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Determinants of SME credit worthiness under Basel rules: the value of credit history information

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1. Introduction

The Basel III Accord is strengthening bank capital requirements. It directs the international credit system to pay closer attention to measuring and managing credit risk. The adoption of the Internal Ratings-Based approach (IRB), which requires banks to develop a specific rating system for credit worthiness evaluation, is more favourable for banks. This is true also for Small – and Medium – Sized Enterprise (SME) positions, as demonstrated under Basel II rules (Altman and Sabato, 2005; Saurina and Trucharte, 2004). Automatic credit scoring models for SMEs are quickly developing (Berger and Frame, 2007). Thus, these new rules are expected to impact SME financing.

Given this background, the research question is: what are the factors on which SME credit worthiness is based under the IRB approach? The increasing interest in this topic and the implications for future economic growth are discussed by Claessens *et al*. (2005): "Much of the academic research on credit risk also focused on the large corporate credit market where data were more easily available to researchers. While the research on risk measurement and capital modelling for retail credits has increased in recent years, this remains a relatively underdeveloped area of research."

The literature points out the necessity of building a specific failure prediction system for these retail firms, distinct from corporate positions (Leeth and Scott, 1989; Berger and Udell, 1995; Claessens *et al*., 2005; Jacobson *et al*., 2005; Altman and Sabato, 2007). For this reason, we develop a failure prediction model exclusively focused on SMEs.

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Looking at the model, both the literature and the Basel Accord consider historical credit data to be essential to build a rating system for SMEs (Pompe and Bilderbeek, 2005; Altman and Sabato, 2007). To our knowledge, our model is the first attempt to run both historical credit data and financial information.

To operationalise the model, we have chosen the variables/indicators that are, potentially, best able to predict default probabilities from several sources: a) literature on failure prediction models, mainly developed for corporate firms; b) literature on financial statement analysis; c) central bank instructions about the use of historical credit data.

Examining the literature concerning the effects of the Basel Accord on SME banking credit, we can state some research hypotheses. The hypotheses are tested on a sample of Italian SMEs held in trust by an Italian primary bank. The sample complies with the Basel II definition of SMEs, which remains valid in the new version of Basel III.

Results show that the quality of the credit relationship, expressed by the usage ratio of short-term lines of credit, is the main determinant of the rating. Moreover, the rating depends on the operating profitability. For sure, this last measure might be more linked to the industry's characteristics than other variables. In any event, it underlines the centrality of competitive factors for the default evaluation process. We might think that the margins on sales are quicker than debt ratios in responding to the effects of a loss of competitiveness. In fact, an increase in the capitalisation level is not able to improve the firm's rating, as commonly stated and verified for corporate positions. The same conclusion is valid for the weight of the borrowing cost.

The second section of the study discusses the literature on which the hypotheses are formulated. The third section presents and motivates all of the variables that will be used. We discuss the choice of the model and its structure in the subsequent section. We describe the application of the model to our sample in the fifth section. Finally, we present and discuss the results in the sixth section, while the last section is dedicated to conclusions.

2. Literature review and research hypotheses

Despite the great importance of SMEs in the economy, the default analysis of SMEs was not explored in depth before the introduction of the new Basel rules (Edmister, 1972; Keasey and Watson, 1987; Laitinen, 1992; Claessens *et al.*, 2005). Recently, this topic has received increasing interest (the historical and cultural reasons are debated by Claessens *et al.*, 2005). The literature examines the expected effects of the Basel Accord on the banks' capital requirements from different points of view: the lender portfolio risk (Dietsch and Petey, 2004; Jacobson *et al.*, 2005), the amount of capital requirements as a function of the credit worthiness evaluation (Schwaiger, 2002), the link between the Basel approach adopted by a bank and the characteristics of the lenders and capital needs (Saurina and Trucharte, 2004; Altman and Sabato, 2005; Berger, 2006; Pagliacci, 2006).

A few studies, of greater interest to our purpose here, focus on the connections between the type of credit and the features of the bank and the firm in financial distress (Hancock and Wilcox, 1998; Jiménez and Saurina, 2004; Berger *et al.*, 2005; Berger, 2006; Berger and Frame, 2007).

This literature points out that the automatic credit worthiness systems standardize the credit evaluation procedures. This standardization implies a change in the evaluation systems. The systems move from a subjective assessment of lending relationships, mainly based on credit historical data and on the acquaintance with the entrepreneur (Petersen and Rajan, 1994; Berger and Udell, 1995; Avery *et al.*, 1998), to a more objective firm evaluation, which emphasizes financial statement data (Berry and Robertson, 2006; Berger and Frame, 2007; Brewer, 2007). This phenomenon is particularly important for SMEs (Berger and Frame, 2007).

This literature affirms that credit judgment is sensitive to financial leverage ratios, which are considered to be the most predictive of probabilities of default, especially for corporate positions (Standard & Poor's, 2006). The topic of debt is particularly important for SMEs, which usually have high levels of indebtedness (Thomsen and Pedersen, 2000; Altman and Sabato, 2005). Looking at this statement, we formulate our first hypothesis: *increasing levels of capitalization improves a SME's rating*.

If leverage ratios play a central role in rating systems, even the weight of the borrowing cost is a variable that influences the default score (Altman and Sabato, 2005). Thus, it is natural to verify, in parallel with our first hypothesis, the second research hypothesis: *an increase in the weight of borrowing cost worsens the SME's rating*.

Under Basel rules, the closer attention paid by rating systems to financial statement data does not diminish the importance of historical credit data. Empirical studies reveal the prevalence of this data in the credit worthiness valuation of an SME (Petersen and Rajan, 1994; Jiménez and Saurina, 2004). This drives our third research hypothesis: *historical credit data is the most important variable for SME credit worthiness.*

Within the credit history, the trend of short-term lines of credit is said to be very important for a bank (Bank of Italy, 2002; Centrale dei Rischi, 2004). The fourth research hypothesis is: *among credit history, the usage level of short-term lines of credit represents the main determinant of SME credit worthiness*.

The financial structure is not the only determinant of the default probability measured by rating systems. Even profitability performances play a relevant role in the credit evaluation process of a SME (this is true from Edmister, 1972; to Pagliacci, 2006). This statement can be verified by testing our fifth hypothesis: *an increase in profitability of a SME improves its rating*.

3. The variables for failure prediction

Failure prediction models are based on a set of variables/indicators. Following the literature (Beaver, 1967; Altman, 1968; Edmister, 1972; Chen and Shimerda, 1981; Caouette *et al*., 1998; Pompe and Bilderbeek, 2005), we have divided the indicators of default into three 'branches':

a. Loss of profitability and competitive strength due to a fall in demand or a drop in internal efficiency;

b. Deterioration of solvency and liquidity conditions due to an increase in debt weight by external events (e.g. raising of interest rates) or by internal causes such as reduced cash flow or an unbalanced financial structure;
c. Deterioration in the quality of the credit relationship, especially in relation to short term lines of credit.

A group of indicators (all expressed as percentages) has been gathered under each ‘branch’ of the default causes (table 1).[1]

First, we have considered all those ratios based on financial statement data coming from failure prediction studies (Beaver, 1967; Altman, 1968; Edmister, 1972; Deakin, 1976; Chen and Shimerda, 1981; Caouette *et al.*, 1998; Pompe and Bilderbeek, 2005). These variables are integrated with the most commonly used indicators in the financial statement analysis literature (Foster, 1986; Penman, 2001).

The Basel Accord, moreover, requires the IRB models to include as many variables as possible to estimate probabilities of default. Moving in this direction, the biggest contribution of our work is the inclusion of credit history in the models, starting from conclusive research provided by Altman and Sabato (2007). Credit history, in fact, is considered fundamental to financial distress prediction of SMEs (Kallberg and Udell, 2003; Pompe and Bilderbeek, 2005). To our knowledge, only Kallberg and Udell (2003) and Behr and Güttler (2007) employ information about business payment history in their failure prediction models. However, they only use one summary statistic, instead of all variables employed in an IRB model.

Nevertheless, we do not consider qualitative information even if the literature has shown its importance (Lehman, 2003; Grunert *et al.*, 2004). In the case of SMEs, however, ‘soft’ information on credit systems highly varies across banks.

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[1] Each indicator has been rewritten in a different manner in order to identify the shape that better predicts the default. For example, the credit granted to the firm can be monitored by the following: a) credit granted/turnover; b) credit granted/net investments; c) credit granted/value added; d) credit granted/total assets; e) credit granted/net assets. At the end, ‘credit granted/net investments’ is the best form, in terms of predictive power.

We have chosen historical credit variables both from the literature (Berger and Udell, 1995; Estrella, 2000; Falkenheim and Powell, 2000; Jiménez and Saurina, 2004; Agarwal *et al.*, 2006; Sufi, 2009) and from banking standards (Bank of Italy, 2000; Centrale dei Rischi, 2004).

In addition, we have employed a third class of measures in which credit history and financial statement data are mixed to build new indicators that are potentially useful for failure prediction (e.g., 'short term credit granted/Net Assets').

4. The failure prediction model

The literature underscores the importance of developing specific and rigorous rating systems for SME positions (Leeth and Scott, 1989; Berger and Udell, 1995; Jacobson *et al.*, 2005). Empirical evidence shows that a specific model for SMEs has a higher prediction ability than a model built on a broad-spectrum borrower portfolio (Altman and Sabato, 2007).

In practice, however, there are few studies that attempt to design a specific failure prediction system for SMEs (Edmister, 1972; Altman and Sabato, 2007), and only one of them is developed in the Basel II environment (Altman and Sabato, 2007).

Among the methodologies that can be employed for estimating default risk (see, among others, Scott, 1981; Altman and Saunders, 1998; Crouhy *et al.*, 2000; Hastie *et al.*, 2002; Bank of International Settlements, 2005; for the Italian experience see Altman *et al.*, 1994), the logistic regression (logit) is the preferred one for at least four reasons: a) its output is directly expressed as a measure of default probability (Bank of International Settlements, 2006); b) it is able to handle both qualitative and quantitative explanatory variables and allows simple testing of the significance of coefficients; c) it is sufficiently solid from a scientific perspective and from experimentation in applications; and d) currently, it is the most commonly applied methodology by bank credit risk systems (see, among others, Bank of Italy, 2000; Westgaard and Van der Wijst, 2001; Standard & Poor's, 2006).

Moreover, the model has to estimate one-year default probabilities, according to the Basel Accord. Taking into consideration the sample, it has to be consistent with the specifications of the Accord. The sample has to contain firms with turnovers between 5 and 50 million euros and a credit position of over 1 million Euros and/or retail positions.

For these reasons, our study does the following: a) adopts a logit approach; b) builds a model only for SME economies; and c) complies with Basel rules, even if we base it on a more stringent definition of 'default'.

In contrast to other works on the topic (developed for the sake of determining corporate positions), financial and credit historical data have been used simultaneously in the model. These two sources of information usually feed separate models, which are 'harmonized' in a subsequent step using somewhat ad hoc methods; as a result, the model loses explanatory power. We experienced this with our data; the implementation of two separate models (a first one based on accounting data and a second one based on credit history) gave very different results relative to considering them simultaneously. Another advantage to operating with a single model is the possibility to employ 'hybrid' indicators, which combine financial statement data and credit history.

5. The default prediction model built on Italian SMEs

5.1. The data

The sample used to build the failure prediction model consists of 232 Italian companies held in trust by an Italian primary bank. In order to satisfy Basel II requirements, the firms have a turnover of between 5 and 50 million Euros and a credit position of at least 1 million euros. To avoid taking into account systematic risk, we chose to focus on the fashion industry only (73 clothing producers, 40 shoe producers, 62 textile producers, 26 knitwear producers, and 31 wool mills); conclusions based on a single industry, however, do require some care in generalizing the results. 29% of the firms in the sample are located in the North-West, 13% are located in the North-East, 37% are located in the Centre, and 21% are located in the South. The firms in the sample cover 3.4% of the turnover of the entire Italian fashion industry.[2]

In building the sample, we considered all 66 firms that defaulted, between 1998 and 2006, in the segment detailed before. The default state refers to the 'bad debt status' assigned by the bank. Note that the Basel II definition of 'default' is slightly broader in that it also includes other non-performing loans (i.e. substandard and past-due loans). The 66 defaulted companies were paired with 166 non-defaulted firms, randomly selected from the bank data (over the same period and industry) according to size and geographic location.[3]

To estimate a one-year default probability according to Basel II recommendations, our database consists of the financial statements of the fiscal year (all closed at the end of December) before the default date[4] and the credit history at the same time.[5]

Before processing data, we excluded from analyses companies whose financial statements reported a turnover equal to zero and/or negative net assets.[6] This reduced the data to 187 observations (53 defaults).

In order to diminish the possible impact of outliers in the analyses, we Winsorised each indicator, adjusting the values outside the Winsorisa-

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[2] The evaluation of the industry turnover comes from "Federazione delle imprese tessili e moda italiane – Centro Studi – La filiera tessile abbigliamento moda – indagine 2006" (available at http://www.smi-ati.it/).

[3] Such a strategy implies that the paired variables lose their possible discriminatory power. If of interest, however, an evaluation of their predictive ability can be retrieved by means of internal or external data and used for re-calibrating the estimated model.

[4] By 'default date,' we mean the month of default for defaulted companies and the matching month for non-defaulted companies.

[5] The lack of a panel dimension is a limitation of the analysis, particularly for the credit history variables. In fact, while accounting data is available on an annual basis, and the last one encompasses almost all accounting information of interest, an appropriate treatment of historical credit data, which is more frequently available, generally suggests the adoption of panel data methodologies. In particular, high levels of 'credit usage' ratios may relate to a default situation but may also be an effect of a poor company management team, whose final outcome is the default. A panel framework could mitigate this reverse causality situation to the extent that a firm effect is able to serve as a proxy for the 'quality' of firm management. Although it is not guaranteed that panel methodologies are able to capture such 'firm ability,' they can at least test and control for it.

[6] Because negative net assets contrast with the Italian Civil Code (art. 2446), we removed the corresponding observations despite the fact that this process may diminish the predictive power of certain accounting indicators.

tion interval (different for each indicator) by replacing them with the closest extreme in the interval. The Winsorisation interval has been computed so as to adjust 10% of the observations; depending on the nature of the indicator, the adjustment has involved the left (10%), the right (10%) or both tails (5%-5%) of its distribution (see table 1, column 3). Descriptive statistics of all the indicators are reported in the appendix.

5.2. Preliminary analyses

Before carrying out the multivariate analysis, we checked the predictive ability of each indicator with univariate logit-linear models.[7] Table 2 (column 2) reports the p-values of the independent variables considered in the univariate models. 28 indicators out of 55 are significant at 5%; the figure becomes 42 if we consider a conservative significance level of 30% (unusual for multivariate models but adequate for a preliminary analysis – see Hosmer and Lemeshow, 2000, p. 95). Both historical credit and accounting data seem potentially useful for modelling the default probabilities. The best predictors are among the indicators of solvency and liquidity conditions and a couple of indicators of the quality of the credit relation; in contrast, the profitability conditions seem to have hardly any power to predict default.

In order to check for possible non-linearities, we complemented the above analysis with univariate logit-nonlinear models based on splines (Generalized Additive Model or GAM – see Wood, 2006) to evaluate the significance of the possible non-linear contribution of each indicator. Table 2 (column 3) reports the corresponding p-values. Only nine indicators have a non-linear pattern significant at 5%; there are 23 indicators at a significance level of 30%. Several indicators of profitability, of solvency and of liquidity conditions and a couple of indicators of the quality of the credit relation seem to have a significant non-linear influence on the default probability. We caution, however, that such an analysis (similarly to any alternative method to evaluate non-linearities in a univariate framework) is prone to misleading results, as models including only one indicator are likely incorrectly specified.

[7] Data is handled using the R statistical environment (see http://www.r-project.org/), estimating the model with the *glm*() function.

Table 1 – *Default estimation indicators (candidate independent variables)*

Category	Variable	Expected sign of the coefficient	Winsorization type
Profitability conditions	ROE1 = earning from continuing operations / net assets	-	LR
	ROE2 = net profit / net assets	-	LR
	ROA = EBIT / total assets	-	LR
	ROI = EBIT / net investments	-	LR
	ROS = EBIT / turnover	-	LR
	turnover / total assets	-	R
	total purchases / turnover	+	R
	net assets / turnover	-	LR
	total assets / turnover		R
	labour costs / value added	+	LR
	labour costs / turnover	+	R
	cost of sales / turnover	+	R
	depreciation rate	-	R
Solvency and liquidity conditions	ROD = interests on debt / financial debt	+	R
	ROI – ROD	-	LR
	ROA – ROD	-	LR
	working capital / turnover	+	LR
	trade receivables days	+	R
	stock in hand days	+	R
	trade payable days	-	R
	cash and cash equivalents / total assets	-	R
	operating cash flow / short term debt	-	LR
	operating cash flow / financial debt	-	LR
	operating cash flow / interests on debt	-	LR
	short term credit granted / net assets		LR
	short term credit granted / total assets		R
	(revolving credit facilities granted + overdraft credit facilities granted) / net investments		R
	current assets / current liability	-	R
	(current assets – stock) / current liability	-	R

Table 1 continues

Table 1 continued

	net financial position / turnover	+	LR
	net financial position / net assets	+	LR
	net financial position / total assets	+	LR
	short-term debt / long-term debt	+	R
	short-term debt / net assets	+	LR
	short-term debt / total assets	+	R
	long term credit granted / tangible assets		R
	liabilities / net assets	+	LR
	liabilities / total assets	+	R
	retained earnings / net assets	-	LR
	retained earnings / total assets	-	R
	funded credit granted / turnover		R
	funded credit granted / net assets		LR
	funded credit granted / total assets		R
	unfunded credit granted / turnover		R
	unfunded credit granted / net assets		LR
	unfunded credit granted / total assets		R
	(revolving credit facilities + overdraft credit facilities – financial investments) / turnover	+	LR
	(revolving credit facilities + overdraft credit facilities – financial investments) / net assets	+	LR
	(revolving credit facilities + overdraft credit facilities – financial investments) / total assets	+	LR
Quality of the credit relation	usage ratio of revolving credit facilities	+	R
	usage ratio of continuous credit lines	+	R
	usage ratio of funded credit	+	R
	usage ratio of unfunded credit	+	R
	usage ratio of overdraft credit facilities	+	R
	revolving credit facilities utilized / accounts receivable	+	R

Note: Column expected sign refers to the sign of the corresponding coefficient. Column Winsorisation type refers to the type of Winsorisation (cf. section 5.1: L = left, R = right, LR = both).
Source: authors’ elaboration on ad hoc database provided by an Italian lender.

Table 2 – *Results of univariate analyses*

Variable	Univariate logit	Univariate logit-nonlinear
ROE1 = earning from continuing operations / net assets	0.0132	0.0111
ROE2 = net profit / net assets	0.0228	0.8302
ROA = EBIT / total assets	0.0603	0.0078
ROI = EBIT / net investments	0.1066	0.0186
ROS = EBIT / turnover	0.1133	0.0006
turnover / total assets	0.0172	0.7495
total purchases / turnover	0.0098	0.1252
net assets / turnover	0.3130	0.0017
total assets / turnover	0.0092	0.8262
labour costs / value added	0.0317	0.1813
labour costs / turnover	0.8221	0.2497
cost of sales / turnover	0.0106	0.2867
depreciation rate	0.5758	0.7702
ROD = interests on debt / financial debt	0.7151	0.6855
ROI – ROD	0.2571	0.6638
ROA – ROD	0.3316	0.3632
working capital / turnover	0.2865	0.3782
trade receivables days	0.0125	0.2904
stock in hand days	0.0384	0.7999
trade payable days	0.0149	0.1347
cash and cash equivalents / total assets	0.0288	0.0778
operating cash flow / short term debt	0.2352	0.0160
operating cash flow / financial debt	0.0241	0.4963
operating cash flow / interests on debt	0.0056	0.0236
short term credit granted / net assets	0.9395	0.4291
short term credit granted / total assets	0.1020	0.5993
(revolving credit facilities granted + overdraft credit facilities granted) / net investments	0.0078	0.8407
current assets / current liability	0.0594	0.3714
(current assets – stock) / current liability	0.0584	0.7579
net financial position / turnover	0.0019	0.3387
net financial position / net assets	0.0001	0.2084
net financial position / total assets	0.0050	0.2449
short-term debt / long-term debt	.	.
short-term debt / net assets	0.0003	0.4289
short-term debt / total assets	0.2136	0.6632
long term credit granted / tangible assets	0.7226	0.7363
liabilities / net assets	0.0001	0.5191
liabilities / total assets	0.0015	0.7424
retained earnings / net assets	0.0103	0.1485
retained earnings / total assets	0.0000	0.2177

Table 2 continues

Table 2 continued

funded credit granted / turnover	0.0726	0.5757
funded credit granted / net assets	0.0904	0.4720
funded credit granted / total assets	0.3047	0.6606
unfunded credit granted / turnover	0.4938	0.5551
unfunded credit granted / net assets	0.0146	0.6812
unfunded credit granted / total assets	0.7325	0.2227
(revolving credit facilities + overdraft credit facilities – financial investments) / turnover	0.0474	0.7133
(revolving credit facilities + overdraft credit facilities – financial investments) / net assets	0.0014	0.9655
(revolving credit facilities + overdraft credit facilities – financial investments) / total assets	0.7051	0.9700
usage ratio of revolving credit facilities	0.1563	0.1708
usage ratio of continuous credit lines	0.0009	0.0017
usage ratio of funded credit	0.0252	0.0072
usage ratio of unfunded credit	0.0000	0.6068
usage ratio of overdraft credit facilities	0.6828	0.5332
revolving credit facilities utilized / accounts receivable	0.0716	0.9909

Notes: column linear refers to the p-value of the coefficient in the logit-linear univariate model; column nonlinear refers to the p-value in testing of nonlinearity of the contribution of the variable in the univariate logit-nonlinear (GAM) model.
Source: authors' elaboration on ad hoc database provided by an Italian lender.

5.3. Multivariate analysis

Regarding the multivariate model, we have employed the following selection strategy. Considering only indicators with p-values from the univariate logit-linear analysis of less than or equal to 0.30 and avoiding those pairs of indicators whose Pearson (or Spearman) correlation levels are above 0.8 in absolute value, we run a stepwise (forward-backward) model selection aimed at optimizing AIC.[8] If all indicators in the final

[8] The AIC (Akaike Information Criterion) is an index for comparing non-nested models. It is given by:

$$AIC = -2l + 2p\,,$$

where l denotes the log-likelihood and p denotes the number of parameters. An alternative criterion is the BIC (Bayesian Information Criterion)

$$BIC = -2l + \ln(n)p\,,$$

model are significant and if the coefficients have the expected sign (see table 1, column 2), we stop the search; otherwise, we exclude the indicator with the largest non-significant p-value or with the wrong sign coefficient and restart the model selection. Because the correlation bound mentioned before forces an a priori choice between highly correlated indicators, we compared results obtained by different starting sets and chose, at the end, the model with the smallest AIC. The resulting model is shown in table 3 and will be discussed below.

As a final analysis, we have checked for possible non-linear effects in the multivariate model with a GAM (Wood, 2006), paralleling the univariate analysis. In order to avoid overfitting and to simplify the interpretation of the resulting model, we have imposed monotonicity for the contribution of each indicator, suitably reducing the corresponding smoothing parameter when its estimated value gives a non-monotonic curve. Firstly, we tested non-linearities of the independent variables resulting in the logit-linear model (table 3); secondly, we have checked, one at a time, the possible non-linear contribution of the variables excluded from such a logit-linear model and with a p-value lower than 0.3 in the univariate analysis (cf. table 2, column 3). No significant (monotone) non-linearities emerged, which means the model of table 3 can be considered the final version.

The Hosmer-Lemeshow statistic (Hosmer and Lemeshow, 2000, ch. 5), computed using 10 intervals, has a p-value of 0.896, indicating that the selected model provides an adequate representation of the data.[9]

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where *n* denotes the number of observations. In both cases, the aim is to find the model with the smallest index.

[9] The Hosmer-Lemeshow statistic is:

$$HL = \sum_{g=1}^{G} \left[\frac{\overline{y}_g - \overline{\widehat{\pi}}_g}{\overline{\widehat{\pi}}_g (1 - \overline{\widehat{\pi}}_g)/n_g} \right]^2$$

where *G* indicates the number of sets, built on the basis of the *G* quantiles fitted default probabilities $\widehat{\pi}_i$, in which the observations are grouped; $\overline{y}_g$, $\overline{\widehat{\pi}}_g$ and n_g denote, respectively, the averages of the observations, the average of the fitted probabilities and the number of observations in the *g*-th group. Under the null hypothesis that the observations come from the model under analysis, *HL* follows a $\chi^2(g-2)$ distribution.

The *ROC* (Receiver Operating Curve) seems to indicate good predictive characteristics of the model (figure 1), as confirmed by the value (0.899) of the corresponding index.[10]

As a final check, we tried to insert into the model the variables used for pairing non-defaulted companies to defaulted ones: as expected, they are not significant.

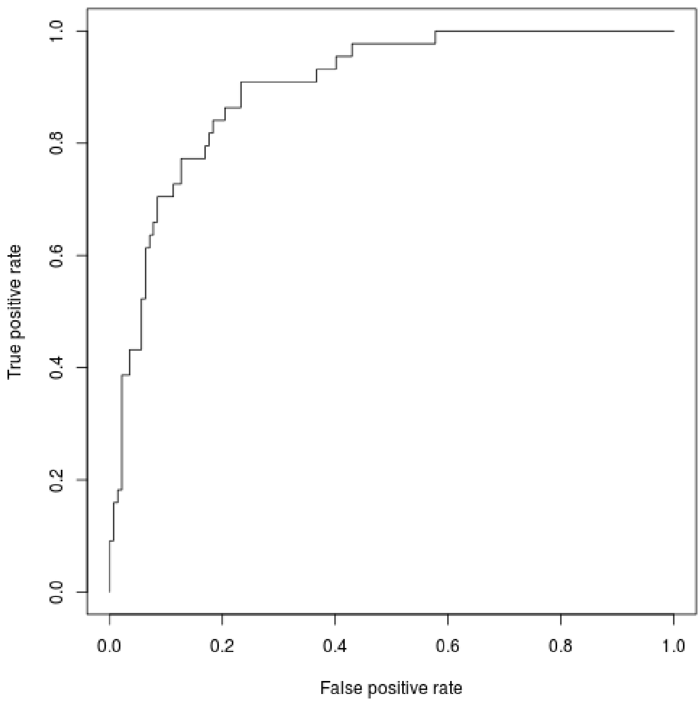
The credit historical information appears to play a dominant role in the model, confirming some results from the preliminary analysis. This can also be appreciated by comparing table 3 with the models emerging from using separate accounting and historical data (tables 4 and 5). The historical data based model includes the same two variables selected in the final multivariate model and shows better diagnostics, as denoted by the *R*-squared (0.33 against 0.24) and AUROC (0.87 against 0.82) values, despite the fact that the accounting data based model is composed of four independent variables (the two selected in the final multivariate model and two additional variables).

5.4. Out-of-sample performance

As a final check, we investigated the out-of-sample performance of our model. A genuine out-of-sample exercise would require us to split the data into two sub-samples: one (the training set) for the model selection and the estimation, the remaining one (the test set) for testing the out-of-sample performance of the selected model. However, because our sample is relatively small, this strategy is not recommended. As a consequence, we have used the following procedure: 1) we have randomly removed from the sample 50 observations relative to the last year of data to try and mimic an out-of-time situation; 2) we have estimated the formulation se-

[10] The ROC provides an image of the classification ability of a classification model. It is built by plotting the false (*x* axis) and the true positive rates (*y* axis) for all possible values of the cut-off (starting from 0 at the (1, 1) corner, and ending at 1 at the (0, 0) corner). The worst possible model has a straight line-shaped ROC (the (0, 0) – (1, 1) segment); the perfect model has an angular-shaped ROC (the (0, 0) – (0, 1) – (1, 1) broken line). The area under the ROC, between 0.5 and 1, is used as an index for evaluating the classification ability of the model (higher is better).

Figure 1 – *The ROC curve*



Source: authors' elaboration on ad hoc database provided by an Italian lender.

lected in the multivariate analysis for the remaining 137 observations; 3) we have tested the out-of-sample performance by means of the Hosmer-Lemeshow statistic and the AUROC. This procedure was replicated 500 times, and some statistics are reported in table 6.

We note that the Hosmer-Lemeshow statistic tends to deteriorate when moving from the training sample to the test sample: the percentage of rejections is around 23% for the full model and above 30% for the model based on credit history variables, in sharp contrast with the same statistics computed in the sample. What is remarkable, however, is the stability of the same quantity in the accounting variable based model. This

Table 3 – *Final multivariate model*

	Estimate	Std. Error	Z value	$\Pr(>\lvert z\rvert)$
(Intercept)	-5.3687	1.1130	-4.824	0.0000 ***
Turnover/total assets	-1.2348	0.5731	-2.154	0.0312 *
Cost of sales/turnover	4.4858	1.5413	2.91	0.0036 **
Usage ratio of continuous credit lines	0.0142	0.0061	2.331	0.0198 *
Usage ratio of unfunded credit	0.0290	0.0049	5.934	0.0000 ***
R-squared	0.3939			
AIC	133.34			
BIC	149.47			
Hosmer-Lemeshow diagnostic *	3.5357		0.8964	
AUROC	0.8993			

* for the Hosmer-Lemeshow diagnostic, the p-value of the statistic is shown.

Table 4 – *Multivariate model resulting from using accounting data only*

	Estimate	Std. Error	Z value	$\Pr(>\lvert z\rvert)$
(Intercept)	-4.95915	1.0834	-4.5780	0.0000 ***
Turnover/total assets	1.90001	0.5477	3.4690	0.0005 ***
Cost of sales/turnover	3.96847	1.3412	2.9590	0.0031 **
Liabilities/net assets	0.04903	0.0232	2.1170	0.0343 *
Retained earnings/total assets	-11.77224	3.6358	-3.2380	0.0012 **
R-squared	0.2356			
AIC	168.6024			
BIC	184.8111			
Hosmer-Lemeshow diagnostic*	8.0396		0.4296	
AUROC	0.8183642			

* for the Hosmer-Lemeshow diagnostic, the p-value of the statistic is shown.

Source: authors' elaboration on ad hoc database provided by an Italian lender.

Table 5 – *Multivariate model resulting from using historical data only*

	Estimate	Std. Error	Z value	$\Pr(>\lvert z\rvert)$
(Intercept)	-4.360109	0.6511	-6.6970	0.0000 ***
Usage ratio of continuous cred-it lines	0.012105	0.0055	2.2070	0.0273 *
usage ratio of unfunded credit	0.028601	0.0047	6.1430	0.0000 ***
R-squared	0.3349			
AIC	141.7105			
BIC	151.4038			
Hosmer-Lemeshow diagnostic*	2.7673		0.4296	
AUROC	0.8738			

* for the Hosmer-Lemeshow diagnostic, the p-value of the statistic is shown.

Source: authors' elaboration on ad hoc database provided by an Italian lender.

fact suggests attributing this behaviour to the credit history variables: their statistical treatment appears adequate in the full sample but not perfect when a portion of the data is removed.

In contrast, the out-of-sample predictive performance, as measured by the AUROC, remains good, without deteriorating in comparison to the training set and definitely in line with the values obtained in the whole sample (tables 3 to 5). Again, the use of both kinds of variables is confirmed as superior to the models with separate variables, although credit history information dominates. This out-of-sample analysis supports the validity of our model.

6. Discussion of results

In the final model, four variables with the expected sign result are significant. Such a limited number of variables reduces the risk of overfitting, which is always possible with a relatively small number of observations. The correlations among the selected variables are rather small.

As noted above, the model built using both sources of data simultaneously (table 3) is different from that obtained by running separate models for accounting (table 4) and historical credit data (table 5), with only a partial overlap in the variables included in the two sources model. The ratio between the residual deviance and the null model deviance confirms the dominance, in terms of predictive capability, of the historical credit variables. the most significant of which being the 'usage ratio of unfunded credit.'

The elaborated model produces the results that answer the hypotheses.

Looking at the first hypothesis, the capitalisation level seems not to have a direct effect on the probability of default. With reference to our case, we can state the following conclusion: *a higher capitalisation of an SME does not generate a direct increase in its credit standing.*

Looking at the first hypothesis, the capitalisation level seems not to have a direct effect on the probability of default. With reference to our

Table 6 – *Out-of-sample tests*

	Hosmer-Lemeshow						AUROC			
	In-sample			Out-of-sample			In-sample		Out-of-sample	
Model	Mean	Median	Significant	Mean	Median	Significant	Mean	Median	Mean	Median
Full	4.67	4.26	0 %	12.08	10.50	23.0%	0.903	0.903	0.898	0.900
Accounting based	6.74	6.36	0.2%	7.20	6.90	0.2%	0.800	0.800	0.832	0.834
Credit History based	5.92	5.83	0%	13.77	12.95	30.8%	0.880	0.881	0.876	0.878

Source: authors' elaboration on ad hoc database provided by an Italian lender.

case, we can state the following conclusion: *a higher capitalisation of an SME does not generate a direct increase in its credit standing.*

This conclusion is strengthened by the evidence regarding our second hypothesis, which concerns the role played by the weight of borrowing cost. First, there are no indicators concerning the weight of the cost of debt in our final model. Secondly, there are not even any net profitability variables on which an increased level of interest could have an effect. Hence, we can draw this conclusion: *the increase in the weight of borrowing cost does not have direct effects on the SME's rating.*

Nevertheless, for an SME in crisis, an increase of indebtedness and/or a heavier cost of debt could be, indirectly, risky, as they can cause additional financial stresses.

This consideration turns attention towards our third hypothesis, which concerns the importance of credit historical data. Among the four explanatory variables that are pointed out by our model (see table 3), two of them measure the credit relationship quality: *usage ratio of unfunded credit* (with positive sign) and *usage ratio of continuous credit lines* (with positive sign). Substantially, they measure the same phenomenon, the short-term cash needs of a company in comparison to its relative banking credit. Thus, we reach our fourth conclusion: *the usage ratio of short-term lines of credit is the main determinant of the rating.*

The fact that the most explanatory variable comes from credit history confirms our third hypothesis, leading us to conclude: *historical credit data is prevalent in the IRB systems for SMEs*.

Finally, the results point out that if net profitability measures are not predictive of a default, operating profitability measures are. In fact, *cost of sales/turnover* and *turnover/total assets* are the other two significant variables in the model. Thus, our last hypothesis is confirmed: *an increase in profitability improves an SME's rating*.

7. Conclusions

The Basel III Accord is strengthening bank capital requirements, and it is expected to impact SME financing.

In order to investigate the determinants of SME credit worthiness in banks that have adopted an IRB approach, we developed a logit model for a one-year estimation of the probability of default, The model is exclusively calibrated for SMEs (as defined by the Accord). We considered credit historical data in addition to financial statement data.

All of the variables/indicators found in the literature and in banking standards were collected under three main branches: profitability conditions, solvency and liquidity conditions and credit relationship quality.

The model, through the application of the logit methodology to 188 Italian SMEs, confirms that credit historical data is predominant in the credit rating of an SME, Looking at its determinants, two main factors of crisis seem capable of better detecting and perceiving the likelihood of default: loss of profitability and deterioration of the quality of the credit relation. The most important factor is the credit relation, expressed by the usage ratio of short-term lines of credit. The second cause is a drop in profitability, which is measured by operating margins and efficiency of capital employed.

For sure, this last measure, based on profitability measures, may be more linked to industry characteristics than other variables. In any event, it underlines the centrality of competitive factors for the default evaluation process. We could think the margins on sales are quicker than debt ratios in responding to the effects of a loss of competitiveness. In fact, an increase in the capitalisation level is not able to improve the firm's rating, as commonly stated. The same conclusion is valid for the weight of the borrowing cost.

Assuming a macroeconomic point of view, credit worthiness systems based on profitability measures, instead of leverage, should make the credit allocation process more efficient, linking the financing of SMEs to their competitive strength. On the other hand, the different phases of the economic cycle are reflected in the profitability levels. It could cause procyclical effects in the financing system, penalizing SMEs right at the moment when they should be bolstered to a greater extent (Saurina and Trucharte, 2007).

This work focuses on a specific sector of activity. Thus, it does not take into account the industry risk. A future attempt could be made to test the weight of the industry risk on the determinants we have found. Another limitation concerns the defaulted companies included in our sample. They occupy the 'bad debt status' positions assigned by the bank, and this is not fully compliant with Basel II rules, which maintains a broader definition of 'default.'

Moreover, the model we have developed does not include qualitative information. Future research could aim to set out the qualitative determinants in the rating judgment and how this data affects financial and credit historical determinants.

Finally, because of the high heterogeneity in the economic and market characteristics of the different countries, it might not be correct to extend to other countries the result which was obtained through a sample of Italian SMEs. According to Udell (2004), it could be worthwhile to assess if the bank rating systems for SMEs developed in other countries are based on the same determinants defined by our work and, if necessary, to examine the differences.

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Appendix 1 – *Descriptive statistics for the default estimation indicators*

	Mean	S.D.	Min	Q1	Median	Q3	Max
ROE1 = earning from continuing operations / net assets	0.624	1.218	-2.593	0.057	0.319	0.915	9.684
ROE2 = net profit / net assets	-0.071	0.686	-7.118	-0.079	0.028	0.125	0.928
ROA = EBIT / total assets	0.048	0.075	-0.324	0.015	0.057	0.091	0.300
ROI = EBIT / net investments	0.124	0.202	-0.716	0.037	0.117	0.210	0.832
ROS = EBIT / turnover	0.035	0.110	-0.809	0.016	0.049	0.076	0.490
turnover / total assets	1.139	0.522	0.083	0.786	1.044	1.443	2.972
total purchases / turnover	0.475	0.216	0.000	0.343	0.472	0.575	1.982
net assets / turnover	0.278	0.652	0.002	0.062	0.142	0.295	6.564
total assets / turnover	1.200	1.204	0.336	0.693	0.958	1.273	11.990
labour costs / value added	0.558	1.318	-16.349	0.493	0.616	0.800	2.748
labour costs / turnover	0.161	0.114	0.004	0.072	0.133	0.226	0.625
cost of sales / turnover	0.480	0.282	0.000	0.332	0.463	0.578	3.074
depreciation rate	0.080	0.067	0.000	0.041	0.061	0.101	0.438
ROD = interests on debt / financial debt	0.123	0.205	0.000	0.061	0.083	0.134	2.460
ROI – ROD	0.004	0.263	-2.022	-0.074	0.026	0.097	0.792
ROA – ROD	-0.074	0.202	-2.278	-0.090	-0.038	-0.004	0.171
working capital / turnover	0.327	0.286	-0.597	0.168	0.289	0.458	1.513
trade receivables days	132.657	105.205	0.000	84.129	116.066	152.766	1148.350
stock in hand days	96.222	74.235	0.000	41.771	82.112	135.922	483.046
trade payable days	148.275	206.975	0.000	94.004	114.373	143.720	1878.423
cash and cash equivalents / total assets	0.044	0.079	0.000	0.002	0.020	0.051	0.595
operating cash flow / short term debt	3.869	28.024	-0.973	0.126	0.253	0.524	323.085
operating cash flow / financial debt	1.860	14.906	-0.973	0.096	0.187	0.335	191.534
operating cash flow / interests on debt	4.672	18.561	-9.183	1.281	2.053	3.877	191.534
short term credit granted / net assets	607.140	1272.226	0.000	58.554	223.288	662.294	12111.521
short term credit granted / total assets	67.869	89.033	0.000	5.597	35.439	92.654	528.743
(revolving credit facilities granted + overdraft credit facilities granted) / net investments	181.940	193.780	0.000	65.430	122.952	228.162	1352.452
current assets / current liability	1.214	0.425	0.155	0.988	1.142	1.389	4.196
(current assets – stock) / current liability	0.800	0.401	0.129	0.587	0.716	0.919	4.196
net financial position / turnover	0.433	0.490	-0.763	0.186	0.340	0.554	5.024

Appendix continues

Appendix continued

	Mean	S.D.	Min	Q1	Median	Q3	Max
net financial position / net assets	4.833	7.015	-5.329	0.999	2.446	6.189	45.382
net financial position / total assets	0.346	0.207	-0.595	0.251	0.365	0.485	0.748
short-term debt / long-term debt	10.511	51.972	0.000	1.011	2.262	4.904	518.222
short-term debt / net assets	3.964	6.096	0.000	0.777	1.854	4.794	36.097
short-term debt / total assets	0.281	0.157	0.000	0.187	0.286	0.370	0.853
long term credit granted / tangible assets	1650.042	4098.766	0.000	67.967	529.212	1467.239	34546.553
liabilities / net assets	16.191	89.282	0.229	2.460	5.064	11.668	1225.395
liabilities / total assets	0.754	0.157	0.185	0.659	0.788	0.871	0.990
retained earnings / net assets	0.421	0.473	-0.687	0.122	0.397	0.663	4.337
retained earnings / total assets	0.085	0.116	-0.134	0.009	0.038	0.127	0.582
funded credit granted / turnover	115.752	355.567	0.000	0.000	20.340	121.505	4493.910
funded credit granted / net assets	773.927	1873.673	0.000	0.000	164.259	746.720	14901.964
funded credit granted / total assets	73.233	100.055	0.000	0.000	26.074	117.233	541.005
unfunded credit granted / turnover (x 1000)	0.245	0.549	0.005	0.063	0.141	0.281	6.579
unfunded credit granted / net assets (x 1000)	3.315	6.615	0.014	0.332	0.979	3.009	48.426
unfunded credit granted / total assets (x 1000)	0.237	0.276	0.006	0.055	0.143	0.324	2.141
(revolving credit facilities + overdraft credit facilities – financial investments) / turnover	263.518	202.173	-0.018	137.083	227.271	365.677	1523.502
(revolving credit facilities + overdraft credit facilities – financial investments) / net assets	3418.202	5020.253	-0.259	612.330	1665.904	4019.570	30766.058
(revolving credit facilities + overdraft credit facilities – financial investments) / total assets	261.034	173.165	-0.049	137.667	245.256	377.614	967.239
usage ratio of revolving credit facilities	61.441	33.401	0.000	40.602	64.982	82.082	249.425
usage ratio of continuous credit lines	56.883	60.961	0.000	0.000	54.212	88.760	540.244
usage ratio of funded credit	77.164	35.890	0.000	61.729	87.510	100.000	208.242
usage ratio of unfunded credit	91.489	164.602	0.000	14.177	57.588	106.052	1724.947
usage ratio of overdraft credit facilities	50.445	113.533	0.000	0.000	0.000	96.625	1339.332
revolving credit facilities utilized / accounts receivable	760.705	1637.691	0.000	297.320	562.822	876.677	21861.375

Source: authors' elaboration on ad hoc database provided by an Italian lender.