Finance and innovation: essays on credit, investment and regulation

Elisa Ughetto

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Executive Summary

This dissertation, which takes the form of five essays, presents an analysis of the role exerted by finance and financial intermediaries in the development of innovation and R&D activities. “Finance and innovation” is a broad topic, which I try to investigate through different perspectives and by means of both econometric and qualitative analysis. The following essays address research questions which are very much related to each other, concerning the strength of financing constraints for R&D, the effects of regulation and geographical proximity on the credit rationing behavior of banking institutions, as well as a more topic-specific issue on credit risk assessment for small firms. The results presented are supported by a large descriptive evidence.

The common underlying hypothesis that I wish to test is that firms may find it difficult to raise external finance for R&D/innovation in a freely competitive market place. From the perspective of investment theory, R&D has a number of characteristics that makes it different from ordinary investment: high adjustment costs, high degree of uncertainty associated with its outputs, limited availability of collateral to secure debt, strong information asymmetries between borrowers and lenders. All these features make debt a poor substitute for internal finance. For that reason it is interesting to explore if credit constraints actually apply to Italian firms performing R&D or innovation activities and to envisage which factors could potentially alleviate such constraints.

The first part of the dissertation is aimed at testing whether financing constraints apply for firms performing R&D activities. The empirical test of the importance of financial constraints for investments is based on the standard investment accelerator model augmented with cash flow. The methodology consists in identifying financially constrained firms through a proxy (firm size) and then in estimating the sensitivity of investments to cash flow for such firms. If cash flow has a bigger effect on the investment of firms more likely to face financial constraints, this can be interpreted as evidence for the existence of information-driven capital market imperfections.

When survey data on firms’ access to external finance are available, it is possible to investigate the issue drawing on the direct evidence reported by firms. In that way, the identification of information and incentive problems is not simply inferred from the use of proxies, but rather through a declaration of the firms themselves. Also, this allows to distinguish between the concept of financial constraints, which arise when there is a wedge between the cost of internal and external finance, and that of credit rationing (the firm does not get as much credit as it wants, although it is willing to meet the conditions set by the lender). In this dissertation I also follow this approach, using survey responses to examine whether credit rationing occurs for firms performing innovative activities.

Besides testing for the presence of financing constraints for innovative firms, I explicitly take into account potential alleviation or worsening effects to such constraints. I analyze the role played by geographical proximity and by the introduction of new regulatory rules for financial intermediates. While a reduced physical distance between borrowers and lenders, sustained by informal practices of *relationship lending*, is deemed to have a positive impact on lending conditions (on both availability and amount of credit), the implementation of new regulatory rules (Basel II) on capital requirements might have a much controversial effect.

This latter issue paves the way to some important reflections concerning the screening procedures adopted by banks in assessing their borrowers' creditworthiness and is corroborated by the estimation of a default prediction model. In particular, it is a matter of fact that banks are actually changing their rating systems architecture in order to comply with the new regulation but it is still controversial the weight assigned to innovation variables in the credit assessment procedure.

I now briefly outline the content of the five essays of the dissertation.

In **Essay 1** ***"Does internal finance matter for R&D? New evidence from a panel of Italian firms"***, I investigate the relationship between finance and R&D for a panel of more than 1,000 Italian manufacturing firms from 1998 to 2003. The dataset is derived from two waves of the "Survey on Italian manufacturing firms" conducted by Capitalia (Mediocredito Centrale) in 2001 and 2004. Accounting data are extracted from the AIDA database provided by Bureau Van Dijk, which reports financial accounting data for public and private Italian firms with more than 10 employees.

The issue of financing constraints to R&D is examined by complementing accounting data with firm-level survey data. While Italian firms obtain a significant share of their financing from debt, the results from this unique survey show that firms use virtually no debt to finance R&D. Internal cash flow finances nearly 50 percent of physical capital investments, but more than 80 percent of R&D investments. Bank lending is quite important for capital investments, but it is almost trivial for R&D spending. Because Italian firms typically do not receive external equity, the obvious source of innovation financing appears to be internal cash flow.

The standard approach to testing for the presence of financing constraints to investments consists in adding a proxy for the availability of internal funds/net worth (typically cash flow or other stock measures of liquidity) to an investment accelerator model and in investigating whether this proxy is significant for the firms that are thought more likely to face information problems. The underlying hypothesis is that their investment is likely to be more sensitive to fluctuations in net worth. This approach has been introduced in the economic literature by Fazzari et al. (1988). I therefore use an investment accelerator model augmented with cash flow to estimate the sensitivity of capital investment to cash flow, testing for the presence of informational frictions in the credit market for companies performing R&D activities.

Due to the lack of firm-level data on R&D expenditures (the declaration of this information is not compulsory in Italy), the methodology consists in capturing the innovation dimension of the firms in the sample through dummy variables measuring R&D activity and the belonging to a high-tech sector, and then testing for financing constraints using data on physical capital.

It is clear that both cash flow and investments can be correlated with the expected future revenues of the firm, which are linked to a large set of endogenous and exogenous factors (mostly unobserved). The inclusion of Tobin's Q or the growth rate of sales allows to avoid, to a certain extent, a situation in which the relationship between cash flow and investment could stem from the correlation between cash flow and omitted or mis-measured investment opportunities. A further way to by-pass this criticism is to adopt a comparative approach between groups of firms, which are thought a priori to be more and less likely to face information and incentive problems. Accordingly, I split the sample between small and medium-large firms. Small firms are supposed to have more difficulties in obtaining external finance due to their "informational opacity", compared to larger businesses which can provide detailed financial information.

Results are first estimated using the within-firm estimator, which controls for unobservable firm effects. However, the presence of simultaneity between contemporaneous regressors and disturbances might lead to inconsistent estimates. The proper tool to be used is the GMM method which eliminates the firm-specific effects by differencing and controls for endogenous explanatory variables by using lagged levels of endogenous variables as instruments.

Results show that cash flow plays an important role in explaining capital investment, especially for small firms. Interestingly, when I consider measures of firms' innovative activities, I find significant differences between the sub-samples of small and medium-large firms. While small innovative firms are subject to relevant financing constraints, larger companies investing in R&D have easier access to external financing. This evidence highlights that the dependence of investment on internal sources cannot be fully attributed to a credit rationing behavior due to firms' in-house innovation activities.

In **Essay 2** ***"Industrial districts and financial constraints to innovation"***, I look at the relationship between innovation and credit availability in the context of Italian industrial districts, using a cross-section of Italian manufacturing firms from the same database provided by Capitalia. Theoretical models predict a positive impact of relationship distance on lending conditions. In industrial districts credit suppliers benefit from the geographical concentration of firms because they can easily gather better information on borrowers' characteristics, thus reducing problems of adverse selection. Furthermore, geographical proximity enables banks to monitor borrowers constantly, closely, and almost without effort or cost, to preventing possible moral hazard behaviours from occurring.

In the essay I discuss three main research hypotheses: that firms located in industrial districts face lower credit constraints, that innovative firms are more likely to be credit rationed and lastly, that innovative firms have easier access to external finance when they are located in industrial districts. While the first two hypothesis have been tested by several works, although with different methodologies, the last hypothesis has so far remained relatively unexplored.

Direct information based on each firms' assessment is used to characterize the existence of credit constraints. I define a firm as credit rationed if it declared it wanted more credit and was willing to pay either the current or a higher interest rate but, once applied, was turned down. I identify district firms departing from the ISTAT list of municipalities and checking, for each firm in the sample, its location. After tracking all firms located in district municipalities, I apply a filter based on ATECO classification codes to avoid to pick up firms operating in a sector other than the one in which the district is specialized.

The econometric approach consists in a bivariate probit model with sample selection. It allows to investigate the factors affecting a firm's probability of being credit rationed, after controlling for the determinants of its antecedent decision to request additional credit. Observing a credit-constrained firm is in fact conditional on the firm's need for more credit and a sample selectivity bias may arise if the probability of wishing more credit is not distinguished from that of being turned down when applying for it.

The evidence, after controlling for traditional measures of firms' financial performance, is in line with the results of the extant literature. I observe a higher probability of being denied credit for innovative firms, with a weaker effect when measures of R&D intensity are considered. This last result might be interpreted according to two different perspectives. On the one hand, it could be argued that companies characterized by high R&D intensities are those with a better financial position. Hence, these firms do not require additional financial resources for the simple reason that they entirely build R&D investment strategies on the availability of internal resources. On the other hand, it could be suggested that the non-significance of the coefficient of the R&D variable is due to the limited accountability of intangible assets, the potential impact of which is, in turn, underestimated by financial intermediaries.

The results confirm that the reduced geographical distance with credit suppliers in district areas can lead to overcoming information asymmetries between lenders and borrowers. Results also suggest an inverse relationship between being located in a district and the probability of needing extra-funds. If I move to consider firms engaged in substantial R&D activities located in a district, evidence suggests that they are less likely to suffer from credit constraints.

Overall, it can be argued that firms' R&D activity alone does not accurately reflect the nature of problems leading to potential credit market failures and that banks show a lower propensity to grant credit to innovative firms only when they do not have long-lasting credit relationships with them. In industrial districts a bank can possibly share the risk of financing R&D investments with other banks, since firms usually rely on more than one bank. Also, firms undertaking innovation in industrial districts are likely to cooperate with neighbor firms at different stages of their R&D activity, leading local banks to have a better perception of their creditworthiness.

In Essay 3 ***"The Basel II reform and the provision of finance for R&D activities in SMEs: an analysis for a sample of Italian companies"***, I investigate the issue of the financing of R&D investments in SMEs in Italy with respect to the future changes in the banking system, which will be driven by the adoption of the new version of the Basel Capital Accord. In particular, I consider the part of the Accord which requires the adoption by banks of a new system for fixing capital requirements as a function of the creditworthiness of borrowers and I analyze to what extent such new practices might influence lending strategies for SMEs involved in product innovation. Again, the study relies on the Capitalia database.

The analysis is twofold: I initially implement a probit model in order to observe whether, after controlling for standard measures of firms' financial performance and profitability, indicators of product/process innovation and R&D intensity exert a significant influence on the probability that companies declare the need of additional credit. I then perform a simulation on the potential impacts of the adoption of the Basel II Capital Accord by Italian banks. The rationale for the latter analysis is the following one: the Accord introduces a system for fixing bank capital requirements as a function of the degree of risk of borrowers. Hence, if innovative SMEs show a higher idiosyncratic risk, the bank in its portfolio optimization process might either ask to this category of firms higher interest rates to compensate for higher capital requirements, or simply deny credit to them. Previous studies, also in Italy, have investigated the effects of the new Basel Capital Accord on bank credit exposures to SMEs, but there is no previous evidence for the specific impact on small and medium firms involved in innovative activities.

The results of the probit model show that standard financial accounting ratios (indexes of companies' leverage, liquidity and profitability) have significant effects on the probability for a company of declaring the need of additional credit. The different proxies used to map the presence of innovative activities, through dummy variables, show significant positive effects on the probability that the company declares of having desired an additional amount of credit. At the same time, when moving to an analysis of the impact of R&D intensity measures, I find a negative and non significant impact.

The results of the simulation suggest that the introduction of the new rules is likely to have a moderate impact on banks' capital requirements when considering the possibility for the bank to pool together all the companies. However, when focusing on the sub-sample of companies which declare to be involved in innovative activities, I obtain an increase in banks' capital requirements, which in turn might cause a deterioration in the expected credit conditions applied to this sub-sample of companies. It is worth stressing that in its actual implementation, the Basel II Accord will potentially deliver significantly different results, in terms of lending conditions, as a consequence of the alternative rules banks are allowed to choose, of differences in banks' internal methodologies of risk assessment and on subjective judgments in the validation of such methodologies by supervisors. With respect to the latter points, I carry out a sensitivity analysis for a set of parameters used to estimate capital requirements. In particular, I obtain that expected bank's capital requirements reveal to be highly sensitive to changes in Loss Given Default (LGD, the share of the loan which is lost by the bank in case of firm's default). I argue that this feature might exert a major impact, especially for small innovative companies endowed with a limited amount of collateralisable assets and, as a consequence, characterized by higher expected LGD.

In Essay 4 "***The financing of innovative activities by banking institutions: policy issues and regulatory options***", I explore to what extent the convergence of banks over risk-adjusted capital standards induced by the Basel II Accord may affect the way in which they screen innovative firms. More precisely, I examine whether banks rely and will rely on non-financial parameters to assess the creditworthiness of a potential borrower. Basel II opens up the possibility for banks to use qualitative criteria together with quantitative information in appraising the creditworthiness of their borrowers. A qualitative assessment of a company might take into account the role played by intangible assets as well. In other words, the traditional assessment of a borrower's level of risk thought to fit firms whose activity is primarily of a manufacturing or a mercantile nature, could be broadened to reflect intangibles and other qualitative information. From this point of view innovative firms, which would not ordinarily be eligible for bank funding because of limited financial track records and lack of collaterals, may have the chance to be granted credit if their qualitative rating is good. I test this research question by undertaking a survey on a sample of 12 Italian banking groups, through direct interviews with bank managers. Results show that the majority of banks does not consider intangibles as meaningful determinants in credit risk assessment. This is primarily the result of a regulatory caveat which prevents banking institutions from inferring appropriate information on firms' innovation activity from financial statements, rather than banks' reluctance in considering such factors to a greater extent. Even though a wider recognition of qualitative elements in credit risk assessment is on the way, the sole implementation of the Accord might not lead to reduce informational asymmetries between lenders and borrowers, at least in the short run. This seems to be acknowledged by the fact that banks have started to conceive some forms of credit support for R&D activities which wouldn't be necessary if the implementation of the Basel II Accord could really lead banks to screen innovative firms in a better way.

In **Essay 5 *"Guarantee-backed loans and credit risk: a default prediction model"*,** I explore the issue of credit assessment of potential borrowers by estimating a default prediction model with selection. In that regard, I use a dataset provided by Eurofidi, an Italian mutual guarantee consortium, which facilitates access to financing for SMEs, mainly located in Piedmont. The strength of the dataset is the peculiar information it provides on the past and current status of guarantee-backed loans, together with data on the amount and duration of loans and guarantees. Moreover, it is also a source of information on both approved and rejected applications.

The model consists of two simultaneous equations: the first one estimates Eurofidi's binary decision to approve or reject the loan application through a preliminary screening and the second one, conditional on the loan having being granted, relates to the borrower's ability to pay it off or not. The model allows to by-pass a typical source of bias in credit scoring models, which arises from the fact that they are usually calibrated on the repayment behaviour of applicants who have been accepted for credit in the past. However, the performance of those applicants who have been previously rejected is not observed. The model is built upon a set of financial ratios among the most widely used in the literature as well as the most predictive ones of the probability of default. Non-financial variables indicating the purpose of the loan, the amount of the loan, the presence of other on-going loans and the age and size of the borrower are included in the model.

I perform two different estimates: a bivariate probit model with sample selection and a standard probit model. In order to assess the discriminatory power of the estimated models, I perform a ROC (Receiver Operating Characteristics) analysis. Given the weak correlation between the unobservables of the selection and the outcome equation, the estimates of both models are very similar and consequently they have similar predictive performance. Furthermore, both models suffer from a low accuracy in classifying bad loans, due to the extremely unbalanced proportion of the sample with only about 10% of observations defaulting.

Although the bivariate probit specification performs no better than an ordinary probit, results may be still interesting in order to comment on Eurofidi's risk minimization behavior. Unfortunately, only financial variables have opposite signs in both the outcome and selection equations, whereas for the other variables this requirement does not hold. In particular, looking at the signs of the estimated coefficients for the dummies of loan destination (fixed investments, R&D investments and liquidity), it appears that, although they all have a lower probability of being a bad loan, they also have a lower probability of being accepted. Micro firms have a higher default probability than small and medium firms but also a higher probability of acceptance of their application. Interestingly, the number of previous on-going loans has a stronger non-linear explanatory power in the selection equation than in the outcome equation: a small amount of previous accepted loans is perceived by the lending institution as a signal of "good reputation", even if after a certain threshold concern may arise on the reliability of the applicant on refunding all the loans and thus increasing its probability of default. Finally, the relative size of the loan has a positive (although nonlinear) effect on the probability of default, whereas the age of the applicant has a negligible effect in both the equations.

ESSAY 1

Does internal finance matter for R&D? New evidence from a panel of Italian firms

1. Introduction

In the long run, the key determinant of economic progress is the rate of technological change. The idea that technological progress, through innovative activities and knowledge creation, represents the main engine for economic growth is not a new one in economics. One of the first economists to stress the crucial importance that innovation and knowledge accumulation have for long-term growth was Schumpeter. In his 1942 contribution, Schumpeter also alluded to the importance of internal finance for innovation by defending the monopoly power of large corporations, which can plough back their past profits into uncertain innovative activities. Since then, the role played by financial factors in firms' investment decisions has been intensively debated (see Hall, 2002 and Hubbard, 1998 for a review).

Numerous scholars have argued that financing constraints should apply to R&D, perhaps more severely than to fixed capital investment. Due to capital market imperfections, the financing of R&D-intensive projects can be subject to relevant informational frictions between lenders and borrowers. Moreover, the limited availability of collateral to secure firm's borrowing, the high degree of risk which characterizes R&D investment and the complexity of evaluating the expected future prospects of innovative activities, make debt a poor substitute for equity finance. Such an effect becomes more intense when innovative firms are also small-size enterprises. Due to their "informational opacity," small firms are in fact more likely to face credit constraints compared to larger businesses which can provide detailed financial information.

Although evidence on the influence of internal equity finance on R&D is mixed, it seems plausible that R&D investment is predominantly financed by internally generated cash flow in most advanced economies. Internal equity has in fact several advantages over debt: there are no collateral requirements, it does not create adverse selection problems and does not magnify problems associated with financial distress

(Brown et al. 2007). However, innovative firms may face problems if they finance their R&D exclusively with internal finance. First, and most obvious, innovative firms may have profitable and socially desirable R&D opportunities that require more finance than can be obtained from existing profits. This point is especially relevant to young, fast-growing firms. Second, since R&D investments require a rather smooth investment path over time, volatile profits due to business cycles create undesirable instability in the flow of internal funds for R&D.

This paper investigates the relationship between finance and R&D for a panel of more than 1,000 Italian manufacturing firms. I depart from the work of Brown et al. (2007) to explore, at a micro-level, whether internal finance matters for firms investing in R&D in Italy. Brown et al. (2007) examined a panel of 1,347 US publicly traded high-tech firms from 1990 to 2004 and found that supply shifts in equity finance (both internal and external) had an aggregate effect on R&D, thus explaining most of the dramatic 1990s R&D boom in the US. Their results suggest that stock markets contribute to economic growth by directly funding innovation. This is not surprising since stock markets are well developed in the US, while financial intermediation is relatively weak.

While the US has market-based financial systems, continental European countries like Italy have strongly relied on relationship banking to channel funds to their most productive investments. The relatively modest role exerted in Italy by the stock market can be inferred from the low stock market capitalization and the very small venture capital industry. In 2004 the stock market had a capitalization of 45.76 percent relative to GDP, compared with 139.11 percent in the USA (IMD, World Competitiveness Yearbook 2006). The data provided by AIFI (Italian Private Equity and Venture Capital Association) for the years following the stock market bubble in 2000 highlight that in the Italian market, venture capital plays a small, and recently declining, role. While in 2000, an amount of €540 million was invested, investment funded by venture capital fell to €59 million in 2003 and to €30 million in 2005.

It is beyond the scope of this paper to debate which financial system is better for promoting long-run economic growth. Many economists have argued that bank-based systems are better at mobilizing savings and identifying good investments, while others have emphasized the advantages of markets in allocating capital and mitigating the problems associated with excessively powerful banks (see Levine R., 2005 for a detailed survey). However, I argue that if finance is a key determinant for R&D

investment, a good financial system, in terms of its capability to enhance technological progress, is the one that channels funding to research and innovative activities.

The reliance on bank lending as the only source of external financing can produce long-run detrimental effects on growth and competitiveness because, for the reasons I mentioned earlier, banks can be better suited to financing innovation embodied in physical capital rather than technological progress. While Italian firms obtain a significant share of their financing from debt, the results from a unique survey show that firms use virtually no debt to finance R&D. Internal cash flow finances nearly 50 percent of physical capital investments, but more than 80 percent of R&D investments. Bank lending is quite important for capital investments (40 percent), but it is almost trivial for R&D spending (less than 6 percent). This finding is consistent with theory that implies debt is not well suited for R&D-intensive activities. Because Italian firms typically do not receive external equity, the obvious source of innovation financing is internal cash flow.

I examine a six-year time panel of more than 1,000 Italian firms, resulting from the merge of two waves of the Survey on Italian Manufacturing Firms, undertook by Capitalia. A large proportion of these firms are not quoted on the stock market.

Therefore, I perform the analysis on the sensitivity of capital investments to cash flow, testing for the presence of informational frictions in the credit market for firms performing R&D activities. It is clear that both cash flow and investments can be correlated with the expected future revenues of the firm, which are linked to a large set of endogenous and exogenous factors (mostly unobserved). Tobin's Q or sales, even if included in investment regressions as proxies for firms' investment opportunities, might not properly measure them. If this were the case, then the coefficients on cash flow could be biased due to the correlation between cash flow and investment opportunities. Following Fazzari, Hubbard and Petersen (1988), I by-pass to a certain extent the criticism according to which cash flow might be an important determinant of investment, simply because it accounts for expected future profitability, by adopting a comparative approach between groups of firms.[1] Therefore, I split the sample according to measures of firm size (small and medium-large firms).

The models are estimated using a first-difference GMM method which controls for firm-specific effects and endogenous explanatory variables. Within-group OLS estimates are reported for comparison.

Internal equity finance appears to play an important role in explaining capital investment expenditures, with a larger coefficient for small firms. This is consistent with common belief that financing constraints are less tight among large firms, not only because they can more easily raise funds directly from the market, but also because they can provide more reassurance to a bank that its loan will be repaid. Moreover, as underlined by Guiso (1998), larger firms have more "visibility" which reveals to financial intermediaries their quality, allowing banks to charge the proper interest rate on the loan instead of cutting its amount. Interestingly, when I consider measures of firms' innovative activities, I find significant differences between the sub-samples of small and medium-large firms. The point estimates for cash flow interacted with dummy variables measuring R&D activity are positive and highly statistically significant for the sub-sample of small firms. On the contrary, medium-large innovative companies have lower or not significant investment-cash flow elasticities.

The estimated results highlight that the dependence of investment on internal sources cannot be fully attributed to a credit rationing behavior due to firms' in-house innovation activities. It appears that firm size exerts a significant impact on the availability of external financial sources to be channeled into R&D.

The remainder of the paper is organized as follows. Section 2 discusses background material on R&D and internal equity finance. Section 3 provides a description of the dataset, together with some summary statistics. Section 4 describes the baseline specification and the estimation method; section 5 presents empirical results. Section 6 presents alternative specifications of the model and robustness tests. Section 7 summarizes the paper.

2. Investment and financing of R&D

The rate of technological change in an economy has long been considered the key determinant to understand the process of economic growth, the competitive performance of firms and industries, as well as the evolution of their structure of production. Expenditure on research and development allows the generation of new knowledge and the development of creative ideas into products, processes and services that drive economic growth. Even if the vast majority of R&D projects fail to materialize any tangible results, these failures contribute to generate the corpus of knowledge needed to stimulate the innovation process.

By the early 1940s, Schumpeter (1942) recognized the role of large firms as engines for economic growth by accumulating knowledge in specific technological areas and markets. This view is sometimes referred to as "creative accumulation". Recently Schumpeter's insights have been formalized by scholars in the field of (endogenous) growth models[2]. These models generally predict that incremental changes in the innovation activity result in substantial social gains for the entire economy, as the innovation is adapted and diffused. Arrow (1962) also points out that the knowledge embodied in new technologies cannot be fully appropriated by its creators. To the extent that knowledge cannot be kept secret because it is a non-rivalrous good (the consumption of one individual does not detract from that of another) with incomplete excludability (it is difficult to exclude an individual from enjoying it), a market failure leading to underinvestment in R&D takes place[3]. Empirical support on this point is documented by Griliches (1992), who shows that the social rate of return on investment in R&D is greater than the private rate.

Arrow also argues that a wedge exists between the private rate of return of R&D investment and the cost of capital when innovators and providers of finance are different entities. The presence of capital market imperfections makes financing R&D-intensive projects by means of external financial resources difficult. This assumption clearly challenges the Modigliani-Miller theorem (1958) by which any desired investment project with positive net present value can be financed either internally or externally, since external funds can costlessly substitute for internal capital.[4]

One implication of the theories of the firm under imperfect capital markets is that financial factors, such as retained earnings and the availability of new debt or equity, determine firm's investment decisions. In particular, R&D investment seems to be predominantly financed by internally generated cash flow (Himmelberg and Petersen, 1994) in most advanced economies. This evidence obviously raises the question of whether the large use of internal finance out of profits as a means to finance R&D investments is a reflection of a voluntary firm strategy or is rather the result of financial constraints. The first interpretation can be traced back to the "free cash flow" argument (Jensen, 1986): managers overinvest in projects with negative net present value, simply because their objective function does not align with stakeholders' interest in maximizing corporate value. The second interpretation seems to fit well with the "pecking order theory" of financing (Myers, 1984), according to which firms face a hierarchy of financial sources in terms of costs. The wedge in the cost of financial resources, which is due to the limited capability of lenders or outside equity investors in valuing future cash flows deriving from investment projects, leads to an under-investment effect by the companies, which are forced to forego some projects with positive net present value. Therefore firms exhaust internal equity financing first and then, if demand for funds is high enough, turn to debt and external equity. The specific characteristics of the Italian SMEs included in the sample, which commonly show an extremely concentrated ownership structure (they are often wholly-owned family companies), obviously limit the potential impact of managerial cash flow. Hence, it is plausible to hypothesize that the observed reliance of R&D investments on internal financial resources is mainly driven by credit market conditions.

The reasons why internal equity finance is preferred to debt or external equity for R&D investment have been identified in the recent past by numerous scholars. First, frictions due to asymmetric information are more severe for R&D because innovative projects are not easily understood by outsiders, or at least entrepreneurs have a better perception of their likelihood of success than providers of external funds. This situation can create moral hazard and adverse selection problems, as suggested by Jensen and Meckling (1976) and Stiglitz and Weiss (1981). Second, the returns to high-tech investments are skewed and highly uncertain because R&D projects have a low probability of success (Leland and Pyle, 1977; Carpenter and Petersen, 2002). Third, investments in innovation create largely intangible assets (that are predominantly salary payments) which cannot be used as collateral to secure firms' borrowing (Lev, 2001; Berger and Udell, 1990).[5] Fourth, the expected future revenues of an uncertain activity like scientific and technological research are difficult to estimate without proper analytical tools[6]. There is an additional argument, suggested by Bhattacharya and Ritter (1985), that stresses the reluctance of firms to finance their R&D externally for strategic reasons. Firms have little incentive to disclose information on their innovative projects to lenders since this knowledge could leak out to competitors. Therefore managers prefer to rely on internal sources of funding to finance their investments. This attitude is likely to be even stronger for smaller companies which are not able to protect their innovations through complementary assets, such as established distribution networks (Scellato, 2007). Finally, financial distress can be particularly harmful for R&D firms because of their concentrated, firm-specific assets, which constitute non-redeployable capital due to the absence of a secondary market for innovation. When innovative firms face financial distress, their market value, which is based on future growth options, rapidly decreases (Cornell and Shapiro, 1988).

Empirical analysis has investigated the role of financial factors on both firms' capital and R&D investments, although the number of studies dealing with the latter is significantly lower. Most of the papers on the relationship between internal finance and capital investment find an important role for internal finance (see for example Fazzari et al., 1988; Hoshi et al., 1991; Devereux and Schiantarelli, 1989; Oliner and Rudebusch, 1992; Vogt, 1994; Chirinko and Schaller, 1995). Evidence regarding R&D investments is instead more mixed.[7] Early empirical cross-section analysis (Scherer, 1965; Mueller, 1967 and Elliott, 1971) found no relationship between internal finance and R&D. However, as emphasized by Himmelberg and Petersen (1994), these studies considered only large firms, which typically have more cash flow than they need for investments. Most of the subsequent papers identify a positive and significant impact of cash flow on R&D investments (Himmelberg and Petersen, 1994; Mulkay et al., 2001; Hao and Jaffe, 1993; Hall, 1992), although for some of them that relationship does not always hold (Harhoff, 1998; Bond et al, 1999). Hall (1992) examines the degree of correlation between R&D and cash flow for a large panel of US manufacturing firms using an accelerator type model and finds a strong effect of cash flow on R&D expenditures, together with a negative correlation between R&D expenditures and the degree of leverage. Himmelberg and Petersen (1994) focus on a panel of 179 US small firms in high-tech industries, suggesting that internal financial resources are a major determinant of R&D expenditure decisions. Hao and Jaffe (1993) come to the same results by splitting their sample by firm size. They find support for the hypothesis that R&D is liquidity constrained, although their results suggest that there is no liquidity effect for large firms. Harhoff (1998) reports a significant sensitivity of R&D investments to cash flow for small firms using an error correction model. However, no conclusions on R&D could be drawn from the Euler equation and the accelerator model. A recent study by Brown et. al (2007) analyses the effect of cash flow and external equity on aggregate R&D investment. Their findings provide further support for the view that supply shifts in equity finance are important factors driving economic growth.

3. Dataset and summary statistics

The dataset is derived from two waves of the "Survey on Italian manufacturing firms" conducted by Mediocredito Centrale (MCC) in 2001 and 2004.[8] Each survey covered the three years immediately prior (1998-2000, 2001-2003) for samples of more than 4,000 firms. I merged the data from the two surveys and I matched the database with complete accounting information for years 1998-2003. The initial sample comprises 1,422 firms.

Following the standard practice in the literature, I trimmed outliers in all key variables at the one-percent level and I excluded from the sample firms with incomplete accounting information. The final sample consists of 1,106 firms over a six-year period. The surveys provide information on each firm's structure, labor force, investment, export strategies and financial situation but their strength, for my specific purposes, is the rich information on firms' innovation activity and financial sources for both fixed and R&D investments.

I approximated the extent of potential informational frictions in the credit market by means of dummy variables measuring R&D activity. RD is a dummy which is equal to 1 if the company declared having performed R&D activities in panel years and 0 otherwise. In the questionnaire Research and Development is defined as "a creative activity which is undertaken with the aim of increasing knowledge and using such knowledge to create new applications, like technologically new or improved products and processes." R&D activity includes any in-house or external research (or a combination of the two) undertaken by the firm. HIGHTECH is a dummy variable which takes the value of 1 if the firm belongs to a high-tech sector according to the Ateco classification and 0 otherwise. More precisely, a firm is defined as high-tech if it belongs to the following industrial sectors: chemicals and drugs (Ateco 24), mechanical machinery (Ateco 29), computer equipment (Ateco 30), electronic components and machinery (Ateco 31), communication equipment (Ateco 32), medical, optical and precision equipment (Ateco 33) and transportation equipment (Ateco 34-35).[9] These seven industries have the highest R&D intensity (calculated as the ratio of R&D to R&D plus physical investment) and they account for approximately 61 percent of the total amount spent on R&D in 1998 through 2003 in this sample.

The database was split into small and medium-large firms, following the European Union classification.[10] Even if I included the ratio of sales to capital in the model, one may argue that these specifications do not completely control for the expectations role played by cash flow. In this context, it may be helpful to split the sample, since the possible correlation between expectations and cash flow presumably affect all firms, while financial constraints are likely to have differential effects across firm groups with different characteristics that affect their access to finance.

Table 1 summarizes information on the R&D activity of the sample firms. Out of 1,106 firms, 474 belong to the high-tech sector. The dataset is largely skewed towards small firms, which represent nearly 70 percent of the total sample and 66 percent of the sub-sample of high-tech firms. Medium-large firms account for 30.65 percent of the total sample (34 percent of the sub-sample of high-tech companies). As expected, high-tech firms are more R&D intensive than non-high tech firms. The percentage ratio of R&D expenditures over total investment expenditures (R&D + capital investments) for high-tech companies is twice as high as for the non high-tech sector. However, across the seven high-tech industries the ratio varies substantially: 19.91 percent for chemicals and drugs, 27.54 percent for mechanical machinery, 29.47 percent for computer equipment, 24.37 percent for electronic components and machinery, 39.69 percent for communication equipment, 41.45 percent for medical, optical and precision equipment and 10.28 percent for transportation equipment. Although the level of R&D intensity does not vary much across small and medium-large firms, R&D intensities tend, however, to increase with firm size. This is consistent with the idea that investments in innovation generate increasing returns: large firms are more willing to engage in innovative activities because they can more easily amortize such costs over larger output. In addition, it may be easier to finance R&D investments in large firms which are well-known and have longer relationships with external investors or lenders. Small firms exhibit the highest growth rate of R&D investments over the years (with an average growth rate of 12.26 percent per year), while the value is 7.50 percent for medium-large firms.

[Insert Table 1 here]

In Table 2 I provide evidence on how both fixed and R&D investments are financed. The data are extracted from the survey. A first look at the composition of financial sources for both capital and R&D investments clearly supports the importance of internal equity through retained earnings over other potential financial sources. Internal funds (cash flow) finance nearly 50 percent of physical capital investment and a remarkable 83 percent of R&D investment. The data show the almost negligible role of private external equity finance in the Italian industrial system which accounts for only 0.69 percent of financial sources for fixed investment and 0.09 percent for R&D investments. Public funding represents a small, but non-trivial, source of financing for

R&D. The existence of capital market imperfections and the absence of a complete appropriability of the returns to R&D, could lead to a low propensity by private firms to invest in research relative to the social optimum. Thus, public intervention could be helpful.

The most striking fact in Table 2 is the difference in the share of bank loans as a source of funds for fixed capital (40.45 percent) compared with R&D (5.83 percent). Because of banks are by far the most important source of external business finance in Italy, the fact that loans provide such a large share of fixed investment financing is not surprising. In contrast, however, bank lending seems almost trivial as a source of funds for R&D, for firms of all sizes. It is widely believed (see Levine, 2005) that bank-based financial systems are better suited to financing innovation embodied in physical capital rather than high-tech research. In addition to the arguments presented in the previous section, there is the fact that banks have no expertise in assessing innovative projects but simply channel funds into resource-demanding investments that the introduction of new technologies entails.[11] By contrast, market-based financial systems (such as those in the US and UK) may be optimal for promising high-tech start-ups and mature R&D performers. Heterogeneity across countries' financial systems has been relatively well documented in terms of their potential effects on company investment.[12]

While there are good reasons to focus on credit market constraints, little attention has been given to the role played by the different sources of financing for both capital and R&D investments. Most studies simply ignore the separate sources of finance for R&D and physical investments. In addition there are no cross-country comparisons on the relative weight of financial sources for different kinds of investment decisions.

The data confirm that firms rely on different financial sources for different kinds of investment: while debt is a major source of funding in Italy only for fixed investments, R&D is almost entirely financed by internal equity. One implication of a strong dependence of investments on present cash flow is that shifts in the supply of internal equity finance, and hence on business cycle movements, may lead to associated changes in the level of R&D investments[13]. This is generally acknowledged as a major drawback for investments in innovation, which typically require smooth and continuous expenditure profiles over time. However, because of high adjustments costs for R&D, innovative firms are likely to set the level of R&D investment according to a “permanent” level of internal finance, irrespective of transitory changes in the flow of funds.[14]

It appears that small firms make comparatively less use of loans than medium-large firms for R&D investments. Conversely, they seem to rely on bank debt more than medium-large firms for capital investments. A possible explanation is that leasing, which was included in the category “loans” for capital investments accounts for 46.13 percent of total debt in small firms, a percentage which is significantly higher than in medium-large firms. Besides of the high variance of returns and lack of collateral for R&D investments, small firms likely face more severe information problems that make external finance considerably difficult to obtain (see Berger and Udell, 1995).

[Insert Table 2 here]

The evidence that internal finance is the major source of finance for R&D investments is not surprising since, for R&D-intensive firms, information asymmetry problems and the high idiosyncratic risk of innovative activities make debt a poor substitute for equity finance. Yet, previous empirical studies have found mixed evidence of such a relationship by relying only on balance sheet information. To my knowledge, this is the first paper to investigate the effect of internal finance on capital investments undertaken by innovative firms by complementing accounting data with firm-level survey data.

I explore the impact of fluctuations of internal finance for capital investments, testing for the presence of informational frictions in the credit market for firms performing R&D activities. It is important to underline that it is not possible to use firm-level data on R&D expenditures, as the declaration of this information is not compulsory in Italy. Given this limitation, the methodology consists in capturing the innovation dimension of the firms in the sample through dummy variables measuring R&D activity and then testing for financing constraints using data on physical capital.

Table 3 presents descriptive statistics for the variables used in the econometric analysis between 1998-2003. I follow the standard practice in the investment literature of scaling each variable by the beginning-of-period replacement value of capital stock. Fixed investment is computed as the difference between the book value of tangible fixed assets of end of year t and end of year t-1 adding depreciation of year t. The replacement value of capital stock is based on the reported net book value of tangible fixed capital assets.[15] Cash flow is defined as the sum of after-tax profit and depreciation. All the variables are deflated by a two-digit price index provided by the national Institute of Statistics (ISTAT). Following Himmelberg and Petersen (1994), Bond et al. (2003) and Scellato (2007), I use the sales-capital ratio to control for expected future profitability. The rationale is that this variable should allow to disentangle the variance in investment opportunities due to expected profitability from that due to financial availability. A large number of empirical studies use Tobin's Q (defined as the market value of the firm divided by the replacement value of its capital stock) to capture the possible role of expectations.[16] However, this approach is not possible in this dataset, because only a small percentage of firms are listed on the stock exchange. RD and HIGHTECH are dummy variables.

Capital ratios for small and medium-large firms are quite similar at the mean level, but medium-large firms show slightly higher capital intensities at the median level. The sales to capital ratio at the median remains fairly constant across the groups, although smaller firms display a higher value. The mean of the cash flow ratio is larger for small firms although the median is highest for the medium-large group. Investing in R&D is more likely among medium-large firms: the share of medium-large firms belonging to a high-tech sector is 47.4 percent, compared with 40.8 percent of small firms. Medium-large firms are also more deeply involved in R&D activities: the share of R&D performers is in fact smaller among small firms (43.2 percent) than among the medium-large ones (72.8 percent).

[Insert Table 3 here]

4. Empirical specification and estimation method

The empirical specification is based on Himmelberg and Petersen (1994). I consider a simple investment accelerator model for capital investments augmented with cash flow. The baseline specification is:

$$I_{it}/K_{i(t-1)} = \beta_0 I_{i(t-1)}/K_{i(t-2)} + \beta_1 CF_{it}/K_{i(t-1)} + \beta_2 S_{it}/K_{i(t-1)} + v_i + v_t + \varepsilon_{i,t} \quad (1)$$

where I is the firm's capital investment, K, the value of its capital stock, CF the firm's cash flow and S the level of sales. The subscript i indexes firms and t, time (1998-2003). The error term consists of three components: v_i which is a firm-specific component, v_t a time-specific component accounting for possible business cycles effects and interest rates, and $\varepsilon_{i,t}$, an idiosyncratic component. In the other specifications of the model I use dummy variables measuring R&D activity as interactions on the cash flow term.

I first estimate equation (1) using the within-firm estimator[17]. This approach controls for unobservable firm effects. However, the presence of simultaneity between contemporaneous regressors and disturbances might lead to inconsistent estimates. Therefore results are estimated using a first-difference Generalized Method of Moments (GMM) approach which eliminates the firm-specific effects by differencing and controls for endogenous explanatory variables by using lagged levels of endogenous variables as instruments.[18] As noted in Bond et al. (2003), if the error term in levels is serially uncorrelated, then the error term in first differences has a moving average structure of order one. Hence, independent variables lagged twice or more will be valid instruments. If the error term in equation (1) has a moving average structure, then longer lags must be used for the instruments. I adopt as instrumental variables the values of all independent variables lagged two periods. In order to evaluate whether the instruments used are correct, I test for serial correlation in the residuals in the differenced equations using the Lagrange Multiplier test, respectively of order one (M1) and two (M2). These are asymptotically standard normal under the null of no serial correlation of the differenced residuals. They provide a further check on the specification of the model and on the legitimacy of variables dated t-2 as instruments in the differenced equations.

5. Empirical results

Tables 4 and 5 present estimation results for equation (1) when the sample is split into small and medium-large size categories. Both tables report either the within-firm and first-difference GMM estimates. For the GMM regressions, I report direct tests for first-order (M1) and second-order (M2) serial correlation in the differenced residuals. Neither the M1 test, nor the M2 test for second-order autocorrelation of the differenced residuals indicate problems with the specification of the model or with the choice of the instruments.

Table 4 presents estimated results for the sub-sample of small firms. The coefficient associated with the cash flow to capital ratio suggests that current cash flow plays a positive and statistically significant effect on capital investment in the OLS and GMM regressions. The estimated magnitudes are sensitive to the econometric technique: current cash flow has a coefficient of 0.562 in the GMM regression which is 1.6 times larger than the corresponding value in the OLS-within regression (0.349). Also, coefficients associated with the interaction between cash flow and the HIGHTECH and RD dummies are substantially larger in the GMM regression.[19]

The magnitude of the cash flow coefficients is quite large compared with other estimates in the literature. The GMM estimate above 0.47 is larger than even the biggest effects found in early research on this topic by Fazzari et al. (1988), and their estimates are larger than the coefficients in most of the following literature.

The ratio of sales to capital is significant in all the model specifications. Belonging to the high-tech sector and being involved in some R&D activities has a positive and significant effect on investment-cash flow elasticity for small firms.

[Insert Table 4 here]

The sensitivity of investment spending to fluctuations in cash flow appears to be much greater for small firms than for medium-large firms. It appears that, although statistically significant, large firms' cash flow has a smaller effect on capital investments.

The overall evidence points to the presence of less tight financing constraints in the medium-large firm sample, while significant effects of internal equity finance on capital investments are found for small firms. The larger financial effect for small firms is expected because small firms are usually characterized by short track records, higher idiosyncratic risk and low real assets that make external finance a poor substitute for internal equity. On the contrary, large firms may have better access to external finance because they are typically long-established companies with financial track records and good credit ratings. Moreover, they can generate cash flow in excess of investment needs.

Most importantly, performing R&D activities has a negative and significant effect on the sensitivity of investment to cash flow. Also, large high-tech firms have lower investment-cash flow elasticity.

[Insert Table 5 here]

The estimated results highlight that the dependence of investment on internal sources cannot be fully attributed to a credit rationing behavior due to firms' in-house innovation activities. As extensively discussed in previous sections, the capability to invest by high-tech firms is relatively more conditional on the amount of internal resources than that by firms not involved in R&D activities. Although this can be interpreted as the presence of more binding financial constraints in the industries that are perhaps the most important for innovation and growth, it is clear that firm size is what mostly affect the decision of external investors to grant credit. When high-tech firms are also small size enterprises, financing constraints can become tighter. This is almost clear in the regressions for which cash flow has a significant effect for small high-tech or R&D companies, while it does not influence investment by medium-large innovative firms.

6. Alternative specifications and robustness tests

I have explored a set of alternative specifications. The baseline model (1) was augmented with the one-year lagged value of cash flow and the one-year lagged value of sales to capital ratio. The overall interpretation I give to the baseline results remains largely unchanged, for both samples of small and medium-large firms.

Considering the dynamic model specification for the sub-sample of small firms, no significant changes in the values and statistical significance of cash flow take place (the cash flow coefficient increases from 0.562 to 0.578). Lagged cash flow has a statistically significant coefficient as well as lagged sales to capital ratio. The M2 test does not indicate any problem with the specification of the model. The high dependence of investment on internal sources for small firms operating in a high-tech sector or investing in R&D is confirmed by the positive and statistically significant impact of the dummies interacted with cash flow on capital investment. Coefficients are respectively 0.205 for high-tech firms and 0.127 for firms undertaking R&D investments.

When I consider the sub-sample of medium-large firms and I add to the baseline model the lagged values of the explanatory variables, the cash flow coefficient increases from 0.250 to 0.305. The lagged value of cash flow tends to be positive and statistically significant, as well as the lagged value of sales to capital. Also in this case, the explanatory power of cash flow is robust to the inclusion of the lagged values of cash flow and sales to capital ratio. The p-values for M1 and M2 statistics indicate the presence of first-order autocorrelation in the estimated errors, but cannot reject the null of the absence of second order autocorrelation. The coefficient resulting from the interaction between R&D dummies and firms' cash flow is negative and not statistically significant.

7. Conclusions

In this paper, I have examined whether internal finance is the principal determinant of capital investments for a short panel of Italian manufacturing firms, testing for the presence of informational frictions in the credit market for firms performing R&D activities. I have estimated a simple accelerator model using a GMM method which controls for biases due to un-observed firm-specific effects and endogenous explanatory variables. Within-groups estimates have been reported for comparison. The sample has been split into groups, presumably accounting for different levels of financing constraints (small and medium-large firms).

Results, which are generally robust to a variety of estimators and control variables, suggest that internal equity finance plays an important role in explaining capital investment expenditures, especially for small firms. This suggests that large firms' investment is less constrained by access to external finance, while for small firms binding financing constraints make capital investment more sensitive to changes in internal finance. I find significant differences between the two groups of firms when I consider measures of firms' innovative activities. The point estimates for cash flow interacted with dummy variables measuring R&D activity are positive and highly statistically significant for the sub-sample of small firms. On the contrary, medium-large innovative companies have lower or not significant investment-cash flow elasticity. The estimated results highlight that the dependence of investment on internal sources cannot be fully attributed to a credit rationing behavior due to firms' in-house innovation activities. It appears that firm size exerts a significant impact on the availability of external financial sources to be channeled into R&D.

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9. Tables

Table 1- R&D intensity by firm size and sector

	Number of firms	R&D/(R&D+INV) %
HIGH-TECH	474	20.06
NON HIGH-TECH	632	9.35
TOTAL	1106	14.08
SMALL	767	11.78
Small (high-tech sector)	313	16.51
Small (non high-tech sector)	454	8.34
MEDIUM-LARGE	339	18.33
Medium-large (high-tech sector)	161	25.80
Medium-large (non high-tech sector)	178	11.43

Table 2- R&D and investment financing (percent)

Capital Investments			
	Total Sample	Small	Medium-Large
Private equity	0.69	0.66	0.74
Internal funds	49.95	47.36	55.11
Loans	40.45	43.2	34.91
Public funds	3.86	3.78	4.04
Tax incentives	3.9	4.22	3.26
Other	1.15	0.78	1.94
TOTAL	100	100	100
R&D Investments			
	Total Sample	Small	Medium-Large
Private equity	0.09	0.16	0.02
Internal funds	83.13	85.88	79.93
Loans	5.83	3.81	8.17
Public funds	7.93	7.78	8.13
Tax incentives	2.23	1.62	2.90
Other	0.79	0.75	0.85
TOTAL	100	100	100

Table 3- Sample descriptive statistics

	Total Sample	Small	Medium-Large
$I_{it}/K_{i(t-1)}$			
Mean	0.354	0.363	0.333
St. Dev.	0.766	0.839	0.568
Median	0.163	0.156	0.179
$CF_{it}/K_{i(t-1)}$			
Mean	0.459	0.488	0.393
St. Dev.	0.832	0.910	0.648
Median	0.262	0.260	0.264
$S_{it}/K_{i(t-1)}$			
Mean	9.97	11.28	7.00
St. Dev.	12.14	13.40	7.87
Median	5.57	6.07	4.75
HIGHTECH (0;1)			
Mean	0.428	0.408	0.474
St. Dev.	0.494	0.491	0.499
Median	0	0	0
RD (0;1)			
Mean	0.523	0.432	0.728
St. Dev.	0.499	0.495	0.444
Median	1	0	1

Table 4- Investment regression. Testing for the effect of innovation activities (sub-sample of small firms)

	SMALL FIRMS					
	OLS-WITHIN			FIRST-DIFFERENCE GMM		
	Model I	Model II	Model III	Model I	Model II	Model III
$I_{(t-1)}/K_{i(t-2)}$				0.031** (0.017)	0.028** (0.017)	0.028** (0.017)
$CF_{it}/K_{i(t-1)}$	0.349*** (0.026)	0.270*** (0.036)	0.321*** (0.036)	0.562*** (0.045)	0.406*** (0.061)	0.495*** (0.056)
$S_{it}/K_{i(t-1)}$	0.035*** (0.002)	0.035*** (0.002)	0.035*** (0.002)	0.009** (0.005)	0.011** (0.005)	0.009** (0.005)
$CF_{it}/K_{i(t-1)}$ *HIGHTECH		0.135*** (0.043)			0.210*** (0.064)	
$CF_{it}/K_{i(t-1)}$ *RD			0.048** (0.044)			0.114** (0.062)
R-sq	0.29	0.29	0.29			
Obs.	3068	3068	3068	2301	2301	2301
Test LM1				-13.99 [0.000]	-14.00 [0.000]	-14.16 [0.000]
Test LM2				-0.80 [0.424]	-0.28 [0.776]	-0.67 [0.505]

Note: Estimated with year dummies (not reported). Robust standard errors are reported in parenthesis.
***: significant at the 5% level **: significant at the 10% level

Table 5- Investment regression. Testing for the effect of innovation activities (sub-sample of medium-large firms)

	MEDIUM-LARGE FIRMS					
	OLS-WITHIN			FIRST-DIFFERENCE GMM		
	Model I	Model II	Model III	Model I	Model II	Model III
$I_{(t-1)}/K_{i(t-2)}$				-0.007 (0.029)	-0.011 (0.029)	-0.012 (0.028)
$CF_{it}/K_{i(t-1)}$	0.239*** (0.032)	0.390*** (0.084)	0.323*** (0.085)	0.250*** (0.038)	0.514*** (0.122)	0.462*** (0.111)
$S_{it}/K_{i(t-1)}$	0.044*** (0.004)	0.041*** (0.004)	0.041*** (0.004)	0.039*** (0.006)	0.029*** (0.007)	0.030*** (0.007)
$CF_{it}/K_{i(t-1)}$ *HIGHTECH		-0.167** (0.086)			-0.273** (0.120)	
$CF_{it}/K_{i(t-1)}$ *RD			-0.093 (0.086)			-0.218** (0.110)
R-sq	0.29	0.29	0.28			
Obs.	1356	1356	1356	1017	1017	1017
Test LM1				-10.56 [0.000]	-10.99 [0.000]	-10.61 [0.000]
Test LM2				0.12 [0.905]	-0.09 [0.928]	-0.03 [0.977]

Note: Estimated with year dummies (not reported). Robust standard errors are reported in parenthesis.
***: significant at the 5% level **: significant at the 10% level

10. Footnotes

[1] This sample-splitting methodology, which has been widely used in the literature on financing constraints and investment since the work of Fazzari et al. (1988), was criticized by Kaplan and Zingales (1997). They assumed that all firms face binding financial constraints and they provided a counter-example in which a firm that faces a greater cost premium for the use of external finance could have a lower sensitivity of investment to internal finance. Also see, however, the response in Fazzari, Hubbard and Petersen (2000).

[2] See Aghion and Howitt (1992) on these modern Schumpeterian approaches.

[3] This argument is usually used to justify such interventions as government support of R&D, the intellectual property system and R&D tax incentives.

[4] The authors assume the simultaneous presence of a perfect informational context, an efficient capital market and the absence of bankruptcy costs.

[5] A large body of research pointed to the importance of collateral for debt finance. Bester (1985) and Hubbard (1998) showed how this condition may badly affect the possibility to access external finance for innovative firms. Berger and Udell (1990) found a negative correlation between leverage and intangible assets for a large sample of US companies. Močnik (2001), using a sample of Slovene firms, found support for the hypothesis that firms with a high level of intangible assets should be characterized by a lower debt/equity ratio.

[6] If the investment has not been undertaken before (as it happens for investments in innovation) it is impossible to observe the systematic risk of similar projects in other firms and thus to determine the appropriate discount rate to be used in the calculation of the net present value of the project, as the CAPM or arbitrage pricing theory predict.

[7] See Hall (2002) for an excellent review of the existing literature.

[8] The two surveys, although not identical in their questions, are very similar and they are representative of the universe of Italian manufacturing firms with more than 10 employees. All firms with more than 500 employees were included, while firms with 11–500 employees were selected according to a stratified sampling method based on size, industry, and location. Previous releases of the survey have been used extensively in the literature (see Detragiache et al. 2000; Bagella et al., 2001; Angelini and Generale, 2005; Benfratello et al. 2006, Herrera and Minetti, 2007)

[9] Industrial sectors are identified through the two-digit Ateco classification which is provided by ISTAT (the Italian National Institute of Statistics) and it is similar to the international SIC classification. A similar set of industries are identified as science-based by Himmelberg and Petersen (1994), Benfratello et al. (2006), Brown et al. (2007).

[10] The European Union has had a common classification of firms since 1996 that was updated in 2003 (Commission Recommendation 96/280/EC of April 3, 1996, updated in 2003/361/EC of May 6, 2003). Accordingly, firms are classified as “micro” (less than 10 employees or a turnover of less than €2 million),“small” (less than 50 employees or a turnover of less than €10 million), “medium” (less than 250 employees or a turnover of less than €50 million) and “large” (more than 250 employees or a turnover more than €50 million).

[11] See Ughetto (2007) for an analysis of recent changes occurring in the Italian banking system to assist firms' technology-based activities in Italy. Banks have recently launched specific loan programs to support product and process innovation and other forms of innovation. Technological assessment of the projects is provided mostly by external teams of engineers, except for a few banks which have their own internal evaluation teams.

[12] Bond et al. (2003) found that cash flow and profits appear to be both statistically and quantitatively more significant for capital investments in the United Kingdom than in Belgium, France and Germany. Similar findings are provided by Hall et al. (1999) for a panel of high-tech firms in France, US, and Japan. Bond et al. (1999) compared the relative sensitivities of R&D investments to cash flow for two samples of German and British firms operating in high-tech sectors and showed that financial constraints are important for UK firms, while a similar effect is not identified for Germany. Similarly, Mulkay et al. (2001) undertook a cross-country comparison by analysing two samples of large French and US manufacturing firms. Their results suggested that financial constraints both to R&D and physical capital investments are much tighter in the US than in France, although differences are much less obvious when it comes to R&D investments.

[13] See Brown et al. (2007) for an analysis of the extent to which internal and external equity finance supply shifts affect aggregate R&D investment growth.

[14] High adjustment costs for R&D are due to the fact that most of R&D spending is in qualified workers' salaries. Temporary hiring or firing of researchers can be very costly for firms because scientists or engineers have a firm-specific knowledge that would disappear or be transmitted to competitors if they left the company. High adjustment costs of R&D activities can also be explained by the long-term perspectives of investments. These aspects, together with the indivisibility and modularity of the innovation process, induce firms to smooth their R&D expenditures over time. Another potential consequence is that firms will engage in R&D activities only if they do not expect to be seriously affected by credit constraints. See Hall (2002) for a discussion of this point.

[15] I have also experimented with the standard perpetual inventory method to measure the stock of capital at current replacement cost. The perpetual inventory formula is the following one: $p^I_t K_t =(1\text{-dep.})(p^I_{t-1} K_{t-1})(p^I_t / p^I_{t-1})+ p^I_t I_t$ where dep. is the depreciation rate, which I assumed to be constant and equal to 8% and p^I_t is the price of investment goods, which I proxied with the implicit deflator for gross fixed capital formation. The results remained similar with this alternative measure of the capital stock.

[16] An alternative model, which leads to a similar regression specification, is the Euler equation approach (Bond and Meghir, 1994) derived from the firm's intertemporal maximization problem under the assumption of symmetric, quadratic costs of adjustment.

[17] Within-firm estimation consists in transforming variables to deviations from their firm-specific means.

[18] See Arellano and Bond (1991) on the application of the GMM approach to panel data.

[19] Himmelberg and Petersen (1994) explain the potential downward bias associated with the within-firm estimates for R&D firms, pointing to the existence of high adjustment costs that prevent them from responding to transitory movements in cash flow. This effect is similar to measurement error since actual cash flow is a noisy signal of permanent cash flow, and instrumental variable estimation may be helpful.

ESSAY 2

Industrial districts and financial constraints to innovation

1. Introduction

The issue of the informational wedge that exists between banks and borrowers has been largely investigated in recent years. Problems of information asymmetries are particularly acute for firms involved in research and development (R&D) activities. This stems from the fact that entrepreneurs are usually better informed than lenders as to the likelihood of success for their innovation projects, and they have poor incentives to disclose information to investors since this might reveal useful information for competitors (Bhattacharya and Ritter, 1983). Moral hazard effects can then hamper the external financing of innovative projects since entrepreneurs could change ex-post their behaviour by choosing to implement higher risk projects. Therefore, if the borrower cannot commit ex-ante to non-opportunistic behaviour, the funding decision may not be fully efficient (Hall, 2002; Carpenter and Petersen, 2002b).

There are a number of additional factors which make innovative firms unsuitable for debt financing: the limited availability of collateral to secure firm's borrowing, the high degree of risk which characterizes R&D investments and the complexity of evaluating the expected future prospects of innovative activities.[1] As a result, financial intermediaries may end up denying credit to companies involved in substantial R&D activities (see Santarelli, 1995 for a survey and discussion on this topic).

Such an effect becomes more intense when innovative firms are also small size enterprises. Due to their "informational opacity", small firms are in fact more likely to face credit constraints compared to larger businesses which can provide detailed financial information.

A large number of studies have pointed to relationship lending as the most powerful way to reduce information asymmetry problems for financing small firms (Berger and Udell, 2002; Petersen and Rajan, 1994). Under relationship lending, the lending decision of a bank is based on "soft information" acquired over time through contacts with the firm, the owner, and the local community.[2]

Relationship finance is associated with "informational distance", which normally coincides with physical distance (Hauswald and Marquez, 2000). The costs of generating borrower-specific information are, in fact, increasing with territorial distance and the co-location of banks and firms in the same area facilitates the exchange of relevant information upon which relationships of mutual trust can be built. This is the case of Italian industrial districts in which socio-economic interactions, both at the firm and credit market level, are favored by spatial concentration (Becattini, 1990).

If a reduced physical distance between a bank and a firm contributes to the reduction of information asymmetries, the question of whether the same applies to innovative firms becomes a fundamental one.

For this category of firms, the market of choice for external financing is the private equity market, which is not constrained into territorial boundaries. Innovative firms willing to invest in high-risk, high-rewarding projects can presumably be financed by a foreign venture capital operating thousands of miles away. However, in many European countries like Italy, the venture capital market seems to be rather underdeveloped.[3] Italy's financial system can definitely be considered as bank-based and the stock market plays a very limited role in providing external financing to firms at any stage of their life cycle. This situation calls for a deeper reflection on the role of traditional credit suppliers in supporting innovative activities.

The paper contributes to shed some empirical light on the relationship between innovation and credit availability in the context of Italian industrial districts, using recent survey data from the Mediocredito database.[4] To my knowledge, this is the first study that investigates the issue of credit constraints for innovative firms located in industrial districts.

Traditionally, the empirical literature on credit constraints has looked for indirect evidence, identifying financially constrained firms through several proxies (firm size, interest rates, dividend payouts, or group membership).[5] These indirect indicators are undoubtedly useful but they share a common drawback: they may be well correlated with financial constraints but may also pick up some other effects which have nothing to do with them. The methodology used in this paper is exempt from these objections because it allows me to detect liquidity constraints directly from survey questions.

The econometric approach follows that of Piga and Atzeni (2007), who use a bivariate probit with sample selection to investigate the factors affecting a firm's probability of being credit rationed, after controlling for the determinants of its antecedent decision to request additional credit.

In this paper I discuss three main research hypotheses:

H1. Firms located in industrial districts face lower credit constraints;

H2. Innovative firms are more likely to be credit rationed;

H3. Innovative firms have easier access to external finance when they are located in industrial districts.

H1 is consistent with theoretical models which predict a positive impact of relationship distance on lending conditions. The local nature of industrial districts gives a bank a comparative advantage in dealing with asymmetric information and agency problems (Diamond, 1984; Ramakrishnan and Thakor, 1984). Proximity to the borrower can lead financial intermediaries to bear lower costs in collecting "soft" information. Moreover, monitoring efforts are significantly reduced if community members control each other (peer monitoring). The informational monopoly, resulting from long-lasting lending relationships that geographical proximity allows, is not used to extract rents from close borrowers. On the contrary, close borrowers have better access to external finance.

The empirical analysis is aimed at examining the extent to which firm-bank territorial proximity may ease financial constraints. To that purpose, I try to assess the magnitude of credit constraints on firms belonging to district areas. The results confirm that the reduced geographical distance with credit suppliers in district areas can lead to overcoming information asymmetries between lenders and borrowers. Being located in a district significantly reduces the probability of being credit rationed by 0.5 percentage points. Results also suggest an inverse relationship between being located in a district and the probability of needing extra-funds.

H2 is in line with the theoretical predictions of the literature on financing constraints and R&D investments. I assume that under-lending best describes the relationship between lenders and innovative firms. Credit rationing is more likely to occur for innovative firms because their investments' returns are uncertain, they have little collateral and their capital, which is mostly intangible, is hardly re-deployable in alternative settings.

The evidence, after controlling for traditional measures of firms' financial performance, is in line with the results of the extant literature. Indeed, I observe a higher probability of facing financial constraints for firms undertaking innovative activities, with a weaker effect when measures of R&D intensity are considered. Such a situation is reflected in the summary data on financial sources for innovation projects: on average, retained earnings cover nearly 81 percent of the annual expenditures, while long-term debt accounts for only 8.7 percent of them.

I complement the two previous hypotheses with a last one (H3). I assume that information frictions can be alleviated if a firm undertaking innovative activities is located in a district area. District firms can benefit from long-term social and business relationships with local banks, that can easily gather information on borrowers at low costs and consequently facilitate companies' access to finance. If the firm is well-known and has developed long-term credit relationships with the bank throughout the years, it is less likely that credit tightening occurs, even when the firm engages in R&D activities. Another interpretation is that a bank can possibly share the risk of financing R&D investments with other banks in the district. In Italy most of small firms rely on multiple lending[6] and survey data show that, on average, district firms borrow from more than one bank. Moreover, firms undertaking innovation in industrial districts are likely to cooperate with neighbor firms at different stages of their R&D activity. Following Chiesa (2005), if cooperation is not undermined by agency problems, finance can be provided by the more established and liquid company. If cooperation is not optimal, then financing is provided by the bank. In this last case, banks assume that the risk concerning the R&D investment is shared between the two firms. Consequently, innovative firms are less likely to be rationed.

Empirical results suggest that innovative firms operating in industrial districts are less likely to suffer from credit constraints at 10 percent level of significance. An inverse relationship, although not significant, can be found between performing R&D activity in district areas and the probability of desiring more credit.

The rest of the paper is organized as follows: Section 2 reviews the extant literature on financial constraints, innovation and territorial proximity. Section 3 introduces the data and provides some relevant descriptive statistics. Section 4 presents the empirical model. Section 5 displays and comments on the empirical results. Section 6 concludes the paper.

2. Theoretical foundations and empirical evidence

2.1 Innovation and financing constraints

It is a widely held view that research and development activities are potentially subject to severe borrowing constraints. This argument relies on theoretical models which date back to the classic articles of Nelson (1959) and Arrow (1962), although the idea itself was alluded to by Schumpeter (1942).[7] Arrow (1962) points out that the knowledge embodied in new technologies cannot be fully appropriated by its creators. To the extent that knowledge cannot be kept secret because it is a non-rivalrous good with incomplete excludability, a market failure leading to underinvestment in R&D takes place. He also suggests that external finance opportunities for innovative activities can be hampered by moral hazard problems.

However, it is only with Akerlov's (1970) landmark study on the role of asymmetric information in the market for "lemons" that adverse selection and moral hazard considerations begin to fuel the economic debate. Moving from this initial input, the asymmetric information literature postulates the existence of an informational advantage of entrepreneurs over financiers about the quality of their investment projects, thus predicting the existence of rationing when external finance is represented by bank debt (Jaffee and Russel, 1976; Stiglitz and Weiss, 1981; Myers and Majluf, 1984). The authors of this strand of literature clearly challenge the Modigliani-Miller theorem (1958), by which any desired investment project with positive net present value can be financed either internally or externally, since external funds can costlessly substitute for internal capital.[8]

Jensen and Meckling (1976) argue that the presence of limited liability debt is likely to give rise to moral hazard problems, because firms may choose to opt for risky investment projects, although value decreasing. When debt-holders anticipate this behaviour, they will demand a premium on the debt that restricts the firm's future use of debt. In a context where lenders have less information than entrepreneurs, a limit on the amount of credit extended might turn out to be the optimal policy for the financial intermediary (Jaffee and Russell, 1976). Stiglitz and Weiss (1981) show that banks end up rejecting some borrowers because of negative adverse selection effects. Since the project risk is unobservable, lenders cannot discriminate between good and bad borrowers. When interest rates increase, more risk-adverse borrowers, who choose relatively safe investment projects, drop out of the market since only those with riskier investments will apply for a loan at a higher interest rate.

One implication of the theories of the firm under imperfect capital markets is that financial factors, such as retained earnings and the availability of new debt or equity, determine firm's investment decisions. Evidence in most advanced economies shows that R&D investment is predominantly financed by internally generated cash flow (Himmelberg and Petersen, 1994).

Besides the arguments developed by the literature on information asymmetries, the reasons why internal equity finance is preferred to debt or external equity for R&D investment concern the specific characteristics that distinguish R&D investments from ordinary investments. First, the returns to high-tech investments are skewed and highly uncertain because R&D projects have a low probability of success (Carpenter and Petersen, 2002b). Therefore it is possible that early in the life of an R&D project the profits will be insufficient to cover any interest payments on a debt instrument used to finance it. Second, investments in innovation create largely intangible assets (that are predominantly salary payments) which cannot be used as collateral to secure firms' borrowing (Lev, 2001; Berger and Udell, 1990).[9] Third, the expected future revenues of an uncertain activity like scientific and technological research are difficult to estimate without proper analytical tools.[10] There is an additional argument, suggested by Bhattacharya and Ritter (1983), that stresses the reluctance of firms to finance their R&D externally for strategic reasons. Firms have little incentive to disclose information on their innovative projects to lenders since this knowledge could leak out to competitors. Therefore managers prefer to rely on internal sources of funding to finance their investments. This attitude is likely to be even stronger for smaller companies which are not able to protect their innovations through complementary assets, such as established distribution networks (Scellato, 2007). A stimulating theoretical hint related to this point is provided in the paper by Chiesa (2005), which examines a model where an established firm and a start-up engage in R&D and subsequently compete in the product market. The author shows that if cooperation is optimal, then financing is provided by the established firm. By contrast, if cooperation is not optimal, then the investor will be a pure financial institution so as to minimize information leakages to rivals. Finally, financial distress can be particularly harmful for R&D firms because of their concentrated, firm-specific assets, which constitute non-redeployable capital due to the absence of a secondary market for innovation. When innovative firms face financial distress, their market value, which is based on future growth options, rapidly decreases (Cornell and Shapiro, 1988).

The traditional empirical approach used to test for the presence of financing constraints at the firm level is based on a *a priori* identification of relatively more financially constrained firms and an econometric estimation of an investment demand function. Since the first approach by Fazzari, Hubbard and Petersen (1988), a considerable number of studies applied the analysis of investment-cash flow sensitivities to investigate the effects of financial markets' imperfections on innovation.

Hall (1992) examines the degree of correlation between R&D and cash flow for a large panel of US manufacturing firms using an accelerator type model and finds a strong effect of cash flow on R&D expenditures, together with a negative correlation between R&D expenditures and the degree of leverage. Himmelberg and Petersen (1994) focus their analysis on a panel of 179 small US firms in high-tech industries, suggesting that internal financial resources are a major determinant of R&D expenditure decisions. Hao and Jaffe (1993) come to the same results by splitting their sample in groups according to the size of firms. They find support for the hypothesis that R&D is liquidity constrained, although their results suggest that there is no liquidity effect for large firms. Scellato (2006), using a panel of 804 Italian companies observed through the years 1995-2000, finds that only firms showing lower financial constraints are able to keep a sustained patenting profile through time. Moreover, the presence of liquidity constraints on physical capital investments forces medium-sized enterprises to delay the initial start of in-house research and development activities for product enhancement.

The main problem of testing the impact of financial constraints on R&D investments is that both the level of expenditures on R&D and measures of liquidity might be correlated with a third variable, namely the expected future revenues of the firm.[11] In order to avoid the traditional problems linked to the interpretation of cash flow effects, there are a few other studies which address the issue of financial constraints to innovative activities by relying on surveys (Guiso, 1998; Savignac, 2005; Piga and Atzeni, 2007). Savignac (2005) estimates the impact of financial constraints on the decision to engage in innovative activities through a recursive bivariate probit model. He shows that the likelihood that a firm will start innovative projects is significantly reduced by the existence of financial constraints. Moreover, the fact of being credit constrained is dependent on the firm's ex-ante financial structure, past economic performance, and sector-based factors.

For the Italian context, Guiso (1998) relates the probability of being credit constrained to observable characteristics of firms, grouping companies into high-tech and low-tech ones. The estimates show that high-tech firms are more likely to be constrained in credit markets than firms undertaking traditional investment projects. Different results are provided by Piga and Atzeni (2007) who estimate a bivariate probit model to capture both the extent to which R&D intensive firms are liquidity constrained and their decision to apply for credit. The authors find that firms with high-levels of R&D expenditures do not seem to be credit rationed, suggesting an inverse U-shaped relationship between R&D activity and the probability of being liquidity-constrained.

2.2 Territorial proximity and financing constraints

Financial constraints have been proven to be a serious barrier for growth perspectives of small and medium sized firms suffering from asymmetric information (Becchetti and Trovato, 2003; Becchetti, 1995). In particular, the growth rate of small firms is likely to depend upon the availability of internal finance, being the wedge between the cost of internal and external finance larger for small firms (Carpenter and Petersen, 2002a).[12]

A significant strand of literature investigates whether and to what extent territorial proximity between lenders and borrowers might reduce information asymmetries and prevent credit rationing from occurring. I restrict myself here to a discussion of theoretical and empirical contributions which are most relevant for the study.

Two main lines of reasoning on the way proximity affects financing constraints can be identified.

According to the first one, the physical closeness to the local economy allows banks to collect over time "soft information" on small firms. Local banks, through long-term credit relations, gain a comparative advantage in terms of quality of information on local borrowers (which is costly to acquire for outside banks) that improves borrowers' screening and monitoring (see Boyd and Prescott, 1986; Diamond, 1984; Ramakrishnan and Thakor, 1984).[13] In this way the probability of erroneously denying credit to good borrowers is reduced and the borrower is likely to receive better terms on loans, either in the form of more advantageous interest rates or a higher supply of credit. In other words, closer customer relationships help overcome information asymmetries, producing a gain in allocative efficiency. The bank shares this gain with the firm by increasing credit availability and by lowering interest rates and collateral requirements (Diamond, 1991; Boot and Thakor, 1994). According to Diamond (1991) it is a reputation effect that induces borrowers to prefer safe projects to more risky ones. Boot and Thakor (1994) model an infinitely repeated game between lenders and borrowers. They demonstrate that, with an optimal credit contract, the borrower is initially charged an above-market interest rate and must post collateral, but after providing proof that investment projects have been concluded successfully, he will enjoy improved credit conditions.

Territorial proximity may also adversely impact financing constraints. In location differentiation models, borrowers incur distance-related transportation costs when visiting their banks (Hotelling, 1929; Salop, 1979). Banks price uniformly if they cannot observe borrowers' locations or are prevented from charging different prices to different borrowers. However, since banks invariably know the address of their loan applicants, they can engage in spatial price discrimination, charging a higher interest rate to firms located closest (Degryse and Ongena, 2005). The underlying hypothesis is that firms would ultimately face higher transportation costs when visiting more distant competing banks (Lederer and Hurter, 1986).

Empirical findings seem to support both the positive and negative implications of bank-firm proximity. Degryse and Ongena (2005) study the effect of geographical distance between firms, the lending bank and other banks in the vicinity on loan conditions, using contract information from more than 15,000 bank loans to small firms provided by a large Belgian bank. They find that the physical closeness between a firm and its lending bank is associated with higher interest rates, whereas its closeness to the lender's competitors reduces interest rates. Carling and Lundberg (2005) use data on granted loans between 1994 and 2000 for 53,383 small and medium-sized Swedish firms to test whether geographical proximity between the borrowing firm and the lending bank matters in credit risk management. Their hypothesis is that a bank might expose itself to a greater risk by lending to distant firms and should, therefore, respond by rationing credit. However, the authors find no evidence that a geographical credit rationing is occurring. Bonaccorsi and Gobbi (2001), using Italian data, find that the density of branches is positively correlated with the credit availability for firms (particularly for small firms), while it is negatively associated with the share of bad loans. Alessandrini et al (2006) assess what effects operational proximity and functional distance of the banking system have on borrowers' financing constraints. Their results suggest that the functional distance adversely affects the availability of credit to local firms.

For the Italian context, the issue of territorial proximity between financial intermediaries and firms has been largely examined with respect to the analysis of industrial districts (Baffigi et al. 1999; Finaldi Russo and Rossi, 2001; Becattini, 1990). Becattini (1990) emphasizes the role of local banks in easing access to credit in industrial districts: credit suppliers benefit from the geographical concentration of firms because they can easily gather better information on borrowers' characteristics, thus reducing problems of adverse selection. Furthermore, geographical proximity enables banks to monitor borrowers constantly, closely, and almost without effort or cost, to preventing possible moral hazard behaviours from occurring. Finaldi Russo and Rossi (2001) analyze a panel of 1,700 Italian firms over the 1989-1995 period and find that firms located in industrial districts have an advantage in terms of financial relations with the banking system: both the cost of credit and the probability of facing financial constraints are lower. On the contrary, Baffigi et al. (1999) show that investment by firms operating in industrial districts is more closely correlated with their cash-flow than those of non-district firms, although the pattern varies across regions and economic sectors.

3. Sample characteristics and descriptive statistics

The dataset is derived from a survey on Italian manufacturing firms[14] undertaken in 2004 by Mediocredito Centrale, a credit institution currently part of Capitalia, an Italian banking group. The survey data is coupled with complete balance sheet information for the years 2001-2002 to avoid simultaneity problems. The DELPHION[15] database was then used for patent portfolio information.

The initial sample consisted of 4,289 Italian manufacturing firms. I limited my analysis to those companies answering to the question of whether they would have wanted an additional amount of credit in the relevant years. As it is further discussed, credit-constrained firms are identified within the sub-sample of firms needing more credit.

Moreover, I removed from the sample firms with missing or non-manufacturing activity codes, as well as firms with missing values for the variables used in the econometric estimates. I also excluded observations under the first and above the last percentile of Liabilities/Total Assets and Working Capital/Total Assets because of very large figures (in both directions) in the tails of the distribution.

The final dataset includes a total of 3,129 firms. The paper discriminates between district and non-district firms following the definition of municipalities given by ISTAT, the Italian National Institute of Statistics (Istat, 2001).[16] Departing from the list of municipalities identifying industrial districts, I checked, for each firm in the sample, its location. In that way I tracked those firms located in district municipalities.

Then I applied a filter based on ATECO classification codes[17] to avoid to pick up firms operating in a sector other than the one in which the district is specialized. A total of 572 firms in the sample are located in industrial districts.

3.1 Defining credit constrained firms

The Mediocredito Centrale survey investigates the issue of firm financing by including three specific questions regarding the firm's access to the credit market: 1) whether the firm wanted an additional quantity of credit at the market interest rate 2) whether the firm was willing to pay a higher interest rate to obtain that additional quantity 3) whether the firm asked for a loan but this was denied. Such direct information based on each firms' own assessment is used to characterize the existence of credit constraints. Following earlier approaches (Guiso, 1998[18]; Angelini and Generale, 2005; Piga and Atzeni, 2007), I define a firm as credit rationed if it declared it wanted more credit and was willing to pay either the current or a higher interest rate but, once applied, was turned down. This definition is in line with the assumptions set by Stiglitz and Weiss (1981), according to which a firm is credit rationed if it does not get as much credit as it wants, although it is willing to meet the conditions set by the lender.

In the overall sample, 13.5 percent of the surveyed companies declared they would have needed additional credit, while 5.2 percent applied for credit but this was denied.[19] However, the percentage of constrained firms is 38.37 percent (165 out of 430) if only the sub-sample of firms wishing more credit is considered. Hence, the indicator of credit constraints (RAT) is a dichotomous variable which is equal to 1 if the firm applied for credit and this was denied and 0 otherwise. Since this situation only occurs for the sub-sample of firms wishing more credit, I construct a second binary dependent variable by taking the response to two questions concerning each firm's need of additional credit and their availability to pay a higher interest rate. MORE is equal to 1 if the firm declared it wanted more credit and was willing to pay either the current or a higher interest rate and 0 otherwise.

3.2 Firms and innovation

Data on R&D expenditures at the firm level are derived directly from the survey.[20] Out of 3,129 firms, 1,445 reported having sustained expenditures for R&D during the years 2001 to 2003. Of these 1,445 innovative firms, 294 are located in an industrial district.

However, the nature of such expenditures is rather difficult to assess, since R&D activities carried out within firms are often embedded in standard production processes or, more generally, take the form of informal research or externally acquired services. Moreover, it is not possible to ascertain the real amount of funds allocated to R&D activities because in Italy R&D expenditures are not compulsorily reported in the balance sheet. The possibility that firms overstate or understate their innovation activity occurs even when I turn to output measures of the innovation process. Nearly 41.77 percent of firms declared to having introduced product innovation and another 43.72 percent reported process innovation in the years 2001 to 2003.[21]

[Insert Table 1 here]

This evidence needs to be considered carefully, due to a possible wrong perception of the novelty of products and processes by firms. Products or processes could indeed be "new to the firm," but not "to the market." For this reason, I also collected patent portfolio data for all the companies analyzed. I referred to European patents, and I split the time window for the selection of the relevant patents into two periods (1998-2000; 2001-2003). In particular, I considered both patents already granted and patents which are presently still under screening by the European Patent Office (EPO).

The data reported in Table 2, when contrasted with the results about the introduction of innovative products/processes, show a dramatic divergence which can be explained in several ways. On the one hand, as previously recalled, there is the possibility that companies overstate the degree of novelty embedded in their products; on the other hand, it also might be the case that firms are simply less sensitive to the incentive structure underlying the patenting activity, preferring other tools to protect their intellectual property. Out of 1,445 firms which declared to be involved in R&D activities, only 145 firms have at least one patent (either an application or a granted patent).

[Insert Table 2 here]

This general framework is necessary to understand why the relationship between finance and innovation is heavily skewed towards the use of internal sources of finance by the firms in the sample. A first look on the composition of financial sources for R&D investments clearly stresses the relevance of self-financing through retained earnings over other potential financial sources. Self-financing accounts for nearly 81 percent in sustaining R&D investments, while venture capital support appears to be rather insignificant (only 0.72 percent). A strong dependence on present cash flow, and hence on business cycle movements, is acknowledged as a major drawback for investments in innovation, which typically require smooth and continuous expenditure profiles over time.

[Insert Table 3 here]

With respect to this situation, the question of whether such a dramatic incidence of cash-flow as a mean to finance R&D investments is a reflection of a voluntary firm's strategy or rather of a credit rationing phenomenon is a fundamental one. A relatively modest incidence of bank debt (8.67 percent), compared to a much higher percentage (17.57 percent) in the case of fixed investments would seem to confirm the presence of credit constraints for R&D activities.

3.3 Overall descriptive statistics

Tables 4a and 4b summarize the relevant statistics for firms wishing or not more credit, financially constrained and non-financially constrained firms, as well as for companies investing or not investing in R&D and belonging or not to an industrial district. The variables used in the regression analysis are broken down into four main categories: firm characteristics, firm's accounting ratios, location characteristics, and innovation performance.

A commonly held opinion is that credit tightening is less likely among large firms, not only because they can more easily raise funds directly from the market, but also because they can provide more reassurance to a bank that the loan will be repaid. Moreover, as underlined by Guiso (1998), larger firms have more "visibility" which reveals to financial intermediaries their quality, allowing banks to charge the proper interest rate on the loan instead of cutting its amount. Data on firm size (approximated by the total number of employees) confirm that large firms are less likely to desire additional quantities of credit. The share of firms asking for more credit is in fact lower among the bigger firms by a certain margin. Size seems to affect also a lender's decision to grant credit. The high dispersion of firm size suggests that the sample includes a few large companies, although most firms are rather small (the median size is around 47 employees).

The capacity of a company to innovate is often associated with the presence of qualified workers, who are usually regarded as a signal of quality as to how a firm is run and organizes its production activity. The rate of workers holding a degree over total employees is associated with a higher demand for credit and a higher probability that a loan is granted.

Long-term credit relationships should improve the information set available to the bank and thus reduce credit rationing. Overall, the evidence supports this hypothesis: non-rationed firms show longer relationships with their main bank (17.6 years) than rationed firms (14.9 years).

Liquidity constraints are less severe for firms which are subsidiaries of a group and for those showing a good liquidity, while they increase for more indebted firms. This is consistent with the common belief (Berger and Udell, 2002; Cole, Goldberg and White, 2004) that lenders provide credit only when they have high expectations of being repaid and, thus, favor borrowers with good financial records, since they offer more assurance to reimburse the loan.

Wishing additional quantities of finance is more likely in the South than in the North. It is not clear, however, how the geographical location can affect a lender's decision to grant credit. Among the credit-constrained firms, the share of firms located in the South (North) is 20 (63) percent, compared with 25 (55) percent among the non-rationed. Firms located in industrial districts are less subject to financial constraints than those operating outside district areas. The share of district firms is in fact smaller (14 percent) among the rationed than among the not-rationed ones (19 percent). District firms also show a lower propensity to desire additional quantities of external finance.

Table 4a conveys some useful descriptive information supporting hypothesis which are worthy of a further investigation in the regression analysis. According to the main strand of literature on financial constraints and innovation, R&D intensive firms are supposed to be liquidity constrained, due to their intrinsically higher level of risk. They are more likely to desire extra-funds than non-R&D firms since innovative activities require large amounts of money to be implemented. However, as Hall (2002) points out, the common behavior of R&D firms is to engage themselves in R&D projects only when a sufficient amount of internal financial sources is available.

Among the credit-rationed firms, the share of companies reporting innovation training expenses is 56 percent, compared with a 49 percent among the non-rationed. The same line of reasoning emerges from the analysis of mean values of output measures of innovation: firms with higher ratios are more likely to be denied credit. Financially constrained firms have a higher ratio of intangible assets over total assets (it amounts to 2.50 percent for unconstrained firms and to 3.12 percent for financially constrained ones). Large immaterial expenditures are, in fact, a risk factor which may induce some reluctance by external investors to grant credit. The descriptive statistics also show that the share of R&D expenditures over total assets is slightly higher, although not significantly different, for firms needing external finance and facing difficulties in accessing the credit market. Carrying out either product or process innovations seems to affect the decision to apply for credit and to reject an application.

[Insert Table 4a here]

The notable differences in the R&D sub-sample regard size, group belonging and location characteristics. R&D firms are on average larger than non-R&D firms and more likely to be a subsidiary of a group. R&D firms show a higher share of qualified workers, intangible assets, they are more likely to implement product or process innovations and to belong to a high-tech sector. With respect to the 572 district firms, 62 percent of them declared to invest in either product or process innovation and 37 percent declared to perform innovation training expenditures. Considering other parameters of innovation performance, they show lower levels of intangible assets compared to non-district firms. They are also less likely to belong to a high-tech sector. On average firms located in a district are also smaller, less likely to belong to an industrial group, more liquid and less exposed towards the banking system.

[Insert Table 4b here]

4. Empirical specification and estimation method

The empirical specification is based on Piga and Atzeni (2007). The authors use a two-equation approach to distinguish between the determinants of extra credit's need and those influencing the decision of a lender to grant credit. Observing a credit-constrained firm is in fact conditional on the firm's need for more credit: only those firms giving a positive answer to the question "Was the company willing to take more credit, by paying the current or a higher interest rate?" responded to the question "Did the company asked for more credit being denied?". Piga and Atzeni (2007) point out that a sample selectivity bias may arise if the probability of wishing more credit is not distinguished from that of being turned down when applying for it.

This approach has been widely used in the credit scoring literature (see Boyes et. al (1989); Jacobson and Roszbach (2003); Greene (1998)) to tackle the sample selection bias that affects default prediction models, which are usually calibrated on the repayment behaviour of accepted applicants but do not consider those who have been previously rejected.

To address the sample selectivity issue, I estimate a bivariate probit model with sample selection. The model consists of two simultaneous equations: the first one estimates the probability of a firm wishing additional quantities of external finance (y_{2i}) and the second one, conditional on the firm's need for more credit, relates to the lender's decision to deny it(y_{1i}).

Let the superscript * indicate an unobserved variable and assume that y_{1i} and y_{2i} follow:

$$y_{1i}^* = X_{1i}\beta_{1i} + u_{1i}$$

$$y_{2i}^* = X_{2i}\beta_{2i} + u_{2i} \qquad \text{for } i=1, 2, \dots N \qquad (1)$$

where $X = (x_1, x_2, \dots, x_k)$ is a vector of variables completely observed for each firm. The disturbances are assumed to be zero-mean, bivariate normal distributed with unit variances and a correlation coefficient ρ.

The binary outcome y_{2i} takes value 1 if the firm wished more credit ($y_{2i}^* > 0$) and 0 otherwise. The binary variable y_{1i} is equal to 1 if the firm applied for credit but the financing was denied ($y_{1i}^* > 0$) and 0 otherwise. y_{1i} is observed only when $y_{2i} = 1$.

The model is estimated via maximum likelihood (MLE) by maximizing the following log-likelihood by iterative maximization techniques:

$$L = \sum_{\substack{y_1=1\\y_2=1}} \ln[\Phi_2(X_{1i}\beta_{1i}, X_{2i}\beta_{2i}, \rho)] + \sum_{\substack{y_1=0\\y_2=1}} \ln[\Phi_2(-X_{1i}\beta_{1i}, X_{2i}\beta_{2i}, -\rho)] + \sum_{y_2=0} \ln[1 - \Phi(X_{2i}\beta_{2i})] \qquad (2)$$

where Φ_2 is the cumulative bivariate normal distribution function, Φ is the standard cumulative normal and $\rho = \mathrm{cov}(u_1, u_2)$.

5. Results

The econometric model presented in the previous section tests three main hypotheses: first, that innovative firms are more likely to be credit rationed than non-innovative firms; second, that firms located in industrial districts have a lower probability of being denied credit; and lastly, that innovative firms operating in district areas face lower financial constraints.

The variables used in the regression analysis are listed in the Appendix. To address possible time inconsistency problems, all relevant regressors are pre-dated with respect to the year of reference for the dependent variable.

I assume that a bank's decision to grant or refuse credit to a firm is inferred from a set of observable financial characteristics of the firm. The reported models contain a set of financial accounting variables, which can be grouped into two categories describing a company's financial profile: leverage and liquidity. Selected financial ratios are among those conventionally used in credit risk analysis; hence, they should correspond reasonably well to the data used by banks in making their loan decisions. Liabilities/Total Assets is defined as the ratio of the Total Liabilities (Current Liabilities + Long Term Liabilities + any other miscellaneous liability the company has) over Total Assets (Current Assets + Long-Term Assets). Working Capital/Total Assets is measured by the ratio of Working Capital (Current Assets - Current Liabilities) over Total Assets.
I also control for measures of firm size, relationship lending, education and group belonging. Size is approximated by the total number of employees. Relationship length is computed as the number of years of the relationship between the firm and its main bank. Subsidiary is a dummy variable which is equal to 1 if the firm is a subsidiary of a group and 0 otherwise. Qualified is the number of workers holding a degree over total employees. The specifications include 10 industry dummies and 2 geographic dummies (North and South) in order to control for sectoral fixed effects and for the unobserved specificity of Italian macro-regions.

Indicators of innovation activity include variables concerning process and product innovation, the incidence of Intangible Assets over Total Assets, the belonging to a high-tech sector, R&D expenses over Total Assets, and innovation training expenses. Process or Product Innovation is a dummy variable which takes the value of 1 if the firm declares having carried out either process or product innovations and 0 otherwise. The variable R&D/Total Assets is computed as R&D expenses normalized by Total Assets, while the variable Innovation Training Expenses represents the training expenses for the introduction of new products/processes over the average R&D expenses in the years 2001-2002. Intangible measures the incidence of intangible assets over total assets. Pavitt is a dummy variable which is equal to 1 if the company belongs to an industry classified as "science-based" according to Pavitt's taxonomy[22] and 0 otherwise. It has to be noted that, while industry dummies rely on a broad definition of industries, Pavitt's taxonomy is based on a finer sectoral classification. As a result, I do not observe any collinearity between the dummy Pavitt and the 10 sectoral dummies (the largest linear correlation coefficient is equal to 0.17). District is a dummy variable that is equal to 1 if the firm is located in an industrial district and 0 otherwise.

The estimates are presented in Table 5. The last row of the Table reports the correlation coefficient (ρ) which is significantly different from 0 in all specifications. The strong correlation between error terms of the two equations implies that the Wald test of independent equations $H_0 : \rho = 0$ is rejected even at 1 percent level of significance. This test indicates the appropriateness of the approach used here and confirms that separate probit estimations could not be run.

Statistical results are completed with the marginal effects of the changes in the explanatory variables (Table 6) of the bivariate probit model.

[Insert Tables 5 and 6 here]

The results show that balance sheet variables are important in determining access to external finance. In particular, a high incidence of Total Liabilities on Total Assets significantly raises the probability of being refused a loan. High levels of debt are accompanied by high interest payments which, in turn, might induce indebted firms to apply for more credit. Of course, applications from highly indebted firms are also more likely to be rejected. Similar results can be found in Guiso (1998) with a particularly strong effect for short-term liabilities. Working Capital/ Total Assets has an opposite impact: liquidity reduces the need of external finance and a more liquid firm is likely to provide stronger prospects for repayment. The expected negative correlation with the probability of wishing more credit and of being rationed is confirmed in the regressions. Such effect is stable and significant at 1 percent level in all the different model specifications. The estimates of the marginal effects show that when the variable Total Liabilities/Total Assets moves from zero to its mean value, the probability to face financial constraints increases by approximately 18 percent. The impact reduces when Working Capital/Total Assets is considered (7 percent).

Firm size effects are likely to reflect the bargaining power of larger borrowers. Size shows a negative sign, confirming the common conjecture that smaller firms are more likely to need extra-funds and to be rationed due to a lack of transparency, higher risk of default and limited access to financial markets. In fact banks generally perceive larger firms as better able to meet their financial obligations. Firms' dimension seems to be significantly correlated with the probability of wishing more credit at 5 percent level of significance. The variable loses significance in the RAT equation. The magnitude of the coefficient is very small as well as the marginal effect (-0.001 at the sample mean), revealing a weak economic effect of the variable.

Concerning the geographic dimension, it is not clear how the geographical location affects a lender's decision to grant credit. I find a positive relationship between being located in the South and the likelihood to apply for more funds and to be denied credit. This regressor is highly significant in the MORE equation but it is not statistically significant in the RAT equation. Firms located in the North are less likely to need extra-funds but when they do, they show a positive, although not significant, correlation with the probability of being denied credit. Similar results can be found in Piga and Atzeni (2007) for North-Central Italy.

The dummy Subsidiary aims at capturing the effects that being part of a group of companies engenders the likelihood of needing extra-funds. While a parent company has significant financial needs which cannot be entirely covered by internal funds, subsidiaries are less likely to wish additional credit because of the funds channeled by the parent company. From the creditors' point of view, subsidiaries are considered more reliable in repaying the debt because of the funds and guarantees provided by the head of the group. Various studies have recognized that group organization alleviates financial constraints (Schiantarelli and Sembenelli, 2000; Guiso, 1998). This variable does not seem to exert any influence in the MORE equation. It was also highly insignificant in the RAT regression and was then dropped without affecting the other estimates.

A long credit relationship with borrowers should grant the bank an information advantage vis à vis potential competitors. I expect that long-term credit relationships reduce the probability of rejection. The length of credit relationships has a positive and significant effect on credit availability, whereas its impact on the desire of additional funds is positive but insignificant. This result is robust across the alternative specifications presented.

The results concerning the different proxies of innovation activity deserve some comments. The five innovation-related sets of regressors are not jointly used to avoid collinearity problems. As far as these parameters are concerned, they all display a positive effect on the probability of being denied credit but differences in the level of significance can be noted between models 1,3,4 and models 2 and 5.

Innovation Training Expenses and the incidence of Intangible Assets over Total Assets are correlated with the probability of being credit constrained respectively at 5 percent and 10 percent level of significance. A change from zero to the mean values of the variable Intangible appears to be associated with large changes in the probability to be credit-rationed (12.2 percent), while marginal effects for Innovation Training Expenses are trivial (0.2 percent). The large presence of intangible assets, which cannot be used to secure loans, can represent a serious obstacle affecting the lender's decisions to grant credit.[23] Shortages in liquidity due to costly training schemes may be perceived by a lender as detrimental to a firm since innovation training expenditures can turn into sunk costs if workers leave the company. This effect is particularly acute for R&D companies where engineers or scientists have a firm specific knowledge that would disappear or be transmitted to competitors if they left the company (Hall, 2002).

The dummy for process or product innovation is significant at the 5 percent level in both equations. The increase in the likelihood of credit rationing due to marginal increases in process or product innovation is approximately of 0.7 percent. Performing process or product innovation has a positive and significant impact on the probability of requiring additional funds.

The common belief that informational frictions may be more severe with regard to high-tech industries is confirmed by the positive correlation of the variable Pavitt with the dependent variable in the RAT equation. Although this relationship is not significant in the regression, belonging to a high-tech sector according to Pavitt's taxonomy increases the probability that a bank is reluctant to provide substantial funding by nearly 2.5 percent at 5 percent level of significance. This finding is consistent with Guiso (1998), who identifies high-tech firms following ISTAT's sector-based classification. Even though the evidence is acknowledged to be blurred with measurement problems in the proxies used, the author finds that credit rationing is more likely among high-tech firms. Conversely, belonging to a high-tech sector reduces the need for extra-credit, although not in a statistically significant way.

The variable R&D/Total Assets has a positive effect on both the probability of demanding credit and being constrained but its coefficient is not statistically different from zero.[24] It might be suggested that the non-significance of the coefficient is due to the limited accountability of R&D expenses, the potential impact of which is, in turn, underestimated by the provider of financial resources.[25] On the other side, it could be argued that companies characterized by high levels of R&D spending are those with a better financial position. Hence, these firms do not require additional financial resources for the simple reason that they entirely build R&D investment strategies on the availability of internal resources. In other words, such evidence might be a reflection of the conservative investment behavior of managers, who prefer to set up R&D facilities only when they have secured sufficient internal financial resources. A possible interpretation is that a great proportion of R&D spending corresponds to wages to R&D personnel and firms prefer to delay R&D investments until an adequate amount of internal funds is available in order to avoid having to lay off qualified workers. This explanation finds support in the summary data about the financial sources for R&D investment previously presented (more than 80 percent coming from self-financing). Piga and Atzeni (2007) find mixed results for Italian companies after splitting the sample in Low-R&D and High-R&D firms. Firms with low R&D intensity are less likely to request extra funds, but when they do, they face a higher probability of being denied credit. By contrast, R&D top performers are less likely to be financially constrained. The authors suggest the presence of an inverted-U shape in the relationship between R&D intensity and the probability to be credit-rationed. However, they results concerning R&D activity lack statistical significance.

The other important result emerging from the analysis is that firms located in an industrial district face a lower probability of facing credit tightening. Being located in a district area significantly reduces such probability by 0.5 percentage points. The coefficient from model 6 (Table 5) also suggests an inverse relationship between being located in a district and the probability of needing extra-funds at 5 percent level of significance. This effects are consistent with the peculiar socio-economic features characterizing the organization of a district. Local banks play an important role in sustaining SMEs's growth thanks to the informationally-intensive relationships with firms and to the integrated economic environment that industrial districts allow. Finaldi Russo and Rossi (2001) find similar results.[26] There is indeed evidence that distance matters in lending relationships, particularly for small firms that may find greater difficulties in establishing relationships with credit suppliers in other geographical areas or in accessing funds in the open market.

In model 7, I introduce an interaction term between District and R&D/Total Assets to assess whether the impact of innovation on the probability of credit rationing is smaller for firms belonging to industrial districts. Results suggest an inverse relationship, although not statistically significant, between performing R&D activity in district areas and the probability of desiring more credit. Conversely, a clear pattern emerges when the probability of being credit rationed is considered. Innovative firms operating in industrial districts are less likely to suffer from credit constraints at 10 percent level of significance. The interaction variable has a large and significant marginal effect.

Two interpretations can arise from these results. First, it may be that firms' R&D activity alone does not accurately reflect the nature of problems leading to potential credit market failures. In other words, banks show a lower propensity to grant credit to innovative firms only when they do not have long-lasting credit relationships with them. If the firm is well-known and has developed long-term credit relationships with the bank throughout the years, it is less likely that credit tightening occurs even when the firm engages in R&D activities. This interpretation is consistent with the effect of relationship lending on credit availability reported in Table 5. Second, small firms in Italy usually borrow from more than two banks (multiple lending). Therefore a bank can possibly share the risk of financing R&D investments with other banks in the district. Third, cooperation among firms in industrial districts is usually cemented by finance provision and equity participation. Alliances between companies at the different stages of the R&D process can lead more liquid firms to channel funds into partners with limited internal financial resources. This happens if, as underlined by Chiesa (2005), cooperation is optimal and takes place in sectors where innovations are primarily incremental and cannot meet patentability requirements. This interpretation finds support in the low patent intensity of the firms in the sample. Following this line of reasoning, innovative companies are less likely to need extra funds because they are nourished by existing strategic partnerships. Also, it can be assumed that local banks have a better perception of the creditworthiness of a firm that shares the risk of its R&D activity with another company.

6. Conclusions

In an imperfect information setting, adverse selection and moral hazard problems, and the associated costs of monitoring and enforcement of debt contracts, might increase firms' difficulties to resort to external finance. This is especially true for small firms and, among these, for enterprises engaged in relevant R&D activities. A large strand of literature pointed to relationship finance (and territorial proximity) as a way to overcome informational asymmetries for small businesses: closer relationships between borrowers and lenders should, in principle, affect the ability of banks to gather information on borrowers and this, in turn, might help to ease credit rationing.

This paper uses an extensive dataset of Italian manufacturing firms to investigate the factors affecting a firm's probability of being credit rationed, after controlling for the determinants of its antecedent decision to demand additional credit. The issue of credit constraints is investigated for innovative firms, for firms located in a district and for innovative firms operating in industrial districts.

The evidence, after controlling for traditional measures of firms' financial performance, is in line with the results of the extant literature. I observe a higher probability of being denied credit for innovative firms, with a weaker effect when measures of R&D intensity are considered. This last result might be interpreted according to two different perspectives. On the one hand, it could be argued that companies characterized by high R&D intensities are those with a better financial position. Hence, these firms do not require additional financial resources for the simple reason that they entirely build R&D investment strategies on the availability of internal resources. This hypothesis finds support in the summary data on financial sources for R&D investments. On the other hand, it could be suggested that the non-significance of the coefficient of the R&D variable is due to the limited accountability of intangible assets, the potential impact of which is, in turn, underestimated by financial intermediaries.

Results also show that firms located in an industrial district have easier access to external finance. Being located in a district area significantly reduces the probability of credit rationing by 0.5 percentage points. This effects are consistent with the peculiar socio-economic features characterizing the organization of a district. District firms can benefit from long-term social and business relationships with local banks, that can easily gather information on borrowers at low costs and consequently facilitate companies' access to finance.

If I move to consider firms engaged in substantial R&D activities located in a district, evidence suggests that they are less likely to suffer from credit constraints at 10 percent level of significance. It can be argued that firms' R&D activity alone does not accurately reflect the nature of problems leading to potential credit market failures and that banks show a lower propensity to grant credit to innovative firms only when they do not have long-lasting credit relationships with them. Moreover, small firms in Italy usually borrow from more than two banks (multiple lending). Therefore a bank can possibly share the risk of financing R&D investments with other banks in the district. Also, it can be assumed that, since firms undertaking innovation in industrial districts are likely to cooperate with neighbor firms at different stages of their R&D activity, local banks have a better perception of the creditworthiness of a firm that shares the risk of its R&D activity with another company.

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8. Tables

Table 1- Incidence of firms that declare having introduced innovations in years 2001-2003

	Total sample	
Type of innovations	Freq	%
product innovation	1,307	41.77%
process innovation	1,368	43.72%
organizational innovation related to product innovation	646	20.65%
organizational innovation related to process innovation	871	27.84%
none	1,099	35.12%

Table 2- Summary statistics on patent portfolio for the sub-sample of companies with at least one patent in the period 1998-2003

	Mean	Std.Dev	Min	Max
average N patents (applications 1998-2000)	1.2	1.74	1	12
average N patents (applications 2001-2003)	1.85	2.09	1	15
average N patents (granted 1998-2000)	0.33	0.71	1	4
average N patents (granted 2001-2003)	0.36	0.77	1	5

Table 3-Percentage incidence of different financial sources for R&D investments

	Total sample
private equity	0.72
self financing	80.68
long-term debt at market conditions	5.44
long-term debt at advantageous conditions	3.23
national and EU public funding	6.02
tax incentives	2.99
other sources of financing	0.92
TOTAL	100

Table 4a-summary statistics (credit rationed, non-credit rationed, desiring more credit, not desiring more credit)

	NOT RAT			RAT			NOT MORE			MORE		
Variable	mean	median	st.err	mean	median	st.err	mean	median	st.err	mean	median	st.err
Firm characteristics												
total number of employees	71.21	40	5.40	69.32	37	5.70	106.69	48	4.73	79.33	40	5.63
workers holding a degree/ total employees %	5.64	3.33	0.45	5.35	3.26	0.67	5.25	3.25	0.15	5.53	3.33	0.37
firm is a subsidiary of a group (0,1)	0.15	0	0.02	0.13	0	0.02	0.16	0	0.01	0.14	0	0.02
relationship length	17.58	15.50	0.73	14.89	10	0.90	17.63	15	0.23	16.57	15	0.57
Firm's accounting ratios												
liabilities/total assets %	77.77	81.30	0.98	84.07	86.8	0.96	71.95	74.76	0.32	80.19	84.10	0.72
working capital/total assets %	71.73	69.91	1.01	68.64	67.45	1.17	71.54	73.18	0.28	68.70	69.47	0.76
Location characteristics												
firm is located in a district (0,1)	0.19	0	0.02	0.14	0	0.02	0.18	0	0.01	0.13	0	0.02
south (0,1)	0.25	0	0.02	0.20	0	0.03	0.14	0	0.01	0.22	0	0.02
north (0,1)	0.55	1	0.03	0.63	1	0.03	0.68	1	0.01	0.58	1	0.02
Innovation performance												
intangible assets/total assets %	2.50	0.85	0.29	3.12	1.56	0.33	2.01	0.68	0.08	2.73	1.14	0.22
R&D expenditures/Total Assets%	0.78	0.06	0.20	0.82	0.10	0.16	0.83	0.08	0.13	0.86	0.11	0.13
process or product innovation (0,1)	0.62	1	0.03	0.65	1	0.03	0.60	1	0.01	0.63	1	0.02
Pavitt (0,1)	0.02	0	0.01	0.04	0	0.01	0.03	0	0.01	0.03	0	0.01
innovation training expenses	0.49	0	0.13	0.56	0	0.17	0.28	0	0.03	0.50	0	0.10

The (0,1) notation means that the variable is a dummy equal to 1 if the firm has the specified characteristics; 0 otherwise. For these variables the Table reports the share of firms in the sample with the given characteristics.

Table 4b-summary statistics (R&D firms, non R&D firms, located in a district, not located in a district)

	NOT R&D			R&D			NOT DISTRICT			DISTRICT		
Variable	mean	median	st.err	mean	median	st.err	mean	median	st.err	mean	median	st.err
Firm characteristics												
total number of employees	63.66	34	2.21	150.03	65	9.29	106.60	46	5.39	89.93	49.5	5.33
workers holding a degree/ total employees %	3.86	1.88	0.15	6.97	4.74	0.24	5.58	3.44	0.16	3.97	2.27	0.25
firm is a subsidiary of a group (0,1)	0.15	0	0.01	0.17	0	0.01	0.17	0	0.01	0.13	0	0.01
relationship length	17.32	15	0.29	17.69	15	0.32	17.36	15	0.24	18.02	15	0.52
Firm's accounting ratios												
liabilities/total assets %	72.88	76.3	0.42	73.02	76.2	0.44	73.17	76.2	0.34	71.90	75.8	0.73
working capital/total assets %	71.04	69.2	0.38	71.04	71.4	0.40	70.44	72.3	0.30	73.74	75.6	0.64
Location characteristics												
firm is located in a district (0,1)	0.16	0	0.01	0.20	0	0.01						
south (0,1)	0.20	0	0.01	0.09	0	0.01	0.17	0	0.01	0.07	0	0.01
north (0,1)	0.60	1	0.01	0.74	1	0.01	0.67	1	0.01	0.64	1	0.02
Innovation performance												
intangible assets/total assets %	1.74	0.51	0.09	2.46	0.93	0.12	2.19	0.74	0.09	1.53	0.94	0.12
R&D expenditures/Total Assets%							0.86	0.10	0.14	0.71	0.10	0.07
process or product innovation (0,1)	0.41	0	0.01	0.83	1	0.01	0.60	1	0.01	0.62	1	0.02
Pavitt (0,1)	0.02	0	0.01	0.04	0	0.01	0.03	0	0.01	0.02	0	0.01
innovation training expenses	0	0	0	0.67	0	0.07	0.29	0	0.03	0.37	0	0.10

The (0,1) notation means that the variable is a dummy equal to 1 if the firm has the specified characteristics; 0 otherwise. For these variables the Table reports the share of firms in the sample with the given characteristics.

Table 5-Bivariate probit with sample selection estimation results†

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	RAT	MORE	RAT	MORE	RAT	MORE	RAT	MORE	RAT	MORE	RAT	MORE	RAT	MORE
Liabilities/Total Assets	2.186*** (0.30)	2.034*** (0.21)	2.200*** (0.30)	2.031*** (0.21)	2.193*** (0.30)	2.033*** (0.21)	2.132*** (0.30)	1.977*** (0.21)	2.183*** (0.30)	2.028*** (0.21)	2.162*** (0.30)	2.004*** (0.20)	2.249*** (0.29)	1.986*** (0.20)
Working Capital/Total Assets	-0.825*** (0.28)	-0.961*** (0.21)	-0.856*** (0.28)	-0.965*** (0.21)	-0.822*** (0.28)	-0.965*** (0.21)	-0.737*** (0.28)	-0.873*** (0.21)	-0.821*** (0.28)	-0.963*** (0.21)	-0.842*** (0.28)	-0.953*** (0.21)	-0.767*** (0.28)	-0.990*** (0.21)
Innovation Training Expenses	0.028** (0.01)	0.026** (0.01)												
Pavitt (0;1)			0.428 (0.32)	-0.129 (0.18)										
Intangible							1.467* (0.91)	1.575*** (0.65)						
Process or Product Innovation (0;1)					0.114** (0.08)	0.085** (0.06)								
R&D/Total Assets									0.369 (1.36)	0.080 (0.41)			0.201 (1.21)	0.073 (0.41)
District (0,1)											-0.062* (0.11)	-0.164** (0.08)	-0.100* (0.13)	-0.173** (0.09)
District*R&D/Total Assets													-0.381* (1.58)	-0.130 (1.03)
South (0;1)	0.211 (0.14)	0.300*** (0.10)	0.211 (0.14)	0.298*** (0.10)	0.218 (0.14)	0.303*** (0.10)	0.230 (0.14)	0.312*** (0.10)	0.211 (0.14)	0.300*** (0.10)	0.196 (0.14)	0.272*** (0.10)	0.224 (0.14)	0.269*** (0.10)
North (0;1)	0.041 (0.12)	-0.067 (0.08)	0.053 (0.11)	-0.062 (0.08)	0.048 (0.11)	-0.063 (0.08)	0.052 (0.11)	-0.058 (0.08)	0.048 (0.11)	-0.062 (0.08)	0.037 (0.11)	-0.075 (0.08)	0.059 (0.11)	-0.082 (0.08)
Size	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)	-0.001 (0.01)	-0.001*** (0.01)
Relationship Length	-0.007** (0.01)	0.001 (0.01)	-0.007** (0.01)	0.001 (0.01)	-0.007** (0.01)	0.001 (0.01)	-0.006** (0.01)	0.001 (0.01)	-0.007** (0.01)	0.001 (0.01)	-0.007** (0.01)	0.001 (0.01)	-0.007** (0.01)	0.001 (0.01)
Subsidiary (0;1)		-0.023 (0.72)		-0.044 (0.07)		-0.057 (0.07)		-0.059 (0.07)		-0.056 (0.07)		-0.042 (0.07)		-0.078 (0.07)
Qualified Workers		0.508 (0.35)		0.572 (0.37)		0.609 (0.37)		0.577 (0.37)		0.629 (0.36)		0.621 (0.36)		0.523 (0.36)
constant	-2.696*** (0.32)	-1.795*** (0.23)	-2.664*** (0.32)	-1.793*** (0.23)	-2.691*** (0.31)	-1.794*** (0.23)	-2.749*** (0.32)	-1.852*** (0.23)	-2.688*** (0.32)	-1.788*** (0.232)	-2.643*** (0.32)	-1.731*** (0.23)	-2.780*** (0.32)	-1.692*** (0.22)
rho	0.833***		0.834***		0.829***		0.836***		0.843***		0.833***		0.840***	
n. observations	387	2327	387	2327	387	2327	387	2327	387	2327	387	2327	387	2327

† Robust z-statistics in parentheses

***: significant at the 1% level, **: significant at the 5% level, *: significant at the 10% level. Industry dummies are included in the regressions (not reported)

Table 6-Marginal effects (dy/dx), with y=Pr(RAT=1 | MORE=1), from the bivariate probit model in Table 5, calculated at the regressors' mean values†

	Modello 1	Modello 2	Modello 3	Modello 4	Modello 5	Modello 6	Modello 7
Liabilities/Total Assets	0.182*** (0.02)	0.183*** (0.02)	0.187*** (0.02)	0.177*** (0.02)	0.183*** (0.02)	0.181*** (0.02)	0.178*** (0.02)
Working Capital/Total Assets	-0.068*** (0.02)	-0.071*** (0.02)	-0.070*** (0.02)	-0.061*** (0.02)	-0.068*** (0.02)	-0.070*** (0.02)	-0.060*** (0.02)
Innovation Training Expenses	0.002** (0.01)						
Pavitt (0;1)[a]		0.025** (0.01)					
Intangible				0.122* (0.07)			
Process or Product Innovation (0;1)[a]			0.007* (0.02)				
R&D/Total Assets					0.030 (0.11)		0.015 (0.09)
District (0,1) [a]						-0.005* (0.01)	-0.008 (0.01)
District*R&D/ Total Assets							-0.064** (0.16)
South (0;1)[a]	0.019 (0.01)	0.019 (0.01)	0.020 (0.01)	0.022 (0.01)	0.020 (0.01)	0.018 (0.01)	0.020 (0.01)
North (0;1)[a]	0.003 (0.01)	0.004 (0.01)	0.003 (0.01)	0.004 (0.01)	0.004 (0.01)	0.003 (0.01)	0.004 (0.01)
Size	-0.001 (0.01)	-0.001 (0.01)	-0.001 (0.01)	-0.001 (0.01)	-0.001 (0.01)	-0.001 (0.01)	-0.001 (0.01)
Relationship Length	-0.001** (0.01)	-0.001** (0.01)	-0.001** (0.01)	-0.001** (0.01)	-0.001** (0.01)	-0.001** (0.01)	-0.001** (0.01)

† Robust z-statistics in parentheses

[a] dy/dx is for discrete change of dummy variable from 0 to 1

***: significant at the 1% level **: significant at the 5% level, *: significant at the 10% level

9. Appendix

9.1 Sample composition

The sample is stratified by geographical location (67% North, 18% Centre and 15% South of Italy), firm size and industries on the basis of the whole distribution of Italian manufacturing firms. In the following Table, I present the distribution by sectors of the analyzed companies and of the firms belonging to a district, according to the ATECO classification codes.

Table A1- Distribution by sector of the sample and of the firms belonging to a district

Ateco code	Industry	Total sample	%	Belonging to a district
11	oil and natural gas extraction	1	0.03%	0
14	mining and quarrying	2	0.06%	0
15	beverage and food industry	351	11.22%	39
17	textile industry	256	8.18%	139
18	textile product industry	102	3.26%	35
19	leather and leather products manufacturing	128	4.09%	67
20	wood and wood products manufacturing	88	2.81%	22
21	pulp, paper and paper products manufacturing	87	2.78%	8
22	publishing, printing	87	2.78%	3
23	petroleum and coal products manufacturing	19	0.61%	1
24	chemical industry	170	5.43%	1
25	plastics and rubber manufacturing	169	5.40%	11
26	non-metallic mineral product manufacturing	191	6.10%	27
27	metallurgy	116	3.71%	2
28	metal products manufacturing	435	13.90%	35
29	mechanical machinery and equipment manufacturing	413	13.20%	96
30	computer and electronic manufacturing	5	0.16%	0
31	electrical machinery and equipment manufacturing	115	3.68%	17
32	telecommunication machinery and equipment manufacturing	52	1.66%	4
33	medical, optical and precision equipment manufacturing	60	1.92%	9
34	transportation equipment manufacturing	47	1.50%	0
35	other transport equipment manufacturing	22	0.70%	0
36	other manufacturing industry	206	6.58%	55
37	recycling	2	0.06%	0
45	construction	5	0.16%	1
	TOTAL	3129	100.00%	572

9.2 Variables definitions

Liabilities/Total Assets: ratio of Total Liabilities over Total Assets, average for years 2001-2002

Working Capital/Total Assets: ratio of Working Capital over Total Assets, average for years 2001-2002

Size: computed as the total number of employees, average for years 2001-2002

South: dummy variable which is equal to 1 if the company is located in the South of Italy; 0 otherwise

North: dummy variable which is equal to 1 if the company is located in the North of Italy; 0 otherwise

Relationship Length: number of years of the relationship between the firm and its main bank

Qualified Workers: number of workers holding a degree over total employees, average for years 2001-2002

Subsidiary: dummy variable which is equal to 1 if the company is a subsidiary of an industrial group; 0 otherwise

Innovation Training Expenses: training expenses for the introduction of new products or processes over average R&D expenses in years 2001-2002

Pavitt: dummy variable which is equal to 1 if the company belongs to an industry classified as “science-based” according to Pavitt’s taxonomy; 0 otherwise

Intangible: Intangible Assets over Total Assets, average for years 2001-2002

Process or Product Innovation: dummy variable which is equal to 1 if the company declares having carried out either process or product innovations; 0 otherwise

R&D/Total Assets: R&D expenses normalized by Total Assets, average for years 2001-2002

District: dummy which is equal to 1 if the firm is located in an industrial district; 0 otherwise

District*R&D/Total Assets: interaction variable

Industry dummies: 15-beverage and food industry; 18-textile product industry; 19-leather and leather products manufacturing; 20- wood and wood products manufacturing; 21-pulp, paper and paper products manufacturing; 24- chemical industry; 25-plastics and rubber manufacturing; 28- metal products manufacturing; 29-mechanical machinery and equipment manufacturing; 33-medical, optical and precision equipment manufacturing. Each dummy takes the value 1 if the firm’s main activity is in that industry; 0 otherwise.

9.3 Pairwise correlation matrix

The linear correlation analysis among the regressors is reported in Table A2. The Table shows that the value for the correlation between two regressors is never higher than 0.21 (Qualified Workers and Pavitt). The exception is the expected correlation between North and South (-0.609). The 10 sectoral dummies are not reported to save space. The largest correlation coefficient for one of these dummies and the variables reported in the Table equals 0.20 and corresponds to the correlation between the dummy for the beverage/food industry and the variable South.

Table A2-Pairwise correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Liabilities/ Total Assets (1)	1													
Working Capital/Total Assets (2)	0.132	1												
South (3)	-0.109	-0.194	1											
North (4)	0.049	0.106	-0.609	1										
Relationship Length (5)	-0.108	0.021	-0.126	0.119	1									
Size (6)	-0.027	-0.115	-0.034	0.044	0.015	1								
Subsidiary(7)	-0.020	-0.047	0.017	0.001	-0.111	0.138	1							
Innovation Training Expenses (8)	0.003	-0.008	-0.019	0.034	0.031	0.035	0.011	1						
Qualified Workers (9)	-0.010	0.025	0.048	-0.013	-0.025	0.079	0.100	0.015	1					
Pavitt (10)	-0.030	0.027	-0.003	0.007	0.010	0.075	0.015	-0.007	0.214	1				
Process or Product Innovation (11)	-0.021	-0.017	-0.063	0.062	-0.006	0.111	0.009	0.103	0.125	0.123	1			
Intangible (12)	0.098	-0.161	-0.022	0.013	-0.056	0.077	0.061	-0.005	0.082	0.062	0.040	1		
R&D/Total Assets (13)	0.007	0.024	-0.036	0.036	0.028	0.014	-0.006	-0.007	0.042	0.048	0.073	0.024	1	
District (14)	-0.037	0.071	-0.104	-0.031	0.011	-0.017	-0.030	0.017	-0.083	-0.049	0.019	-0.057	0.035	1

10. Footnotes

[1] There is in fact a poor availability of analytical instruments able to capture and correctly estimate the expected future revenues of innovative activities (Encaoua et al, 2000) and also a limited reliability of public information for investors (in every country firms are not obliged to report R&D expenses separately from other costs of production in their financial statements).

[2] Berger and Udell (1995) distinguish between "transaction lending" that is based primarily on "hard" quantitative data and is focused on informationally-transparent borrowers and "relationship lending", which is based on "soft" qualitative information.

[3] The data provided by AIFI (Italian Private Equity and Venture Capital Association) for the years following the stock market bubble in 2000 highlight that in the Italian market the share of Venture Capital investments in the early stage phase have heavily declined. While in 2000, an amount of €540 mln was invested, investments fell to €59 mln in 2003 and to €30 mln in 2005.

[4] The survey is run by the "Osservatorio sulle Piccole e Medie Imprese" (Observatory over SMEs), an institution associated with Capitalia, an Italian bank. More detailed information about the survey can be found at the web site www.capitalia.it

[5] Petersen and Rajan (1994) argue that firms that are willing to borrow at high interest rates are financially constrained. Gertler and Gilchrist (1994) use firm size as the identification criterion, assuming that larger firms have easier access to credit. Cleary (1999) identifies firms which cut dividends as financially constrained, while Fazzari et al. (1988) separate firms on the basis of their dividend policy, hypothesizing that those with higher earnings retention ratios are more likely to face informational asymmetry problems. Hoshi et al. (1992) rely on the fact that in Japan companies belonging to a group present closer financial ties to the group's main bank. Such a condition is likely to mitigate information problems and, consequently, firms with close ties are less likely to be credit-constrained.

[6] See Detragiache et al. (2000) for a theory of multiple lending.

[7] For Schumpeter views of the potential importance of internal finance for innovation, see Schumpeter (1942), chapter 8. One of Schumpeter's defenses of monopoly practices was that they could provide resources for financing the innovation process.

[8] The authors assume the simultaneous presence of a perfect informational context, an efficient capital market and the absence of bankruptcy costs.

[9]A large body of research pointed to the importance of collateral for debt finance. Bester (1985) showed how this condition may badly affect the possibility to access external finance for innovative firms.

[10] If the investment has not been undertaken before (as it happens for investments in innovation) it is impossible to observe the systematic risk of similar projects in other firms and thus to determine the appropriate discount rate to be used in the calculation of the net present value of the project, as the CAPM or arbitrage pricing theory predict.

[11] Fazzari et al. (1988) propose to address this problem by comparing different groups of firms, which were supposed to face, a priori, a different degree of financial constraints.

[12] This issue has received considerable attention in policy circles and many countries have operated government-backed loan guarantee schemes to help provide financing to small enterprises (Parker, 2002).

[13] The bank that provides the largest share of external finance to a firm and that entertains long-term relationships with it, is usually referred to as a "house bank". There are a number of studies that examine the effect of multiple relationships on credit availability. The existence of multiple relationships reduces the value of information acquisition by any one bank (Thakor, 1996), leading to an increase in the cost of credit and to a decrease in the credit availability (Petersen and Rajan, 1994).

[14] The survey, which is representative of the universe of Italian manufacturing firms with more than 10 employees, considers a stratified sample of 4,289 Italian firms. It has run every three years since 1992 and collects information on each firm's structure, labor force, investment, export strategies and financial situation. Previous releases of the survey have been used extensively in the literature (see Bagella et al., 2001; Piga and Vivarelli, 2004; Piga and Atzeni, 2007; Angelini and Generale, 2005)

[15] DELPHION is a privately edited database containing world-wide patent portfolio information.

[16] The national territory is divided into local labor systems (LLS), which are territorial groupings of municipalities, characterized by a certain degree of commuting. A LLS is defined as an industrial district if 1) the proportion of employment in the manufacturing sector is greater than the national average; 2) in at least one manufacturing sub-sector in which the LLS is specialized there is a higher than average proportion of employment in small local productive units (no more than 250 employees); 3) the degree of concentration of employment in small local productive units must be greater than the national average; 4) employment in one of the sub-sectors satisfying condition 2 must exceed 50 percent of total manufacturing employment in the same LLS. A total of 156 industrial districts have been identified in 2001.

[17] The Ateco classification is provided by ISTAT (the Italian National Institute of Statistics) and it is similar to the international SIC classification.

[18] Guiso (1998) identified credit constrained firms in an exactly identical manner using another dataset on Italian manufacturing firms provided by the Bank of Italy. Unlike the approach of this paper, he modeled the probability of being credit rationed using a single equation model.

[19] These figures are consistent with those reported in Piga and Atzeni (2007) (14 percent and 31 percent respectively) using older versions of the survey. Also, the proportion of firms being constrained ranges between 2.7 percent and 4.3 percent, depending on the business cycle, in Guiso (1998).

[20] In the questionnaire Research and Development (R&D) is defined as "a creative activity which is undertaken with the aim of increasing knowledge and using such knowledge to create new applications, like technologically new or improved products and processes." R&D activity includes any in-house or external research (or a combination of the two) undertaken by the firm.

[21] The same concern has been arisen by Herrera and Minetti (2007). However, the authors are confident of the trueness of firms' declarations for the following two reasons: first, the Italian Law (675/1996) on the treatment of personal data forbids using them for objectives different from that mentioned in the survey, namely the elaboration of statistics. Therefore, firms have no incentives to lie on their innovations in order to establish a record as appealing borrowers. Second, the personnel employed to handle survey

data is highly qualified and firms' answers are passed through several filters and double checks before being released.

[22] Pavitt (1984) aggregated manufacturing sectors into four categories: supplier dominated, scale-intensive, specialized equipment suppliers, and science-based.

[23] Berger and Udell (1990) find a negative correlation between leverage and intangible assets for a large sample of US companies. Močnik (2001), using a sample of Slovene firms, finds support for the hypothesis that firms with a high level of intangible assets should be characterized by a lower debt/equity ratio.

[24] I also experimented with other measures of R&D intensity (R&D expenditures over total investments, R&D expenditures over total sales) but the variables turned out to be not significant across all experiments.

[25] In many OECD countries, like Italy, companies are free to book expenditures for scientific or technical research either as fixed assets or as expenses. Therefore, most intangible investments are not reflected in the balance sheet but immediately expensed in the income statement.

[26] However, the empirical evidence is mixed. For example Baffigi et al. (1999) report a higher sensitivity of investments to cash-flow for firms in the districts, which could point to the existence of financial constraints, although once replicating their regressions at regional level, they find that the impact is substantially different across regions.

ESSAY 3

The Basel II reform and the provision of finance for R&D activities in SMEs: an analysis for a sample of Italian companies

1. Introduction

In recent years, numerous scholars have highlighted how financial constraints to investments in intangible capital might have a significant impact upon the pace of technological change, particularly for economies characterized by a distribution of firm size heavily skewed towards small and medium enterprises (Carpenter and Petersen, 2002). Such a situation calls for a deeper reflection on the role of traditional financial intermediaries in supporting innovative activities. This issue has been investigated according to different perspectives. On one side, an important stream of literature has supported the key role of financial institutions in selecting more valuable innovators, hence enabling and fostering technological change and growth (King and Levine, 1993). Most of these studies focus on the analysis of the general relationship, for different geographical levels, between the degrees of development and density of the financial system and local growth rates or innovation performances.[1]

A second stream of studies has focused on the dynamics of the credit market for innovative firms. In this case, the literature seems to highlight a rather limited capability of traditional financial intermediaries in sustaining investments in innovation.[2] These contributions are based on the asymmetric information literature (Myers and Majluf, 1984) which suggests the presence of a wedge between the cost of internal and external financial resources. The premium on external resources tends to be higher for small innovative companies lacking collateral assets. Scellato (2006) explored this issue adopting the modeling approach based on the analysis of investment-cash flow sensitivities with panel data (Fazzari et al. 1988; Cleary, 1999). The results stressed the actual presence of liquidity constraints on physical capital due to capital market imperfections, leading medium-sized Italian manufacturing companies to delay the initial start of in-house research and development activities for product enhancement.

In this paper I focus on the potential changes in lending conditions to Italian SMEs, accounting for the future changes in the banking regulation, which will be driven by the adoption of the new version of the Basel Capital Accord, scheduled to be implemented after 2006. In particular, I address the part of the Accord which requires the adoption by banks of a new system for fixing capital requirements as a function of the creditworthiness of borrowers and I analyze to what extent such new practices might influence lending strategies for SMEs involved in product innovation. To the extent that the specific characteristics of innovative SMEs (in terms of collateralisable assets, financial ratios and certainty about future cash flows) negatively affect banks' capital requirements, the adoption of the Basel II rules might generate an increase in the cost of capital for these companies.

Our analysis is based on survey data for 2168 companies in year 2003, matched with complete financial accounting information. I initially implement a probit model in order to observe whether, after controlling for standard measures of firms' financial performance and profitability, indicators of product/process innovation and R&D intensity exert a significant impact on the probability that companies declare the need of additional credit. Standard financial accounting ratios (indexes of companies' leverage, liquidity and profitability) show significant effects on the probability for a company of declaring the need of additional credit. At the same time, when moving to innovation-related indicators, I obtain that different R&D intensity measures do not show a significant impact.

I then perform a simulation on the potential impacts of the adoption of the Basel II Capital Accord by Italian banks. The rationale for the latter analysis is the following one. To the extent that in banks' risk assessment R&D-related variables appear to be out-weighted by standard indicators concerning firms' financial structure, it might be the case that a positive correlation between unobserved R&D intensity and default predictions based on standard models will cause an additional contraction in the availability of financial resources for innovative SMEs. In exploring this hypothesis, I implement a simulation on our sample of 2168 manufacturing companies introducing the rules for bank capital requirements imposed by the new Basel Accord. The Accord introduces a system for fixing bank capital requirements (minimum capital requirements currently amount to 8% of exposures) as a function of the degree of risk of borrowers. Hence, if innovative SMEs show a higher idiosyncratic risk, the bank in its portfolio optimization process might either ask to this category of firms higher interest rates to compensate for higher capital requirements, or simply deny credit to them. Previous studies, also in Italy, have investigated the effects of the new Basel Capital Accord on bank credit exposures to SMEs, but there is no previous evidence for the specific impact on small and medium firms involved in innovative activities.

The results of our simulations suggest that the introduction of the new rules is likely to have a moderate impact on banks' capital requirements when considering the possibility for the bank to pool together all the companies. However, when focusing on the sub-sample of companies which declare to be involved in innovative activities, I obtain an increase in banks' capital requirements, which in turn might cause a deterioration in the expected credit conditions applied to this sub-sample of companies. It is worth stressing that in its actual implementation, the Basel II Accord will potentially deliver significantly different results, in terms of lending conditions, as a consequence of the alternative rules banks are allowed to choose, of differences in banks' internal methodologies of risk assessment and on subjective judgments in the validation of such methodologies by supervisors.

With respect to the latter points, I carry out a sensitivity analysis for a set of parameters used to estimate capital requirements. In particular, I obtain that expected bank's capital requirements reveal to be highly sensitive to changes in Loss Given Default (LGD, the share of the loan which is lost by the bank in case of firm's default). I argue that this feature might exert a major impact, especially for small innovative companies endowed with a limited amount of collateralisable assets and, as a consequence, characterized by higher expected LGD.

The overall evidence seems to suggest the presence of a situation characterized by a still limited role of the banking sector in R&D-related financing for small and medium enterprises. In fact, besides our models' results, such situation is well reflected by summary data on financial sources for innovation projects for the sample of companies: on average retained earnings cover nearly 80% of the annual expenditures, while long-term debt accounts for only 9.7% of them. This implies a pro-cyclical investment behavior, which turns to be highly incompatible with the smooth investments path typically required to sustain innovative processes. Within such context, the new Basel II rules, the impact of which for banks is rather limited, due to the possibility to pool risk together, do not appear to ease fundraising for small companies endowed with limited collateral physical assets, which is typically the case for R&D intensive growing firms.

The paper is organized as follows. In section two I survey the main contributions on the theme of financial constraints to investment in innovation. The third section is devoted to a brief overview of the contents of the new Basel Accord, focusing the analysis on the issues related to banks' capital requirements. In that section, I also review some empirical papers that have explored the expected effects of the introduction of the new Accord rules on SMEs. In section four I show the main characteristics of the data used. Section five reports summary statistics and results. Finally, section six provides concluding remarks on the potential implications of the analysis within the specific context of the Italian economy.

2. Contributions on financial constraints and innovation

It is a widely held view that research and development activities are potentially subject to severe borrowing constraints. The theoretical foundations of this evidence pertain the asymmetric information literature, which postulated the existence of an informational advantage of entrepreneurs over financiers about the quality of investment projects, thus predicting the existence of credit rationing when external financing is represented by bank debt (Jensen and Meckling (1976); Stiglitz and Weiss (1981); Myers and Majluf (1984); Hellmann and Stiglitz (2000)). This stream of literature essentially addressed credit rationing in a context of investment in tangible capital. The shift towards R&D investment clearly introduces an additional set of issues which are likely to exacerbate informational problems.

Following Hall (2002), it is possible to summarise such effects according to the following points. First, innovative investments contain a large part of intangible assets which cannot be used as collateral to secure firms' borrowing (Lev, 2001). A second pervasive aspect is related to the uncertainty which characterizes R&D investments and to the absence of a secondary market for R&D assets. Lastly, there is a poor availability of analytical instruments able to capture and correctly estimate the expected future revenues of innovative activities (Encaoua et al, 2000). The empirical measurement of the presence and extent of financial constraints to investment has undergone a long debate about the best suited econometric tools, since the approach developed by Fazzari, Hubbard and Petersen (1988), which was based on the analysis of investment-cash flow sensitivities. Adopting a pecking-order theoretical approach (Myers and Majluf, 1984)[3], they suggest that investment decisions of firms that are more likely to face financial constraints are more sensitive to firm's liquidity than those of less constrained firms. Hence, high investment-cash flow sensitivities along time can be interpreted as evidence for the existence of capital market imperfections.

A large literature on the relationship between cash flow and investment followed Fazzari et al. (1988)'s work (see Hubbard (1998) for a review). Different studies have found a significant cash flow effect on R&D investments, interpreting this as evidence that innovative firms are more exposed to credit constraining (Himmelberg and Petersen (1994); Mulkay et al., 2001; Hao and Jaffe (1993); Hall (1992); Harhoff (1998); Bond et al (1999)). Few other studies have addressed the issue of financial constraints for innovative companies by relying on survey data (Guiso (1998); Atzeni and Piga (2005)). For the Italian context, Guiso (1998) related the probability of being credit constrained to observable characteristics of firms, grouping companies into high-tech and low-tech. The estimates showed that high-tech firms are more likely to be credit constrained than firms undertaking traditional investment projects. Different results are provided by Atzeni and Piga (2005) who estimated a bivariate probit model to capture both the extent to which R&D intensive firms are liquidity constrained and their decision to apply for credit. The authors found that firms with high levels of R&D expenditures do not seem to be credit rationed, suggesting an inverse U-shaped relationship between R&D activity and the probability of being liquidity-constrained.

3. The main features of the Basel II Capital Accord

In June 2004 the Basel Committee on Banking Supervision issued a revised framework on International Convergence of Capital Measurement and Capital Standards that became known as the Basel II Accord. The reform relies on three pillars: a new capital requirements system, the assessment of risk control systems and capital adequacy policies by national supervisory authorities, and a more efficient use of market discipline. This paper deals with the expected effects of the first pillar of the agreement. The revision of the 1988 version of the document[4] (which set a capital ratio at 8% of risk-adjusted assets) was done with the aim of improving the risk-sensitivity of capital requirements, providing more flexibility in their calculation and reducing the scope for regulatory arbitrage.

The Accord proposes a two-layer regime for the relationship between capital requirements and the treatment of credit risk: a standardized approach[5], where risk weights are partially based on external ratings (such as those provided by rating agencies or other qualified institutions); an internal ratings-based approach (IRB), which gives the bank varying degrees of autonomy in the estimate of the parameters determining risk weightings. The latter system is clearly expected to be the most widely used, given the limited availability of external ratings, particularly for those economies in which there are few listed companies and SMEs account for the largest share of the overall firms' population. The IRB system is in turn divided into two different methodologies which can be adopted by the bank: the Foundation Approach and the Advanced Approach. Under the Foundation, only the probability of default (PD) is internally estimated, while loss given default (LGD), exposure at default (EAD) and maturity (M) are assigned on the basis of supervisory rules. Conversely, if adopting the Advanced Approach, a bank can also produce its own estimates for LGD, EAD and M.[6] Regulatory capital requirements are then derived given the distribution of the whole population of borrowers across different rating classes.

A wide debate emerged in relation to the treatment of bank credit exposures to small and medium sized enterprises in terms of minimum capital requirements (see Dietsch and Petey, 2002; Meier-Ewert, 2002). Serious concerns were raised that the proposed formulas for the calculation of capital requirements for SMEs were too stringent (leading to too high capital charges and consequently to credit rationing), since they relied on the assumption that small firms are generally characterized by relatively high probabilities of default, as compared with large business. As a result, from the beginning of the capital adequacy reform process (1999), formulas to calculate risk weights linked to SMEs were changed three times. More precisely, the Basel Committee introduced different risk-weight functions for SMEs and large business, with a size-adjustment in the risk-weight formula for firms with turnover between €5 and €50 million (June 2004, par. 272-273).[7] Moreover banks are allowed to consider as retail SMEs with turnover between €1 and €5, provided that their total exposure to any one firm remains below €1 million. In that case the credit must be managed as a retail exposure on a pooled basis (June 2004, par. 330).

Following the above considerations on the Basel II agreement, I now turn to briefly review some of the contributions which have dealt with the possible effects of the implementation of the Accord on SMEs. On the whole, the empirical analyses seem to agree on the fact that the new Basel Capital Accord will not lead to higher capital charges for SMEs, either if the Standardized or the IRB approach is used. Altman and Sabato (2005), using data on SMEs from three different countries (USA, Italy and Australia), quantified the expected effects on bank capital requirements when considering a small firm as either retail or corporate. In particular, their results showed that for all countries, banks will have significant benefits, in terms of lower capital requirements, when considering SMEs as retail. However, the same does not always hold when they are treated as corporate exposures. Schwaiger (2002) calculated bank capital requirements for a sample of Austrian enterprises with revenues between €1 and €50 million, using the formula contained in the October 2002 version of the Accord and considering SMEs only as corporate. According to the author's estimates, the new Accord will lower banks' capital requirements for the SMEs' segment. The same exercise is undertaken by Saurina and Trucharte (2004) for the Spanish economy. The authors argued that capital requirements for exposures to SMEs might diminish substantially with the new Accord using the Standardized Approach. Their conclusion was that there is not a significant incentive for Spanish banks to adopt the IRB approach.

Hence, most of the present evidence based on simulations seems to agree on a positive or at least neutral future impact of the Basel II rules on conditions for the provision of finance to SMEs. However, it is important to highlight that these studies have pooled together all the sample companies used in the simulations, while it might be the case that specific segments of companies (characterised by peculiar characteristics in terms of financial ratios and collateral physical assets) will experience detrimental effects from the application of the same rules. The objective of the analysis presented in the following sections specifically addresses this latter point, with a focus on the segment of SMEs involved in product innovation.

4. Sample characteristics and summary statistics

The paper is based on a dataset which is derived from a survey on Italian manufacturing firms undertaken in 2004 by Mediocredito Centrale, a credit institution currently part of Capitalia, an Italian banking group. The survey involves 4289 Italian firms and the sample is stratified according to industry and geographical location. The survey data is coupled with complete financial accounting data for fiscal year 2003.

A series of selection criteria have been applied to the sample. Firstly, I considered only those firms with total sales for year 2003 between €5 millions and €50 millions, in order to comply with the Basel II definition of SMEs.[8] In particular, I excluded the companies with a turnover below €5 millions, so that in our simulation I will consider all lending as corporate lending. Out of 2309 firms, I dropped all those firms other than joint stock companies and those presenting missing values in the part of the survey dedicated to the assessment of financial constraints. Our final dataset includes a total of 2168 companies. In Table 1 I present the sectoral distribution of the analyzed companies according to the ATECO industry classification codes. In Table 2 I summarize the size distribution of the companies included in the final sample.

[Insert Table 1 here]

[Insert Table 2 here]

Since I am interested in the relationship between innovative activities and financial strategies of the analyzed companies, in Tables 3 and 4 I provide evidence of the incidence of the different financial sources both on fixed and R&D investments. The data are extracted from the survey. A first look on the composition of financial sources for investments clearly stresses the relevance of the phenomenon under investigation. In fact, it emerges a clear-cut evidence about the absolute dominance of self-financing through retained earnings with respect to other potential financial sources.

Self-financing accounts for nearly 47% in supporting physical capital investments, while such percentage increases to 79% when R&D investments are considered. The data stress the relatively modest role exerted in the Italian industrial system by the private equity industry which accounts for only 1.2% (fixed investments) and 0.8% (R&D investments) of financial sources. Bank debt is still the main source of external financing for fixed investments, but its weight falls abruptly when investments in innovation are considered.

[Insert Tables 3 and 4 here]

With respect to the situation outlined above, one is then legitimate to ask whether such large incidence of internally generated cash flow as a mean to finance R&D investments is indeed a reflection of a voluntary firm's strategy or rather the result of a credit rationing phenomenon. Following Hadlock (1998) and Degryse and Jong (2006), it is possible to attribute investment-cash flow sensitivities to the presence of two different factors: asymmetric information on capital markets or internal agency problems leading to overinvestment by the management (Jensen, 1986). According to the asymmetric information approach, the wedge in the cost of financial resources is due to the limited capability of lenders in valuing future cash flows deriving from investment projects. This leads to an under-investment effect by the companies, which are forced to drop some projects with positive net present value. On the contrary, according to the free cash flow theory, the positive relationship between investment and internal finance might be the result of overinvestment by managers, whenever their objective function differs from the maximisation of corporate value.

The specific characteristics of the Italian SMEs included in our sample, which commonly show an extremely concentrated ownership structure (they are often wholly-owned family companies), obviously limit the potential impact of managerial cash flow. Hence, it is plausible to hypothesize that the observed reliance of investments on internal financial resources is mainly driven by credit market conditions. A strong dependence on contingent cash flow, and hence on business cycle movements, is acknowledged as a major drawback for investments in innovation, which typically require smooth and continuous expenditures profiles over time.

The second set of variables that will be used in our study concerns the degree of innovativeness of the analyzed companies. A reliable and effective accounting of research activities carried out within companies is acknowledged to be a rather difficult task. This is particularly true when dealing with data for Italian firms, since according to the Italian law, R&D expenditures are not compulsorily reported on balance sheet data. For these reasons, in assessing the actual degree of innovation intensity of the companies analyzed, I opted for pooling different kind of data deriving from the survey. Out of 2168 firms, 49.8% declared to having sustained expenditures for R&D during the years 2001-2003. However, the actual nature of such expenditures is rather difficult to be assessed, since R&D activities carried out within SMEs are often embedded in standard production activities or, more generally, take the form of informal research or externally acquired services[9]. When looking at traditional measures of R&D intensity within the sample I obtain the data showed in Table 5.

[Insert Table 5 here]

When moving from the above input measures of the innovation process to the output side, the survey explicitly asks firms about the introduction of process or product innovations in the years 2001-2003. These qualitative variables will be used in the following simulations to identify innovative companies. In Table 6 I report the main evidence.

[Insert Table 6 here]

The Mediocredito Centrale survey investigates the issue of firm financing by including specific questions concerning firm's financial needs and difficulties in accessing external financing.

The condition of being financially constrained has drawn the attention of several researchers, dating back to Stiglitz and Weiss (1981), who defined a firm as credit rationed if it does not get as much credit as it wants, although it is willing to meet the conditions set by the lender. A similar view is provided by Hall (2002), according to whom a financial constraint is said to exist when a firm cannot raise external funding at the market price or in order to access external financing it has to pay over it. In a recent study, Atzeni and Piga (2005) applied the concept of credit rationing to those firms that declared they wanted more credit and were willing to pay either the current or a higher interest rate but, once applied, were turned down. Guiso (1998) identified analogously credit constrained firms using another dataset on Italian manufacturing firms provided by the Bank of Italy.[10]

The direct information based on each firms' own assessment provided by the survey is used to characterize the existence of financial constraints. More in detail, I define a firm as financially constrained if it answered "yes" to the question: "In 2003 the firm would have desired more credit at the interest rate agreed with the bank?" In the overall sample, 12.55% of the surveyed companies declared they would have needed additional credit. Hence, the indicator of financing constraints is a dichotomous variable which is equal to 1 if the firm wished an additional amount of credit and 0 otherwise.[11]

5. Models and results

Our analysis moves from the investigation of the impact of firm-specific R&D related variables on the probability of observing a desire of additional quantities of credit.

In order to explore the potential determinants of such a phenomenon, I rely on a set of traditional financial accounting ratios that are expected to affect the decision of the bank in its lending decisions. Our modeling approach is based on a probit model. The model contains a set of financial accounting variables, which can be grouped into three categories describing the main aspects of a company's financial profile: leverage, liquidity and profitability. All the financial ratios are calculated for year 2003. The list of variables is reported in Table 7.

[Insert Table 7 here]

PROD is a dummy variable which is equal to 1 if the firm declares of having carried out product innovations, PROC is a dummy variable which is equal to 1 if the firm declares of having carried out process innovations. CASH is a dummy variable which equals one, if the company shows a negative cash flow in year 2003. SETPAV is a dummy variable which is equal to one if the company belongs to an industry classified as "Science Based" according to Pavitt's (1984) taxonomy. I also introduce in the model a dimensional variable (ASSET) defined as the logarithm of firms' total assets in year 2003.

In Tables 8 and 9 I report the results obtained for the different specifications of our model, in which I use different proxies for the presence of R&D related activities. In the first model, I focus on the effects exerted on the probability of observing a higher desire of credit by variables simply indicating the fact that the company declares of having been involved in product or process innovation. In the second set of models I then move to an analysis of the effects of R&D intensity variables. In all the models I maintain the set of control variables based on standard financial accounting ratios.

[Insert Table 8 here]

As expected, the standard financial accounting ratios show significant effects on the probability for a company of desiring more credit. In particular, higher previous incidence of debts in a firm's capital structure (LEV) significantly raises such probability, possibly due to a debt-overhang phenomenon (Hart and Moore, 1985). Such effects turn to be stable with respect to different model specifications. At the same time, a higher value of the acid test index (ACID) is likely to lessen financial constraints. A similar effect, as it could be expected, is played by our measure of profitability (EBS). The dummy PAV has a positive and significant effect, confirming how SMEs operating in industries characterized by a higher incidence of intangible assets are more exposed to financial constraints. What is relevant for our analysis are the different proxies of innovative activity introduced in models 2 and 3. First, the dummy variable accounting for product innovation shows a positive significant effect on the probability of requiring more credit. At the same time, the dummy variable for process innovation has a negative and non significant effect. Such evidence appears to be reasonable, given the potential differences in the costs involved in the development of new products rather than the incremental change in production processes. Furthermore, the specific degree of uncertainty, as well as asymmetric information between lenders and borrowers, can be reasonably expected to be lower in the case of process innovation. Finally, when inserting the dummy for the presence of R&D expenditures I find a positive, but not significant, effect on the probability that a company requires additional credit.

Parisi et al. (2006), using previous versions of the survey, investigated the effects of process and product innovation on productivity. They found that the introduction of process innovation has a larger effect on productivity than product innovation. R&D spending is also strongly positively associated with the probability of introducing a new product rather than a new process.

[Insert Table 9 here]

The results reported in Table 9, in which I have included our measures of R&D intensity, highlight a rather counterintuitive evidence: in fact, the ratio of yearly R&D expenditures either on total sales or assets shows a negative and non significant effect on our dependent variable. Such evidence may be interpreted according to different perspectives. On one side, one might argue that, considering the summary data about the financial sources for R&D investment previously presented (on average 79% coming from self-financing), the companies characterized by higher R&D intensities are those with better financial positions and profitability. Hence, those companies do not require additional financial resources for the simple reason that they entirely build R&D investment strategies on the availability of internal resources. Put differently, the results might be the reflection of a high degree of risk aversion by company managers which delay R&D investments until a sufficient amount of internal financial resources is available. On the other side, one might suggest that the non-significance of the coefficient related to different measures of R&D activity is due to the limited accountability of intangible assets, the potential impact of which is in turn underestimated by the provider of financial resources. Hence, the standard financial accounting ratios based on tangible assets would nearly completely govern the decision of banks. Finally, one might also argue that the non significant effect of R&D intensity measures is a reflection of non-linear phenomena in the relationship between R&D

volumes and financial position. Atzeni and Piga (2005) find analogous results for Italian companies and, after splitting the overall sample, focusing on the top-R&D performers, they suggest the presence of an inverted-U shape in the relationship between R&D intensity and the probability of desiring more credit.

However, the ascertainment of an univocal causal nexus between financial position and R&D investment decisions is still unclear and the cross-sectional nature of the data does not allow to test for causality nexuses. Independently of the specific hypotheses, what is relevant for our study is that the data highlight the presence of a disproportionate composition of financial sources to sustain R&D investment activities, with a prominent role of self-financing. Even if I am not able to disentangle how much the above evidence is due to a particularly conservative investment behavior, rather than a limited capability of financial intermediaries in assessing the expected cash flows from R&D investments, the fact that standard financial ratios are strictly linked to the desire of additional amounts of credit poses some relevant concerns. In fact, in such context, it might be the case that the introduction of the new rules imposed by the Basel II Capital Accord will further indirectly affect the provision of finance for innovation. Under the hypothesis of limited observability of the actual intensity of R&D effort within the companies, the new rules might produce a negative impact on innovative SMEs if the latter show a higher default probability, based on standard observable financial variables. The following paragraph is dedicated to an analysis of such potential impacts through a simulation on our sample of companies.

5.1 A simulation on the expected effects of New Basel Capital Accord

As outlined in section 2, in order to implement the methodology introduced in the new Accord, banks will have to estimate their own probability of default for each potential borrower. Then, the distribution of borrowers among different rating classes will determine the overall capital requirements for the bank.

In order to compute one-year probability of default for the companies included in our sample I referred to a set of published models, which are based on financial accounting ratios and are derived through logit models on samples of defaulted/non defaulted companies. The chosen models are those by Shumway (2001) and Altman and Sabato (2005), which seem to better fit to the specific characteristics of our sample. A major problem in the selection of public models for the computation of default probabilities is related to the fact that most of them include among their variables either the market value of the companies (which I do not have since none of our firms is listed on a stock market) or the amount of retained earnings (which cannot be derived from Italian balance sheet data). Shumway (2001) develops an hazard model for a sample of firms (3182 firms with 300 bankruptcies). The study by Altman and Sabato (2005) focuses on the Italian economy and is based on data from the Bank of Italy on 20,193 SMEs. In Table 10 I report the financial ratios used in the two studies.

[Insert Table 10 here]

I applied the two models to predict the one-year probability of default of each company, on the basis of 2003 balance sheet data. I then proceeded to a classification of firms within rating classes. Given that banks must comply with the Basel II requirement (June 2004, par. 404) of having a minimum of seven borrower grades, I adopted the S&P rating system with a scale of 21 levels. I then assigned each company to a specific rating class on the basis of the previously computed default probability. In Table 11 I show our results. The distribution of companies is strongly concentrated, for both probabilities of default, in the classes going from B- to BB+, which account for nearly half of the sample. Such evidence confirms some previous results from studies which have specifically analyzed Italian SMEs. [12]

[Insert Table 11 here]

From the data reported in Table 11 it is evident that the specific model adopted for evaluating probabilities of default is likely to significantly affect the distribution of companies across rating classes. For this reason, in the following analysis, I will treat separately data coming from the two models presented for the estimation of default probabilities. The next step of our analysis was to investigate the effects of Basel II on bank capital requirements for small and medium sized enterprises, operating a discrimination on those firms that are involved in innovative activities and others that are not.

Our simulation is based on the assumption that banks will use the IRB Foundation approach. Analogously to some previous studies (Schwaiger, 2002), I assumed a fixed Loss Given Default of 45%, as it is suggested in the Foundation IRB approach[1] for senior loan exposures (Basel Accord - June 2004, par. 287), and I used the percentage of firms in each rating class as weight for capital requirements. Moreover a maturity of 3 years was assumed. Since in our simulation I consider all SMEs as

[1] The LGD is the share of the loan which is lost by the bank in case of default.

corporate (in fact our sample consists of firms with turnover €5-50 million), I had to make an additional assumption on the amount of sales to be used for the size adjustment. I then computed, for each class, the average level of turnover (S) of the included companies in year 2003, which is used, according to the Basel II requirements, to rescale capital requirements. Below I report the calculation used to compute capital requirements for each rating class, which is then cumulated to obtain the overall capital requirement for a bank that is able to fully diversify its portfolio across all the analyzed companies. Firstly, each company has been associated to the upper level of probability of default (PD) corresponding to the rating class in which it has been included. I then computed for each class the correlation parameter R:

R=0.12*(1-EXP(-50*PD))/(1-EXP(-50))+0.24*(1-(1-EXP(-50*PD))/(1-EXP(-50)))-0.04*(1-(S-5)/45) (1)

I also calculated the maturity adjustment parameter B, which generates a negative correlation between the probability of default and the length of the loans (which will be fixed in our simulation to three years):

B =(0.11852-0.05478*Ln(PD))^2 (2)

Given the above parameters I calculated capital requirements (K) for each rating class according to the following formula:

K=(LGD *N((1 -R)^-0.5 *G (PD) + (R / (1 - R))^0.5 * G(0.999)) - PD * LGD) * (1 - 1.5 * b)^ -1 * (1 + (M - 2.5) * B) (3)

In the above expression Ln denotes the natural logarithm, N(x) the cumulative distribution function for a standard normal random variable and G(z) the inverse cumulative distribution function for a standard normal random variable, M is the debt maturity. Finally, cumulated capital requirements are calculated by multiplying the level (K) for the weight of the specific rating class with respect to the whole sample of companies (column WEIGHT in Tables 12-13). Given the impossibility to observe the actual amount of loans for each company, I had to weight each rating class just on the basis of the incidence of the number of firms. Incidentally, this approach has been adopted in all the previous studies which have tried to assess the potential impact of the Basel Accord rules.

In Tables 12 and 13 I report our results. Total bank capital requirement turns to be on average 8.52% according to the Shumway (2001) probability of default and 8.66% according to the Altman and Sabato (2005) probability of default. Hence, the results suggest that when considering the full sample of companies, the aggregated capital requirements for a bank do not differ substantially from the level of 8% fixed before the introduction of the new rules of the Basel II Capital Accord. The slight increase in capital requirements is fully in line with previous simulation studies.

[Insert Tables 12 and 13 here]

All the previous empirical analysis which have investigated the effects of the Basel Accord have mainly tackled changes in capital requirements with respect to the whole sample of SMEs, while I proceed by focusing on the specific issue of innovation activities. For this reason, in the second part of the simulation exercise, I split our sample of firms according to a specific measure which should capture their degree of innovation and then compare the cumulated capital requirements for the obtained sub-sample. To the extent that including in the portfolio of borrowers those companies which are involved in innovative activities would generate an increase in capital requirements, then one might argue that the bank could either charge higher interest rates to such firms in order to compensate the higher capital requirements or simply deny credit to them. In principle, banks might be able to operate a distinction between innovative and non-innovative firms. However, the actual assessment of the characteristics and intensity of innovation effort represents a rather difficult task, given the limited accountability of R&D activities and the well known problems related to disclosure incentives by innovative companies. In such context, it is likely for a bank to mainly refer to standard financial and expected profitability measures to evaluate default probabilities which in turn will determine risk classification and capital requirements' needs. Following this rationale, in Table 14 I computed capital requirements for the sub-sample of 951 companies which declared in the survey of having been involved in product innovation.

[Insert Table 14 here]

On average, the results show the presence of an increase in banks' capital requirements when considering only a portfolio of innovative SMEs. Such change turns to be relatively larger, but always less than 100 basis points, also in the case of the Altman and Sabato (2005) probability of default. However, it is important to stress that the sub-sample of companies involved in R&D activities might be in principle endowed by a relatively smaller amount of tangible assets to secure the loans (see Carpenter and Petersen, 2002 for a discussion on this point). Since the above computations have been operated according to a LGD equal to 45%, in Table 15 I perform a sensitivity analysis with respect to this parameter. In fact, to the extent that R&D activities are firm-specific and generate assets which are often non re-deployable in case of firm's default, the actual LGD might be higher than the one previously assumed.

[Insert Table 15 here]

The data reported in Table 15 clearly highlight the elevated sensitivity, according to the methodology defined in the Basel II Accord, of capital requirements to changes in the average LGD. I claim that this feature might exert a major impact, particularly for smaller innovative companies which are endowed with a still limited amount of collateralisable assets. In this perspective, the new rules might exacerbate a phenomenon, namely credit rationing related to the lack of tangible assets, which has been largely proved in previous empirical analysis on financial constraints and innovative activities (Scellato, 2006).

In table 16, I carried out a sensitivity analysis with respect to the assumed maturity of debt. Also in this case, given all other variables, an increase in the average debt maturity causes an increase in capital requirements which goes beyond the level of 8%. However, for this latter variable it is less obvious the specific impact on the provision of finance for companies involved in innovative activities. Nevertheless, it is worth recalling two aspects which to some extent might indeed be related to debt maturity and R&D: first, in general R&D projects require a rather stable and smooth investment path along years; second, the amount of resources required to start R&D projects is likely to generate the need, particularly for less financially endowed companies, to spam the debt over longer time windows.

[Insert Table 16 here]

6. Conclusions

In this paper I have investigated the issue of the provision of finance for innovative SMEs in Italy, focusing on the expected impact of the new Basel Accord rules on banks' capital requirements, which in turn might affect lending strategies for different kinds of borrowers. In order to give a correct interpretation of final results it is fundamental to consider the statistical evidence deriving from the analysis of the financial sources for investments for our sample of 2168 SMEs. In recent years, among the potential sources, self-financing accounts for a share of 47% in case of standard investments, while such percentage rises to 79% in case of R&D investments. Such evidence calls for a deeper reflection on the actual dynamics affecting the relationship between R&D investment and the banking sector, at least for this typology of companies. In this perspective, the results emerging from our probit models suggest a rather articulated situation.

The different proxies used to map the presence of innovative activities, through dummy variables, show significant positive effects on the probability that the company declares of having desired an additional amount of credit. At the same time, when moving to an analysis of the impact of R&D intensity measures, I find a negative and non significant impact. Such evidence might be interpreted according to different perspectives. On one side, one might argue that, considering the summary data about the financial sources for R&D investment previously presented, the companies characterized by higher R&D intensities are those with a better financial position and profitability. Put differently, the results might be the reflection of a high degree of risk aversion by company managers which delay R&D investments until a sufficient amount of internal financial resources is available. On the other side, one might suggest that the non-significance of the coefficient related to different measures of R&D activity is due to the limited accountability of intangible assets, the potential impact of which is in turn underestimated by the provider of financial resources. Therefore, the standard financial accounting ratios based on tangible assets would nearly completely govern the decision of banks in granting credit. Even if I am not able to disentangle how much the above evidence is due to a particularly conservative investment behavior of managers, rather than a limited capability of financial intermediaries in assessing the expected cash flows from R&D investments, the fact that standard financial ratios are strictly linked to the desire of additional quantities of credit poses some relevant concerns. In fact, in such context, it might be the case that the introduction of the new rules imposed by the Basel II Capital Accord will further indirectly affect the provision of finance for innovation.

The results of our simulations suggest that when considering the overall sample of companies, the aggregated bank capital requirements do not differ substantially from the level of 8% fixed before the introduction of the new rules of the Basel II Capital Accord. When restricting the analysis to the sub-sample of companies involved in product innovation, the results show the presence on average of an increase in banks' capital requirements, which is in the order of 100 basis points. Moreover, when moving to a sensitivity analysis with respect to the Loss Given Default parameter used to compute capital requirements, I obtain a significant increase in them for relatively small changes in LGD. This particular feature might generate a net disincentive for the financing of these companies which are endowed with a more limited amount of collateral assets. In our analysis of the effects of the Basel Capital Accord on banks' capital requirements, I used two different methods to estimate each firm's probability of default, which is indeed the key parameter to compute banks' capital requirements. The results obtained turn to be rather sensitive to the specific methods used. For this reason the future development of this research will be mainly devoted to an extension of the models used to estimate firms' probability of default, including besides financial accounting ratios also a proper set of qualitative and industry-specific variables.

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8. Tables

Table 1-Sectoral distribution of companies

ATECO code	Industry	N. of firms	%
15	beverage and food industry	235	10.84%
17	textile industry	187	8.63%
18	textile product industry	71	3.27%
19	leather and leather products manufacturing	83	3.83%
20	wood and wood products manufacturing	60	2.77%
21	pulp, paper and paper products manufacturing	58	2.68%
22	publishing, printing	46	2.12%
23	petroleum and coal products manufacturing	13	0.60%
24	chemical industry	135	6.23%
25	plastics and rubber manufacturing	121	5.58%
26	non-metallic mineral products manufacturing	119	5.49%
27	Metallurgy	90	4.15%
28	metal products manufacturing	268	12.36%
29	mechanical machinery and equipment manufacturing	309	14.25%
30	computer and electronic manufacturing	4	0.18%
31	electrical machinery and equipment manufacturing	79	3.64%
32	telecommunication machinery and equipment manufacturing	35	1.61%
33	medical, optical and precision equipment manufacturing	36	1.66%
34	transportation equipment manufacturing	28	1.29%
35	other transport equipment manufacturing	19	0.88%
	other manufacturing industry	172	7.93%
		2168	100.00%

Table 2-Summary statistics on firm size

Variables	Mean	Std. Dev.	Min	Max
n. of employees	80.5	69.5	11	1138
sales (€ mln)	15.96	10.23	5	49.86
total assets (€ mln)	15.58	14.15	10.95	245.52

Table 3-Percentage incidence of different financial sources for fixed investments, average over the sample of 2168 firms

FINANCIAL SOURCES (FIXED INVESTMENTS)	%
private equity	1.2
self financing	47.2
short-term debt	7.1
long-term debt at market conditions	11.8
long-term debt at advantageous conditions	8
public funding	3.1
tax incentives	4.4
leasing	16
loans from the group	0.8
loans from other firms	0.1
other sources of financing	0.3

Table 4-Percentage incidence of different financial sources for R&D investments, average over the sub-sample of companies with positive R&D

FINANCIAL SOURCES (R&D INVESTMENTS)	%
private equity	0.8
self financing	79.4
long-term debt at market conditions	5.9
long-term debt at advantageous conditions	3.8
national and EU public funding	5.8
tax incentives	3.4
other sources of financing	0.9

Table 5-R&D intensity measures for companies which declare of having invested in R&D, year 2003

Measure	Mean	Std. Err.
R&D expenditures/sales (2003)	1.98%	0.0843
R&D expenditures/total assets (2003)	1.94%	0.0853
R&D expenditures/ total investments (2003)	35.13%	0.2980

Table 6- Incidence of firms that declare of having introduced innovations

Type of innovations	Freq	%
Product innovation	951	43.82%
Process innovation	987	45.53%
Organizational innovation related to product innovation	471	21.73%
Organizational innovation related to process innovation	639	29.47%
None	690	31.83%

Table 7-List of variables

Variable	Definitions
LEV	Liabilities/(liabilities + equity), for year 2003
ACID	Short term activities / short term debt, for year 2003
EBS	EBIT/sales, for year 2003
ASSET	Logarithm of total assets, for year 2003
AGE	Logarithm of age
CASH	Dummy
PAV	Dummy
RD	Dummy
PROC	Dummy
PROD	Dummy
RDINV	R&D expenses/total investments, for year 2003
RDS	R&D expenses/total sales, for year 2003
RDTA	R&D expenses/total assets, for year 2003

Table 8-Probit model results, dependent variable: dummy for declaring credit constraints†

	Model 1	Model 2	Model 3
LEV	1.775** (6.33)	1.755** (6.24)	1.764** (6.29)
ACID	-0.643** (-2.44)	-0.668** (-2.53)	-0.645** (-2.45)
EBS	-0.890* (-1.80)	-0.913* (-1.85)	-0.900* (-1.82)
AGE	0.172** (2.77)	0.169** (2.72)	0.166** (2.66)
ASSET	0.037 (0.70)	0.037 (0.69)	0.032 (0.59)
CASH	0.183** (2.18)	0.176** (2.08)	0.183** (2.17)
PAV	0.369* (1.96)	0.353* (1.87)	0.358* (1.89)
PROD		0.181** (2.39)	
PROC		-0.093 (-1.22)	
RS			0.058 (0.78)
Const	-3.410** (-5.53)	-3.420** (-5.53)	-3.356** (-5.41)

† Robust z-statistics in parentheses **: significant at the 95% level; *: significant at the 90% level

Table 9-Probit model on the effects of R&D intensity measures, dependent variable: dummy for declaring credit constraints †

	Model 1	Model 2	Model 3
LEV	2.097** (4.72)	2.099** (4.72)	1.935** (4.13)
ACID	-0.912** (-2.01)	-0.902** (-1.99)	-0.905* (-1.94)
EBS	-2.742** (-2.81)	-2.727** (-2.79)	-3.395** (-3.31)
AGE	0.287** (2.92)	0.284** (2.88)	0.273** (2.62)
ASSET	-0.523 (-0.65)	-0.055 (-0.68)	-0.085 (-1.01)
CASH	0.121 (0.94)	0.122 (0.95)	0.179 (1.34)
PAV	0.528** (2.00)	0.544** (2.04)	0.637** (2.34)
RDS	-0.264 (-0.32)		
RDTA		-1.383 (-0.53)	
RDINV			-0.037 (-0.19)
Const	-3.103** (-3.31)	-3.051** (-3.24)	-2.612** (-2.68)

† Robust z-statistics in parentheses
**: significant at the 95% level; *: significant at the 90% level

Table 10- List of variables used in Shumway (2001) and Altman and Sabato (2005)

	Shumway (2001)	Altman and Sabato (2005)
Leverage	Total Liabilities / Total Assets	Debt/Equity
		Bank Debt/ (Total Assets – Bank Debt)
		Long Term Liabilities / Total Assets
Profitability	Net Income/Total Assets	Economic Value Added/Total Assets
Liquidity	Current Assets / Current Liabilities	Cash Flow/Total Assets
		Tangible Assets/Total Assets
		Accounts Payable/ Total Assets
		Long Term Bank Debt/Bank Debt
Other	Log(Age)	

Table 11-Distribution of companies across bond-equivalent rating classes for S&P.

	One-Year Probability of default and Bond Equivalent Ratings				
	Default probability	Number of firms and percentage			
	%	Shumway (1999)		Altman and Sabato (2005)	
AAA	0.02	0	0.00%	0	0.00%
AA+	0.03	1	0.05%	0	0.00%
AA	0.04	3	0.14%	0	0.00%
AA-	0.05	6	0.28%	3	0.14%
A+	0.07	5	0.23%	4	0.18%
A	0.09	11	0.51%	7	0.32%
A-	0.14	7	0.32%	14	0.65%
BBB+	0.21	39	1.80%	10	0.46%
BBB	0.31	63	2.91%	31	1.43%
BBB-	0.52	160	7.38%	54	2.49%
BB+	0.86	232	10.70%	296	13.65%
BB	1.43	343	15.82%	591	27.26%
BB-	2.03	320	14.76%	445	20.53%
B+	2.88	385	17.76%	153	7.06%
B	4.09	356	16.42%	273	12.59%
B-	6.94	175	8.07%	198	9.13%
CCC+	11.78	29	1.34%	33	1.52%
CCC	14	9	0.42%	25	1.15%
CCC-	16.7	3	0.14%	7	0.32%
CC	17	6	0.28%	9	0.42%
C	18.25	10	0.46%	15	0.69%
D	20	5	0.23%	0	0.00%
TOT		2168	100.00%	2168	100.00%

Table 12-Computation of capital requirements for the Shumway (2001) distribution of probabilities of default.

	PD	Number Firms	WEIGHT	R	B	K	Capital Requirements (Cumulated)
AAA	0.0002	0	0	0.216584	0.342332	0.009294438	0.00%
AA+	0.0003	1	0.000461	0.215991	0.316834	0.011732791	0.00%
AA	0.0004	3	0.001384	0.215402	0.299342	0.013855412	0.00%
AA-	0.0005	6	0.002768	0.214815	0.286115	0.015762147	0.01%
A+	0.0007	5	0.002306	0.21365	0.266737	0.01912502	0.01%
A	0.0009	11	0.005074	0.212497	0.252706	0.022062467	0.02%
A-	0.0014	7	0.003229	0.209665	0.228957	0.028209823	0.03%
BBB+	0.0021	39	0.017989	0.205817	0.208195	0.035030523	0.09%
BBB	0.0031	63	0.029059	0.200548	0.18918	0.042634552	0.22%
BBB-	0.0052	160	0.073801	0.190304	0.165334	0.054043788	0.62%
BB+	0.0086	232	0.107011	0.175839	0.143681	0.065834304	1.32%
BB	0.0143	343	0.15821	0.156481	0.12334	0.077387589	2.55%
BB-	0.0203	320	0.147601	0.141266	0.110227	0.084861162	3.80%
B+	0.0288	385	0.177583	0.126209	0.097872	0.092381131	5.44%
B	0.0409	356	0.164207	0.113303	0.086219	0.101182153	7.10%
B-	0.0694	175	0.08072	0.101512	0.070048	0.120277	8.07%
CCC+	0.1178	29	0.013376	0.09811	0.055546	0.147007189	8.27%
CCC	0.14	9	0.004151	0.097887	0.051177	0.156189395	8.33%
CCC-	0.167	3	0.001384	0.097806	0.0469	0.165042309	8.36%
CC	0.17	6	0.002768	0.097802	0.046478	0.165885839	8.40%
C	0.1825	10	0.004613	0.097791	0.044817	0.169126272	8.48%
D	0.2	5	0.002306	0.097783	0.042719	0.17297094	8.52%
Cumulated		**2168**					**8.52%**

Table 13-Computation of capital requirements for the Altman and Sabato (2005) distribution of probabilities of default.

			WEIGHT	R	B	K	C (Cumulated)
AAA	0.0002	0	0	0.216584	0.342332	0.009294438	0.00%
AA+	0.0003	0	0	0.215991	0.316834	0.011732791	0.00%
AA	0.0004	0	0	0.215402	0.299342	0.013855412	0.00%
AA-	0.0005	3	0.001384	0.214815	0.286115	0.015762147	0.00%
A+	0.0007	4	0.001845	0.21365	0.266737	0.01912502	0.01%
A	0.0009	7	0.003229	0.212497	0.252706	0.022062467	0.01%
A-	0.0014	14	0.006458	0.209665	0.228957	0.028209823	0.03%
BBB+	0.0021	10	0.004613	0.205817	0.208195	0.035030523	0.05%
BBB	0.0031	31	0.014299	0.200548	0.18918	0.042634552	0.11%
BBB-	0.0052	54	0.024908	0.190304	0.165334	0.054043788	0.24%
BB+	0.0086	296	0.136531	0.175839	0.143681	0.065834304	1.14%
BB	0.0143	591	0.272601	0.156481	0.12334	0.077387589	3.25%
BB-	0.0203	445	0.205258	0.141266	0.110227	0.084861162	4.99%
B+	0.0288	153	0.070572	0.126209	0.097872	0.092381131	5.65%

B	0.0409	273	0.125923	0.113303	0.086219	0.101182153	6.92%
B-	0.0694	198	0.091328	0.101512	0.070048	0.120277	8.02%
CCC+	0.1178	33	0.015221	0.09811	0.055546	0.147007189	8.24%
CCC	0.14	25	0.011531	0.097887	0.051177	0.156189395	8.42%
CCC-	0.167	7	0.003229	0.097806	0.0469	0.165042309	8.47%
CC	0.17	9	0.004151	0.097802	0.046478	0.165885839	8.54%
C	0.1825	15	0.006919	0.097791	0.044817	0.169126272	8.66%
D	0.2	0	0	0.097783	0.042719	0.17297094	8.66%
Cumulated		**2168**					**8.66%**

Table 14-Computation of capital requirements for the Shumway and Altman distributions of probabilities of default, for the sub-sample of companies involved in product innovation

		Shumway			**Altman**		
	PD		**Weight**	**C**		**Weight**	**C**
AAA	0.0002	0	0	0.00%	0	0	0.00%
AA+	0.0003	1	0.001052	0.00%	0	0	0.00%
AA	0.0004	3	0.003155	0.01%	0	0	0.00%
AA-	0.0005	4	0.004206	0.01%	3	0.003155	0.00%
A+	0.0007	3	0.003155	0.02%	2	0.002103	0.01%
A	0.0009	7	0.007361	0.03%	4	0.004206	0.02%
A-	0.0014	5	0.005258	0.05%	5	0.005258	0.03%
BBB+	0.0021	11	0.011567	0.09%	3	0.003155	0.04%
BBB	0.0031	21	0.022082	0.18%	9	0.009464	0.08%
BBB-	0.0052	78	0.082019	0.63%	12	0.012618	0.15%
BB+	0.0086	87	0.091483	1.23%	75	0.078864	0.67%
BB	0.0143	101	0.106204	2.05%	207	0.217666	2.36%
BB-	0.0203	147	0.154574	3.36%	198	0.208202	4.12%
B+	0.0288	161	0.169295	4.93%	87	0.091483	4.97%
B	0.0409	202	0.212408	7.08%	141	0.148265	6.47%
B-	0.0694	90	0.094637	8.21%	153	0.160883	8.40%
CCC+	0.1178	16	0.016824	8.46%	22	0.023134	8.74%
CCC	0.14	4	0.004206	8.53%	18	0.018927	9.04%
CCC-	0.167	1	0.001052	8.54%	3	0.003155	9.09%
CC	0.17	2	0.002103	8.58%	4	0.004206	9.16%
C	0.1825	5	0.005258	8.67%	5	0.005258	9.25%
D	0.2	2	0.002103	8.71%	0	0	9.25%
		951		**8.71%**	**951**		**9.25%**

Table 15-Cumulated capital requirements with respect to different average levels of Loss Given Default, sample of 951 companies involved in product innovation

Average LGD	Shumway (1999)	PD Altman and Sabato (2005)
45%	8.71%	9.25%
55%	10.64%	11.31%
65%	12.57%	13.36%
75%	14.51%	15.42%

Table 16-Cumulated capital requirements with respect to different average levels of Debt Maturity, sample of 951 companies involved in product innovation

Debt Maturity	Shumway (1999)	Altman and Sabato (2005)
3 years	8.71%	9.25%
4 years	9.55%	10.10%
5 years	10.39%	10.96%
6 years	11.23%	11.81%

9. Footnotes

[1] For country level analyses see Rajan and Zingales (1998) and Guiso et al. (2004). For an analysis of the Italian context at provincial level see Benfratello et al. (2006).

[2] See Hall (2002) for a review on this topic.

[3] According to the "pecking order theory of financing" firms face a hierarchy of financial sources in terms of costs. They prefer to use internal funds first, then external debt and finally external new equity to fund investments. The latter form of financing is in fact subject to elevate *lemon's premia* since shareholders are reluctant to issue new stock because they believe that management is acting on behalf of the existing shareholders and, as a consequence, the firm is expected to be overvalued.

[4] See Basel Committee on Banking Supervision (1988)

[5] The standardized approach represents an updated version of the risk-weighting scheme set out in the original 1988 Agreement. This approach is likely to be adopted by less sophisticated banks which do not dispose of the historical data on their loan portfolio performance that are necessary to comply with the requirements imposed for the IRB approach.

[6] The PD is the probability of default of a borrower over a one-year horizon. LGD, which is the complement to one of the recovery rate, is determined considering the specific features of the operation. EAD is the credit exposure on the obligation at the time of default.

[7] The main difference with the final Basel II formulas is that expected losses (PD*LGD) are not subtracted from the capital requirements.

[8] It is remarkable that there is not a worldwide uniform and accepted criterion to determine when a firm is large, medium-sized or small. Criterions vary from country to country and within common economic zones (EU, USA), as well as the economic measures to establish their definitions (number of employees, total assets, annual turnover..). According to Basel II, a SME is a firm with less than €50 million of annual sales.

[9] In the questionnaire Research and Development is defined as " a creative activity which is undertaken with the aim of increasing knowledge and using it to create new applications, like technologically new or improved products and processes."

[10] A similar definition can be found in Angelini and Generale (2005), Bagella et al. (2001).

[11] The survey provides two other questions concerning each firms' availability to pay a higher interest rate and the actual rejection of a loan application ("Would the company have accepted a higher interest rate in order to have additional credit?" and "Did the company ask for more credit being denied?"). Although it can be argued that only firms answering "yes" to the last question should be labeled as credit rationed, problems associated with the low percentage of firms answering to that question (5% of the sample) and with the treating of missing values led us to consider as financially constrained the group of companies wishing additional credit. The same approach is followed by Angelini et al. (1998) and Alessandrini et al (2006). Moreover, our objective is not to single out the extent of financing constraints but to estimate the correlation between financial ratios and the prospective need of financial resources by firms.

[12] See for example the study carried out by Unioncamere in 2004. 65% of the firms considered in the study is reported to belong to rating classes ranging from BBB- and BB-.

ESSAY 4

The financing of innovative activities by banking institutions: policy issues and regulatory options

1. Introduction

It is a widely held view that firms characterized by high levels of research and development (R&D) spending are very likely to undergo financial constraints. This line of reasoning has been originally addressed by two influential papers by Nelson (1959) and Arrow (1962), which pointed to the incomplete appropriability of the returns to R&D as the potential source of the limited private incentives to the allocation of financial resources to basic and applied research. The argument of the market failure for R&D investments was later investigated by many researchers in economics and finance (see Hall, 2002 for a review). A common theoretical framework to these studies is that they mostly explain credit rationing or the extension of credit only on unfavourable terms to innovative firms with the presence of information asymmetries between lenders and borrowers. Generally entrepreneurs are better informed than lenders as to the likelihood of success for their innovation projects and usually they have poor incentives to disclose information to investors since this might reveal useful information for competitors (Carpenter and Petersen, 2002; Bhattacharya and Ritter, 1983). Thus investors have more difficulty in distinguishing good projects from bad ones, making credit rationing more probable (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). Also moral hazards problems can hamper the external financing of innovative investments since entrepreneurs could change ex-post their behaviour by replacing low risk-low return projects with high risk-high return ones (Hall, 2002; Carpenter and Petersen, 2002).

Alternative or additional explanations of credit rationing highlight that investments in innovation contain a large part of intangible assets (that are predominantly salary payments) which cannot be used as collateral to secure firms' borrowing (Lev, 2001; Bester, 1985). Physical investments designed to embody R&D results are likely to be firm specific and have little collateral value. Therefore expenditure on R&D can only be backed by the revenue it generates, which is in turn highly uncertain and skewed because R&D projects have a low probability of financial success.

There are in particular two lines of reasoning which have remained relatively unexplored compared to the debate on information asymmetries. The first one is related to the unsuitability of the banking system to support R&D activities because of a general lack of interest in financing innovation and a shortage of adequate instruments to evaluate innovation projects and innovative firms. What drives a bank to issue a loan is by and large the ability of the obligor to repay the debt. It is a matter of limited interest whether the loan is used to sustain a research activity or the purchase of equipment and machinery. Moreover the inability of banks to understand and properly classify innovation projects into classes of risk is the result of a lack of specialized technical knowledge. It is also fair to say that, at least until a few years ago, most banks have relied virtually exclusively on subjective analysis to assess the credit risk on corporate loans. The judgment of a banker as to whether or not to grant credit has been mainly based upon considerations on the reputation, leverage, volatility of earnings of the borrower and presence of collateral (Altman and Saunders, 1998). Qualitative aspects such as investments in intangibles have received very little attention.

An additional cause of the credit rationing phenomenon is the poor availability of analytical instruments able to capture and correctly estimate the expected future revenues of innovative activities (Encaoua et al, 2000). Investments in intangibles are in most cases not reflected in the balance sheet due to the existence of very restrictive criteria for the recognition of assets and their valuation. As a consequence, financial statements are becoming less informative on the firm’s current financial position and future prospects because they do not provide relevant estimates of the value of companies (Caňibano et al., 2000).

These issues, although not sufficiently investigated by scholars, are likely to become relevant in the near future, with the recent display of interest among banks on innovation financing, the adoption of the New Basel Capital Accord framework by banks, and the endorsement of the International Accounting Standards (IAS) by firms. As far as the first issue is concerned, it is a matter of fact that banks are showing an increased interest in the support of innovation-related activities. This stems from the belief that investments in research and development, information technology and human resources become essential in order to maintain firms’ competitive position in a knowledge-based, fast-changing and technology-intensive economy. Banks are moving away from a cautionary approach to innovation financing towards a greater involvement in the support of R&D activities. Indeed, beside government-backed loan schemes both at national and regional level, some specific loan programs have been recently launched by financial intermediaries.

The second aspect that needs to be underlined concerns the consequences of the implementation of the New Basel Capital Accord on the credit risk assessment of innovative firms. As previously noted, the very core of banking is the classification of loan applications into risk categories, a process which has traditionally been hidden by strict secrecy and complemented by informal practices of 'relationship banking'. Under Basel II banks are prompted to move towards more objectively based evaluation systems and to compete for the best classification procedures. Precisely, they are encouraged to systematically assess risk relative to capital within their organizations, according to an internal ratings-based approach (IRB) ,[1] subject to the meeting of specific criteria and to validation by the relevant national supervisory authority. This opens up the possibility for banks to use qualitative criteria together with quantitative information in appraising the creditworthiness of their borrowers.

A qualitative assessment of a company might take into account the role played by intangible assets[2] as well. Intangibles may encompass patents, trademarks, brands, franchises, research and development, advertising, organizational coherence and flexibility, customer satisfaction, intellectual capital and so forth, depending on the different classification perspectives taken by researchers (see Caňibano et al., 2000 for a review). In other words, the traditional assessment of a borrower's level of risk thought to fit firms whose activity is primarily of a manufacturing or a mercantile nature, could be broadened to reflect intangibles and other qualitative information. Given that intangible assets are likely to be progressively more considered in credit decision making, it follows that firms which would not ordinarily be eligible for bank funding because of limited financial track records and lack of collaterals, may have the chance to be granted credit if their qualitative rating is good. In this context innovative firms should have theoretically a lower likelihood of being credit constrained, although this conclusion cannot be taken for granted, at least until the implementation of internal rating models and procedures by major banking institutions is fully completed.

While intangible investments may become an important concern for creditors, the same doesn't seem to hold for accounting standard setting bodies. The recently issued IAS regulation embraces a rather restrictive and conservative approach towards accounting for intangibles. IAS 38 considers R&D as a category of internally generated intangible items and as such it requires the full expensing of research, allowing only certain development costs to be carried forward as assets. If most intangible investments are not reflected in the balance sheet but immediately expensed in the income statement, financial statements fail to provide a true estimate of the value of companies. It follows that banks are prevented from getting reliable information on the innovative activity of firms, leading to an unfair or inaccurate credit risk evaluation.

The aim of the paper is to investigate to what extent the convergence of banks over risk-adjusted capital standards may affect the way in which they screen innovative firms. More precisely, it is worth exploring to what extent banks actually rely and will rely once implementing the Basel II Accord on non-financial parameters to assess the creditworthiness of a potential borrower.

Results from a survey conducted in January and February 2006 on a sample of 12 Italian banking groups show that the majority of banks does not consider intangibles as meaningful determinants in credit risk assessment. This could imply that the sole implementation of the Accord might not lead to reducing informational asymmetries between lenders and borrowers as it could be expected. Hence, if innovative firms show a higher idiosyncratic risk, the bank in its portfolio optimization process might continue either to ask them higher interest rates or simply to deny credit to them. However, such an effect could be compensated by specific measures provided by single financial intermediaries. Current trends suggest that banks are paying an increasing attention to the issue of innovation financing, as it is witnessed by recently launched loan schemes, specifically devoted to sustain technology-based investments.

The remainder of this paper is organized as follows. Section two discusses the recent literature on banks' internal rating systems and on the role of non-financial factors in credit risk models. Section three describes the architecture of the internal rating systems at the surveyed banks. In particular I want to take a closer look at what types of information are being used to determine corporate ratings. Section four gives an overview of the products banks have in place to finance innovative activities. Section five offers concluding remarks and some policy indications.

2. Overview of the related literature

Since June 2004, when the Basel Committee on Banking Supervision issued a revised framework on International Convergence of Capital Measurement and Capital Standards (hereafter ‘Basel II’), the debate on internal ratings has gained increasing importance within banking institutions. Internal rating systems are expected to play a central role not only in credit granting decisions, but in the determination of regulatory capital adequacy as well (June 2004, par.6). Whereas academic literature has by far dealt with the various methodologies for the prediction of default and the use of financial ratios in credit risk models, a limited interest has been shown in the structure of internal rating systems, in their use of non-financial factors and in the envisaged procedures and internal controls. Earlier empirical analysis of corporate bankruptcy prediction based on financial ratios date back to Beaver’s univariate model (1966). Since then a plethora of multivariate methods have been developed by researchers (see Altman and Saunders, 1998; Szegö and Varetto, 1999 for a review): discriminant analysis, linear probability models, logit and probit regression analysis, or, more recently, recursive partitioning algorithm, multicriteria decision aid methods, expert systems and neural networks. The large number of financial factors proposed in the literature can be gathered into three main groups: those concerning the capital structure, the profitability and the liquidity of a firm. Although accounting based credit-scoring models are widely accepted because of their relatively high discriminary power, they have been subject to at least three criticisms (see Altman and Saunders, 1998, Szegö and Varetto, 1999). Firstly, they are empirical models lacking an underlying theory of business failure, where explanatory variables are chosen according to their accuracy in predicting default for a specific sample of observations. Secondly, as financial factors are mostly backward-looking point in time measures, these models fail to capture fast-moving changes in borrowers’ conditions. Thirdly, these models can hardly maintain their diagnostic potential through time because a variety of elements intervene to jeopardize their temporal stability (for example structural changes in the economic cycle, inflation rate variations, changes in banking decision-making procedures and so on..)

Drawing on the last criticism, researchers have started to include variables other than financial in their models, in order to capture macro-economic, industry-specific and qualitative factors. Macro-economic variables for failure prediction have been proposed by Foster (1986), Rose et al. (1982), El Hennawy and Morris (1983). Mensah (1984) aggregates sample data into four sub-periods of US business cycle from January 1972 to June 1980 (steady growth, recession, steady growth, stagflation and recession) and notes that different economic environments lead to different models for the prediction of failure. Izan (1984) uses industry relative accounting ratios, rather than simple firm specific accounting ratios, to control for industry variation and he demonstrates stable classification results both ex post and ex ante. Platt and Platt (1990, 1991) add to their industry-relative model a measure of industry growth to test specific busyness cycle effects on corporate failure. The industry relative accounting ratio model outperforms the unadjusted model.

Other studies include qualitative data in the analysis of corporate failure. Zopounidis (1987) employs a set of 'strategic criteria' to assess the risk of failure of French enterprises, such as quality of management, research and development level, diversification stage, market trend, market niche/position, cash out method and world market share. Tennyson et al. (1990) consider the information which is contained in annual reports (financial management decisions, influence of external environment on earnings and stockholders, production capacity, variations of exchange rates, new firm strategies..), while Laitinen (1993) extends the analysis of the information content of narrative disclosures to their layout, length, language. Keasey and Watson (1987), Daily and Dalton (1994), D'Aveni (1989) consider qualitative variables related to management characteristics, the composition of board of directors, corporate governance and company's reputation.

It is probably fair to say that most of these studies have contributed to shape the architecture of the most recent credit risk systems adopted by financial institutions. As noted earlier, the literature on banks' internal ratings is still scarce, and this is possibly due to the reluctance of banking institutions to disclose information on the structure and input factors of their internal rating systems.

Empirical analysis examine the architecture and the use of internal ratings. Udell (1989) looks at the internal rating systems of a sample of Midwestern US banks as part of a broader study of such banks' loan review system. Treacy and Carey (2000) shed light on the use and design of internal risk ratings at large US banks. English and Nelson (1999) describe the internal rating scales of a sample of US banks, reporting the distribution of loans across grades. They also show that ratings are reflected in loan pricing, while non-price terms generally do not rise or fall monotonically with the loan risk rating. An overview of international best practice rating standards in the banking industry is carried out by the Basel Committee Models Task Force (Basel Committee on Banking Supervision, 2000), while information on the operational design of rating systems at Italian banks is provided by Banca d'Italia (2000) and De Laurentis, Saita (2004). Santomero (1997) surveys internal rating systems as a part of a study on bank's credit risk management practices. Other studies use data on internal ratings to perform specific analysis. Machauer and Weber (1998) study loan pricing patterns using German banks' internal ratings. Drawing on bank-internal borrower rating data to evaluate borrower quality, Elsas and Krahnen (1998) provide a direct comparison between housebanks and normal banks as to their credit policy in Germany. Grunert et al. (2005) analyze SMEs' credit file data of four major German banks from 1992 to 1996. The authors find evidence that the combined use of financial and non-financial factors leads to a more accurate prediction of future default events than the single use of each of these factors. Brunner et al. (2000) show that 'soft' (qualitative) factors have a significant and positive impact in determining the overall rating of a borrower. Carey (2001) analyses the extent of banks' rating disagreements for given borrowers. Rating disagreements are less likely for large borrowers and for borrowers that have not drawn down much on their lines of credit, while a bit more likely for high-quality borrowers. Tabakis and Vinci (2002) assume that rating inconsistencies derive from a different evaluation of non-financial factors. They therefore compare credit assessments of different financial institutions (rating agencies, banks, other credit assessment institutions). A more normative approach to the issue is taken by Crouchy et al. (2001), who show how an internal rating system can be organized in order to rate creditors systematically. A framework for evaluating the quality of a standard rating systems is also suggested by Krahnen and Weber (2001), who advocate fourteen principles that ought to be met by good rating practices.

3. Results of the survey on internal ratings

In the following sections I present the results of a survey conducted during January and February 2006 on 12 main Italian banking groups, selected according to dimensional criteria (with total assets more than €30 billion)[3]. Information was collected through structured extensive interviews with bankers operating both in the risk management area and in other units dealing with incentives to R&D and long-term credit. Overall, a total of 24 interviews were conducted, precisely two interviews per banking group.

Although the institutions I surveyed are the first largest 12 banks in Italy, their business segmentation[4] is not the same, as it is shown in Table 1. In order to maintain the confidentiality of data, banks are numbered randomly, that is being ranked as bank number one does not mean to be the largest Italian bank. Four banks indicated that it was not advisable to release such information. Market segments are defined following Basel II classification (June 2004, par. 232 and 273): large corporate/corporate with total turnover above €50 million, middle market with total annual sales between €5-50 million and small business with turnover below €5 million and exposures to the bank below €1 million. As it is evident from the Table, Italian banks are largely oriented towards the middle-market segment. This is not surprising considering that the percentage of SMEs (with less than 500 employees) out of the total number of firms in Italy is greater than 86 percent[5]. A few differences can be detected referring to the large corporate/corporate and small business segments. More than a half of the respondent banks seem to rely on small business borrowers more than large corporate /corporate customers, whereas the opposite trend is shown by only three banks.

[Insert Table 1 here]

Bankers working in the risk management area were addressed questions regarding the architecture and operating design of their bank's internal rating system (the degree of fineness, the statistical models used, the extent to which judgmental considerations are taken into account, the weight of non-financial factors, the link between ratings and loan price/non-price terms, the organization of the monitoring and rating review activity and so on). Under Basel II it is highly recommended that banks adopt a two-tier rating system that is an independent evaluation of the default probability of the borrower (PD) and of loss given default (LGD), namely the fraction of the loan's value that is likely to be lost in the event of default. While the first dimension is associated with the borrower, regardless of the structure and type of product, the second one considers the specific features of the operation, such as its maturity, structure and guarantees.

I decided to maintain the focus of the interviews on the first of these two dimensions, the obligor rating. This was done primarily because few banks have already in place a facility rating that assigns grades to facilities. The overwhelming majority declared that transaction characteristics are explicitly considered in the process of credit risk assessment, but they are still working at developing models of LGD sound enough to get through the validation of the Bank of Italy.

Results are presented in an aggregated form because some banks, by virtue of very strict policies of non-disclosure, explicitly asked me not to make the information released public.

3.1 Internal rating systems: architecture

Like a public credit rating produced by agencies such as Moody's or Standard & Poor's, a bank internal rating is meant to summarize the quality of an obligor and the risk of loss due to his failure to repay the debt. While external ratings by agencies are available since many years, internal ratings by commercial banks began to be introduced only in the last decade.

According to the New Basel Capital Accord 'the term rating system comprises all the methods, processes, controls and data collection and IT systems that support the assessment of credit risk, the assignment of internal risk ratings and the quantification of default and loss estimates' (Basel Committee, 2004, pp. 82).

Of the 12 banks interviewed, all declared to having an internal rating system, though a few are currently in an introductory or experimental phase. In particular one bank has just set up the preliminary architecture of the rating system, while at least two banks are testing the soundness of the models and processes with the minimum standards and practice guidelines which have been established by the Basel Committee.

The survey highlighted that internal rating systems differ, at least slightly, across banks in their architecture, methodology and application. The structure of statistical models, the number of grades, the decisions about who assigns ratings or the way in which the review process is conducted reflect alternative approaches. However, a considerable number of common elements can be identified.

All the interviewed banks base their ratings primarily on a statistical default/credit scoring model. Such models may be all developed internally, as it is the case of four banks, in part purchased by suppliers and in part developed internally (five banks) or developed internally with the support of a consultancy firm (three banks). These models are by and large constructed using internal data.

As it is defined by Brunner et al. (2000), a scoring methodology specifies a number of criteria a_i, one or a number of value functions v_i and an aggregation rule, usually linear, which assigns weights k to single criteria to form an overall score ($v(a)$). The score, which is indicative of a probability of default, is then converted into a rating grade.

$$v(a)=\sum_i k_i v_i(a_i) \quad (1)$$

Although this general framework applies to every bank, differences in terms of selected criteria, aggregation rules, weights, rating scales, influence of judgmental factors characterize the several approaches.

Banks reported having several rating models according to customers' segments (for example large corporate, corporate, SMEs, small business, bank and so on..). The number of models goes from an average of two-three to about fifteen. To a considerable extent, such differences may depend on the core business of a bank and on its use of internal ratings for different purposes. Banks in few lines of business are more likely to design their rating system with a limited number of models. As noted earlier two banks are currently working to improve their rating system and to extend it to more customer segments. It is important to stress, though, that bankers described the models employed in different ways. The low number of models is not always indicative of the degree of accuracy and sophistication of rating systems because macro-models are sometimes divided into several sub-models. On average, in each model a further partition can be found, either by sector (for example real estate, services, industry, commerce), legal form or balance sheet structure (for example holding, leasing company, manufacturing firm).

Rating models are generally built upon three parts based respectively on financial statement data (cash flow, profitability, short-term and long term debt, debt-equity ratio and so on), behavioral and loss data (both internal and external from Centrale dei Rischi, the national central credit register) and qualitative information. Quantitative criteria are typically backward-looking, while qualitative criteria reflect actual or forward-looking information.

Two-thirds of the surveyed banks used two-stage scoring models which imply that the scores produced respectively by quantitative, qualitative and behavioral models are aggregated by means of a second rule to form the overall score. One bank added to this architecture an additional layer: a market model. Two banks followed the above scheme for corporate and small business segments, while for large corporate borrowers a constrained expert judgment-based process was implemented beside the financial analysis. Only one bank declared to having simply a quantitative model and to be about to realize the qualitative part.

The relative importance of the each of the above mentioned modules and the weighting schemes adopted vary widely across banks. Since the dataset is not usually homogeneous (it can be that balance sheet information date back up to five-ten years before, while the qualitative questionnaire has been introduced only one year ahead), banks can use different weighting schemes for quantitative and qualitative data. One bank reported weighting quantitative factors more than qualitative ones mainly for that reason. A vast majority of the interviewed banks outlined that qualitative and behavioral data seem to play a greater role for small business borrowers, where the shortage of financial statement information needs to be somehow counterbalanced. Yet qualitative modules appear to be implemented mainly for small businesses with turnover above € 1.5 million.

While in almost every bank qualitative factors enter the statistical model, sometimes they are rather standardized inputs (for example payment history, industry sector, geographic location). In that case qualitative considerations drive the process of upgrading/downgrading by the rater, who adjusts up or down the rating to a specific limited degree based on his judgment.

There appears to be a relatively limited set of techniques employed in the statistical models. For the vast majority of banks (nine) the calculation engine is based upon logit regressions. To put it briefly, logit analysis uses a set of accounting variables to predict the probability of borrower default which takes a logistic functional form and is constrained to fall between zero and one. Discriminant analysis ranks second, being used by three banks, sometimes together with linear or logistic regressions. Discriminant analysis seeks to find a linear function of accounting variables that best distinguishes between two groups of firms, defaulted and non-defaulted, by maximizing the between group variance while minimizing the within group variance. It is quite surprising that discriminant analysis, which is the most frequently used method in the academic literature dealing with bankruptcy prediction, is so poorly widespread among commercial banks.

It is my impression that, although banks rely on statistical models as important elements of the rating process, expert judgment still plays a fundamental role in assigning a final grade to a counterparty. Especially for large exposures the current limitations of statistical models[6] are such that processes based on constrained or unconstrained expert judgment are commonly used to deliver a more accurate estimate of risk.

Most of the rating systems were numerical (eight), with the lowest risk borrowers rated 1 and higher ratings implying higher risk. Just one numeric system was in reverse order (1 was the rating for the worst loan rather than the best). Two banks declared to having alpha numeric grades (a mixture of letters and numbers), while two others reported following a master scale based on letters similar to the Standard and Poor's one but with a higher granularity in the medium grades. The number of grades conceived by the different banks may vary according to the business segment. The largest part of the banks (eight) surveyed have a standardized number of grades for both corporate and non-corporate borrowers (small and medium enterprises and small business). Retail counterparties are normally rated under a smaller number of classes of risk. Among the banks I interviewed, three have a higher grades-scale for corporate and large corporate borrowers. This is because for those banking groups which do a significant share of their commercial business in the large corporate and corporate loan market, making fine distinctions among low risk borrowers is more important in that market than in the middle market. However, it is somehow difficult to make an accurate taxonomy of the forms of categorization employed by banking institutions because different sorting criteria (for example based on firms' turnover) are used to classify borrowers into business segments. In fact the precise boundary between corporate and middle-market borrowers or between middle-market and small business obligors varies by bank. Larger banks are more likely to have rating systems with a larger and more detailed number of pass categories, though the gap with smaller banks is not so big. Banks with large business loans portfolios (with total assets more than €70 billion) averaged 14 ratings, while those with smaller portfolios (with total assets from €30 to 70 billion) averaged 10.8 for corporate borrowers. All banks comply with the Basel II requirement (June 2004, par. 404) of having a minimum of seven borrower grades for non-defaulted borrowers and one for those that had defaulted. On average banks' master scale goes from nine to twenty-two non-defaulted categories, with a number of defaulted categories varying from one to four. Only three banks reported conceiving modifiers ('+' or '-') to alpha (two banks) or numeric grades (one bank). Ten banks declared to being satisfied with the actual number of pass grades, while two would like to modify their master scale either by splitting the existing pass categories into a larger number or by adding $\pm$ modifiers to the scale in order to reflect a better distribution of exposures across grades. The two banks that expressed the desire to increase the number of grades on their scales have an actual scale of nine classes of risk. Several of the banks officials I spoke with indicated that, although internal rating systems with larger number of grades are more costly because of the extra work needed to distinguish finer degrees of risk, they are especially valuable to pricing and capital allocation models. Typically, banks with the highest degree of differentiation appeared to be those using ratings in pricing decisions.

About two-thirds of the interviewed banks declared that the largest part of their corporate loans is concentrated in the upper investment grade categories, revealing a loan distribution skewed towards lower-risk classes. One-third reported a distribution of corporate exposures which approximates a Gaussian distribution, in which loans are centered mostly in the middle classes of risk, while low percentages get into bottom and upper risk grades. A few banks did not answer to that question.

The survey asked banks whether there was a direct link between loan terms (such as spreads, size, collateralization) and ratings. More than a half of the banks surveyed highlighted that loan pricing can vary depending on the risk rating of the obligor. However, just for three of them pricing always reflects borrower's risk, while for the other ones ratings are relevant components of pricing decisions although they are not binding. This means that commercial and relationship reasons still play an important role either in the approval process and in the assessment of loan terms. Risk-adjusted pricing is becoming a common practice within large banking groups, while smaller ones are still far away from using ratings to set loan pricing. According to four banks taken from the sub-sample of the last seven by size, ratings currently influence loan origination and monitoring. The target is to begin to use ratings in pricing, capital allocation models and in setting reserves in the near future.

3.2 Internal rating systems: the role of qualitative factors

The survey provides interesting insights on the use of qualitative criteria in credit risk assessment. The results are in line with the requirement of the Basel Committee that banks not only have to consider quantitative but also qualitative factors such as the availability of audited financial statements, the conformity of accounting standards, the depth and skills of management to effectively respond to changing conditions and deploy resources, the firm's position within the industry and its future prospects (June 2004, par. 411; Second Consultative Document, January 2001, par. 265). In all the banks but one (which declared to being about to realize the qualitative part), qualitative inputs, taken from a questionnaire filled in by the line staff, enter the qualitative module of the rating model. All banks reported that the combined use of financial and non-financial factors leads to a more accurate prediction of default events than their single use.

Questionnaires are more or less detailed and extended depending on the bank, but they usually average 20 questions and they are differentiated by sector and borrower. Most of them have been framed internally, while other banks have adopted the CEBI questionnaire, elaborated by Centrale dei Bilanci.

The qualitative analysis is usually concerned with the quality of management, the firm's competitiveness within its industry, as well as the vulnerability of the firm to technological, regulatory and macro-economic changes. In Table 2 I provide a taxonomy of the main 'soft information' that were cited by bankers as being examined in credit risk assessment.

Since I wanted to explore the extent to which innovation-related parameters are considered in credit ratings, I asked risk managers whether or not they were included in the questionnaire. Nearly two-thirds of the surveyed banks reported having only a few direct questions on patent activity, R&D intensity and innovation capability. However innovative activity can be inferred from other questions, such as the technological level of facilities or processes, the quality and technological content of goods, the brand, image and reputation of the firm's products. Moreover the technological capability of a borrower can be further investigated by the relationship manager whenever he is supposed to integrate his own judgmental evaluation to the grade assigned by statistical models.

The reasons why innovation-related parameters do not normally enter statistical models (or have a significantly low weight once entered) mainly relate to two sets of explanations. The first one is that it is very difficult for a bank to identify an innovative company, simply because the only reliable information it can get comes from balance sheet data when intangibles are capitalized. However, the decision to capitalize intangible assets like R&D expenses is in most cases driven much more by fiscal reasons than by disclosure policies. As I earlier noted, the implementation of IAS is not going to change anything in this respect.

The second explanation is of a purely statistical nature. Firstly, since the percentage of innovative firms in Italy is very limited, a bank cannot set a default prediction model on the basis of innovative firms' characteristics because a statistical model needs to be as general as possible. Secondly, there are some qualitative components (such as management quality, ownership structure and competitive position) which make the difference, by upgrading or downgrading an obligor rating. Conversely, innovation-related factors are likely to contribute to the final rating not more than a notch. Therefore collecting too many data may not always reveal helpful.

[Insert Table 2 here]

4. Results of the survey on financial support measures to R&D

This section of the paper gives a brief overview of existing banks' loan schemes devoted to sustain firms' technology-based activities in Italy (see the Appendix for a detailed description of the programs). As previously anticipated, information was collected from interviews with senior bankers working in the medium-long term credit divisions.

These consultations indicated that only four banking groups have conceived specific programs to support R&D investments, with different degrees of specification: Banca Intesa, Sanpaolo IMI, Unicredit and BPU. All the remaining banks declared to participating to government-backed funding programs, both at national or regional level.[7]

As it emerges from Table 3, all programs are devoted to support product and process innovation and other more specific forms of innovation. Technological assessment of the projects is provided mostly by external teams of engineers, except for two banks which have their own internal teams. The loan schemes applied show common features across different banking groups: they are all medium-long term grants and usually advantageous conditions are applied both in terms of interest rates or collateral requirements. Two banks also provide some consultancy support both prior to the presentation of the project and during its actual implementation.

[Insert Table 3 here]

5. Conclusions and policy orientations

It is widely perceived that Italy suffers from an 'equity gap', since the venture capital industry, that should solve the problem of financing innovation for new and young firms, is rather absent. Banks, it is argued, may ration credit to new enterprises, strangling dynamic and innovative future giants at birth. This is because of a lack of track records and collateral and because information about these firms may be limited and asymmetrical, stacked on the side of the borrower at the lender's hazard. Moreover banks have difficulty in understanding innovative projects since past experience or observed past realizations can offer little guidance in assessing the prospects of truly new projects.

There is recent evidence that this scenario is somehow progressively changing. Banks are encouraged, under Basel II, to incorporate qualitative information in their internal rating models. This is clearly an important issue that cannot be underestimated. Ratings take more and more the form of objectively-based 'screening devices' that can alleviate asymmetric information problems between borrowers and lenders, and in doing so they account for information other than simply financial to appraise the creditworthiness of obligors. In that way innovative firms should theoretically have the chance of being less credit constrained.

However, the evidence suggests that innovation-related parameters are not yet taken into account by Italian banks in a systematic way. In fact the majority of banks does not consider intangibles as meaningful determinants in credit risk assessment. This is primarily the result of a regulatory caveat which prevents banking institutions from inferring appropriate information on firms' innovative activity from financial statements, rather than banks' reluctance in considering such factors to a greater extent. Even though a wider recognition of qualitative elements in credit risk assessment is on the way, the sole implementation of the Accord might not lead to reducing informational asymmetries between lenders and borrowers, at least in the short run. This seems to be acknowledged by the fact that banks have started to conceive some forms of credit support for R&D activities which wouldn't be necessary if the implementation of the Basel II Accord could really lead banks to screening innovative firms in a better way.

Given these current trends, I positively advocate a regained role of the banking system in supporting science and technology-based activities. It is my opinion that the expansion of banks' activities in terms of innovation financing is likely to have a positive and strong impact on the whole Italian industrial system, largely constituted by small and medium enterprises. Banks are territorially distributed and may respond efficiently to SMEs, strongly locally featured and mostly incapable of building lasting relationships with the international capital. Therefore the banking system could bring about the innovation-based development process of the Italian industrial system, helping it to reach that dimensional threshold to get to other forms of financing.

Indeed, working on the criticalities which have traditionally characterized borrower-lenders relationships is a necessary requirement if banks intend to start offering to their customers not only products, but also solutions. In this respect universities and research centers may contribute to alleviate information asymmetries, by giving a technology assessment of innovation projects and collecting all the relevant information to orientate credit granting decisions.

In conclusion, the future challenge for economic development is to plan the emergence of virtual spaces of overlapping institutional spheres for science and technology-based activities. A new organizational environment should emerge in which industry, financial institutions, universities/research centres and government tend to integrate their own interests and goals when carrying out, financing and regulating investments in research and development.

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7. Tables

Table 1-Market segmentation and relative weight of business areas by the largest 12 Italian banks

	large corporate/ corporate	middle market	small business
1	29%	40%	31%
2	26%	58%	16%
3	32%	30%	38%
4	28%	49%	23%
5	nd	nd	nd
6	20%	40%	40%
7	45%	45%	10%
8	nd	nd	nd
9	15%	45%	40%
10	20%	40%	40%
11	nd	nd	nd
12	nd	nd	nd

Table 2-Overview of qualitative criteria for credit risk assessment

	QUALITATIVE FACTORS
BUSINESS PROFILE	Core business and related business activities
	Evolutionary stage of activity (start-up, maturity, decline)
QUALITY OF MANAGEMENT	Managerial and entrepreneurial capability (flexibility of addressing problems promptly, of introducing or updating methods and technologies when warranted..)
	Risk tolerance and risk propensity
	Morality (also financial)
	Professional experience and human resources policies
	Presence of management succession plans
OWNERSHIP STRUCTURE	Group belonging
BEHAVIOUR	Presence of writs, lawsuits or judgments
	Correct behavior towards employees
QUALITY OF FINANCIAL REPORTING	Clarity, completeness and punctuality in financial data presentation
	Transparency and prudentiality of accounting information
IINDUSTRY OUTLOOK	Features of the industry and relative position of the firm within its industry
	Competitive arena and competitive position of the firm
BUSINESS RISK	Vulnerability to macro-economic environment (economic downturns, movements in interest rates and exchange rates..)
	Vulnerability to long-term trends that affect demand (lifestyle changes and consumer attitudes)
	Vulnerability to technological change
	Impact of environmental and antitrust regulations, fiscal policy, direct and indirect taxation

Table 3-Banking programs to sustain innovative activities

	INTESA	SANPAOLO IMI	UNICREDIT	BPU
LOAN SCHEMES	**1) IntesaNova**	**1) Innovation-Buy** **2) Applied Research**	**1) Technological Innovation**	**1) Support to R&D**
ELIGIBLE PROJECTS	• product and process innovation • innovation connected with the diffusion of ICT	• product and process innovation • purchased innovation	• product and process innovation • industrial research	• product and processes innovation • organizational innovation • protection of the environment and energy conservation
TECHNOLOGICAL ASSESSMENT	• internal (teams of engineers) • external (network of universities)	• Internal (teams of engineers)	• External (national/local associations)	• External (local industrial associations)
GRANT DECISION	• financial/technological evaluation of the project • assessment of the creditworthiness of the borrower (rating between 1-6)	• financial/technological evaluation of the project	• financial/technological evaluation of the project	• financial/technological evaluation of the project
LOAN TERMS	• medium-term financing (3-5 years) • no collateral requirement • variable Euribor interest rate + 1-2% range depending on the rating	• medium-long term financing (3-7 years) • variable Euribor 3m interest rate • two subsequent anticipations of 50% of the loan • rewards for successful and completed projects	• medium-long term financing (until 5 years) • variable Euribor 3m interest rate, correlated on rating classes • no collateral but covenants	• medium term financing (up to 5 years) • advantageous conditions
CONSULTANCY SUPPORT	• prior to the presentation of the project • during the implementation of the project	• prior to the presentation of the project • during the implementation of the project		–

8. Appendix

I give a brief overview of the products developed by the interviewed banks to sustain R&D intensive activities.

INTESA GROUP

Intesa Group has launched two specific programs related to R&D support: IntesaNova and Eurodesk.

IntesaNova

- IntesaNova is a funding scheme purposely thought for companies involved in substantial research activities. Firms can submit their research project to the bank and getting financing at advantageous conditions and without collateral requirements. Innovation projects above €200.000 up to €1 million are normally assessed by an internal team of engineers. For higher levels of complexity or cost amounts above €1 million, the bank gets the support of a network of outstanding Italian universities (Politecnico di Torino, Politecnico di Milano, Università degli Studi di Trento Politecnico di Bari). The evaluation of the project implies an assessment of its costs, degree of innovation, realization time, as well as considerations on the competitive position of the firm and its implementation capacity. On the basis of a technological/financial evaluation of the project and the creditworthiness of the firm (which can be eligible only if it has a rating ranging between one and six), the bank issues a medium-term loan (three-five years), with a variable Euribor interest rate plus a 1 or 2 percentage range depending on the rating. Universities also provide technological support when the project reaches the implementation phase (auditing of the product/process development, prototype realization, laboratory experimentation, consultancy for patenting, marketing of technologies). The program currently applies to two product families: product and process innovation and innovation connected with the diffusion of information and communication technologies. In only one year of effectiveness of the program, about 800 projects have been examined and 600 financed.

Eurodesk

- In the light of the 7th Framework Program of the European Commission, Banca Intesa intends to support the participation of Italian companies through a cooperation with research centers and universities. This means offering consultancy for the entire life of approved projects and acting as a trait d'union with the academic world. In this perspective IntesaNova can be extended, thanks to EU funding opportunities, to a wider spectrum of R&D activities and universities involved.

SANPAOLO IMI GROUP

Sanpaolo IMI Group has recently launched two programs specifically devoted to support R&D and technologically-driven investments: Applied Research and Innovation-Buy. These schemes are thought to respond to company's requirements about demand and supply of innovation. Firms willing either to develop a technologically advanced product, service or process, or to buy innovation from external sources, can submit their project to the bank which, upon acceptance, will finance it at favorable terms. A technological evaluation of the project is carried out by an inside team of engineers, specialized in different technological sectors. Marketing and profitability analysis complement the technological validation of the project.

Applied Research

- Applied Research is aimed at financing R&D projects directed either to the realization/completion of new technologically advanced products, processes, services or to the technological improvement of existing products, processes or services. It is a long term loan scheme with a loan period between three-five years, including a pre-amortization that ends up six months after the end of the project. The loan covers up to 100 percent of the cost of the project, which does not have to be below €250.000 or above €4.000.000. The project can last one or two years. A variable interest rate Euribor 3m applies for the entire loan period. An interesting point that needs to be underlined in this respect is that the bank anticipates 50 percent of the loan when the contract is drawn up and another 50 percent when half of the cost of the project is overcome. Moreover for completed and successful projects a kind of reward is applied: a 20 percent spread reduction if the project is brought to an end and a two-year increase of amortization if it has a positive outcome. One year after the launch of the program at the end of 2004, 550 projects have been financed with a total cost of €550 million. Around 30 projects were not admitted. The large majority of the funded projects are devoted to product innovation (65 percent). A smaller percentage applies to process innovation (21 percent) and product/process innovation (14 percent). Request of funds is markedly affected by geographical location: firms from the North of Italy (Lombardy and Piedmont above all) have been granted more funds, although a notably reverse trend is shown by the region of Campania. Innovation projects mainly concern mechanical and ICT sectors.

Innovation-Buy

- Innovation-Buy is aimed at financing the purchase of innovation in its different forms (technologies, tangible and intangible goods, training). It is a medium-long term loan scheme with a loan period between five-seven years, including a pre-amortization of two years. The loan covers up to 100 percent of the cost of the purchase, which does not have to be below €250.000 or above €4.000.000. The investment can last up to 18 months. A variable interest rate Euribor 3m applies for the entire loan period. Even in this case the bank anticipates 50 percent of the loan when the contract is drawn up and another 50 percent when half of the cost of the investment is overcome. For completed projects a kind of reward is applied: a 15 percent spread reduction for five-year transactions and 10 percent spread reduction for transactions beyond five years. The program was born in November 2005. A pilot experiment has taken place in December 2005 in the Brescia area and within four weeks 34 demands have been presented for a total financing of €30 million.

UNICREDIT GROUP

Technological Innovation

- Unicredit provides a plafond of medium-long term loans (up to five years) to sustain firms in their product and process innovation and industrial research. Interest is calculated on Euribor3m and it is correlated with rating classes. A technological evaluation of the project is carried out by national or local associations. Covenants but not collaterals are required.

BPU

Support to R&D

- BPU has recently created a credit line to sustain R&D activities. A technology check-up of companies' research projects is carried out by local industrial associations. Upon such evaluation, BPU issues a medium-term loan (up to five years), including a pre-amortization of 12 months. The loan covers up to 100 percent of the cost of the project. Projects can be devoted to the realization of new products or processes, to technological and organizational innovation, to the protection of the environment and energy conservation. The plafond, which is about to be extended, is around €70 million.

9. Footnotes

[1] The IRB approach gives the bank varying degrees of autonomy in the estimate of the parameters determining risk weightings and consequently, capital requirements: under the Foundation only the probability of default (PD) is internally estimated, while under the Advanced a bank can also produce its own estimates for the loss given default (LGD) and exposure at default (EAD).

[2] IAS 38 defines intangible assets as non-physical and non-monetary sources of probable future economic profits accruing to the firm as a result of past event or transactions.

[3] The banking groups are the following ones: Intesa, Unicredit, Sanpaolo IMI, Capitalia, Monte dei Paschi di Siena (MPS), Banca Nazionale del Lavoro (BNL), Banche Popolari Unite (BPU), Banco Popolare di Verona e Novara, Banca Antoniana Popolare Veneta, Banca Popolare dell'Emilia Romagna, Bipiemme, Banca Lombarda e Piemontese.

[4] I just consider the percentage of claims on corporate, SMEs, small business segments on the total claims on firms. Loans to sovereign entities, banks, retail are therefore excluded.

[5] Istat, I gruppi di imprese in Italia, 2003

[6] It is indeed very difficult to distinguish between defaulted and non-defaulted firms for large corporate customers which are usually characterized by low default rates and consequently to construct a statistical model. Therefore judgmental factors tend to have a more prominent role in corporate and large corporate lending rather than in middle-market or small business lending.

[7] Capitalia, through MCC (Mediocredito Centrale), is responsible for the management of numerous national subsidy programs devoted to the support of R&D activities (FAR, FIT, Fondo agevolazione regionale, Fondo Capitale di Rischio, Fondo Garanzia). Surveyed banks reported being involved in subsidy lending for different of these government-backed loan schemes.

ESSAY 5

Guarantee-backed loans and credit risk: a default model with selection

1. Introduction

Financial institutions usually adopt credit scoring/default prediction models to evaluate loan applicants, in order to distinguish those who are expected to pay back their debt from those who are likely to default. Although default prediction models cannot perfectly separate the applicants who will fully repay the loan from defaulters, they can significantly improve the allocation of financial resources, enabling lenders to grant credit to borrowers who could potentially have been excluded despite being creditworthy.

Credit risk modeling is expected to play a central role not only in credit granting decisions, but in the determination of regulatory capital adequacy as well. Under the new Basel Capital Accord, banks are encouraged to systematically assess risk relative to capital within their organizations and to adopt credit scoring models with good predictive power. Interestingly, the Basel Committee on Banking Supervision (June 2004; par. 417) states that "the model must be accurate on average across the range of borrowers or facilities to which the bank is exposed and there must be no known material biases".

A typical source of bias in credit scoring models is that they are usually calibrated on the repayment behaviour of applicants who have been accepted for credit in the past. The performance of those applicants who have been previously rejected is not observed. The estimated parameters are therefore subject to a sample selection bias when they are applied to all applicants.

The aim of this paper is to estimate a default prediction model that addresses the sample selection problem. I use a dataset provided by Eurofidi, an Italian mutual guarantee consortium, which facilitates access to financing for SMEs, mainly located in Piedmont. The strength of the dataset is the peculiar information it provides on the past and current status of guarantee-backed loans, together with data on the amount and duration of loans and guarantees. Moreover, it is also a source of information on both approved and rejected applications.

I depart from Boyes et. al (1989) and Jacobson and Roszbach (2003) by estimating a bivariate probit model with sample selection. The model consists of two simultaneous equations: the first one estimates Eurofidi's binary decision to approve or reject the loan application through a preliminary screening and the second one, conditional on the loan having being granted, relates to the borrower's ability to pay it off or not. The underlying assumption of the model is that the distribution of the population of accepted applications is different from that of the rejected ones.

The model is built upon a set of financial ratios among the most widely used in the literature as well as the most predictive ones of the probability of default. Non-financial variables indicating the purpose of the loan, the amount of the loan, the presence of other on-going loans and the age and size of the borrower are included in the model.

I compare the parameters estimated from the bivariate probit model with sample selection with a standard probit model, using a training sample of 2,272 observations randomly drawn from the whole sample of 3,441 approved loans. Given the weak correlation between the unobservables of the selection and the outcome equation, the estimates of both models are very similar and consequently they have similar predictive performance. Therefore, I can conclude that the bivariate probit specification performs no better than an ordinary probit model with this typology of data.

The remainder of the paper is organized as follows. Section II discusses background material on failure prediction models. Section III provides a description of the dataset, together with some summary statistics. Section IV describes our baseline specification and the estimation method; section V presents empirical results. Section VI summarizes the paper.

2. Overview of the literature

The literature on default prediction methodologies has grown considerably over the last 40 years. Since Beaver's univariate model (1966) and Altman's multivariate model (1968), a plethora of methodologies have been developed to predict corporate bankruptcy using a set of financial ratios: discriminant analysis, linear probability models, logit and probit regressions, or, more recently, recursive partitioning algorithm, multicriteria decision aid methods, expert systems and neural networks (see Altman and Saunders, 1998 for a review).

By far, the most widely used statistical techniques for default prediction have been discriminant analysis and logit regressions. Over the last decades, logit models and, to a lesser extent probit models, have become increasingly popular in the field of credit scoring due to the limitations of multiple discriminant analysis.[1] After the works of Ohlson (1980) and Zmijewsky (1984), who were the first to apply respectively the logistic and probit analysis to distress prediction studies, most of the subsequent academic literature (Keasy and Watson (1987), Platt and Platt (1990), Altman and Sabato (2005)) used logit and probit models to predict default.

Accounting based credit-scoring models that make use of these methods are widely accepted because of their relatively high discriminatory power. However, they have been subject to a few criticisms (see Altman and Saunders, 1998 and Roszbach, 2004). First, they lack an underlying theory of business failure, and explanatory variables are chosen according to their accuracy in predicting default for a specific sample of observations. Second, as financial factors are mostly backward-looking point in time measures, these models fail to capture fast-moving changes in borrowers' conditions. Third, they suffer from a sample selection bias because they are estimated from a sample of granted loans and the criteria by which applicants are rejected are not considered.

Fairly recent papers have tried to tackle some of these problems, by including qualitative variables in the models in order to capture industry/firm-specific effects or by adopting reject inference techniques to incorporate information on rejected applicants.

Qualitative variables for failure prediction have been proposed by Zopounidis (1987), Keasey and Watson (1987), Tennyson et al. (1990), Grunert et al. (2005). To assess the risk of business failure Zopounidis (1987) employs a set of "strategic criteria" (quality of management, the level of R&D, market niche/position..), while Tennyson et al. (1990) consider the information which is contained in annual reports (financial management decisions, influence of external environment on earnings and stockholders, production capacity, variations of exchange rates, new firm strategies..). Keasey and Watson (1987) estimate a model of distress prediction with a set of non-financial variables which refer to the management structure of the firm and to the presence of audit qualifications and secured loans. Their results indicate that marginally better predictions concerning small company failure may be obtained from non-financial data as compared to those which can be achieved from using traditional financial ratios. Grunert et al. (2005) consider qualitative variables related to management quality and market position. They find evidence that the combined use of financial and non-financial factors (management quality and market position) leads to a more accurate prediction of future default events than the single use of each of these factors.

Various reject inference techniques have been developed to cope with the sample selection bias (extrapolation, re-weighting, bivariate probit…). They all attempt to incorporate information on rejected applicants into a default prediction model based primarily on accepted applicants.[2] However, assumptions on the distribution of the accepted and rejected applicant population are different according to the techniques employed. Augmentation, extrapolation and re-weighting generally assume that the distribution pattern of accepted applicants can be extended to that of rejected ones[3]. The same hypothesis does not hold for bivariate probit models, where the distribution of the population of accepted applications is assumed to be different from that of the rejected ones. Boyes at al. (1989) designed a bivariate probit model with two sequential events as the dependent variables: the bank's decision to grant the loan or not and, conditional on the loan having being provided, the borrower's ability to repay its debt. They found that the granting behavior of lenders was not consistent with a policy of default risk minimization. Estimated coefficients carried equal signs in both equations, so that variables which increased the probability of positive granting also raised the probability of subsequent default. Jacobson and Roszbach (2003) used the bivariate probit approach too in building a credit scoring model and they proposed a method to calculate portfolio credit risk.

3. Dataset and summary statistics

The dataset is provided by Eurofidi, an Italian mutual guarantee consortium which facilitates access to financing for SMEs, mainly located in Piedmont (one of the twenty administrative regions in Italy).[4] Eurofidi provides guarantees on short, medium and long-term loans, commercial paper and investment certificates.[5] It also assists small firms in dealing with the lending institution throughout the duration of the loan guarantee. 31,299 SMEs are members of the consortium, the majority of which are located in Piedmont (72.67%). Target groups include SMEs and micro-firms in the industrial, commercial, services, craft and tourism sectors. In terms of distribution by sectors, commerce accounts for the largest share of borrowers (43%), followed by industry (27%), craft (24%), services (4%) and agriculture (2%). At the end of 2006, the guarantee consortium issued guarantees on loans amounting to over € 3.600 million.

Eurofidi's intervention allows firms to expand their credit capacity, which would otherwise be constrained by their small size. Due to their "informational opacity," small firms are in fact more likely to face credit constraints compared to larger businesses which can provide detailed financial information and more reassurance to a bank that its loan will be repaid (Berger and Udell, 1990). A loan application made through a guarantee fund is seen as more credible than one done by an individual small firm, partly because of rigorous preliminary risk assessment procedures undertook by the guarantee fund, but equally because a small firm may have little, if any collateral, and would not be able to access finance without the guarantee.

SMEs pay a small handling fee to Eurofidi when making a guarantee application. If this is approved, the firm then pays a fixed percentage to Eurofidi as a risk premium. The risk factor does not influence the percentage fee paid by SMEs in exchange for the guarantee but determines the amount of the loan Eurofidi is willing to guarantee. Eurofidi provides guarantees of up to 100% on total loan size but normally this amounts to 50%. The interest rate differential between the rate a SME would pay on the open market and that paid on a guarantee-backed loan is dependent on its risk of default, which is assessed by the financial lending institution. If a small firm defaults on the loan, the guarantee fund immediately pays the creditor. The bank then pursues the firm for reimbursement on Eurofidi's behalf. [6]

The database provides data on each borrower's loan application and request for guarantees (amount and duration, typology of the loan), but its strength, for our specific purposes, is the information I have on the outcome of the internal selection process (whether the loan was granted or rejected by a preliminary screening process undertook by Eurofidi), the development of accepted applications and the different destinations of demands for loans. For example, I know whether a guarantee-backed loan application was accepted or rejected by Eurofidi's pre-screening procedures, which are based on quantitative risk assessment analysis and subjective judgments (peer monitoring, knowledge of the business sectors in which clients operate). I also know whether a granted borrower has got one, two or three delayed payments and whether it was or not able to return to the agreed-upon repayment scheme. In the last case, I have also information that Eurofidi had to pay the bank on its behalf. In addition, for each loan application, Eurofidi complemented information on the amount and duration of guarantee-backed loans with some comments on the future use of them by the applicant firm.

The dataset consists of a total of 38,995 applications for guarantee-backed loans by 11,184 small manufacturing firms since 1995. I matched the database with complete accounting information for the years in which loan applications were forwarded, using the AIDA database[7]. We dropped loan applications dating 1995, 1996 and 1997, for which balance sheet data were not available. Following the standard practice in the literature, I trimmed outliers in all key financial variables used in the econometric model at the one-percent level and I excluded from the sample firms with incomplete accounting information. I only kept observations for guarantee-backed loans with a due date not later than December 31st 2006 or rejected by Eurofidi's pre-screening procedures. The final sample consists of 4,549 observations and 770 firms (which means an average of nearly six loan applications per firm).

I classified a loan as "bad" if, once approved by Eurofidi's preliminary screening, it was forwarded to a debt-collection agency or if the guarantee fund had to pay the bank for it. We decided not to consider a loan to be bad if the borrower received one, two or three reminders because of delayed payments. These are all transient states and once borrowers return to the agreed-upon repayment schemes, the number of reminders is reset to zero.

Table 1 presents the distribution by sectors of the analyzed companies, according to the ATECO classification codes.[8] The greatest number of firms asking for a guarantee-backed loan belong to the metal products manufacturing sector (23.77%), followed by the mechanical machinery and equipment industry (16.23%). Following the European Union classification[9], I distinguished between micro firms (less or equal than 10 employees), small firms (between 10 and 50 employees) and medium firms (more than 50 but less than 250 employees). Most of the firms in the sample are micro and small-sized enterprises (more than 87%) where lack of collateral and track record represent major obstacles to obtaining credit (Table 2).

Credit scoring models are generally based on financial accounting ratios, which are thought to be able to predict the failure of a firm. A large number of financial ratios have been proposed in the literature. Courtis (1978) made an attempt to classify the variables which were more useful in predicting bankruptcy and identified 79 financial ratios which were grouped into three main categories: profitability ratios, managerial performance ratios and solvency ratios. Chen and Shimerda (1981) realized that out of more than 100 financial items, almost 50% were found useful in at least one empirical study. Following this early approaches, I attempted at producing a similar taxonomy with a fewer number of studies (see Table A1 in the Appendix). Due to balance sheet information availability, we calculated 30 of the 53 financial ratios from Table A1. Out of 30 financial ratios, I selected a set of 6 accounting ratios describing the main aspects of a company's financial profile: liquidity, profitability and leverage. Financial variables were chosen according to the following criteria: first, we controlled that the relationship of the financial ratio with the default event was clear and economically intuitive and that the number of observations lost due to missing data for a given variable was very low, second I checked the correlation between selected variables and third I estimated the model eliminating the least helpful covariates, one by one, until all the remaining input variables were enough efficient. All financial variables were normalized by Total Assets in order to avoid scaling issues.

Together with financial accounting ratios, I also included a set of qualitative variables as predictors. The combined use of financial and non-financial factors has been identified as a major improvement in the accuracy of default prediction (Grunert et al., 2005; Brunner et al., 2000). Furthermore, under the new Basel Capital Accord, financial institutions are required to consider qualitative variables in credit risk assessment (June 2004, par. 411).

Table A2 in the Appendix provides a definition of the variables used in the model. I included both qualitative (discrete) and quantitative (continuous) regressors. Among the first group I considered four dummy variables according to the destination of the loan as declared by the applicant: investments in innovation and R&D (RD), capital investments (INV) and liquidity purposes (LIQUID). The excluded category encompasses all other types of destinations (OTHER). In the dataset we found some comments, made by Eurofidi's employees, on the future use of guarantee-backed loans. I analyzed, one by one, the text of the 38,995 comments (one for each loan application) and categorized them in the above-mentioned four categories. I also created three dummies reflecting the size of the applicants if their number of employees was less or equal than 10 (MICRO), between 10 and 50 (SMALL) and larger than 50 (MEDIUM, excluded in the regression). Among the quantitative regressors I considered the relative size of the loan (observed only for the approved applications) normalized by the total assets of the applicant (LOANSIZE), the logarithm of the age of the borrower (AGE), the number of previous guarantee-backed loans of the applicant that are still on-going (ONLOANS) and a set of financial ratios reflecting the applicant's leverage (TLTA, BDTA), liquidity (CFTA, CATA) and profitability (EBITDATA, NSTA). TLTA is defined as the ratio of total liabilities (current liabilities + long term liabilities + any other miscellaneous liability the company has) over total assets (current assets + long-term assets). CATA is measured by the ratio of current assets over total assets. CFTA is defined as cash flow (the sum of after-tax profit and depreciation) on total assets, NSTA is net sales on total assets, EBITDATA is calculated as earnings before interest, taxes, depreciation and amortization over total assets and BDTA is measured as bank debt (short-term + long-term bank debt) over total assets.

Table 3 reports the distribution of loan applications by types of destination and status of application. A loan is approved (rejected) when, after a preliminary screening, it is (not) granted. A loan is bad (good) if, once approved by Eurofidi's preliminary screening, it is (not) forwarded to a debt-collection agency or if the guarantee fund has (not) to pay the bank for it. If I consider the full sample, demands for loans to be channeled into capital investment financing account for 16.09%, while liquidity purposes represent the highest percentage (60.91%). Only 234 loans have been asked to finance innovation and R&D activities. Interestingly, when I divide the sample into approved and rejected applications, those having as a main purpose that of increasing firm's liquidity are more likely to be approved by Eurofidi in a preliminary screening. On the contrary, performing R&D or capital investments increases the probability of being rejected. Among the accepted applications, it seems that there is a higher chance that the loan will be repaid (good loan) if its purpose falls in the categories RD and LIQUIDITY. Demands for loans to finance capital investments are comparatively more likely to turn into bad loans (13.54%) than into good loans (12.50%)

Table 4 summarizes the relevant statistics of the variables used in the econometric analysis for the pooled sample and for the sub-samples of approved and rejected applications and, within the sub-sample of accepted applications, for good and bad loans. The share of rejected applications is significantly higher, both at the mean and median level, for more indebted firms. However, once the loan is granted, firms' leverage does not seem to univocally influence the repayment behavior of borrowers. Rejection is less likely for firms showing a good profitability, as well as the probability that a loan will not be refunded. It is less clear why firm's liquidity influences Eurofidi's decision to reject a demand for a guarantee-backed loan. On the contrary, being more liquid clearly improves the probability of paying back the debt. Overall, descriptive statistics reveal that lenders provide credit only when they have high expectations of being repaid and, thus, favor borrowers with good financial records, since they offer more assurance to reimburse the loan. Young firms asking for a loan seem to be more likely to be accepted but they perform less well than older firms in repaying the loan. Also, the amount of granted loans is higher, at the mean level (but it is lower at the median level) for good loans rather than for bad loans. Eurofidi appears to accept more easily applications of borrowers with other on-going loans. The amount of other on-going granted loans is associated with a lower probability of default.

4. Model specification

Credit scoring models are built to predict the default probability of a potential borrower but, as I already mentioned, they are often estimated using only data on applicants who have been accepted for credit in the past. In this setting, limitations on the consistency of the estimates can arise from the non-randomness nature of the population under study. This is obviously due to the fact that credit applications are not accepted at random but depend on credit institutions' acceptance policies.

Formally, if we define with y_1 the observed nature of a loan (0=good, 1=bad), with y_2 the observed outcome of the selection process (0=rejected, 1=accepted) and with $X = (x_1, x_2, ..., x_k)$ a vector of variables completely observed for each applicant, I can classify three different situations with respect to the nature of the selection process (Little and Rubin, 1987):

1) Missing Completely at Random (MCAR): if the acceptance is independent on both X and y_1:

$$P(y_2 = 1 \mid X, y_1) = P(y_2 = 1)$$

2) Missing at Random (MAR): if the acceptance, conditional on X, does not depend on y_1:

$$P(y_2 = 1 \mid X, y_1) = P(y_2 = 1 \mid X)$$

In this special case I also have :

$$P(y_1 = 1 | X, y_2 = 1) = P(y_1 = 1 | X, y_2 = 0) = P(y_2 = 1 | X)$$

i.e., given X, the distribution of y_1 is the same among the rejected and the accepted. Therefore, under MAR condition, valid statistical analysis can be performed without modeling the underlying selection mechanism.

3) Missing Not at Random (MNAR): if the acceptance, even conditional on X, still depends on y_1:

$$P(y_2 = 1 | X, y_1) \neq P(y_2 = 1 | X)$$

This situation typically occurs when the acceptance is partly based on characteristics not included in X (e.g. "expert judgment" of the loan officer on the applicant) and these unobserved characteristics have an additional influence on y_1:

$$P(y_1 = 1 | X, y_2 = 1) \neq P(y_1 = 1 | X, y_2 = 0)$$

In this situation valid statistical analysis cannot be performed without modeling the underlying selection mechanism.

One way to overcome the problem of sample selection is to specify a parametric model for both the outcome and the selection equation and allowing for correlation among the unobservables.[10] In the econometric literature, the probit model with sample selection (Van de Ven and Van Pragg, 1981) assumes that there exists an underlying relationship $y_1^* = X_1\beta_1 + u_1$ (latent equation) such that I observe only the binary outcome $y_1 = (y_1^* > 0)$ (probit equation). However, the dependent variable is observed if $y_2 = (X_2\beta_2 + u_2 > 0)$ (selection equation) and the error terms u_1 and u_2 are assumed to be standard normally distributed with $corr(u_1, u_2) = \rho$.

The formal model can be specified as:

$$y_1 = 1[X_1\beta_1 + u_1 > 0] \qquad (4.1)$$

$$y_2 = 1[X_2\beta_2 + u_2 > 0] \qquad (4.2)$$

where 1 is an indicator function which takes the value of 1 if the expression in squared brackets is satisfied and 0 otherwise and y_1 is observed only when $y_2 = 1$.

This model is estimated via maximum likelihood (ML) by maximizing the following log-likelihood by iterative maximization techniques:

$$L=\sum_{\substack{y_1=1\\y_2=1}}\ln[\Phi_2(X_1\beta_1,X_2\beta_2,\rho)]+\sum_{\substack{y_1=0\\y_2=1}}\ln[\Phi_2(-X_1\beta_1,X_2\beta_2,-\rho)]+\sum_{y_2=1}\ln[1-\Phi(X_2\beta_2)]$$

where Φ_2 is the cumulative bivariate normal distribution function and Φ is the standard cumulative normal.

5. Econometric results

The aim of this section is to compare and analyze the parameters estimated from a standard probit model (PROBIT) and a bivariate probit model with sample selection (HECKPROB) using a training sample of 2,272 observations randomly drawn from the whole sample of 3,441 approved loans.

The dependent variable in both models is the probability of being a bad loan (DEFAULT=1). While in the PROBIT model the sample selection mechanism is ignored and the model is estimated using only the sample of approved applications (2,272 observations), with the HECKPROB model a selection equation (APPROVED=1) is estimated simultaneously with the outcome equation (DEFAULT=1), using both approved and rejected applications (3,373 observations).

According to Boyes et al. (1989) a minimizing default risk behavior of the lending institution with respect to the observed characteristics of the applicant should reflect an opposite sign of the variables of interest in the two equations of the HECKPROB model. This means that variables that increase (decrease) the probability of positive granting decision, should reduce (raise) the likelihood of a default.

As outlined in Table 5, PROBIT and HECKPROB estimates are very similar. This is due to the weak correlations between error terms in equations 4.1 and 4.2: the Wald test of independent equations ($H_0:\rho=0$) is not rejected even at a 25% level of significance. Thus, given the observables, the distribution of the probability of being a bad loan is the same between accepted and rejected (MAR scenario).

However, the estimates in the HECKPROB model are still interesting if we want to verify whether Boyes et al. (1989) assumptions on risk minimization behavior hold in this case. Unfortunately, only TLTA, NSTA and EBITDATA have opposite signs (and only TLTA has a significant explanatory power in both equations), whereas for the other variables this requirement does not hold. In particular, looking at the signs of the estimated coefficients for the dummies of loan destination, I can see that, although all the three types of destination have a lower probability of being a bad loan (with respect to OTHERS) they also have a lower probability of being accepted (RD is also statistically significant at 1% level in both the equations). Micro firms (MICRO) have a higher default probability than small and medium firms but also a higher probability of acceptance of their application. Interestingly, the number of previous on-going loans has a stronger non-linear explanatory power in the selection equation than in the outcome equation: a small amount of previous accepted loans is perceived by the lending institution as a signal of "good reputation", even if after a certain threshold (estimated at about 8-9 on-going loans) concern may arise on the reliability of the applicant on refunding all the loans and thus increasing its probability of default (as partially confirmed by the coefficient of ONLOANSsq in the outcome equation). Finally, the relative size of the loan has a positive (although nonlinear) effect on the probability of default, whereas the age of the applicant has a negligible effect in both the equations.

In order to assess the discriminatory power of the estimated models, I perform a ROC (Receiver Operating Characteristics) analysis. Given the weak correlation between the unobservables of the selection and the outcome equation (4.1 and 4.2), the estimates of the PROBIT and the HECKPROB models are very similar and consequently they have similar predictive performance. This is outlined if I compare the out-of-sample plot of the ROC curve of both models, calculated using 1,169 extra-observations (Figure1). Both models have the same amount of area under the ROC curve and they also share a similar sensitivity/specificity trade-off.[11]

Furthermore, both models suffer from a low accuracy in classifying bad loans, due to the extremely unbalanced proportion of the sample with only about 10% of observations defaulting. This is outlined if I construct a confusion matrix for both the models assuming 0.5 and 0.3 as a cutoff probability (Tables 6.1 and 6.2). By lowering the cutoff threshold I certainly increase the proportion of defaults correctly predicted but I also decrease the overall prediction accuracy of the model.

These results obviously restrict the usefulness of our model only for interpretative purposes. If I want to develop specific models for predicting purposes I should rely on less restrictive methods such as semiparametric[12] or non-parametric models which can ensure a superior predictive power but often at a cost of less interpretative easiness. This exercise will be done in a future version of this paper.

6. Conclusions

Drawing from an original dataset provided by a guarantee consortium, I estimated a default prediction model with two sequential events and assessed its predictive power against a more traditional probit. Both financial and qualitative variables entered the models. The availability of data on rejected and accepted guarantee-backed loan applications allowed us to estimate a bivariate probit with sample selection. I compared the predictive performance of the probit and the bivariate probit using a training sample randomly drawn from the whole sample of approved loans. Results show that the estimates, and consequently the predictive performance of the two approaches, are very similar. Also, both models suffer from a low accuracy in classifying bad loans.

These results obviously restrict the usefulness of the model in interpreting the economic significance of the regressors. In line with Boyes et al. (1989), I find that a set of financial variables that increase (decrease) the probability of positive granting decision do not reduce (raise) the likelihood of a default. On the other hand, dummy variables describing the destination of a loan have a lower probability of being accepted as well as of turning into bad loans, compared to a more general category of loans without a precise purpose.

The paper will be further improved with the estimation of semiparametric or non-parametric models, which have the advantage of being less restrictive (thus ensuring a superior predictive power) but the disadvantage of being less easily interpretable.

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8. Tables

Table 1-Distribution by sector of the firms

Ateco code	Industry	Total sample	%
15	beverage and food industry	36	4.68%
17	textile industry	36	4.68%
18	textile product industry	29	3.77%
19	leather and leather products manufacturing	11	1.43%
20	wood and wood products manufacturing	24	3.12%
21	pulp, paper and paper products manufacturing	17	2.21%
22	publishing, printing	29	3.77%
23	petroleum and coal products manufacturing	2	0.26%
24	chemical industry	25	3.25%
25	plastics and rubber manufacturing	47	6.10%
26	non-metallic mineral product manufacturing	26	3.38%
27	metallurgy	18	2.34%
28	metal products manufacturing	183	23.77%
29	mechanical machinery and equipment manufacturing	125	16.23%
30	computer and electronic manufacturing	9	1.17%
31	electrical machinery and equipment manufacturing	52	6.75%
32	telecommunication machinery and equipment manufacturing	12	1.56%
33	medical, optical and precision equipment manufacturing	11	1.43%
34	transportation equipment manufacturing	18	2.34%
35	other transport equipment manufacturing	9	1.17%
36	other manufacturing industry	48	6.23%
37	recycling	2	0.26%
40	production and distribution of electricity, gas and water	1	0.13%
	TOTAL	**770**	**100.00%**

Table 2-Distribution by size of the firms

Firm size	Number	%
Medium	95	12.34
Small	337	43.77
Micro	338	43.90
Total	**770**	**100**

Table 3-Distribution of loan applications by types of destination and status of application

	Purpose of the guarantee-backed loan			
	LIQUID	INV	RD	OTHER
Total sample	2,771 (60.91%)	732 (16.09%)	243 (5.34%)	803 (17.65%)
Rejected	605 (54.60%)	298 (26.90%)	68 (6.14%)	137 (12.36%)
Approved	2,166 (62.95%)	434 (12.61%)	175 (5.09%)	666 (19.35%)
Bad	196 (54.14)	49 (13.54%)	9 (2.49%)	108 (29.83%)
Good	1,970 (63.98%)	385 (12.50%)	166 (5.39%)	558 (18.12)

*A loan is approved (rejected) when, after a preliminary screening, it is (not) granted. A loan is bad (good) if, once approved by Eurofidi's preliminary screening, it is (not) forwarded to a debt-collection agency or if the guarantee fund has (not) to pay the bank for it.

Table 4-Descriptive statistics of the regressors

	Total sample	Rejected	Approved	Bad	Good
TLTA					
Mean	1.307	1.426	1.269	1.366	1.258
Median	1.332	1.421	1.257	1.409	1.236
Std.Dev	0.268	0.219	0.271	0.289	0.267
CATA					
Mean	0.724	0.721	0.725	0.704	0.727
Median	0.742	0.746	0.742	0.713	0.743
Std.Dev	0.166	0.173	0.163	0.169	0.163
CFTA					
Mean	0.039	0.043	0.037	0.027	0.039
Median	0.039	0.036	0.040	0.031	0.042
Std.Dev	0.083	0.046	0.092	0.082	0.093
NSTA					
Mean	1.093	1.025	1.115	1.015	1.127
Median	1.039	0.956	1.056	0.895	1.063
Std.Dev	0.428	0.412	0.431	0.398	0.433
EBITDATA					
Mean	0.101	0.091	0.104	0.084	0.106
Median	0.092	0.086	0.095	0.077	0.097
Std.Dev	0.062	0.059	0.062	0.074	0.060
BDTA					
Mean	0.279	0.327	0.263	0.207	0.270
Median	0.294	0.355	0.280	0.201	0.285
Std.Dev	0.197	0.191	0.197	0.189	0.196
AGE					
Mean	2.64	2.689	2.636	2.617	2.638
Median	2.708	2.772	2.708	2.639	2.708
Std.Dev	0.693	0.714	0.686	0.605	0.695
LOANSIZE*					
Mean	0.135		0.139	0.137	0.139

Median	0.061		0.058	0.073	0.057
Std.Dev	1.697		1.949	0.193	2.059
ONLOANS					
Mean	2.192	0.181	2.839	2.530	2.875
Median	1	0	2	2	2
Std.Dev	3.054	1.087	3.198	2.871	3.233

*Loan size is observed only for the approved applications
**A loan is approved (rejected) when, after a preliminary screening, it is (not) granted. A loan is bad (good) if, once approved by Eurofidi's preliminary screening, it is (not) forwarded to a debt-collection agency or if the guarantee fund has (not) to pay the bank for it.

Table 5-Probit and bivariate probit with sample selection

	PROBIT			**HECKPROB**					
	P(DEFAULT=1)			**APPROVED=1**			**P(DEFAULT=1)**		
	Coef.	**Rob. SE**	**P>|z|**	**Coef**	**Rob. SE**	**P>|z|**	**Coef**	**Rob. SE**	**P>|z|**
RD	-0.814	0.192	0.000	-0.708	0.133	0.000	-0.762	0.201	0.000
INV	-0.228	0.197	0.247	-0.844	0.076	0.000	-0.177	0.181	0.326
LIQUID	-0.280	0.094	0.003	-0.134	0.069	0.053	-0.275	0.098	0.005
TLTA	0.497	0.249	0.046	-1.436	0.222	0.000	0.578	0.290	0.047
CATA	-0.531	0.376	0.158	-0.183	0.221	0.408	-0.509	0.366	0.165
CFTA	-1.372	0.726	0.059	-1.448	0.622	0.020	-1.271	0.730	0.082
NSTA	-0.273	0.154	0.077	0.050	0.066	0.448	-0.273	0.154	0.077
EBITDATA	-1.701	1.379	0.217	2.129	0.430	0.000	-1.851	1.382	0.180
BDTA	-1.217	0.384	0.002	-0.574	0.115	0.000	-1.173	0.394	0.003
AGE	0.013	0.011	0.254	0.005	0.005	0.279	0.012	0.011	0.252
AGEsq	0.000	0.000	0.230	0.000	0.000	0.043	0.000	0.000	0.230
SMALL	0.081	0.233	0.728	0.240	0.069	0.000	0.074	0.238	0.756
MICRO	0.521	0.230	0.023	0.383	0.070	0.000	0.502	0.242	0.038
LOANSIZE	0.722	0.127	0.000				0.720	0.127	0.000
LOANSIZEsq	-0.007	0.001	0.000				-0.007	0.001	0.000
ONLOANS	-0.066	0.030	0.029	0.870	0.132	0.000	-0.110	0.064	0.085
ONLOANSsq	0.004	0.002	0.089	-0.048	0.008	0.000	0.006	0.003	0.051
constant	-0.663	0.421	0.115	1.781	0.255	0.000	-0.648	0.425	0.127
rho							-0.183	0.168	0.287
	Log pseudolik. = -636.697			Log pseudolikelihood = -1900.108					
	Number of obs = 2272			Censored obs = 1101; Uncensored obs = 2272					
	Pseudo R_2 = 0.1525			Wald test(rho = 0): chi2(1) = 1.13; Prob > chi2 = 0.2870					

*Dummy variables for years 1998-2006 included.
**Robust standard errors clustered around 23 industry sectors (Ateco 2 digits)

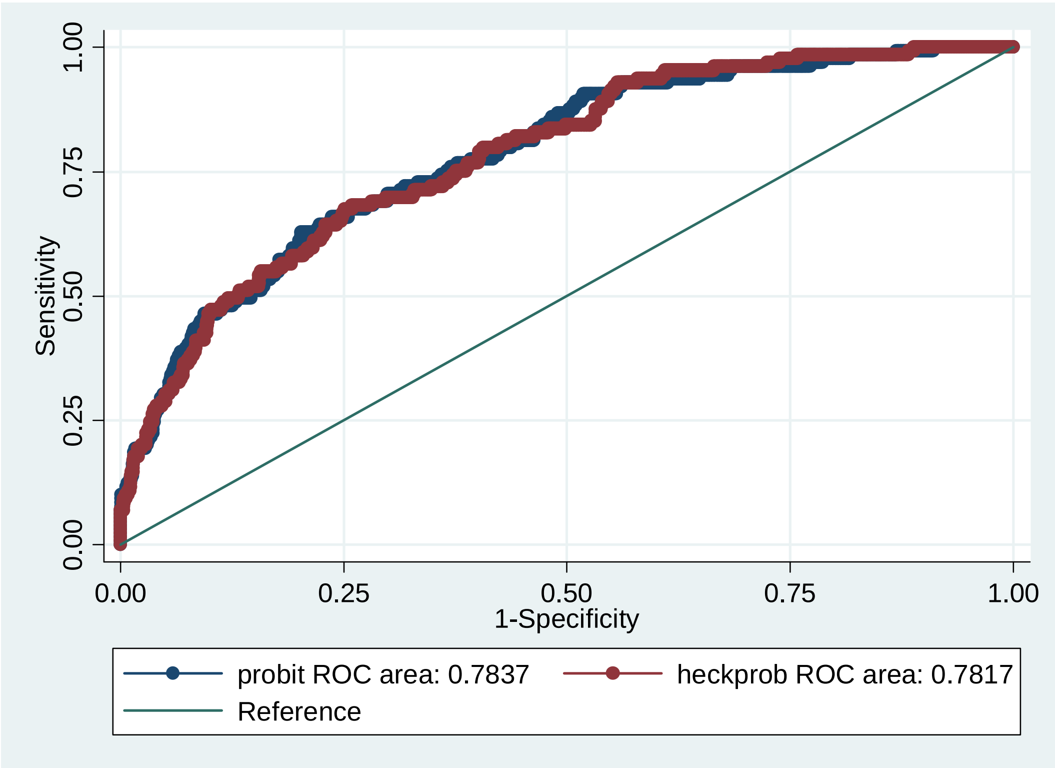
Table 6.1– Predictions for 0.5 threshold

	PROBIT		HECKPROB		
	PREDICTED		PREDICTED		
	0	1	0	1	**Total**
ACTUAL					
0	1,036	4	1,033	7	**1,040**
1	116	13	116	13	**129**
Total	**1,152**	**17**	**1,149**	**20**	**1,169**

Table 6.2 – Predictions for 0.3 threshold

	PROBIT		HECKPROB		
	PREDICTED		PREDICTED		
	0	1	0	1	**Total**
ACTUAL					
0	1,000	40	995	45	**1,040**
1	95	34	93	36	**129**
Total	**1,095**	**74**	**1,088**	**81**	**1,169**

Figure 1 – Receiver operating characteristic curve (obs. 1,169)



9. Appendix

In Table A1, the most important accounting ratios that have been proposed in the literature are listed and grouped according to popular accounting ratio categories.

Table A1: some of the main accounting ratios proposed in the literature

Accounting Ratios	Accounting ratio categories	Authors
LEVERAGE		
Total liabilities / Total assets	Leverage	a, b, f, g
Total liabilities / Tangible assets	Leverage	a,
Long term liabilities / Total assets	Leverage	a, b, d
Equity / Total liabilities	Leverage	e, d
Equity/Total assets	Leverage	m, n
Market-value equity/ Total debt	Leverage	h
Total debt / Total equity	Leverage	d
Short Term Debt / Equity	Leverage	c
Bank debt / Total assets	Leverage	i, l
Bank debt / Net worth	Leverage	i
Bank debt / total liabilities	Leverage	a
Long term bank debt / Bank debt	Leverage	d
Bank Debt/(Total assets - Bank debt)	Leverage	d
DEBT COVERAGE		
EBITDA / Interest expenses	Debt Coverage	c
EBIT/ Interest expenses	Debt Coverage	d, i, m
LIQUIDITY		
Cash flow / Total debt	Liquidity	i, l
Cash flow / Interest expenses	Liquidity	i
Cash flow / Current liabilities	Liquidity	a, b, i
Cash flow/(Total liabilities –Current assets)	Liquidity	n
Cash flow / Net sales	Liquidity	a, i
Cash flow/ Total assets	Liquidity	a, b, c, d, i, m
Cash flow/ Equity	Liquidity	m
Current assets / Total assets	Liquidity	a, b, i
Current assets / Current liabilities	Liquidity	a, b, d, f, I, n
Current assets / Total liabilities	Liquidity	a
Current assets / Net sales	Liquidity	a, i
Current liabilities / Total assets	Liquidity	a
Current liabilities / Current assets	Liquidity	g
Current liabilities / Total debt	Liquidity	i
Accounts payable/Total assets	Liquidity	d
Working capital / Current liabilities	Liquidity	a
Working capital / Total assets	Liquidity	a, b, d, e, g, h
Working capital / Net sales	Liquidity	a, b
Tangible assets/ Total assets	Liquidity	d, i, m
Fixed assets/(equity + long-term liabilities)	Liquidity	n
Quick assets / Net sales	Liquidity	a
Quick ratio	Liquidity	a, b, m
ACTIVITY		
Inventory / Net sales	Activity	a, b

Accounts receivable / Net sales	Activity	b, i
(Accounts receivable + inventory)/Total assets	Activity	i
Accounts receivable / Total liabilities	Activity	a
Accounts receivable / Inventory	Activity	a, i
PROFITABILITY		
Net sales / Total assets	Profitability	a, b, h, i
Operating income / Total assets	Profitability	b
Operating income/Total liabilities	Profitability	g
EBIT / Total assets	Profitability	a, d, e, h, i
EBITDA / Total assets	Profitability	c, l
EBIT / Net sales	Profitability	a
Economic value added/Total assets	Profitability	d
Net income / Total assets	Profitability	a, b, f, i, g, l, m, n
Net income / Net worth	Profitability	i, m
Net income / Net sales	Profitability	a, i
Retained Earnings / Total assets	Profitability	a, b, c, d, e, h

Authors	cod	Authors	cod
Chen and Shimerda (1981)	a	Ohlson (1980)	g
Kahya and Theodossiou (1999)	b	Altman (1968)	h
Altman and Sabato (2006)	c	Platt and Platt (1990)	i
Altman and Sabato (2005)	d	Beaver (1966)	l
Altman (1993)	e	Laitinen (2002)	m
Shumway (2001)	f	Grunert et al. (2005)	n

Table A2-Variables' definition

Variable	Definition
TLTA	ratio of total liabilities over total assets
CATA	ratio of current assets over total assets
CFTA	ratio of cash flow over total assets
NSTA	ratio of net sales over total assets
EBITDATA	ratio of EBITDA over total assets
BDTA	ratio of total bank debt over total assets
AGE	logarithm of the age of the firm
LOANSIZE	ratio of loan amount over total assets
ONLOANS	other on-going loan applications
RD	dummy variable which is equal to 1 if the loan was asked to finance investments in innovation and R&D; 0 otherwise
INV	dummy variable which is equal to 1 if the loan was asked to finance capital investments; 0 otherwise
LIQUID	dummy variable which is equal to 1 if the loan was asked for liquidity purposes; 0 otherwise
OTHER	dummy variable which is equal to 1 if the loan

	was asked for other purposes; 0 otherwise
MICRO	dummy variable which is equal to 1 if the firm is a micro firm (number of employees is less or equal than 10); 0 otherwise
SMALL	dummy variable which is equal to 1 if the firm is a small firm (number of employees between 10 and 50); 0 otherwise
MEDIUM	dummy variable which is equal to 1 if the firm is a medium firm (number of employees larger than 50); 0 otherwise

10. Footnotes

[1] Multiple discriminant analysis (MDA) is based on two restrictive assumptions on the distributional properties of regressors: 1) the predictors are normally distributed 2) the variance-covariance matrices of the predictors are equal across the failing and the non-failing groups of firms. Furthermore, as pointed out by Ohlson (1980), the output of a MDA model is a score which has little intuitive interpretation, since it is basically an ordinal ranking device.

[2] Although sample selection bias are generally perceived as detrimental to default prediction models, mixed results in terms of improvement in models' effectiveness have been found. Crook and Banasik (2004) examined the performance of the reweighting and extrapolation methods and reported that these techniques did not perform better than a model including only accepted applicants. Also, in Banasik et al. (2003) a bivariate probit model with sample selection was found to yield only modest improvement by considering the behavior of rejected applicants.

[3] Extrapolation imputes a good-bad classification to rejected cases on the basis of an initial model estimated using only accepted applicants. A final model is then estimated using all applicants (Crook and Banasik, 2004). Re-weighting implies a two-stage approach. First, a model discriminating between cases which have been accepted and rejected is estimated. Then the inverse posterior probabilities of acceptance of the accepted applicants are taken as sampling probability weights that a case was accepted and a rule that discriminates between only accepted goods and bads is estimated with these weights applied. (Banasik et al., 2003)

[4] Eurofidi is part of Eurogroup and is a limited company. Eurogroup is divided into two sub-branches: Eurofidi, which offers loan guarantees and Eurocons, which provides business support and consultancy services.

[5] Eurofidi co-operates with Mediocredito Centrale, the National Guarantee Fund for SMEs set up by the Italian Ministry of Industry. The National Guarantee Fund provides counter-guarantees on guarantees issued by Eurofidi, further reducing the risk burden. For example, if Eurofidi guarantees 50% of the loan value, the National Guarantee Fund for SMEs counter-guarantees 90% of the Eurofidi guarantee (e.g 45% of the total loan value).

[6] Once the new Basel Agreement on Capital Adequacy is implemented by banks, Eurofidi has the right to pursue SMEs directly for payment.

[7] AIDA is a privately edited database containing all balance sheet data for Italian companies. It is provided by Bureau Van Dijk.

[8] The Ateco classification is provided by ISTAT (the Italian National Institute of Statistics) and it is similar to the international SIC classification.

[9]The European Union has had a common classification of firms since 1996 that was updated in 2003 (Commission Recommendation 96/280/EC of April 3, 1996, updated in 2003/361/EC of May 6, 2003). Accordingly, firms are

classified as “micro” (less than 10 employees or a turnover of less than €2 million),“small” (less than 50 employees or a turnover of less than €10 million), “medium” (less than 250 employees or a turnover of less than €50 million) and “large” (more than 250 employees or a turnover more than €50 million).

[10] See for instance the works of Boyes et al. (1989), Greene (1992), Jacobson and Roszbach (2003) on consumer credit scoring.

[11] See, for instance, Englemann et al. (2003) for a discussion of the ROC curve as a measure of rating accuracy.

[12] See, for instance, Muller and Hardle (2002).