MDA); one of these uses only financial data, whereas the second model includes also intellectual capital variables. The results shown that intellectual capital reduces, and in some cases deletes, both type I and type II errors. Hence, intellectual capital variables, that we have integrated into a MDA scoring model, could help provide a better understanding of firm’s value (financial and intangible value) (Alwert et al., 2009; Guimon et al., 2005). Therefore, our study shows that in order to have a better evaluation of credit risk, it is possible to integrate financial data with intellectual capital variables. Our study proposed:

- an MDA model that uses financial data *only*;
- a second MDA model which *integrates* intellect-tual capital variables within the model, together with the financial variables.

This study highlights that the model which integrates IC and financial variables is more accurate than the model developed using only financial data. This result shows the importance of taking into account some aspects of intangible assets into the credit risk evaluation.

Credit scoring models should be based on the integration of financial and non-financial data. In this paper we considered intellectual capital variables, which can help financial analysts to better classify default and non-default firms. This result can allow financial institutes or banks to support decision making and to better evaluate the financial position of a firm.

Further researches could be focused on: (1) the use of other sophisticated techniques, such as SVM, neural nets, other credit scoring models; (2) the enlargement of the sample; and (3) the analysis on different industrial sectors.

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