The Potential of Top Management Characteristics for Small Enterprise Default Prediction Modelling

FRANCESCO CIAMPI
Department of Economics and Business
University of Florence
Via delle Pandette, 50 100 Florence
ITALY
francesco.ciampi@unifi.it https://www.disei.unifi.it/

Abstract: The aim of this study is to verify the potential of top management characteristics for small enterprise (SE) default prediction modelling. Logistic regression was applied to a sample of 423 Italian SEs, as defined in the Base Capital Accords (firms with a turnover below 5 million Euro) in order to develop a SE default prediction model based on both financial ratios and SE top management characteristics. The predictive power of this model was then compared to that of a second model whose predictive variables were exclusively represented by balance sheet financial ratios. The main findings are: i) managerial characteristics significantly improve the SE default prediction accuracy rates; ii) the smaller is a firm the higher is the increase in prediction accuracy that can be obtained by using managerial characteristics as default predictors; iii) SEs belonging to different size groups need to be treated with different prediction models; iv) SE management's over-confidence in its ability to control the outcome of all events, especially external events, reduces a firm's capacity to survive.

Key-Words: Bankruptcy, Credit rating, Default prediction modelling, Financial ratios, Managerial characteristics, Small enterprise, Top management

1 Introduction

Though the topic of company default prediction has received significative attention in the literature [1, 2, 3, 4, 5, 7, 14, 18, 34, 39, 40, 45, 57, 58, 65], two principal limits can be identified in the large majority of contributions.

First, default prediction models have almost exclusively been built and tested using data from large firms, without demonstrating their validity also in the case of small enterprises (SEs).

The second limitation is due to the fact that prediction models are almost solely based on financial ratios as default predictors. This aspect significantly limits the interpretative and prediction capacities of the developed models, especially in the case of SEs, which have their own specific physiology and characteristics (e.g., the fact that the entrepreneur is often at the same time the majority shareholder and the CEO of the company) which are markedly different from those of larger firms and which make financial ratios particularly weak as default predictors [23].

These elements, together with the fact that SEs play a significant role in the world's economy [1, 38, 56], suggest the opportunity to develop failure prediction models which are specifically developed for SEs and that are at the same time also based on non-financial categories of default predictors.

In this study logistic regression was applied to a sample of 423 Italian SEs, as defined in the Basel Capital Accords, i.e. firms with a turnover below 5 million Euro, with the aim to verify the potential of managerial characteristics as SE default predictors. A first default prediction model was built and tested which was based on both financial ratios and top management characteristics. The predictive power of this model was then compared to that of a second model whose predictive variables were exclusively represented by balance sheet financial ratios.

The next section presents a brief literature review on bankruptcy prediction modelling. It points out that there are only few studies which focus on SE and/or are based on managerial characteristics as predictive variables. In section 3, research hypotheses are presented. Subsequently, the selected predictive variables are described and the sample object of the analysis is presented. Finally, the results are discussed and the conclusions presented.

2 Literature Review

Following the seminal study of Altman [2], many empirical researches have demonstrated the value of financial ratios as enterprise bankruptcy predictors. These studies used different statistical techniques such as the multivariate discriminant analysis [2, 14, 15, 18, 30], the logistic regression analysis [57, 58], and, more recently, genetic algorithms [12, 32] and artificial neural networks [24, 49, 36, 64, 68, 70].

The large majority of these studies developed prediction models based on samples made up solely of large firms. As a consequence, apart from some exceptions [8, 9, 16, 21, 24, 31, 59, 60], the topic of default prediction modelling specifically designed for SMEs still remains largely unexplored [23].

Even less explored is the topic of the potential of management team characteristics as corporate default predictors. In fact, with regard to company bankruptcy prediction, several authors theorized about the importance of managerial characteristics such as family relationships with other business men [25, 52]; the inclination and ability to develop innovations, to face complexity and ambiguity [48], and to take risks [48]; skills concerning strategic planning [42, 67], marketing, finance [52], and other functional areas [42], past managerial experience [25, 50, 52], education [52]; the degree to which a manager believes that he/she has control over the outcome of events, especially external forces (locus of control; [33]); and the level of concern of a manager to set and meet high standards of achievement (need for achievement; [25, 48]). However, when we turn to analyze the empirical studies on this issue we find very scarce literature. Soares, Pina, Ribeiro and Catalào-Lopes [62] pointed out that using predictive variables related to managerial characters, such as previous managerial experience and managerial competences, improves the prediction effectiveness of corporate default prediction modelling. This study is interesting because it outlined the importance of using managerial and qualitative variables for bankruptcy prediction, but it was based solely on the analysis of the opinions expressed by the managers of six Portuguese financial institutions. Von Stein and Ziegler [66] used a sample of 135 defaulting firms and 25 not defaulting SMEs, and demonstrated that using variables related managerial characteristics, such as skills, previous experience, education and risk propensity, significantly improves a default prediction model's accuracy rate. Apart from these few previous contributions, the subject of the potential of management characteristics for SE bankruptcy prediction modelling still remains an unexplored research field. The aim of this study is to give a contribution in order to fill this gap.

3 Research Hypotheses

SEs have their own specific physiology and characteristics which are markedly different from those of medium and large firms. SEs have very simple ownership and management structures, in which only one person or a very small number of people contemporarily play the roles of owners, directors and managers [20, 23]. This allows SEs to be quicker and more reactive than larger firms when facing environmental challenges. On the other hand, a SE's success and survival depend as well on the skills and capabilities of a reduced number of persons, who are usually not endowed with adequate competence regarding accountancy and finance [24]. Furthermore, SE structure, behavior and performance are very sensible to internal or external events, with the consequence that when it is predicted that a SE is likely to default or to survive within a certain period of time, there is a high probability that the prediction will be contradicted because certain events might occur which either unexpectedly save the firm or cause its collapse [23].

Models developed in the literature are almost solely based on financial ratios as default predictors and this aspect significantly limits the interpretative and prediction capacities of the models.

In fact, a firm's accounting figures may have very different meanings depending on the reasons behind them: for example a reduction in the level of turnover may be due to a company's competitive weakness, but it may also be caused by the conscious decision of the firm to reduce the prices of the products in order to improve customer loyalty, which represent a fundamental strength for the survival of the firm of any size; moreover, an increase in the level of salaries of employees may be a symptom of a firm's inefficient management, but it may also be due to the conscious decision of the firm to increase (or maintain) the workforce's high skills level, which also represents a fundamental source of strength in the long run.

Furthermore, financial ratios regard past results and trends of a firm while the probability of a company's default is related to the future. As a consequence, financial ratios based on the last balance sheet may paint a dismal picture of the firm although an effective strategic plan may have been elaborated in the meantime in order to guarantee competitive advantage and value generation in the following years; and/or new capable management members may have been recruited to be integrated and/or substitute older members; and/or a new shareholder may have invested new financial resources that have in the meantime eliminated the firm's financial weakness.

Based on these considerations it is reasonable to expect a higher SE default prediction accuracy for models built on both managerial characteristics and financial ratios as predictive variables compared to models based only on financial ratios. Consequently, the first hypothesis is the following:

H1: When a SE default prediction model is based on both managerial characteristics and financial ratios (Model 2) prediction accuracy will be significantly higher compared to a model based only on financial ratios (Model 1).

Based on the same considerations it can also be expected that the smaller is the size of the firms under analysis, the stronger are the limits of using financial ratios. Furthermore, if SEs do have specific characteristics that make it necessary to have prediction models specifically developed in order to capture and interpret their specificities [24], it can also be expected that if models are calculated separately for different size groups then prediction accuracy rates will be higher. Therefore:

H2: When logistic regression is applied separately to different size groups, both Model 1 and Model 2 will have higher prediction accuracy rates (H2A); Model 2 will continue to be significantly more effective than Model 1 (H2B), and the smaller is the size of the firms which are object of the analysis, the higher are the differences in prediction accuracy rates between the two models (H2C).

4 Variables

4.1 Dependent Variable

This study analyses one dependent variable and two groups of independent variables: financial ratios and management characteristics.

The dependent variable has a value of 1 for defaulted firms and of 0 for non-defaulted firms. In line with Ciampi [23], the default event is defined as the beginning of formal legal proceedings for debt recovery (bankruptcy, forced liquidation, etc.).

4.2 Independent Variables

Based on the frequency with which they have been used in the literature [2, 3, 5, 6, 7, 14, 18, 26, 31], an initial group of 19 financial ratios was analysed (Table 1).

Of these initial 19 financial ratios, the 5 ratios shown in Table 2 were selected by applying a multicollinearity analysis which was carried out using both the Variance Inflation Factor (VIF) method (the ratios with a VIF value of above 3 were excluded), and the stepwise analysis.

Table 1. Initial group of financial ratios

X1	Roe = Net Profit/Equity
X2	Roi = Ebit/Net Operative Assets
X3	Ros = Ebit/Turnover
X4	Value Added/Turnover
X5	Ebitda/Turnover
X6	Interest Charges/Turnover
X7	Interest Charges/Ebitda
X8	Turnover/Number of Employees
X9	Value added/Number of Employees
X10	Cash flow/Total Debts
X11	Cash Flow/Turnover
X12	Interest charges/Bank Loans
X13	Bank loans/Turnover
X14	Total debts/Total Assets
X15	Financial Debts/Equity
X16	Total Debts/Ebitda
X17	Equity/Long Term Material Assets
X18	ATR (Acid Test Ratio)
X19	Turnover/Net operative assets

Ebitda = ebit + depreciation + amortization.

Table 2. Financial ratios selected by VIF and stepwise methods

FINANCIAL RATIOS	P-VALUE
Ebitda/turnover	0.001
ATR (Acid Test Ratio)	0.000
Ros = Ebit/Turnover	0.001
Interest charges/Ebitda	0.001
Bank loans/turnover	0.000

Ebitda = ebit + depreciation + amortization.

Based on the relevant literature indicated in Table 3 an initial group made up of 15 managerial variables was selected (Table 3).

This study controlled for firm location (two dummy variables concerning the geographical location: North, Centre or South Italy; “Centre” was used here as the reference category), firm business sector (two dummy variables concerning the industry: manufacturing, commerce or services; “manufacturing” was used as the reference category), firm age (the number of years since the company was established), firm family ownership (a dummy variable with a value of 1 if the majority of shares with voting rights is owned by members of the same family, 0 otherwise), management team size (measured by the total number of individuals on a company's management team transformed by its square), CEO-duality (a dummy variable with a value of 1 for firms in which the CEO of the firm is also the chair of the board of directors, 0 otherwise), and management being also owner (measured in function of the share of the firm's capital owned by management team members as follows: 1: 0%; 2: >0%<25%; 3: >25%<50%; 4: >50%<75%; 5: >75%).

Table 3. Initial group of independent variables regarding managerial characteristics

VARIABLES	DESCRIPTION/MEASURE	LITERATURE
PROPENSITIES AND BELIEVES		
Propensity to innovate	Inclination to develop product and/or process innovations*	[47]
Propensity to delegate	Inclination to delegate responsibilities and decision taking*	[13]
Propensity to face ambiguity	Inclination to face highly uncertain situations*	[47, 54]
Internal locus of control	Degree to which a manager/entrepreneur believes that he/she has control over the outcome of events*	[32]
SKILLS		
Financial skills	Level of financial skills*	[28, 42, 51]
Marketing skills	Level of marketing skills*	[19, 42, 51]
Operations skills	Level of operations skills*	[42]
Skills in planning processes	Level of skills in planning processes*	[19, 24, 42, 43, 46, 50, 51]
Human Resource skills	Level of Human Resource skills*	[42]
Research & Development	Level of Research & Development skills*	[28, 42]
EXPERIENCE AND EDUCATION		
Managerial experience	1 if at least one management team member had previous managerial experience, 0 otherwise**	[19, 24, 34, 43, 46, 50, 51]
Industry experience	1 if at least one management team member had previous managerial experience in the same industry, 0 otherwise**	[24, 34, 43, 51]
Education	1 if at least one management team member has a degree, 0 otherwise**	[13, 24, 28, 51]
Parent with managerial experience	1 if one of management team member has at least one parent with managerial experience, 0 otherwise**	[24, 51]
Seniority	Mean seniority of the management team members***	[24, 51]

* Measured by Likert Scale from 1 to 5 ** Dummy variable *** In terms of number of years

Table 4. Managerial Variables selected by VIF and stepwise methods

VARIABLES' CATEGORY	P-VALUE
PROPENSITIES AND BELIEVES	
Propensity to delegate	0.000
Propensity to face ambiguity	0.001
Internal locus of control	0.000
SKILLS	
Finance	0.000
Research & Development	0.001
EXPERIENCE AND EDUCATION	
Managerial experience	0.001

In this case too the multicollinearity analysis based on the VIF method and the stepwise analysis were applied which led to the selection of the 6 managerial variables shown in Table 4.

5 Dataset and Methodology

5.1 The Sample Object of the Research

The initial sample object of this study is composed of 4,320 SEs, with a turnover of below 5 million Euro, which were present in the CERVED database (that includes complete financial records of over 1.000,000 Italian companies), and operated in manufacturing, commerce or the service industry. It was made up of two sub-samples. The first sub-sample included all the 2,115 Italian firms with the above-mentioned characteristics which were present in the CERVED database and had failed in 2015. The second group of firms was made up of 2,115 firms with the same characteristics which had not failed at the end of 2015. These firms were selected using stratified random sampling, with the aim to have a sample as similar as possible to the first sub-sample with regard to industry (manufacturing, commerce, service), geographical localization (Northern Italy, Central Italy, Southern Italy), and size group distribution (four size groups based on turnover were built, as in Table 5). A firm's size was determined by its 2011 turnover. Size groups were calculated on the distribution quartiles of the defaulting firms.

Because failures are relatively infrequent, in most of the studies default prediction models are based on a sample which comprehends a much higher number of failed firms than the number corresponding to the percentage of failed firms in the population [61]. The objective of this research was to analyze the relationships between a set of independent variables (management characteristics and financial ratios) and SE default, and not to represent (and investigate) the behaviour of the entire population of Italian small firms. That is why, in line with the prevailing literature [2, 14, 31, 37, 58, 59, 69], half of the samples analysed in this study consisted of failed firms.

With the aim of gathering all the needed information related to the managerial variables, a questionnaire was sent by email to the president of the board and/or the CEO of each of the 4,230 SEs in the sample after it had been pre-tested with a limited number of firms (40), stressing the need to reduce the length and/or modify the form of a significant part of the questions [38, 52].

Considering that the people interviewed were internal to each analysed firm and their answers may have consequently been distorted by their subjective evaluations and convictions, each of them was asked to propose the name of another person, external to the firm and at the same time adequately informed about the characteristics of its top management team (for example a customer or a supplier or an external consultant). A copy of the questionnaire was then sent to this person as well. When the answers from the president of the board (or the CEO) were found different from the answers given by the external person, the latter, considered more unbiased, were used for the analysis. 423 firms (199 defaulting and 224 non-defaulting), corresponding to 9.79% of the initial sample, sent their fully completed questionnaire both from the internal and the external person.

Financial ratios were calculated on the basis of the 2011 accounting data contained in the CERVED database.

Using stratified random sampling, the 423 respondent firms were then split into 2 sub-samples, as similar as possible with regard to industry, size and geographical location. The first sub-sample, made up of 282 firms (133 defaulting and 149 non-defaulting) was used as a training sample and the second one, made up of 141 firms (66 defaulting and 75 non-defaulting), was used as a holdout sample. The structure of the total sample object of analysis is presented in Table 5.

Table 5. The structure of the sample (Percental values)

	Defaulting Firms	Non-Defaulting Firms
Industry		
Manufacturing	44.3	45.9
Commerce	14.6	15.6
Service	41.1	38.5
Geographical Area		
Northern Italy	42.1	40.6
Central Italy	33.9	33.1
Southern Italy	24.0	26.3
Size (turnover in Euro)		
Size group 1 (below 0.2 million)	31.2	37.3
Size group 2 (0.2-0.7 million)	27.4	26.7
Size group 3 (0.7-1.8 million)	19.1	17.2
Size group 4 (1.8 million-5 million)	22.3	18.8
Gender of respondents		
Male	87.3	89.1
Female	12.7	10.9
Mean age of respondents	49.5	52.3
Total	199	224

Compared to non-failing firms the defaulting companies were proportionally more present in the service industry and in Northern Italy and less present in Size Group 1.

The distribution of the 2011 mean values assumed in the two SE training sub-samples (defaulting firms and non-defaulting firms) by each ratio in the initial group of the selected financial ratios (Table 6) shows that, as expected, the non-defaulting SEs had a much higher level of profitability in terms of both Roe (X1) and Roi (X2), a much lower level of financial leverage in terms of both Financial Debts/Equity ratio (X15) and Total debt/Total Assets ratio (X14), and a much better situation regarding liquidity (average Acid Test ratio was 1.3 for non-defaulting firm and 0.7 for defaulting firms).

Table 6. Financial ratios in the SEs of the sample: 2011 mean values

		Defaulting Firms	Non-Defaulting Firms
X1	Roe = Net Profit/Equity	-3.7	2.2
X2	Roi = Ebit/Net Operative Assets	1.3	5.5
X3	Ros = Ebit/Turnover	1.7	3.8
X4	Value Added/Turnover	17.9	23.6
X5	Ebitda/Turnover	2,9	7,3
X6	Interest Charges/Turnover	6.2	4.1
X7	Interest Charges/Ebitda	75.7	44.8
X8	Turnover/Number of Employees	200.6	232
X9	Value added/Numb. of Employees	41.4	54.2
X10	Cash flow/Total Debts	3	9.9
X11	Cash Flow/Turnover	2.1	3.8
X12	Interest charges/Bank Loans	11.4	10.1
X13	Bank loans/Turnover	0.9	0.6
X14	Total debts/Total Assets	83.8	68
X15	Financial Debts/Equity	192.1	106.1
X16	Total Debts/Ebitda	930.2	494.5
X17	Equity/Long Term Material Assets	59.9	82.7
X18	ATR (Acid Test Ratio)	0.7	1.3
X19	Turnover/Net operative assets	133.3	143.5

Ebitda = ebit + depreciation + amortization;

5.2 Research Method

In the bankruptcy prediction literature, the multivariate discriminant analysis has for a long time represented the most frequently used statistical technique [2, 15, 18, 30, 31, 52]. Considering the limitations that characterize this technique when the independent variables are not linear, not normally distributed, and not completely independent of one another [46, 54, 57], and the dependent variable is binary (bankruptcy/non-bankruptcy; [10, 57]), the logistic regression analysis was used in this study to develop prediction models where the dependent variable assumes a value of 1 (company default) or of 0 (company non default) and the vector of the independent variables is composed of a group of financial ratios and a group of variables regarding managerial characteristics.

6 Results and Robustness Checks

6.1 Results and Discussion

The main objective of this research was to verify if a SE default prediction model based on both managerial characteristics and financial ratios (Model 2) would give prediction accuracy rates significantly higher compared to those of a model based only on financial ratios (Model 1).

Both Model 1 and Model 2 were calculated by using data from the training sample. The two regression functions were first calculated at an aggregate level, i.e. on the aggregate sample. Successively, the two models were also separately calculated for each of the different sub-samples corresponding to the 4 size groups indicated in Table 5. The prediction accuracy rates of all the calculated models were then tested by verifying their predictive capacity on the holdout sample.

Tables 7 and 8 show that for both Model 1 and Model 2:

1) all coefficients were significant at the one or five percent level, except the one relating to Ros which was significant only for the logistic function separately calculated for the Size 1 sub-sample;

2) signs were all as expected, with the exception of that relating to the internal locus of control;

3) none of the control variables was significantly correlated with SE default (the coefficients were always not significant at conventional levels), with the exception of that relating to CEO duality.

Table 7. Model 1 logistic regression coefficients calculated on the aggregate sample and for each size sub-samples

Independent Variables	Aggregate Sample	Size 1	Size 2	Size 3	Size 4
Intercept	-3.34**	-2.12**	-4.36**	-7.98*	-12.13**
FINANCIAL RATIOS					
Ebitda/turnover	-2.12**	-4.37**	-7.11**	-9.01**	-3.34*
Acid Test Ratio	-6.19**	-3.23**	-6.78*	-9.54**	-6.37*
Ros	-11.21	-13.78*	-5.58	-7.51	-9.72
Interest charges/ Ebitda	+19.23*	+23.11**	+16.31**	+24.71**	+15.90**
Bank loans/turnover	+6.45**	+2.89**	+7.27*	+5.67**	+8.88**
CONTROL VARIABLES					
CEO duality	-2.45*	-4.67*	-7.09*	-3.90*	-4.78*
Management-Owner	+3.45	+4.67	+7.89	+2.45	+4.67
Firm age	+0.49	+0.56	+1.78	+1.56	+1.34
Firm family ownership	-0.87	-0.46	-0.78	+1.66	-1,89
Management size	+1.45	+2.56	+4.67	+3.78	+2.89
Northern Italy	+3.23	-0.45	+1.89	+1.32	+4.67
Southern Italy	-4.56	+5.67	+7.89	+4.72	+8.29
Commerce	+1.21	+1.45	+2.02	+1.27	+1.89
Services	-0.78	-0.90	-1.13	-0.56	-0.98

*Significant at 5 percent **Significant at 1 percent.

From this it follows that when the object of analysis are SEs, financial ratios remain significantly related to small company default but also managerial characteristics prove to be highly and significantly correlated with SE bankruptcy.

Table 8. Model 2 logistic regression coefficients calculated on the aggregate sample and for each size sub-samples

Independent Variables	Aggregate Sample	Size 1	Size 2	Size 3	Size 4
Intercept	-2.78**	+4.11**	+6.71**	+3.79**	-2.89*
FINANCIAL RATIOS					
Ebitda/turnover	-4.54*	-9.72**	-3.03*	-7.21**	-11.34**
Acid Test Ratio	-9.32*	-11.09**	-7.88**	-5.90**	-10.73**
Ros	-2.88	-3.43**	-2.77	-9.84	-14.78
Interest charges/Ebitda	+6.80**	+11.42**	+4.72*	+8.51*	+2.99*
Bank loans/turnover	+3.11*	+6.67**	+8.10*	+2.93*	+10.48*
PROPENSITIES AND BELIEVES					
Propensity to delegate	-24.78**	-19.53*	-23.67**	-9.70**	-11.43**
Propensity to face ambiguity	-3.99**	-6.17*	-14.65*	-7.32**	-19.56**
Internal locus of control	+19.90**	+22.19**	+45.73**	+39.51**	+23.40**
SKILLS					
Finance	-7.89**	-11.47**	-4.08**	-16.82*	-9.75**
Research & Development	-24.78**	-19.53*	-23.67**	-9.70**	-11.43**
EXPERIENCE AND EDUCATION					
Managerial experience	-3.66**	-5.28**	-18.72*	-7.32**	-9.51**
CONTROL VARIABLES					
CEO duality	-4.67*	-7.87*	-1.54*	-6.89*	-8.67*
Management-Owner	+6.67	+7.89	+4.28	+5.83	+3.67
Firm age	+0.17	+0.32	+0.43	+2.34	+0.98
Firm family ownership	-0.12	-0.17	-0.32	+0,45	-1,43
Management size	+2.21	+4.78	+3.72	+4.67	+5.98
Northern Italy	+2.32	+4.45	+3.67	+3.66	+7.54
Southern Italy	-3.54	-11.45	+4.78	-9.09	-8.43
Commerce	+0.78	+1.23	+1.89	+1.05	+2.04
Services	-0.97	+0.45	-0.73	-0.49	-1.17

*Significant at 5 percent **Significant at 1 percent.

In line with expectations, the managerial skills related to finance and Research & Development, the managerial capabilities to delegate decisions and responsibilities and to face ambiguous and complex situations, as well as the level of previous managerial experiences, are all factors that are significantly and negatively related to company default. Surprisingly, the SE management conviction that he/she has control over the outcome of events instead proved to have a significant but positive correlation with company default. One person or a very small number of people who contemporarily are owners, directors and managers give a SE the capacity to quickly react to environmental changes. However, at the same time the SE entrepreneur has to be aware that due to the small size of the firm and its low contractual and negotiating power, its structure, behavior and performance easily suffer the effects of external events, which they can very rarely fully control. Consequently, a SE manager who is over-confident that he/she can control the outcome of all events, especially external event, endangers a firm's capacity to survive.

With regard to control variables, a negative and significant correlation was found between CEO duality and SE default. As CEO duality is an index of the power of the CEO within the company, this study confirms that in the case of SEs, if such power is reduced by the presence of a chairman of the board other than the CEO, the risk of the company failing grows. This finding is in contrast to the results found in the literature regarding large firms [11, 27, 28, 41, 53], but in line with the SE literature [23].

Table 9 shows the results obtained when testing (on the holdout sample) the prediction accuracy rates of Model 1 and Model 2 calculated using data (from the training sample) at an aggregate level.

Table 9. Test on holdout sample of Model 1 and Model 2 calculated on the aggregate sample (percentages)

Model	Observed state		Predicted State 1	Predicted State 0	Firms correctly classified
Model 2	Defaulting firms	1	85.7	14.3	85.1
	Non-defaulting firms	0	15.5	84.5	
Model 1	Defaulting firms	1	76.8	23.2	73.2
	Non-defaulting firms	0	30.5	69.5	

The "Observed State 1" lines show the percentages of defaulting firms which were classified correctly ("Predicted State 1" column), i.e. 85.7% for Model 2 and 76.8% for Model 1, and the percentages of defaulting firms which were wrongly classified ("Predicted State 0" column; type I error), i.e. 23.2% for Model 1 and 14.3% for Model 2. The "Observed State 0" lines show the percentages of non-defaulting firms which were classified incorrectly ("Predicted State 1" column; type II error), i.e. 30.5% for Model 1 and 15.5% for Model 2, and the percentages of non-defaulting firms which were correctly classified ("Predicted State 0" column), i.e. 84.5% for Model 2 and 69.5% for Model 1. These results show that when compared to the model based only on financial ratios, the model based also on managerial characteristics demonstrates an increase of the accuracy rate of almost 12%, a reduction of the type I error of almost 9% and a reduction of the type II error of 15%. H1 is consequently confirmed.

Table 10 shows the results obtained by testing (on the holdout sample) the prediction accuracy rates of Model 1 and Model 2 separately calculated for each size sub-samples.

Table 10. Test on holdout sample of Models 1 and 2 separately calculated for each size sub-sample (Percentages)

Size	Model 2 correctly class. firms	Model 1 correctly class. firms	Model 2 versus Model: accuracy increase
Size 1	85.6	72.9	12.7
Size 2	85.7	73.5	12.2
Size 3	85.8	74.1	11.7
Size 4	85.9	74.2	11.7
Total	85.8	73.7	12.1

In line with H2A, both Model 1 and Model 2 increase their prediction accuracy rates. Conversely, a first consequence of this finding is that pooling different sizes of firms reduces a model's prediction accuracy. A second consequence is that the predictive functions of banking institutions should be updated frequently and, especially each time the dimensional composition of their actual and/or potential customer portfolio encounter a significant change.

Model 2 continues to give a higher prediction accuracy for all size sub-samples, thus confirming H2B. More importantly, Model 1 prediction accuracy falls as a company size gets smaller (Model 1 prediction accuracy is 74.2% for size group 4 and 72.9 % for size group 1) and, at the same time, the increases in prediction accuracy rates obtained with Model 2 are proportionally higher for size group 1 and 2 (12.7 and 12.2 respectively) compared to size groups 3 and 4 (11.7 for both groups), with the result that Model 2 prediction accuracy rates are very similar for the different size groups. These findings, in line with H2C, demonstrate that using managerial variables, in addition to improving the overall prediction effectiveness of SE prediction models, tends to compensate the fact that financial ratios have a lower predictive capacity for SEs than for larger firms.

As a matter of fact, the limits in using financial ratios for default prediction modelling are stronger when the object of analysis are the SEs which, if compared to larger firms:

- have less articulated accounting obligations and consequently produce less reliable and detailed accounting data [17];
- have simpler and more centralized decision taking systems and mechanisms, which are highly influenced by the gut feelings of the owner-manager [20], and consequently demonstrate strategic, structural and performance changes which are quicker and less expectable;
- have a lower level of negotiating power and are consequently more intensively influenced by their stakeholders: for example, one year

financial ratios may be worse because a key manager and/or a key supplier and/or the most important customer have forced the firm to accept less favourable contractual terms.

These considerations are fully coherent with the significant increase of prediction accuracy of the model based on managerial characteristics when compared to the model based only on financial ratios both in the case of the logistic function calculated at an aggregate level (H1) and in the case of the function separately calculated for each size sub-samples (H2B); moreover, considerations are also coherent with the fact that the smaller is a firm the higher is the increase in prediction accuracy that can be obtained by including managerial characteristics (H2C).

6.2 Robustness of the Findings

In order to verify the robustness of these findings, the prediction capacity of the two developed prediction models (Model 1 and Model 2) was tested using a second holdout sample which was analysed in a different period of time (2012-2016). This second holdout sample was composed of 1,400 SEs, which had a turnover of below 5 million Euro, were present in the CERVED database, and operated in manufacturing, commerce or the service industry. 700 of these firms had failed in 2016 and the other 700 had not failed in the same year. In order to gather all the needed information related to the managerial variables, the same questionnaire described in Section 5.1. was sent to the president of the board and/or the CEO of each of these 1,400 SEs. Subsequently, the same questionnaire was sent to the person, external to the firm and at the same time adequately informed about the characteristics of its management team, who each interviewed firm had indicated and who would confirm and/or complement the potentially subjective evaluations expressed by the president of the board and/or the CEO. 116 firms (54 defaulting and 62 non-defaulting), corresponding to 8.29% of the sample, sent their fully completed questionnaire both from internal and the external interviewees. Financial ratios were calculated on the basis of the 2012 accounting data contained in the CERVED database.

The results obtained by testing the prediction capacity of the developed regression functions on this second holdout sample confirmed the robustness of our findings. In fact:

1) regarding the models calculated by using data from the training sample at an aggregate level: when compared to Model 1, Model 2 gave an increase of the overall accuracy rate of 11.2% (84.2% against 73.0%),) a reduction of the type I error of over 8%, and a reduction of the type II error of over 14%;

2) with regards to models separately calculated for each size sub-samples: Model 2 continued to give a higher prediction accuracy for all size sub-samples, while Model 1 prediction accuracy continued to fall as the company size got smaller (model 1 prediction accuracy was 73.8% for size group 4 and 72.1% for size group 1), and the increases in prediction accuracy rates obtained with Model 2 continued to be proportionally higher for size group 1 and 2 (12.4 and 12.1 respectively) compared to size groups 3 and 4 (11.1 and 11.4 respectively), with the result that Model 2 prediction accuracy rates were very similar for the different size groups.

7 Conclusion

Default prediction models used by banks and rating agencies have been so far mainly, if not exclusively, based on financial ratios as failure predictors. These models are designed on the assumptions that the past results and trends will repeat themselves in future, and that past accounting figures and ratios give an exhaustive picture of a firm capability to survive and create value.

The global financial crisis that broke out in 2008, and that is still conditioning the economic and financial systems of many countries, demonstrated that these models did not function effectively and that consequently these assumptions need to be questioned.

The need, therefore, emerged to develop new and different default prediction processes and models which can capture the symptoms of a company’s financial distress with the highest possible level of anticipation, even when these symptoms have not yet shown accounting consequences.

In this study, logistic regression was applied to a total sample of 423 Italian SEs with the aim of building and evaluating the effectiveness of SE default prediction models based on both financial ratios and managerial characteristics and then comparing the predictive power of these models with that of a second category of models whose predictive variables were exclusively represented by financial ratios.

This research makes the following contributions to the literature on SE default prediction modelling. First, to our knowledge, it is the first time that using a large sized sample of firms, the default prediction capacity of a large group of variables related to managerial characteristics is explored. The findings show that using managerial characteristics as default predictors significantly improve the SE default prediction accuracy rates. More specifically, including variables regarding the skills, propensions, and experience of SE management teams compensates the fact that the predictive power of financial ratios is lower for SEs than it is for larger firms.

Second, this study finds that if it is true that the smaller a firm is the stronger are the limits in using financial ratios for default prediction modelling, at the same time it is also true that the smaller a firm is the stronger is the positive predictive impact of managerial variables.

Third, it confirms that SEs belonging to different size groups need to be treated with prediction models specifically developed in order to capture and interpret the particular characteristics of each size groups. A first consequence of this finding is that pooling different sizes of firms reduces a model's prediction accuracy. A second consequence is that the predictive functions of banking institutions should be updated frequently and, in any case, each time the dimensional composition of their actual and/or potential customer portfolio encounter a significant change.

Fourth, this study outlines that a SE manager who is over-confident that he/she can control the outcome of all events, especially external events, endangers a firm's capacity to survive.

However, this study has also some limitations. First, it is based on a sample of firms located in a specific national context (Italy), whose institutional, economic, financial and industrial specificities certainly have an influence on which and how variables have an effect on the probability of a firm's bankruptcy, thereby limiting the generalizability of the findings.

Second, for both Model 1 and Model 2 the distributions of wrongly classified firms show a prevalence of type II errors, with the consequence that they could suggest to refuse to grant loans to firms that instead deserve to be supported.

Third, the proposed models are based on only one category of non-financial predictive variables, those related to managerial characteristics. Future research should test the default prediction potential of other categories of qualitative variables regarding the structure, behavior, processes and performance of all the subsystems of a small firm, such as those related to a company's competitive or marketing strategy, innovation behaviors and performances, knowledge creation processes and strategies [22], etc.

References:

[1] Aaron, A., Nainggolan, Y. A., Trinugroho, I., Corporate Failure Prediction Model in Indonesia: Revisiting the Z-Scores, Discriminant Analysis, Logistic Regression and Artificial Neural Network, *Journal for Global Business Advancement*, *10*(2), 2017, pp. 187-209.

[2] Altman, E. I., Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *The Journal of Finance, 23*(4), 1968, pp. 589-609.

[3] Altman, E. I., *Corporate Financial Distress and Bankruptcy (2nd ed.)*, Wiley, 1993.

[4] Altman, E. I., *Corporate Credit Scoring Insolvency Risk Models in a Benign Credit and Basel II Environment*, New York University, 2004.

[5] Altman, E.I., Brady, B., Resti, A., Sironi, A., The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications, *The Journal of Business*, *78*(6), 2005, pp. 2203-2228.

[6] Altman, E. I., Haldeman, R. G., Narayanan, P., Zeta-analysis. A New Model to Identify Bankruptcy Risk of Corporations, *Journal of Banking and Finance*, *1*(1), 1977, pp. 29-54.

[7] Altman, E.I., Sabato, G., Effects of the New Basel Capital Accord on Bank Capital Requirements for SMEs, *Journal of Financial Services Research*, *28*(1-3), 2005, pp. 15-42.

[8] Altman, E. I., Sabato, G., Modelling Credit Risk for SMEs: Evidence from the US Market, *Abacus*, *43*(2), 2007, pp. 332-357.

[9] Altman, E. I., Sabato, G., Wilson, N., The value of Non-Financial Information in Small and Medium-Sized Enterprise Risk Management, *The Journal of Credit Risk*, 6(2), 2010, pp. 1-33.

[10] Altman, E. I., Saunders, A., *Credit Risk Measurement: Development over the Last 20 Years*, New York University, 1996.

[11] Argenti, J., Corporate Collapse: The Causes and Symptoms, McGraw-Hill , 1976.

[12] Back, B., Laitinen, T., Sere, K., Neural networks and genetic algorithms for bankruptcy predictions, *Expert System with Applications*, 11(4), 1996, pp. 407-413.

[13] Barkham, R., Gudgin, G., Hart, M., Hanvey, E., *The determinants of Small Firm Growth - An Interregional Study in the UK: 1986-90*, Jessica Kingsley, 1996.

[14] Beaver, W., Financial Ratios Predictors of Failure, *Journal of Accounting Research*, Supplement to Volume 4, 1966, pp. 71-111.

[15] Beaver, W., Alternative Accounting Measures as Predictors of Failure, *The Accounting Review*, *43*(1), 1968, pp. 113-122.

[16] Behr, P., Güttler, A., Credit risk Assessment and Relationship Lending: An Empirical Analysis of German Small and Medium-Sized Enterprises, *Journal of Small Business Management*, *45*(2), 2007, pp. 194-213.

[17] Berger, A. N., Frame, S. W., Small Business Credit Scoring and Credit Availability, *Journal of Small Business Management*, *45*(1), 2007, pp. 5-22.

[18] Blum, M., Failing Company Discriminant Analysis, *Journal of Accounting Research*, *12*(1), 1974, pp. 1-25.

[19] Bruno, A., Leidecker, J., Harder, J., Why Firms Fail, *Business Horizons*, *30*(2), 1987, pp. 50-58.

[20] Burke, I. G., Jarrat, D., The Influence of Information and Advice on Competitive Strategy Definition in Small and Medium Sized Enterprises, *Qualitative Market Research*, *7*(2), 2004, pp. 126-138.

[21] Carter, R., Van Auken, H., Small Firm Bankruptcy, *Journal of Small Business Management*, *44*(4), 2006, pp. 493-512.

[22] Ciampi, F., *The Knowledge Creation Potential of Management Consulting*, IOS Press, 2008.

[23] Ciampi, F., Corporate Governance Characteristics and Default Prediction Modelling for Small Enterprises. An Empirical Analysis of Italian Firms, *Journal of Business Research*, *68* (5), 2015, pp. 1012-1025.

[24] Ciampi, F., Gordini, N., Small Enterprise Default Prediction Modelling through Artificial Neural Networks: An Empirical Analysis of Italian Small Enterprises, *Journal of Small Business Management*, *51*(1), 2013, pp. 23-45.

[25] Cooper, A., Gascon, J., Woo, C., A Resource-Based Prediction of New Venture Survival and Growth, in *Proceedings of the Academy of Management*, 113-119. Academy of Management, 1991.

[26] Crouhy, M., Galai, D., Mark, R., Prototype Risk Rating System, *Journal of Banking and Finance*, *25*(1), 2001, pp. 47-95.

[27] Daily, C. M., Dalton, D. R., Bankruptcy and Corporate Governance: The Impact of Board Composition and Structure, *Academy of Management Journal*, *37*(6), 1994, pp. 1603-1617.

[28] Daily, C. M., Dalton, D. R., Corporate Governance and the Bankrupt Firm: An empirical Assessment, *Strategic Management Journal*, *15*(8), 1994, pp. 643-654.

[29] D'Aveni, R., The Aftermath of Organizational Decline: A Longitudinal Study of the Strategic and Managerial Characteristics of Declining Firms, *Academy of Management Journal*, *32*(3), 1989, pp. 577-605.

[30] Deakin, E. B., A Discriminant Analysis of Predictors of Business Failure, *Journal of Accounting Research*, *10*(1), 1972, pp. 167-179.

[31] Edmister, R. O., An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction, *Journal of Financial and Quantitative Analysis*, *7*(2), 1972, pp. 1477-1493.

[32] Etemadi, H., Rostamy, A. A. A., Dehkordi, H. F., A Genetic Programming Model for Bankruptcy Prediction: Empirical Evidence from Iran, *Expert System with Applications*, *36*(2), 2009, pp. 3199-3207.

[33] Evans D. S., Leighton, L., Some Empirical Aspects of Entrepreneurship, *American Economic Review*, *79*(3), 1989, 519-535.

[34] Figini, S., Savona, R., Vezzoli, M., Corporate Default Prediction Model Averaging: A Normative Linear Pooling Approach, *Intelligent Systems in Accounting, Finance and Management*, *23*(1-2), 2016, pp. 6-20.

[35] Flahvin, A., Why Small Businesses Fail, *Australian Accountant*, *55*(9), 1985, pp. 56-72.

[36] Fletcher, D., Gross, E., Forecasting with Neural Networks: An Application Using Bankruptcy Data, *Information and Management*, *24*(3), 1993, pp. 159-167.

[37] Fulmer, J. G. Jr., Moon, J. E., Gavin, T. A., Erwin, M. J., A Bankruptcy Classification Model for Small Firms, *The Journal of Commercial Bank Lending*, *66*(11), 1984, 25-37.

[38] Gaskill, L. R., Van Auken, H.E., Manning, R.A., A Factor Analytic Study of the Perceived Causes of Small Business Failure, *Journal of Small Business Management*, *31*(4), 1993, pp. 18-31.

[39] Grice, J. S., Ingram, R. W., Tests of the Generalizability of Altman's Bankruptcy Prediction Model, *Journal of Business Research*, *54*(1), 2001, pp. 53-61.

[40] Gupta, V., Analysis of Default Risk for Listed Companies in India: A Comparison of Two Prediction Models, *International Journal of*

Business and Management, *9*(9), 2014, pp. 223-234.

[41] Hambrick, D. C., D'Aveni, R. A., Top Team Deterioration as Part of the Downward Spiral of Large Corporate Bankruptcies, *Management Science*, *38*(10), 1992, pp. 1445-1466.

[42] Haswell, S., Holmes, S., Estimating the Small Business Failure Rate: A Reappraisal, *Journal of Small Business Management*, *27*(3), pp. 1989, 68-74.

[43] Hisrich, R. D., Brush, C., Characteristics of the Minority Entrepreneur, *Journal of Small Business Management*, *24*(1), 1986, pp. 1-8.

[44] Hoad, W., Rosco, P., *Management Factors Contributing to the Success or Failure of New Small Manufactures*, University of Michigan Press, 1964.

[45] Huijuan, L., Default Prediction Model for SME's: Evidence from UK Market Using Financial Ratios, *International Journal of Business and Management*, *10* (2), 2015, pp. 81-106.

[46] Karels, G. V., Prakash, A. J., Multivariate Normality and Forecasting of Business Bankruptcy, *Journal of Business Finance & Accounting*, *14*(4), 1987, pp. 573-593.

[47] Kennedy, C., Thinking of Opening Your Own Business? Be Prepared!, *Business Horizons*, *33*(5), 1985, pp. 38-42.

[48] Koh, H. C., Testing Hypotheses of Entrepreneurial Characteristics: A Study of Hong Kong MBA Students, *Journal of Managerial Psychology*, *11*(3), 1996, pp. 12-25.

[49] Lacher, R. C., Coats, P. K., Sharma, S. C., Fant, L. F., A Neural Network Tool for Classifying the Financial Health of a Firm, *European Journal of Operation Research*, *85*(1), 1995, pp. 53-65.

[50] Larson, C. M., Clute, R. C., The Failure Syndrome, *American Journal of Small Business*, *4*(2), 1979, pp. 35-43.

[51] Lauzen, L., Small Business Failures Are Controllable, *Corporate Accounting*, *3*(3), 1985, pp. 34-38.

[52] Lussier, R. N., A Nonfinancial Business Success Versus Failure Prediction Model for Young Firms, *Journal of Small Business Management*, *33*(1), 1995, pp. 8-20.

[53] Mallette, P., Fowler, K. L., Effects of Board Composition and Stock Ownership on the Adoption of Poison Pills, *Academy of Management Journal*, *35*(5), 1992, pp. 1010-1035.

[54] Martin, D., Early Warning of Bank Failure: A Logit Regression Approach, *Journal of Banking and Finance*, *1*(3), 1977, pp. 249-276.

[55] Mitton, D. G., The Complete Entrepreneur, *Entrepreneurship: Theory and Practice*, *13*(3), 1989, pp. 9-19.

[56] Morrison, A., Breen J., Ali S., Small Business Growth: Intention, Ability, and Opportunity, *Journal of Small Business Management*, *41*(4), 2003, pp. 417-425.

[57] Ohlson, J., Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research*, *18*(1), 1980, pp. 109-131.

[58] Pindado, J., Rodrigues, L., De la Torre, C., Estimating Financial Distress Likelihood, *Journal of Business Research*, 61(9), 2008, pp. 995-1003.

[59] Pompe, P. M., Bilderbeek, J., The Prediction of Bankruptcy of Small-and Medium-Sized Industrial Firms, *Journal of Business Venturing*, *20*(6), 2005, pp. 847-868.

[60] Saurina, J., Trucharte, C., The Impact of Basel II on Lending to Small-And-Medium-Sized Firms: A Regulatory Policy Assessment Based on Spanish Credit Register Data, *Journal of Finance Services*, *26*(2), 2004, pp. 121-144.

[61] Skogsvik, K, Skogsvik, S., On the Choice Based Sample Bias in Probabilistic Bankruptcy Prediction, *Investment Management and Financial Innovation*, *10*(1), 2013, pp. 29-37.

[62] Soares, J. O., Pina, J.P., Ribeiro, M. S., Catalào-Lopes, M., Quantitative vs. Qualitative Criteria for Credit Risk Assessment, Frontiers *in Finance and Economics*, *8*(1), 2011, pp. 69-87.

[63] Tam, K. Y., Neural Network Models and the Prediction of Bank Bankruptcy, *OMEGA: The International Journal of Management Science*, *19*(5), 1991, pp. 429-445.

[64] Tam, K. Y., Kiang, M. Y., Managerial Applications of Neural Networks: The Case of Bank Failure Predictions, *Management Science*, *38*(7), 1992, pp. 926-947.

[65] Traczynski, J., Firm Default Prediction: A Bayesian Model-Averaging Approach, *Journal of Financial and Quantitative Analysis*, 52(3), 2017, 1211-1245.

[66] Von Stein, J. H., Ziegler, W., The Prognosis and Surveillance of Risks from Commercial Credit Borrowers, *Journal of Banking and Finance*, *8*(2), 1984, pp. 249-268.

[67] Weitzel, W., Jonsson, E., Decline in Organizations: A Literature Integration and

Extension, *Administrative Science Quarterly*, *34*(1), 1989, pp. 91-109.

[68] Wilson, R. L., Sharda, R., Bankruptcy Prediction Using Neural Networks, *Decision Support System*, *11*(5), 1994, pp. 545-557.

[69] Zenzerović, R., Business Financial Problem Prediction-Croatian Experience, *Ekonomska Istraživanja*, 22(4), 2009, pp. 1-16.

[70] Zhang, G. P., Hu, M. J., Patuwo E. B., Indro D. C., Artificial Neural Networks in Bankruptcy Prediction: General Framework and Cross-Validation Analysis, *European Journal of Operational Research*, 116(1), 1999, pp. 16-32.