A credit risk model for Italian SMEs

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Abstract

We use a multiple-factor credit risk model to provide new estimates of default probabilities in a sample of Italian Small and Medium-sized Enterprises. Results show that, on average, SMEs are riskier than large businesses within the retail segment. It is possible to distinguish different segments inside the SMEs' population based on geographical location, sector of activity and juridical status.

JEL: G18, G21, G28

Key words: Credit risk, SME finance, probability of default

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1. Introduction

On January 1, 2007 the New Basel capital accord (Basel II) will be implemented in all European countries. The new accord substituting Basel I introduces capital requirements rules for banks depending on different degree of riskiness of the borrowers. The assignment of ratings to each firm allows to define a different capital absorption and - more in general - will deliver creditworthiness on the basis of objective criteria, less prone to idiosyncratic characteristics or subjective to the non-economic terms.

A large body of literature has grown addressing several issues of the Basel II Accord, primarily lead by the need to establish a sound method to estimate the probability of default (PD), as well as to study the effects of the accord on the total capital absorption from bank's perspective.

In the present paper we take a perspective rather different with respect to the existing literature: we consider a sample of 3,900 firms with a turnover less than or equal 5 millions of euros and the PD by using a definition more ample than what has been typically used in the literature. We distinguish among firms having no financial distress at all from firms with several types of financial distress including for example, delay in mortgage payments for more than 90 days, but also delayed repayments. In particular, the event "default" includes loans classified as non performing, substandard and loans past due 90 days, and also the event of delayed payments by the firm for a period between 30 and 90 days. This information is not disentangled from defaults defined in a narrower sense and can be interpreted at least as an early warning to the bank in order to detect future situations of stress in loan repayments and possibly defaults. Because of this feature, we believe that the model developed is suitable to assign an early score to the credit quality of a customer, being helpful in anticipating the event of default.

We develop such a credit risk model for retail portfolios of loans granted to SME firms. We implement a logit estimation through a stepwise variable selection process. The model is specified both in ratios (with respect to total asset value) and in levels and results are not vulnerable to the model specification. Secondly, earning performance ratios are highly significant and negatively correlated with PD[1]. Third, regional and sectorial effects modify substantially the PD on Italian market. We show that the qualitative variable capturing the firm-bank relationship plays an important role in predicting the PD: the longer is the relationship between the bank and a specific firm, the lower is firm's PD. We elaborate our results by conditioning the model with respect to different juridical structures: in particular we differentiate out estimates whether the firms are cooperative firms or share corporate. Also on this case significant differences emerge.

One of the main point of the Basel II accord is given by the different treatment of firms of different size. In fact, the assignment of a rating to a firm is a common (albeit different) exercise of large corporations. The novelty of Basel II is the opportunity to define a rating also for smaller firms, not listed on Stock market. The recent literature on Basel II accord has been mainly concerned with the evaluation of capital requirements and rating evaluation of the firms of large and medium size. However, for some countries SMEs represent the backbone of the economy, constituting an important contribution to their GDP and to the sustainability of their employment levels. Small and micro-firms represent a substantial part of the Italian economy (almost 90 percent of total firms). The largest part of Italian firms are in fact owned by families and are of small size, with a turnover smaller than 5 millions of euros. Therefore, it is extremely important to evaluate the impact of the Basel II accord in for the small firms. The main concern derives from the general perceptions that SMEs carry higher risk and imply higher capital requirements than under Basel I. After several evaluations and simulations, the rules of capital requirements have been weakened with respect to the original version. Under the recent version, the SMEs with turnover less than 5 millions of euros (the sample employed in this study) are classified under the retail sector, implying a capital requirement less severe for all the rating class, if compared with the other firms' size. Within the retail segment, we show that the probability of default appears to be inversely correlated with firm's size, where firm's size is measured both in terms of number of workers and in terms of volume of sales. Saurina and Trucharte (2004) obtained a similar result for Spanish economy measuring firm's size by its volume of sales.

A consequence of Basel II Accord for the banks is that if SME are classified as retail, the credit must be managed as a retail exposure: the exposure must be one of a large pool of exposures which are managed by the bank on a pooled basis. The model we are going to estimate is based on a sample of firms assembled by one of the largest Italian bank in order to be representative of his retail portfolios. This is a novelty, since most of existing studies draw samples from national registers, which collect data on balance sheets and income statements, without constructing representative samples of banks' portfolios.

The literature on Basel II in general finds that both for Europe and US, the new Basel Capital Accord will have beneficial effects on banks capital requirement for the SME segment. In general, it is found that under the Standardized Approach, there are no advantages in computing capital requirements if the SMEs are considered as corporate (8% capital requirement, as before). On the other hand, if SMEs are classified as retail, the risk weight is reduced to 75% (from 100%), implying a capital requirement equal to 6%[2]. For this reason, it is particularly important to have design a credit risk model for the retail able to carefully discriminate among various risk categories, in order to identify an adequate capital requirement. For Italian economy, Altman and Sabato (2004) evaluate the capital requirement for the SMEs segment to be 4.88%, 8.245% for firms with a turnover within the range 5-25 millions of Euro, and 9.656% for the range 26-50 millions of Euros. Lusignani and Bocchi (2004) instead, find an average capital requirement equal of 7.65%. Our study does not deal with the issue of capital requirements, because of the broader definition of "default", that overestimates the probability of default since it includes delayed payments and not proper defaults, according to the definition of Basel II Accord.

The rest of the paper is organized as follows. In Section 2, we briefly review the main aspects of credit risk measurement. Main features of dataset are enlightened in Section 3. Section 4 provides the structure of the developed credit risk model, and the main results regarding the estimated PD for Italian SMEs by means of using default information contained in a retail portfolio of a commercial bank. Section 5 draws some conclusions.

2. Literature review

Traditional models of credit risk measurement focus on estimating PD and typically define "default" as the event of bankruptcy, liquidation or insolvency. The most commonly used traditional credit risk measurement methodology is discriminant analysis, which has been applied successfully to forecast firms' default. Multiple discriminant credit scoring analysis was pioneered by Altman (1968) with z-score model: discriminant analysis identifies financial variables that have statistical explanatory power in differentiating defaulting firms from non-defaulting firms. Once the models' parameters are obtained, loan applicants are assigned a z-score assessing their classification as good or bad[3]. In the original version, Altman used linear discriminant analysis (LDA) to predict up to 3 years in advance bankruptcy in a sample of 33 sound and 33 unsound manufacturing firms, using five economic financial variables. Altman, Hadelman and Narayan (1977) extend z-score approach, including seven explanatory variables and find supporting evidence of predictive ability of LDA on an out-of sample set.

Several studies has been conducted to improve Altman's results, using different parametric, semiparametric and non parametric approach. Among parametric approach[4], logit models[5] are commonly used for scoring purposes both in economic literature and in studies conducted by Central Banks in Italy, Germany, Austria, France, United Kingdom. Altman and Narayanan (1997) surveyed the use of credit scoring models throughout the world, pointing out that all studies limited attention to quantitative data only and found that financial ratios measuring profitability, leverage, and liquidity had the highest statistical explanatory power in differentiating defaulted from non-defaulted firms[6].

A number of studies has been conducted on European data sets[7]. Platt and Platt (1990) applied a logit analysis to predict bankruptcy with interesting results in terms of classification performance. Laitinen (1999) predicted default using a data set on 3,200 Finland firms and selecting 15 variables out of 35; in the out of sample set sensitivity is 93.75% with specificity equal to 96.35%. Dietsch and Petey (2004) develop a one-factor credit risk model to assess estimates of stationary default probabilities and asset correlation for class of small medium firm, in order to assess the effects of new regulation of Basel II. Authors use data on internal ratings assessment from two large European financial information providers for an average 5-year period. Results show that, on average, SMEs are riskier than large businesses; asset correlations in the SME population are very weak (1-3%) and decrease with size. Moreover, they do not find evidence supporting a negative relationship between asset correlations and PD across rating grades as assumed by Basel II; in particular over French data, the correlation increases with PDs, while the relationship is unclear over German data. The authors explained the results in terms of segmentation on the basis of credit quality: while the segment of firms with good credit quality defaults are driven by positions in the business cycle, the one with average credity quality is populated by firms where defaults depend on specific factors of management and access to productive and financial resource; for subprime segment firms with low credit quality tend to be sensitive to macroeconomic conditions. Then this explains the non-monotonic relationship between average PD and asset correlations.

We focus our attention on studies on Italian firms[8]. Cannata, Fabi and Laviola (2002) provide an empirical estimation of PD using a logistic model. The data set consists of quantitative, but not qualitative information on a sample of 180,000 Italian firms, collected by Company Accounts Register

(CERVED) and Credit Register (of the Bank of Italy). Default is defined as the event of non performing loan for the first time in a certain year by lending bank; this is a narrower definition with respect to the one used in Basel II, since it does not include substandard loans and loans past due 90 days. A stepwise procedure is used to select significant explanatory variables and the procedure is run conditionally on the economic sectors (manufacturing, trade, construction) across which SMEs are distributed. They show that SMEs are characterized by higher PDs, with an average PD of 1.6 for SMEs with sales less than 5 million euro. Using the estimated logistic model, Fabi, Laviola and Marullo Reedtz (2003, 2005) show that Basel II Accord will lead to a substantial decrease in capital requirements for banks using Internal Rating Based (IRB) foundation approach; the capital requirement reduction is estimated to be 21% for portfolios constituted by corporate firms, 25% for SMEs, and 29% for SMEs with sales less than 5 million euro. Other studies apply logit model to examine the effect of Basel II Accord on capital requirements for Italian banks. Bocchi and Lusignani (2004) perform an analysis on 75,000 SMEs (according to Basel Committee, April 2003), obtained by pooling data of 15 medium sized banks. 24% of firms in the sample are classified as corporate SMEs and the remaining 76% retail SMEs[9]. This study estimates the PD using a logit model at a-point-in-time basis, assuming Exposition At Default (EAD) equal to zero and a Loss Given Default (LGD) of 43%. Default is defined as the occurrence of non-performing loans, substandard loans, but past due for more than 90 days are not included. In the period under scrutiny, two third of exposures are associated with firms with PD less than 2%. Because at a PD of 2% capital requirement is evaluated at 8%, as in Basel I Accord, the new Capital Accord will reduce capital requirements for higher proportion of SMEs firms. The authors provide evidence of the negative relationship between firm size and PD, assumed by Basel II Accord, since the PD distribution by rating classes of retail SMEs lies to the right of the one derived for corporate SMEs.

A number of papers tried to assess the effect of Basel II on credit pricing. Using data from Bank of Italy, Maino and Masera (2004) show using simulation techniques that the cost of credit should stay the same for averaged rated SMEs (i.e. for those SMEs rated BB), which is in line with market evaluation of risk. On the contrary, SMEs rated below BB will experience a sharp increase in the cost of credit. The main effect on the cost of credit due to Basel II will be to stop cross-subsidization among SMEs, since banks will be able to discriminate across firms on the basis of PDs: less efficient and productive SMEs, with higher PD, will pay a higher cost of credit, reflecting the higher risk banks incurred in financing them.

3. Dataset

The data base we use in our empirical study is provided by a large commercial Italian bank, whose lending activity is concentrated on the Italian market. The data set displays unique features with respect to all the other studies available on Italian firms, as Fabi et (2003), Bocchi and Lusignani (2004), Altman and Sabato (2004).

The data set is representative of the retail portfolio of the commercial bank, from which the sample is drawn. It is designed to replicate the distribution of exposures of the bank's overall retail portfolio both by region, by sector of activity and by firm's size. This offers the possibility to evaluate credit risk for retail portfolios, within the Basel II framework, using similar data available for the bank internal credit risk evaluation system. This constitutes an absolute novelty for studies conducted on Italian firms, since all studies available use information on samples drawn from CERVED's company accounts register, where balance sheets and income statements of a large set of Italian firms are collected, without any reference to the actual bank portfolios.

The data set contains detailed financial information on 3,900 firms whose annual sales are less than 10 millions Euro, classified as SMEs under the broad definition adopted in the latest consultation document (Basel Committee, April 2003). The sample is however concentrated on "retail SME" firms[10]: 98% of the sample firms have annual sales less than 5 millions Euros and exposure with the bank of less than one million Euros.

INSERT TABLE 1

From the inspection of table 2, 95% of firms in the data set have a number of workers less than 4, confirming that the data set is concentrated on small firms. Additionally, more than 90% of firms have the legal form[11] typically chosen by firms with small business, as shown in Table 3. The geographical location of firms is displayed by Table 4: more than three quarters of firms in the sample are located in the Northern and Central part of Italy. The data set displays a higher proportion of firms located in the Northern and Central part of Italy, with respect to average Italian historical data; a possible explanation consists in the fact that the bank's headquarters are located in Northern Italy. Table 5 shows the distribution of firms by sector of activity: firms are more concentrated in manufacturing, service and distribution sectors.

INSERT TABLE 2

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INSERT TABLE 5

The estimates of PD captured in this work are obtained within the framework of internal rating-based models; in particular we use the logit family of statistical models. A logit model is applied to the population of firms in order to assess their PD. This procedure often relies on quantitative and qualitative information; our qualitative information is limited to data on the characteristics of bank-firm relationship, even after the default.

In the following, the default is defined in a broader perspective with respect to Basel II framework: the event "default" includes loans classified as non performing, substandard and loans past due 90 days, but also the event of delayed payments by the firm. For this reason we rename the default as the variable "stress". Stress is equal to 0 for all sound firms and 1 for the unsound ones.

The definition of default is broader with respect to the ones envisaged by the Basel Committee and used in empirical studies on Italian firms[12], as it includes firms which are not up to date with payments of bank debts, but are not necessarily going bankrupt. This information is not disentangled from defaults defined in a narrower way and can be interpreted as an early warning to the bank in order to detect future and more serious problems of loan repayment. Because of this feature of the event "default", we believe that the model developed is suitable to assign an early score to the credit quality of a customer and therefore it could be helpful in order to anticipate the event of default at an intermediate stage in the process of credit quality assessment. This implies that the probability of default will be higher than the usual models. Note that this implies that rating classes are not comparable.

The geographical distribution of sound and unsound firms is reported in table 6, while table 7 reports sound and unsound firms distribution with respect to firm's size.

INSERT TABLE 6

INSERT TABLE 7

4. Main results

We develop a credit risk model for retail portfolios of loans granted to SME firms. From a methodological perspective, according to the nature of data available and methodological research results as in Crouchy, Galai and Mark (2001), a logit regression is used. The estimation procedure is applied to all 3900 firms in the sample. We implement a stepwise variable selection process, based on a likelihood-ratio test and 20 significant explanatory variables are selected out of about 50 ratios proxying for profitability, liquidity, financial structure, size and geographical location of the enterprises.

Descriptive statistics and the correlation matrix between regressors are shown in Tables 8 and 9, while Table 10 reports our main econometric results under logit regression. We first describe results for all the right-hand variables excluding quality variable on bank-firm relationship and then move to comment on this topic.

INSERT TABLE 8

INSERT TABLE 9

INSERT TABLE 10

The economic theory predicts that the firm will experience increasing difficulties to repay the debt the higher is the level of total debts or the higher is the proportion of short term debt with respect to total debt: the more indebted the firm, the higher will be the cost of credit, and the lower firm's profit, other things equal, and the lower will be the ability of the firm to repay a given debt. We include as explanatory variables in the logit regression total debt level of the firm (TD/TA) and the ratio of short term debt versus total debts (SD/TD), as proxies of the financial structure. TD/TA and SD/TD have a positive and significant impact on PD, i.e. the higher total debts, the higher PDs and the higher short term debt proportionally to total debts, the higher PD.

Also liquidity affects the probability of default: the higher cash flows (or other measures of liquidity), the less likely the firm will be in a situation of financial distress that prevents from repaying the debt, i.e. the higher cash flows, the lower is the probability that the firm runs out of cash in the short term and therefore the lower the probability to go bankrupt. In our estimates, all explanatory variables measuring liquidity (NSF/TA and CF/TA) enter with a negative sign, coherent with economic theoretical predictions, except for net self-financing flow. The regressor NSF/TA is rather puzzling: the variable has a positive significant effect on PD. However, at a deeper level of analysis, more than one third of firms in the sample have negative net self-financing flow, which means that the entrepreneur distracts financial funds from the firm; this phenomenon may occur more likely in small family business in a situation of financial distress: the entrepreneur may sell a firm's asset, as the car, in order to distract funds from creditors in this case. We control for positive levels of net self-financing flow by introducing the dummy variable NSF_P, which takes value 1 in case net self-financing flow is positive. It turns out that the dummy variable is highly significant, with negative sign, as expected.

Moving to the regressors varying with individual firm's profitability, we expect that the higher is firm's profitability, as the earning ratios, the higher is the ability of the firm to attract new investments and generate liquidity to repay debts, and the less likely the firm will default. As expected, ROI is highly significant and negatively correlated with PD, i.e. the higher is the profitability of an investment, the lower is the probability of default of the firm, all other things equal. Analogous result is established for EBIDTA/TA. The return on equity (ROE) has no statistically significant effect on PD, contrary to the result established in Altman and Sabato (2004). This result is probably due to low weight of the equities for very small firms.

The PD appears to be inversely correlated with firm's size; in other terms, the smaller the obligor the greater its probability of default. In this study, firm's size is measured both in terms of number of workers (NW) and in terms of volume of sales (S/TA). For Italian data, the size assumption made by the banking industry and by Basel Committee is confirmed. Saurina and Trucharte (2004) obtained a similar result for Spanish economy measuring the size of the obligor by its volume of sales; it is worth to note, however, that this result emerges at the aggregate level, using default information contained in the Spanish Credit Register and for the banking system as a whole and not for a homogenous retail portfolio of a commercial bank. Additionally, we insert the dummy variable XS for firms with a turnover under 250,000 euro, which has a positive significant sign at 5% level. This implies that firms with very small sales have a higher probability of default, all other things equal; this result adds further evidence confirming the negative relation between PD and firm's size.

Firms are more likely to default when they are limited liability companies (SRL) or limited liability cooperative organisations (SCRL). Firms which choose this juridical structure are, unsurprisingly, small business run by families or entrepreneurs beginning a new business.

Firm’s age contributes in a significant way to predict PDs: the older is the firm, the higher its probability of default. The result can be explained in the light of cycle life theory, according to which a firm with a longer history of business has a lower capability to innovate and be competitive on the market, and therefore it is closer to the decision to shut down.

We insert sectorial dummies: manufacturing and transportation sectors are riskier, other things equal. We check also whether regional location of a firm exerts a different effect in the prediction of PD for different sectors of activity: manufacturing and building sectors have a lower PD in Northern Italy, while services are less risky in Southern Italy. The last result can be surprising at first sight: it may reflect a higher relative efficiency of service sector with respect to the other productive sectors in Southern Italy or, rather a lower competitive pressure on service sector.

Even if the data set offers detailed information regarding balance sheets and financial variables, the qualitative variable BFR still plays an important role in predicting the probability of default. The quality of the relationship is measured by the duration of bank-firm relationship, which captures whether the quality of business relation between bank and firm goes on after a default. The variable contributes in a significant and negative way to explain PD according to Table 10: the longer is the relationship between the bank and a specific firm, the lower is firm's PD. In this case the bank relies on a longer history of observations of the firm and is better able to evaluate firm's financial situation and solvency perspectives and to discriminate whether the firm is experiencing only a temporary situation of financial distress or a more permanent crisis. In fact, if the bank continues to offer financing to the firm, she believes that the firm has concrete opportunities to repay the debt, according to the evolution of its financial situation. The role of bank-firm relationship is especially interesting in the light of the definition of default, which includes delays in repayments of loan even for a period of less than 90 days.

The estimates of PD are used to aggregate sample firms on a scale of 13 PD segments, each corresponding to a range of probability of default; the number of segments is chosen to assure a satisfactory differentiation among classes and a low degree of concentration in terms of both numbers of firms represented and amounts. From the inspection of Table 11, we find that the average estimated PD is higher with respect to standard models, but this is not surprising given the definition of the event default. Even if a comparison with usual rating classes is not possible, we believe that results in table 11 show that the estimated model allows to predict future situation of stress. However, because we cannot disentangle from default definition events as delayed loan repayments, we are not able to evaluate the marginal contribution of this information to the overall estimate of PD.

INSERT TABLE 11

The estimation performed in this exercise has only annual validity, but does not represent an average for a period constituted by many years; this is true even in the light of the difficulty to have good quality information on the past for a so wide data set. The estimated PDs contain predictive elements only in the way past helps to explain future behaviours. On the other side, banks have prospective information on firms' situation and on competitive environment and can modify the estimates in a coherent way on the basis of quantitative methodology. As shown in Table 11, the estimated average PD appears higher with respect to other studies on Italian firms; this is due to the definition of "default" used and shows that the credit risk model estimated is suitable to assign an early score to firms in a situation in financial distress, that may or may not lead to non performing loans as defined in Basel II Accord.

The overall performance is also assessed using the power curve, considering the results of the model in the year of estimation. This curve measures the discriminatory power of the function; that is, the overall ability of the model to distinguish sound from insolvent firms. A related measure is the accuracy ratio, the ratio of the area between the power curve and the random model to the area between a perfect model and the random model. The model produced an accuracy ratio of 84.58% for year 2005, quite a good value with respect to standard point of system. The value of accuracy ratios mentioned in studies regarding Italy and other countries normally ranges between 50 and 70%; for example, in Fabi et (2005) the accuracy ratio is estimated to be around 65% or 74% in Cannata et (2004).

INSERT FIGURE 1 ABOUT HERE

4.1 Robustness analysis

We check for robustness in several directions. First, we consider restricted versions of the model, where we specify three alternative estimation equations; in each specification we consider a subset of explanatory variables, in one we limit our attention to either economic performance ratios variables or liquidity variables or debt structure variables. We perform likelihood ratio tests on restricted models and in all three cases we reject the null hypothesis that the omitted variables in the general model (estimated according to Table 10) have no impact on PDs.

Second, the model is robust to an alternative specification of the explanatory variables in levels, instead of ratios. Results are not vulnerable to the different specification: all the signs of explanatory variables are confirmed, except for NSF/TA that loses significance. Moreover, we do not experience any loss in the predictive power of the overall model.

INSERT TABLE 12

Third, the model is robust to alternative specifications of the underlying statistical model. Table 13 reports statistical significance of explanatory variables for a similar probit specification. As shown in Table 13, previous results are robust to an alternative specification of statistical model, including performance measured in terms of accuracy ratio.

INSERT TABLE 13

The model is robust to heteroskedacity of errors in the logit and probit specification, as shown in the following tables:

INSERT TABLE 14

INSERT TABLE 15

The model is robust to probit estimation, when we control for heteroskedastic variance in the form

$$\mathrm{Var}(\varepsilon)=\exp(\gamma' z)$$

The model is robust to the inclusion in error variance of clusters of explanatory variables, in particular we include subset of variables measuring liquidity or economic performance and all results in Table 10 are confirmed.

4.2 Alternative specification

In previous section a logit model is developed and estimated on the overall dataset. In this section, we check for robustness in terms of prediction errors, by examining the model specification on various subsamples. Because of richness of dataset we aim to show whether the overall model captures more specific characteristics of some subsample. We consider three main characteristics observable at firm's level: the economic sector, the legal form and the geographical location.

First, we estimate a separate regression model for each of the following four economic sectors[13]: construction, commerce, services[14] and manufacturing. A stepwise procedure is run conditionally on economic sectors, in order to select significant explanatory variables.

INSERT TABLE 16

From inspection of table 16, a subset of explanatory variables in Table 10 constitutes the main building block which has explanatory power across economic sectors. Four main variables turn out to be crucial in order to assess credit riskiness: AGE as a proxy of individual characteristics of the firm, TD/TA and S/TA as financial economic variables, and BFR as a qualitative variable. The results are quite unsatisfactory for construction, probably because of the bad quality data of the sector, a common problem in empirical literature. Restricting our attention in manufacturing, commerce and service sectors, the main results in Table 10 are relatively stable across economic sectors. However, the submodels produce quite a good accuracy ratio, ranging from 82.66% for manufacturing to 87.24% for commerce. Despite unsatisfactory results, the accuracy ratio is 83% for building sector.

Second, we control for geographical location: the estimation procedure is applied to all firms in the sample divided into three main geographical areas: Northern Italy, Central Italy and Southern Italy. We create a dummy variable indicating whether the firm is located in Northern[15], Central or Southern Italy and a separate logit regression model is estimated for each area. Results are reported in Table 17.

INSERT TABLE 17

Parameters of the model are quite stable in Northern and Central Italy, confirming main results shown in Table 10. The model is instead relatively unstable for Southern Italy, a problem commonly experienced in empirical works on Southern Italy. A good estimation performance is confirmed even for geographical submodels, that produce an accuracy ratio equal to 80.39% in the North, 87.58% in Central Italy and 91% in the South.

Regarding legal form of firm, we limit our attention to firms in the form of limited liability company (SRL) and limited liability cooperative society (SCRL), that constitute 98% of the sample. We run a logit regression conditional on being either a limited liability company or a limited liability cooperative society.

INSERT TABLE 18

We provide a comparative analysis of credit risk associated with loans granted either to no profit or for profit SME firms. This analysis constitutes a useful starting point for credit risk assessment for cooperative firms on Italian market and becomes particularly important in the light of the recent possibility granted to no profit firms to raise financial funds on capital markets under certain conditions. As it can be noted, cooperative firms located in Central Italy appears to be less risky than the ones located in Northern and Southern Italy; in Central Italy the cooperative movement is more deeply rooted in the economic system and appears to have a competitive advantage in terms of higher financial stability. Accuracy ratio is 97.5% for limited liability cooperative association, albeit the quite low number of defaults reduces the reliability of this result.

5. Conclusions

According to Basel II Accord, the trend in retail credit decision making is strongly toward increased reliance on econometric models of credit risk measurement. Retail lending has gradually shifted from relationship lending to transactional (portfolio-based) lending. One problem with transactional lending is that if all banks use the same or similar models, certain borrowers may be rationed out of the market with a higher probability than with relationship lending. Moreover, model risk may cause increased correlations in bank returns, engendering cyclical fluctuations in the financial condition of the banking sector, with potentially macroeconomic consequences.

A great heterogeneity appears to be on credit risk modelling: no standard model emerge from literature, while several proposals use different parametric, semiparametric and non parametric models, stressing on both explicative and predictive capabilities. We estimated a credit risk model to assign an early score to firms going through a situation of financial distress.

In this setting, several financial ratios have a significant effect on PD: sales, EBIDTA and ROI affect negatively PD; on the contrary, proxies for financial structure and debt level affect PD positively.

Size matters also within the retail segment: smaller firms in the SMEs sectors have a higher credit risk, all other things equal. Moreover, the legal form has a significant effect on PD: limited liability and cooperative limited liability firms are riskier, other things equal. Finally, sector and geographical location matter.

References

[1] Allen L., G. De Long and A. Saunders (2004) Issues in the credit risk modelling of retail markets, *Journal of Banking & Finance*, **28**, 727—752

[2] Altman, E. I. (1968) Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance*, **23**, 589—609.

[3] Altman, E. I, R. Hadelman and P. Narayanan (1977) Zeta Analysis. A new model to identify bankruptcy risk of corporations, *Journal of Banking and Finance*, 29--54

[4] Altman, E. I., G. Marco and F. Varetto (1994) Corporate distress diagnosis: Comparison using linear discriminant analysis and neural networks (the Italian experience). J*ournal of Banking and Finance*, **18**, 505—529.

[5] Altman, E. I. and P. Narayanan (1997) An international survey of business failure classification models, *Financial Markets, Institutions and Instruments* **6**.

[6] Altman, E. I. and G. Sabato (2004) Global Effects on the New Basel Capital Accord's Implementation on SMEs, mimeo.

[7] Baetge, J., M. Muss and H. Niehaus (1988) The use of statistical analysis to identify the financial strength of corporations in Germany, *Studies in Banking and Finance*, **7**, 183--196

[8] Barniv, R. and J. B. McDonald (1999) Review of Categorial Models for Classification issues in accounting and finance, *Review of Quantitative Finance and Accounting*, **13**, 39--62

[9] Basel Committee on Banking Supervision, 2001. Results of the Second Quantitative Impact Study, November

[10] Basel Committee on Banking Supervision, 2003. Quantitative Impact Study 3 - Overview of Global Results, May

[11] Basel Committee on Banking Supervision, 2004. International Convergence of Capital Measurement and Capital Standards: a Revised Framework, June.

[12] Bocchi, L. and G. Lusignani (2004) Le nuove Regole di Basilea 2: prime valutazioni di impatto sul Rapporto Banca-Impresa in Italia, Banca, Impresa, Società vol. **XXIII (2),** 209--237.

[13] Cannata, F., F. Fabi and S. Laviola, (2002). Rating interni e gestione del rischio di credito: la misurazione delle probabilità di insolvenza, *Bancaria*, **4,** 45--62

[14] Crouchy, M., D. Galai and R. Mark (2001) A Comparative Analysis of Current Credit Risk Models", J*ournal of Banking and Finance*, **24**, 59--117

[15] Dietsch, M. and J. Petey (2002) The credit risk in SME loans portfolios: Modelling issues, pricing and capital requirements", *Journal of Banking and Finance*, **26**, 303-322

[16] Earl, M. J. and D. Marais (1982) Predicting corporate failure in the UK using discriminant analysis, Accounting and Business Research.

[17] Fabi, F., S. Laviola and P. Marullo Reedtz (2004) The Treatment of SMEs loans in the New Basel Capital Accord: some Evaluations, Moneta e Credito, *BNL Quarterly Review*, **58**, 29—70.

[18] Fabi, F., S. Laviola and P.Marullo Reedtz (2005) The New Basel Capital Accord and banks' lending decisions, *Journal of Financial Stability*, **1**, 501-521.

[19] Fernandez, A. I. (1988) A Spanish model for credit risk classification, *Studies in Banking and Finance*, **7**, 115--125

[20] Laitinen, E. K. (1999) Predicting a corporate credit analyst's risk estimate by logistic and linear models, *International Review of Financial Analysis*, **8(2)**, 97-121

[21] Maino, R. and R. Masera (2004) Medium sized firm and local production system in a Basel II perspective, mimeo.

[22] Marais, D. A. J. (1979) A method of quantifying companies' relative financial strength, Working paper n. **4**, Bank of England, London

[23] Platt, H. D. and M. D. Platt (1990) Development of a class of stable predictive variables: the case of bankruptcy prediction, *Journal of Business Finance and Accounting,* **17**, 31-51

[24] Saurina, J. and C. Trucharte, (2004) 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 Research*, **26**, 121-144

[25] Von Stein, J.H. and W. Ziegler (1984) The prognosis and surveillance of risks from commercial credit borrowers, *Journal of Banking and Finance*, **8**, 249--268

Appendix

Table 1: Sample distribution of sales

Sales (in thousands of euros)	**Percentual Frequency**
<=250	25.54
251-500	18.94
501-1,000	22.05
1,000-5,000	32.11
5,001-10,000	1.36

Table 2: Sample distribution of number of workers per firm

Number of workers	**Percentual Frequency**
0-3	95.33
4-10	1.69
10-20	1.57
>20	1.41

Table 3: Sample distribution of legal form

Legal form	**Percentual Frequency**
SPA	1.98
SCRL	7.47
SRL	90.55

Table 4: Sample distribution of geographical location of firms

Regions	**Percentual Frequency**
NORTH	29.18
NORTH EAST	22.41
NORTH WEST	12.22
CENTER	23.31
SOUTH	12.89

Table 5: Sample distribution of sectors of activity

Sectors	**Percentual Frequency**
OTHER SECTORS	0.69
AGRICULTURE	1.59
TRANSPORTATION	5.13
CONSTRUCTION	9.27
SERVICES	23.23
COMMERCE	28.88
MANUFACTURE	31.21

Table 6: Sample distribution of the event stress across regions

Region /stress	0	1	Total
NORTH	1,042	95	1,137
NORTH EAST	811	62	873
NORTH WEST	435	41	476
CENTER	818	90	908
SOUTH	454	48	502
Total	3,560	336	3,896

Table 7: Sample distribution of the event stress across firm's size

Sale (in thousands of euro) / stress	0	1	Total
<=250	887	108	995
251-500	662	76	738
501-100	804	55	859
1,001-5,000	1,159	92	1,251
5,001-10,000	48	5	53
Total	3,560	336	3,896

Table 8: Variable description and descriptive statistics

The table shows the descriptive statistics for variables used in the regression for each .
Bank-firm relationship: BFR takes value 1 if the bank has a high quality lending relationship for one year and 2 for at least two years.
Firm specific characteristics: AGE measures firm's months of activity, classified into 5 classes:
class 1: <23 months
class 2: 24-71
class 3: 72-143
class 4: 144-288
class 5: >288
NW measures number of workers hired by a firm, classified into 4 classes:
class 1: 0-3 workers
class 2: 4-10
class 3: 11-20
class 4: >20
Debt structure: SD/TD is measured by the ratio between short-term debt and total debt. TD/TA is the normalised total debt level with respect to total asset value.
Liquidity: NSF/TA is the ratio of the flow of net self financing (owned as reserve by a firm) and total asset value. CF/TA is the ratio of cash flows and total asset value. S/TA is the ratio of annual sale volume and total asset value. XS is a dummy variable that takes value 1 if firm's annual sale volume is less than 250,000 euro and 0 otherwise. S is a dummy variable that takes value 1 if firm's annual sale volume is less than 500,000 euro.
Economic performance: EBIDTA/TA measures the ratio of EBIDTA and total asset value. ROI is the measure of the return on investment, according to standard definition.
North is a dummy variable that takes value 1 if the firm is located in a region in Northern Italy and 0 otherwise. South is a dummy variable that takes value 1 if the firm is located in a region in South Italy and 0 otherwise.
Transport is a dummy variable that takes value 1 if the firm operates in the transportation sector and 0 otherwise. Service is a dummy variable that takes value 1 if the firm operates in the service sector and 0 otherwise. Manufacture is a dummy variable that takes value 1 if the firm operates in the manufacturing sector and 0 otherwise.

Regressors	Mean	Standard deviation	Minimum	Maximum
BFR	1.761	0.427	1	2
AGE	2.601	1.246	1	5
NW	1.090	0.444	1	4
SD/TD	0.813	0.205	0	1
TD/TA	0.908	0.628	0	1
NSF/ TA	0.004	0.412	-13.957	9.667
NSF_P	0 .485	0.499	0	1
CF/TA	0 .031	0.451	-13.957	14.667
S/TA	2.152	2.595	0.0133	62.5
XS	0.256	0.436	0	1
S	0.189	0.391	0	1
EBIDTA/ TA	0.087	0.475	-13.587	15.333
ROI				

Table 9: Correlation matrix among regressors

	BFR	*AGE*	*NW*	*SD/TD*	*TD/TA*	*NSF/TA*	*NSP_P*	*CF/TA*	*S/TA*	*XS*	*S*	*EBIDTA/TA*	*ROI*
BFR	1.0000												
AGE	0.0692	1.000											
NW	-0.0010	0.080	1.0000										
SD/TD	-0.0636	-0.019	-0.0068	1.0000									
TD/TA	-0.1398	-0.021	-0.0304	0.0145	1.0000								
NSF/TA	0.0959	0.020	0.0124	-0.0201	-0.574	1.0000							
NSF_P	0.0660	0.023	0.0613	-0.0165	-0.112	0.2317	1.0000						
CF/TA	0.0951	0.008	0.0083	-0.0180	-0.511	0.8179	0.1478	1.0000					
S/TA	-0.0486	-0.057	-0.0308	0.1285	0.1668	-0.0008	-0.0404	0.0100	1.0000				
XS	-0.0700	-0.104	-0.1182	-0.0631	0.0796	-0.0492	-0.1266	-0.0581	-0.0675	1.0000			
S	-0.0145	-0.039	-0.0888	0.0084	-0.006	-0.0046	-0.0350	-0.0014	-0.1116	-0.282	1.0000		
EBIDTA/TA	0.1073	-0.017	-0.0065	0.0110	-0.421	0.6908	0.1138	0.7324	0.0428	-0.068	0.0041	1.0000	
ROI	0.0438	-0.005	0.0859	-0.0003	-0.071	0.0732	0.2208	0.0975	-0.0281	-0.146	-0.0351	0.0734	1.000

Table 10: Credit Risk Model for Italian SMEs under Logit Specification

Dependent variable: stress	Coefficient (standard error)	***Elasticity (standard error)***
BFR	-2.362*** (0.137)	-3.991*** (0.242)
AGE	0.379*** (0.059)	0.947*** (0.148)
NW	-.583*** (0.209)	-0.609*** (0.218)
SD/TD	0.867** (0.351)	0.676** (0.274)
TD/TA	0.376*** (0.104)	0.328*** (0.091)
NSF/ TA	1.370*** (0.372)	0.005*** (0.001)
NSF_P	-0.418*** (0.143)	-0.194*** (0.066)
CF/ TA	-0.927** (0.389)	-0.027** (0.011)
CF-1/TA	0.618* (0.360)	0.009* (0.005)
S/ TA	-0.136*** (0.044)	-0.280*** (0.090)
XS	0.290* (0.177)	0.071* (0.043)
S	0.364** (0.184)	0.066** (0.033)
EBITDA/TA	-0.482** (0.205)	-0.040** (0.017)
ROI	-0.0006*** (0.0002)	-0.301*** (0.116)
SRL	1.494** (0.647)	1.298** (0.562)
SCRL	1.332* (0.701)	0.095* (0.050)
Transport	0.455* (0.265)	0.022* (0.0131)
Manufacture	0.528*** (0.153)	0.158*** (0.046)
Manufacture*North	-0.507** (0.238)	-0.046** (0.022)
Construction*North	-1.030* (0.546)	0.028* (0.015)
Service*South	-2.069* (1.041)	-0.043** (0.022)
Constant	-1.355* (0.808)	
Log-likelihood	-851.88671	
Pseudo R^2	25.53%	

Number of observations	3,890
Area under ROC	84.52%

Notes:

*** indicates significance at 1% level

** indicates significance at 5%

* indicates significance at 10%

Table 11: Firm Distribution across risk class

Risk Class	*Average Class Default Probability*	*Number of stress==1*	*Number of stress==0*	*Number of firms per class*
1	0.0075	0	300	300
2	0.0114	3	296	299
3	0.0154	5	294	299
4	0.0197	7	292	299
5	0.0245	6	294	300
6	0.0305	14	285	299
7	0.0378	11	288	299
8	0.0471	12	287	299
9	0.0623	9	291	300
10	0.0940	19	280	299
11	0.1721	26	273	299
12	0.3091	77	222	299
13	0.9505	147	152	299

Table 12: Comparison Credit Risk Models in Ratio and in Levels

Dependent variable: stress	*Model in ratios (normalised wrt TA)*	*Model in levels*
BFR	+ ***	+ ***
AGE	+ ***	+ ***
NW	- ***	- ***
TA		+ ***
SD/TD	+ ***	+ ***
TD/TA	+ ***	+ ***
NSF/TA	+ ***	+
NSF_P	- *	-
CF/A	- ***	- ***
S/A	- ***	- ***
XS	+**	+
EBITDA/TA	- **	- **
ROI	- ***	- ***
ROE	-	-
SRL	+**	+ **
SCRL	+*	+ *

Notes:
*** indicates significance at 1% level
** indicates significance at 5%
* indicates significance at 10%

Table 13: Credit Risk Model for Italian SMEs under Probit Specification

Dependent variable: stress	Coefficient (robust standard error)	**Elasticity (robust standard error)**
BFR	-1.200***	-4.495***
	(0.069)	(0.303)
AGE	0.190***	1.052***
	(0.031)	(0.178)
NW	-0.268***	-0.623***
	(0.102)	(0.237)
SD/DT	0.565***	0.976***
	(0.178)	(0.310)
TD/TA	0.211***	0.408***
	(0.053)	(0.104)
NSF/ TA	0.748***	0.006***
	(0.202)	(0.002)
NSF_P	-0.225***	-0.232***
	(0.073)	(0.076)
CF/ TA	-0.498**	-0.032**
	(0.215)	(0.014)
CF-1/TA	0.342*	0.011*
	(0.198)	(0.007)
S/ TA	-0.070***	-0.318***
	(0.021)	(0.098)
XS	0.155*	0.084*
	(0.091)	(0.049)
S	0.194**	0.078**
	(0.095)	(0.038)
EBITDA/ TA	-0.289***	-0.053**
	(0.111)	(0.021)
ROI	-0.0003***	-0.372***
	(0.0001)	(0.133)
SRL	0.747**	1.438**
	(0.312)	(0.603)
SCRL	0.654*	0.103*
	(0.341)	(0.054)
Transport	0.276*	0.027*
	(0.080)	(0.015)
Manufacture	0.276***	0.183***
	(0.140)	(0.054)
Manufacture*North	-0.228*	-0.046*
	(0.122)	(0.025)
Construction*North	-0.476*	0.028*
	(0.258)	(0.015)
Service*South	-1.049**	-0.049**
	(0.484)	(0.023)
Constant	-0.917**	
	(0.400)	
Log-likelihood	-852.81166	

Pseudo R^2	25.45%
Number of observations	3,890
Area under ROC	84.61%

Notes:
*** indicates significance at 1% level
** indicates significance at 5%
* indicates significance at 10%

Table 14: Goodness of fit in case of heteroskedastik errors

Goodness of fit (logit version) – controlling for error heteroskedasticity	
Log likelihood	-851.88671
Wald Chi 2 (22)	407.1
Prob>chi2	0.000
Pseudo R^2	25.5%

Table 15: Credit Risk Model for Italian SMEs under Logit Specification and Robust standard errors

Dependent variable: stress	Coefficient (robust standard error)	**Elasticità (robust standard error)**
BFR	-2.354*** (0.142)	-3.979*** (0.249)
AGE	0.376*** (0.049)	0.940*** (0.123)
NW	-0.551*** (0.223)	-0.576*** (0.234)
SD/TD	1.173** (0.362)	0.915** (0.282)
TD/TA	0.381*** (0.136)	0.332*** (0.119)
NSF/ TA	1.371*** (0.336)	0.005*** (0.001)
NSF_P	-0.423*** (0.141)	-0.197*** (0.065)
CF/ TA	-0.924** (0.349)	-0.027** (0.010)
CF-1/TA	0.618* (0.329)	0.009* (0.005)
S/ TA	-0.136*** (0.041)	-0.280*** (0.084)
XS	0.274* (0.165)	0.067* (0.040)
S	0.356** (0.173)	0.065** (0.031)
EBITDA/ TA	-0.482** (0.214)	-0.040** (0.018)
ROI	-0.0006*** (0.0002)	-0.306*** (0.111)
SRL	1.490** (0.681)	1.295** (0.592)
SCRL	1.335* (0.734)	0.095* (0.052)
Transport	0.460* (0.278)	0.023* (0.014)
Manufacture	0.530*** (0.152)	0.159*** (0.046)
Manufacture*North	-0.500** (0.251)	-0.046** (0.023)
Construction*North	-1.000* (0.529)	0.027* (0.014)
Service*South	-2.051* (1.036)	-0.043** (0.022)
Constant	-1.634* (0.838)	
Log-likelihood	-850.66963	
Wald Chi 2 (22)	584.0	

Prob>chi2	0.000
Pseudo R^2	25.64%
Number of observations	3,890
Area under ROC	84.52%

Notes:

*** indicates significance at 1% level

** indicates significance at 5%

* indicates significance at 10%.

Table 16: Comparison of Credit Risk Model for Italian firms conditional on Economic Sectors under Logit Specification

Dependent variable: stress	MANUFACTURE	COMMERCE	CONSTRUCTION	SERVICE
BFR	-2.307***	-3.001***	-2.48***	-2.129***
	(0 .225)	(0.311)	(0.566)	(0.262)
AGE	0 .391***	0.572***	0.448**	0.486***(0
	(0 .089)	(0.115)	(0.229)	.115)
NW	-0.675	-11.730***		-17.177***
	(1.312)	(0.531)		(0.495)
SD/TD	0 .296	1.672**	0.614**	1.401**
	(0 .587)	(0.756)	(1.366)	(0.692)
TD/ TA	0 .980***	0.504**	4.490**	0.343**
	(0.304)	(0.198)	(2.059)	(0.169)
NSF/ TA	2.389 ***	2.057***	5.968	0.399
	(0 .791)	(0.771)	(4.584)	(0.711)
NSF_P	-0.411*	-0.592**	-0.050	-0.168
	(0 .236)	(0.293)	(0.604)	(0.284)
CF/ TA	-2.075***	1.151	-1.978	-1.676*
	(0 .852)	(0.930)	(5.781)	(0.953)
CF-1/TA	1.775	-0.194	0.874	1.607*
	(1.1521)	(0.660)	(5.519)	(0.918)
S/ TA	-0.214**	-0.290***	-0.141	-0.140*
	(0.093)	(0.092)	(0.176)	(0.073)
XS	-0.664	-22.431***		-35.215***
	(3.059)	(0.920)		(0.714)
S	-0.472	-11.127***		-17.302***
	(2.071)	(1.430)		(1.253)
EBITDA/ TA	-0.002	-3.336***	-0.778	0.444
	(0.548)	(0.676)	(1.347)	(0.313)
ROI	-0.0004	-0.001**	0.00003	-0.0005
	(0.0003)	(0.0005)	(0.0007)	(0.0005)
SRL	0.289	0.982		21.607***
	(1.125)	(0.922)		(0.375)
SCRL	-0.153	0.558		21.69063
	(1.304)	(1.245)		
North	-0.487**	0.617**	-1.622**	0.159
	(0.249)	(0.308)	(0.698)	(0.271)
South	0.036	0.271	-1.074	-0.697
	(0.299)	(0.376)	(1.097)	(0.517)
Constant	1.299	33.028	3.838	29.51603
	(4.779)		(2.359)	
Log-likelihood	-318.531	-204.733	-56.166	-229.135
Pseudo R^2	23.72%	37.09%	35.56%	20.86%
Number of observations	1,215	1,122	313	1,104
Area under ROC	82.92%	90.18%	86.19%	81.82%

Notes:
*** indicates significance level at 1%
** indicates significance level at 5%
* indicates significance level at10%

Table 17: A cross regional comparison for Credit Risk Model for Italian SMEs firms under Logit Specification

Dependent variable: stress	NORTH	CENTRE	SOUTH
BFR	-1.985***	-2.985***	-3.591***
	(0.170)	(0.321)	(0.513)
AGE	0.455***	0.272**	0.770***
	(0.068)	(0.117)	(0.215)
NW	0.599	-20.808***	-16.681***
	(1.339)	(0.529)	(0.689)
SD/TD	0.783*	2.715***	0.837
	(0.422)	(0.886)	(1.004)
TD/TA	0.548***	-0.012	0.563
	(0.140)	(0.210)	(0.420)
NSF/TA	1.512***	1.868*	3.110
	(0.483)	(1.103)	(2.110)
NSF_P	-0.381**	-0.396	-0.516
	(0.179)	(0.298)	(0.443)
CF/ TA	-0.811	-1.575	-4.142
	(0.601)	(1.108)	(2.821)
CF-1/ TA	0.679	-0.175	4.461
	(0.539)	(0.672)	(2.816)
S/TA	-0.236***	-0.143*	-0.124
	(0.061)	(0.080)	(0.130)
XS	2.614	-43.415***	-32.806***
	(3.218)	(0.955)	(1.028)
S	1.965		
	(2.004)		
EBITDA/TA	-0.672**	-0.606	0.816
	(0.298)	(0.410)	(1.565)
ROI	-0.0006**	-0.0003	-0.0007
	(0.0003)	(0.0005)	(0.0007)
SRL	0.385	24.763***	21.075
	(0.660)	(0.790)	(0.734)
SCRL	0.103	24.063	21.75088
	(0.738)		
Manufacture	0.332*	0.554*	0.650
	(0.197)	(0.297)	(0.432)
Transportation	0.540	1.007*	0.176
	(0.352)	(0.597)	(0.743)
Service	0.235	-0.416	-2.426
	(0.216)	(0.506)	(1.276)
Constant	-4.468	39.04709	28.48124
	(4.685)		

Log-likelihood	-555.177	-188.6558	-89.1796
Pseudo R^2	19.61%	35.40%	43.41%
Number of observations	2483	895	495
Area under ROC	81.24%	88.38%	93.01%

Notes:
*** indicates significance level at 1%
** indicates significance level at 5%
* indicates significance level at 10%

Table 18: Comparison of Credit Risk Model for Italian SCRL and SRL firms under Logit Specification

Dependent variable: Stress	SCRL		***SRL***	
	Coefficient (standard error)	Elasticity (standard error)	Coefficient (standard error)	Elasticity (standard error)
BFR	-4.474*** (1.349)	-7.988 (2.410)	-2.418*** (0.142)	-4.072 (0.251)
AGE	0.607* (0.391)	1.460 (0.940)	0.463*** (0.057)	1.156 (0.143)
NW	-1.427 * (0.930)	1.630 (1.062)	-0.611 *** (1.200)	-0.627 (1.231)
SD/TD	-3.344* (2.057)	-2.641 (1.625)	1.047*** (0.364)	0.817 (0.285)
TD/TA	5.463*** (1.553)	5.228 (1.487)	0.329*** (0.102)	0.285 (0.089)
NSF/ TA	8.929 *** (3.355)	-0.218 (0.082)	1.429 *** (0.425)	0.005 (0.001)
NSF_P	-4.072*** (1.674)	-1.733 (0.712)	-0.351*** (0.145)	-0.164 (0.068)
CF/ TA	-0.134 (0.634)	0.003 (-0.013)	-1.117** (0.480)	-0.033 (0.014)
CF-1/TA	-0.261 (3.648)	0.006 (-0.089)	0.419 (0.433)	0.008 (0.008)
S/ TA	-1.597*** (0.491)	-4.782 (1.471)	-0.184*** (0.045)	-0.367 (0.090)
XS	4.022 *** (1.494)	1.049 (0.362)	-0.438 (2.708)	-0.402 (2.483)
S	5.226*** (1.804)	-0.03 (0.674)	0.096 (1.636)	0.002 (0.026)
EBITDA/TA	-0.279 (1.731)	-0.004 (0.028)	-0.460** (0.227)	-0.039 (0.019)
ROI	-0.00005 (0.001)	-0.716 (0.309)	-0.0005*** (0.0002)	-0.301 (0.119)
North	-2.687 ** (1.162)	0.716 (0.309)	-0.227 (0.153)	-0.064 (0.043)
South	4.950*** (1.614)	0.704 (0.229)	-0.157 (0.202)	-0.019 (0.025)
Transport	7.810** (2.331)	0.919 (0.274)	0.377** (0.294)	0.017 (0.013)
Services	2.697 *** (1.355)	1.185 (0.596)	-.022 (0.196)	-0.004 (0.040)
Manufacture	2.084 *** (1.588)	0.274 (0.209)	0.411 *** (0.152)	0.129 (0.048)
Constant	-6.497** (3.298)		0.782 (3.924)	
Log-likelihood	-26.1191		-799.418	
Pseudo R^2	61.25%		24.65%	
Number of observations	389		3522	

Area under ROC	97.74%	83.79%

Notes:
*** indicates significance level at 1%
** indicates significance level at 5%
* indicates significance level at 10%

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[1] Altman and Sabato (2004) do not find any evidence about statistical significance of earning performance ratios.

[2] It is probably worth to remember that the Basel II accord can be implemented under several variants: the Foundation Approach (F-IRB), with a fixed Loss Given Default (LGD), and the Advanced approach, where the LGD is estimated as the risk parameters.

[3] The z-score itself can be converted into a PD.

[4] There are four methodological forms of multivariate credit scoring models: (1) the linear probability model, (2) the logit model, (3) the probit model, and (4) the multiple discriminant analysis model.

[5] See Barniv and McDonald (1999), who pointed out that 178 articles in accounting and finance journal in the period 1989-1996 applied a logit model for scoring purposes.

[6] See Allen, De Long, Saunders (2004) for a detailed review on credit risk measurement

[7] See Baetge et all.(1988) Von Stein and Ziegler (1984) for studies on Germany. See Marais (1979), Earl and Marais (1982) for studies on England and Fernandez (1988) on Spain.

[8] See Altman, Marco and Varetto (1994) for an early application of Altman model on Italian data.

[9] According to Basel II Accord, a firm is classified as a corporate SME in case of annual sales between 5 and 50 million euro and a bank exposure above 1 million euro and as a retail SME in case of annual sales below 5 million euro and bank exposure less than 1 million euro.

[10] This distinction has significance for the calculation of capital requirements, since Retail SMEs are eligible for the application of a different, and more favourable weighting schedule given that requirements specified by Basel Committee are met. See BCBS for detailed references.

[11] In Italy the main legal forms adopted for the constitution of a firm are Società per Azioni (SPA), Società a Responsabilità Limitata (SRL) and Società Cooperativa a Responsabilità Limitata (SCRL). A SPA is a limited liability firm, with a minimum social capital of 120,000 euro. A SRL is a limited liability firm, with a minimum social capital of 10,000 euro. A SCRL is a limited liability cooperative firm, with a minimal number of partners equal to 9 and special bounds on the maximal percentage of earnings allowed to be distributed among partners.

[12] Among others, Bocchi and Lusignani (2004), Fabi-Laviola and Marullo Reedtz (2003).

[13] We limit our attention to these four sectors due to lackness of data: we are not able to estimate a separate model for agriculture and other sectors, whose firms constitute around 1% of total firms in the sample.

[14] We merge together observations on transportation and services, due to lack of data on defaults for firms active in transportation sector (which turned out to be not enough in order to estimate a separate model).

[15] We merge together in only one area, called "North" the North Eastern, North Western and Northern areas. Note that we run logit regression conditionally on North Eastern Italy, North Western Italy and Northern Italy separately and we do not obtain any statistically significant differences across these areas.