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R&D investment, Credit Rationing and Sample Selection[**]

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Abstract

We study whether R&D-intensive firms are liquidity-constrained, by also modeling their antecedent decision to apply for credit. This sample selection issue is relevant when studying a borrower-lender relationship, as the same factors can influence the decisions of both parties. We find firms with no or low R&D intensity to be less likely to request extra funds. When they do, we observe a higher probability of being denied credit. Such a relationship is not supported by evidence from the R&D-intensive firms. Thus, our findings lend support to the notion of credit constraints being severe only for a sub-sample of innovative firms. Furthermore, the results suggest that the way in which the R&D activity is organized may differentially affect a firms' probability of being credit-constrained.

JEL classification: D45, G21, G32, E51

Keywords: Bivariate Probit; Innovation; selectivity; in-house R&D.

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1. Introduction

Credit rationing occurs when a firm demands but is refused credit, even if it is willing to pay a higher interest rate (Freixas and Rochet, 1997). Indeed, an interest rate increment has four effects on the lender's return to debt. First, an obvious positive price effect. Second, an adverse selection effect because the best firms drop out of the market. Third, a positive selection effect due to the fact that some low-return high-risk entrepreneurs leave the market. Fourth, an adverse selection effect as some high-return low-risk switch to the equity market (Hellmann and Stiglitz, 2000). When the adverse selection effects dominate the positive effects, the result is an inverse relationship between interest rate increments and return to the bank. The efficient allocation of resources is not reached, and the result is insufficient lending (De Meza and Webb, 2000).

However, information asymmetries in the market do not necessarily lead to a credit rationing outcome. When imperfect information induces banks to pool both high and low quality projects, the volume of lending is not efficient. The occurrence of rationing or that of overlending depends on the distribution of projects characteristics in the pool (Boadway and Keen, 2004). The Stiglitz and Weiss (1981) equilibrium with credit rationing and the de Meza Webb (1987) overlending result should be considered as two special cases. Specifically, in the Stiglitz and Weiss (1981) framework intermediaries know the expected returns of projects, but not their riskness, giving rise to insufficient lending. Conversely, as in the de Meza and Webb (1987) model, if banks know the return of any given projects if successful, but not the probability of success, then too many projects for any level of return are financed.

Boadway and Keen (2004) argue that intermediaries are asked to finance new investment in a situation in which pooled projects have any mix of returns and probabilities of success. As a result underinvestment will occur with low return projects and with high probabilities of success, while the opposite occurs with high return and low probability of success.

Whether the credit market reaches or not an equilibrium with rationing depends also on the availability of substitutes (direct debt emissions, equity, venture capital financing) and on the possibility of other screening device than interest rate. Bester (1985) shows that in equilibrium no borrower is denied credit if banks can simultaneously choose collateral requirements and the interest rate to screen investor riskness. Different contracts work as self-selection mechanism, as borrowers with high probability of default choose a contract with a higher interest rate and lower collateral than low risk borrowers. In the bank competitive equilibrium signalling eliminates demand rationing.

Diamond (1991) combines the possibility of direct debt placement in the market with the cost and the benefit of monitoring when firms are financed by banks. Since high ratings lower the cost of future direct debt emission, borrowers consider the effect on future information of their current actions trying to maintain a good reputation. As reputation may reduce the need for monitoring, given that high-rated borrowers have more to lose revealing bad information, in equilibrium bank loans are used only by borrowers with average credit ratings.

If reputation and collateral requirements play a role in reaching an equilibrium in the credit market, for specific, intangible and highly innovative investments, such as those in R&D, the overlending outcome is unlikely to occur. Carpenter and Petersen (2002) present the reasons why underlending best describes the relationship between innovative firms and lenders (see also Hall, 2002). First, information is not perfect for the very nature of innovation processes. The R&D process is uncertain because of the difficulties, even for the best-informed agent, to forecast output given the inputs employed (Arrow, 1962). R&D returns are, therefore, more unpredictable and uncertain, giving rise to moral hazard and adverse selection problems on the borrower's part. A second aspect is related to the strategic need for secrecy, which causes firms not to share information with the lenders (Himmelberg and Petersen, 1994), although this may exacerbate the moral hazard problem arising because the innovative firm, after obtaining credit, finds it profitable to pursue riskier strategies. More generally, revealing information to the market is costly, reducing the quality of signal about innovative projects (Bhattacharya and Ritter, 1983). Furthermore, because R&D processes involve accumulation of intangible capital, i.e., capital that is hardly re-deployable in alternative settings, such an investment has a low collateral value, thereby limiting the access to credit.[1] Finally, marginal cost of financial distress is likely to rise rapidly with leverage. Firms facing severe financial restrictions may have to abandon critical innovative projects, which crucially determine a firm's growth opportunities. Financial markets usually anticipate this behaviour by lowering a firms' market value (Carpenter and Petersen, 2002).

As the difference between the rate of return required by an external investor may be significantly larger than that required by the entrepreneur investing its own funds, it is difficult or costly to use external sources to finance R&D, even in presence of tax incentives or subsidies (Hall, 2002).[2]

This paper pursues two main objectives. First, it aims to test the hypothesis that highly innovative firms face a more difficult access to debt finance. Therefore, it presents an investigation of the factors affecting a firm's probability of having its credit application rejected, by focusing on a potential differential effect for Low-R&D and High-R&D enterprises. Firms representing the latter group are those with total R&D investment levels in the top decile of our sub-sample of innovative firms, while the remaining ones in the full sample make up the Low-R&D group. Following Guiso (1998) and Berkowitz and White (2004), liquidity-constrained firms are identified by a binary variable derived from the

[1] Močnik (2001), using a sample of Slovene firms, finds support for the hypothesis that firms with a high level of specific, i.e. intangible, assets should be characterised by a lower debt/equity ratio.

[2] Indeed, access to finance is often considered one of the main obstacles hampering a firm's innovation strategy, as many studies based on the Community Innovation Survey (CIS) dataset for various European countries have highlighted (Bayona et al, 2001; Evangelista et al, 2001; Tether , 2002; Veugelers and Cassiman, 1999)

responses to a survey.[3] The evidence suggests a higher probability to be denied credit for the Low-R&D group, and the lack of any significant relationship for the High-R&D one. This is a result that only partly reconciles with existing evidence. Therefore, to check the robustness of these findings, we investigate whether they hold when different measures of R&D expenditures are considered. Quite interestingly, it turns out that using measures of, respectively, Self-Financed R&D outlays and R&D expenditures in internal facilities yields results that are different from those obtained in a model including total R&D expenditures. The evidence suggests that our diverse measurements of R&D activity all contribute to shed some light on the factors affecting a lender's decision to deny credit. Indeed, a high share of self-financed R&D activity may be interpreted as a signal of the good quality of the innovative project. Furthermore, the organizational choice to externalize, at least partly, the R&D investment reduces the amount of intangible assets owned by the firm and the informational asymmetry associated with the project. It is therefore likely to enhance a firm's chance of a successful application.

Second, the paper discusses some limitations of the methodological approaches used in previous similar studies where a single Probit equation model was estimated (Guiso, 1998; Berkowitz and White, 2004). To this end, it proposes a more general methodology that only under certain circumstances can be reduced to the estimation methods previously used.[4] An important feature of the two-equation approach adopted here is the possibility to distinguish between the determinants of extra credit's need and those influencing the success of a credit application. This is an important difference because only the sub-sample of firms needing extra credit should be considered in the analysis of whether a firm's credit application was subsequently rejected. The two-equation approach used here tackles this intrinsic sample selection problem by explicitly taking into account that the observation of a liquidity-constrained firm is conditional on a firm wishing more credit. However, such a consideration is not found in the existing literature. Standard econometric techniques support the appropriateness of the modelling choice made in this study.

Section 2 describes the dataset used and the variables included in the econometric models. It also reports some descriptive statistics. The econometric methodology is described in Section 3. A comment to the results is made in Section 4, which is followed by concluding remarks.

2. Data set and model

The data used in this paper comes from the Survey of Manufacturing Firms (SMF), which was carried out by an Italian investment bank, Mediocredito Centrale (see www.mcc.it), in 1998. The SMF considers a stratified sample of Italian firms with at least 11 and up to 500 employees: the stratification

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[3] This differs from the approach, surveyed in Hall (2002), where liquidity constraints are revealed by the sensitivity of R&D investment to cash-flow shocks that are not signals of future demand increases. For an application, see Bougheas et al (2003).

[4] See Greene (1998 and 2003), and Piga and Vivarelli (2003 and 2004).

was made according to the number of employees, sectors composition and location, taking as benchmark the 1991 Census of Italian Firms. It also includes all the Italian manufacturing firms with more than 500 employees. The SMF contains both questionnaire information about a firm's structure, its behaviour in 1997 and balance sheet data for up to nine years (1989-1997). The wealth of data contained in this and the previous releases of the SMF have been used extensively in the literature (Atzeni and Carboni, 2004; Bagella et al., 2000; Filatotchev et al., 2002; Piga, 2002; Piga and Vivarelli, 2003 and 2004).

The dependent variables

In the SMF there are three questions that can be used to directly evaluate the firm's access to credit market: 1) whether at the current market interest rate the firm wants an additional quantity of credit; 2) whether the firm is willing to pay a higher interest rate to obtain that additional quantity; 3) whether the firm applied but the credit was denied. These are used to construct the two dependent binary variables under study. The first one, MORECRED, is equal to 1 if the firm declares it wanted more credit and was willing to pay either the current or a higher interest rate (see Guiso, 1998, for a discussion). The second dependent variable is denoted as DENIED: it is equal to 1 if the firm declares to have applied for credit and this was denied. Therefore, credit rationing occurs when both MORECREDIT and DENIED are equal to 1. It is worth stressing that credit constrained firms are identified in an exactly identical manner in Guiso (1998), where another dataset collected in 1993 by the Bank of Italy was used.[5] But unlike Guiso (1998), our econometric approach requires an estimation equation for each dependent variable, thereby enabling us to tackle a sample selection problem that has been largely overlooked in the previous literature. Indeed, for reasons further discussed in the Methodology Section, the analysis of DENIED should be made conditional on observing MORECREDIT=1, that is, rejected firms should be studied within the sub-sample of firms needing more credit.

Within a one-equation approach, Berkowitz and White (2004) include among the credit-rationed firms those declaring to be discouraged from applying. Arguably, a discouraged firm is aware of its low credit rating to the extent that it anticipates a negative outcome for its application. Hence, the decision in Berkowitz and White (2004) to classify it as denied. However, Berkowitz and White (2004) do not study the drivers affecting a firm's decision to apply for more credit. In the present setting, a discouraged firm is likely to have declared to wish more credit at the current or higher interest rate (i.e., MORECREDIT=1), although it is not included among the constrained firms as it was not officially denied credit.

The regressors

As mentioned in the Introduction, the purpose of this paper is to shed some empirical light on the relationship between R&D investment and the probability of being credit constrained. In this section we

[5] Indeed, the SMF questionnaire uses exactly the same questions used in the Bank of Italy survey.

define the Low- and High-R&D firms and also present other control variables that are likely to influence a firm's need for more credit and its likelihood to succeed in obtaining credit.

R&D expenditures. To evaluate the relationship between credit rationing and innovation, we consider total R&D, Self financed R&D and internal R&D outlays, all normalized by total assets.[6] In order to identify a potentially different effect for those firms that have invested heavily in R&D, each of these three variables is split into two using the top decile value of R&D expenditures over total asset as the cut-off point.[7] From Table 1 (rows 10-11, column 4) it can be inferred that the ratio of R&D expenditures on total assets for the top decile of firms with positive R&D ranges from at least 4.6% up to 39.8%. Considering that the mean value of such a ratio equals 0.57% for the full estimation sample (see Table 1, row 9, column 2) and 1.94% for the 919 firms with positive R&D, while the 92 firms in the top R&D decile invested on average 8.7% of their assets in R&D,[8] it is worth investigating whether differences exist among this top decile, which we use to single out the High-R&D firms from the firms with no or low R&D investments (henceforth, the Low-R&D group).

+++++++++++Table 1 here=========

Carpenter and Petersen (2002) argue that High-Tech sectors are very R&D intensive and therefore carry out their analysis of the financing of High-Tech firms by selecting a set of high-technology industries based on the U.S. Department of Commerce classification. However, it is possible that firms operating in High-Tech sectors may report no or little R&D activity or that R&D-intensive firms may operate in non-High-Tech sectors. Thus, it would seem inappropriate to look at the relationship between credit rationing and innovative activity by simply identifying whether a firm is part of a High-tech sector, an approach followed in Guiso (1998).[9] However, our study can easily be reconciled with Guiso (1998) and Carpenter and Petersen (2002), which focus exclusively on firms in High-Tech sectors, as a great proportion of firms in the High-R&D group also belong to technologically advanced sectors

Indeed, as Table 2 shows using the industry taxonomy due to Pavitt (1984), the distribution of R&D intensity for the firms in the "Specialised equipment suppliers" and "Science-based" sectors seems to be characterized by values higher than those reported by firms operating in the "Traditional supplier

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[6] The questionnaire included information on the percentage of R&D investments that were self-financed, and the percentage of R&D expenditures incurred while using internal facilities.

[7] The top decile cut-off point for R&D expenditure was determined by using only the sub sample of firms with positive R&D. Thus, for instance, in Table 1 the variable "Total R&D on total asset: first 9 deciles" reports a value of zero for all those observations with no R&D and for the R&D top decile. The proper value is reported otherwise.

[8] The latter two statistics are not reported in Table 1.

[9] Guiso (1998) explains how this approach is motivated by the lack of information about R&D spending.

dominated" and "Scale-Intensive" industries.[10] More precisely, out of the 92 firms defined here as High-R&D, 13 are classified as Science-based, 42 as Specialized Supplier, 20 as Scale-intensive and 17 as Traditional: this corresponds, respectively, to the 19%, 13.2%, 8.6% and 5.7% of the firms with positive R&D in each sectorial Pavitt's macro-group. Thus, in line with previous literature, our category of High-R&D firms comprises a majority (60%) of 55 out of 90 firms operating in High-Tech sectors. Furthermore, it includes firms from less technologically advanced industries which exhibit levels of R&D intensity well above their industry average, and that therefore are worth distinguishing as they are, in theory, more likely to face financing constraints. Indeed, unlike previous studies, such an inclusion of R&D-intensive firms from low-tech sectors among the High-R&D category is meant to emphasize how it is the nature of the R&D investment, and not the type of industry in which a firm operates, that may be ultimately responsible for the capital market imperfections under study.

+++++++++++Table 2 here=========

Data availability enables the adoption, in the present study of the determinants of credit constraint, of more specific measures of R&D intensity, namely the intensity of Self-financed and Internal R&D. Although these have not been used before, understanding the way in which the R&D investment is financed or whether it is organized purely in-house or with external partners can shed some light on a lender's decision to grant credit. Indeed, a greater share of self-financed R&D is associated with a "signalling effect" (Leland and Pyle, 1977), which may induce banks to be more confident in lending to the firm. Thus, higher levels of self-financed R&D investment should reduce the probability to be denied credit. Conversely, a purely internal R&D strategy may reinforce a firm's need for secrecy, thereby exacerbating the information asymmetry between borrower and lender. Furthermore, external R&D entails both an increase in a firm's cost flexibility, as external projects may be more easily cancelled, and a reduction in the amount of "intangible assets": it should therefore enhance a lender's propensity to grant credit. Thus, the organization via a purely internal R&D function might not enhance a firm's chance to obtain credit. While maintaining that the greater the R&D intensity, the greater the probability to be credit constrained, it is hypothesized that Self-Financed and Internal R&D are expected to have a different impact on the probability to be denied credit.

As far as the effect on the need for extra credit is concerned, Hall (2002) argues that firms engage themselves in R&D projects only when they have secured the necessary financial means. Thus, a significant relationship between R&D expenditure and MORECREDIT is not expected, although its magnitude may vary depending on the type of R&D measure being employed.

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[10] In Pavitt's taxonomy. Specialized Suppliers and Science-based macro-sectors are deemed as the ones with the most technologically advanced, knowledge intensive productions.

Control Variables. Most of the control variables employed were widely used in the literature (De Fraja and Piga, 2004; Guiso, 1998; Jensen and Showalter, 2004; Piga, 2002; Showalter, 1999). Their expected signs are reported in Table 1. Higher profitability, measured using Earning Before Interest and Taxes ("EBIT"), and "access to innovative, equity-based forms of financing" (dummy equal to 1 if the firm used them), are both expected to reduce a firm's need for credit and the probability to be denied credit. The latter explanatory variable is used as a control, as in Italy venture capital subscription are quite uncommon, contrary to the United States where R&D intensive firms use equity-based funding extensively (Blass and Yosha, 2003). Indeed, in the SMF a very small fraction of firms (0.8%) sold their shares to financial intermediaries, and only 24 firms to venture capitalists.

Higher levels of working capital such as "Inventories", may increase a firm's need for credit, but can also be used as collateral, thereby affecting positively the decision to be granted credit. Similarly, increasing the number of employees in order to pursue a potentially profitable entrepreneurial opportunity may drive a firm's decision to apply for credit, and may also be perceived by lenders as a positive signal for the presence of growing opportunities. This is captured by the "Net Hiring" variable.

High levels of debt, especially if short-term, are accompanied by high interest repayments which in turn may induce the indebted firm to apply for more credit. Of course, applications from highly indebted firms are also more likely to be rejected.

Certification is often regarded as a signal of quality as to how a firm organizes and carries out its production activity, ultimately leading to lower probability of a plant's break-down and to lower costs. Thus the dummy "ISO9000" is included: it is equal to 1 when this certificate has been obtained. Its expected sign in the DENIED equation is negative.

An inverse correlation is often found between firm size and cost of debt, due to the better diversification of risk that large firms can enjoy. It is not clear, however, how size, here measured as the "log of Sales", can affect a lender's decision to grant credit.

Given the geographical differences that characterize Italy, a dummy if firms are located in the North or Centre Italy is included in both equations. Such a dummy is aimed at capturing the different business opportunities available at the local level, as well as specific effects in the credit market. Indeed, Table 1 (rows 2-3, columns 9-10) shows that a greater proportion of firms in the South wishes more credit and was also denied credit.

Relative to firms selling only in the domestic market, exporting firms are more likely to face exceptional, unforeseen circumstances that may lead to the need to apply for extra funds, unlike firms that are partially owned by a bank or that enjoy a high level of non-debt tax shield, e.g. in the form of depreciation of tangible assets. Thus, the dummy "Export" and "Owned by a Bank", together with the variable "Tax Shield", are included in the MORECREDIT equation.

Finally, following Jensen and Meckling (1976), the agency cost of debt increases with the concentration of insider ownership, due to the managers/owners incentive to “go for broke”, i.e., invest in very risky projects with very high returns. If the investment fails, because of limited liability, lenders bear the consequence. Thus, need for extra credit should be greater in firms exhibiting a highly concentrated ownership, measured by the Herfindhal index of the four main ownership shares (Piga and Vivarelli, 2004).

Analysis of variables

Table 1 reports the descriptive statistics of the dependent and independent variables used. After having dropped missing values, the original sample size of 4495 observations, reduces to 3144. The distribution of missing values does not alter the composition of the estimation sample relative to that of the full sample. To avoid simultaneity problems, all regressors are lagged.

The proportion of firms wishing more credit or being constrained corresponds, respectively, to 14% and 3.1% of the estimation sample (row 2-3, col. 2). The latter figure is consistent with those, ranging between 2.7% and 4.3%, reported in Guiso (1998) for periods of the business cycle characterized by fast growth and easy credit supply. Note, however, that that these proportions should be worked out considering only the sub sample of firms that wish more credit. In this case, the percentage of constrained firms equals 21.72% (96 out of 442, from row 5 and columns 8 and 10). This may be considered as an estimate (possibly downward biased as firms may apply more than once) of the rejection rate of credit applications.

Firms with positive R&D tend to exhibit a greater proportion of constrained firms (3.6%, row 3 column 6), while a higher than average share of firms in the R&D expenditures’ top decile declare to wish more credit (20.7%, row 3 column8). Descriptive statistics for all the regressors show that the 2702 firms not wishing more credit exhibit a higher level of profitability and tax shield, and a lower level of inventories, net hirings and debt (column 7). They are also more likely to be bigger, owned by a bank and located in the North or Centre of Italy. R&D investment does not appear to differ between credit constrained or unconstrained firms. In order to be concise, the linear correlation matrix is not reported: however, no pair of regressors shows linear correlation values above 0.3675.

3. Methodology

Other studies have modeled credit constrained firms using a binary dependent variable and a Probit single equation approach (Berkowitz and White, 2004; Guiso, 1998). Greene (1998) argues that in order to obtain unbiased estimates of the factors affecting the probability of default in credit card loans, it is also necessary to assess the determinants of a credit card’s successful application. In this study we follow the methodology used in Greene (1998) in order to take into account that the analysis of the determinants of a lender’s decision to deny credit is made on a sample of firms which is not randomly selected. Indeed only if MORECRED is equal to 1 (that is, if the firm wishes more credit), the firm may have applied to the bank for additional credit. In other words, because observing a credit constrained firm is conditional on the firm's need for more credit, a sample selectivity bias may arise if the probability of being short of financial resources is not distinguished from that of being turned down when applying for credit.

To address the sample selectivity issue, a bivariate probit model with censoring setting is employed (Greene, 2003, pp.713-714). Formally the model can be represented as follows:

(1) $y^*_{i1} = \beta'_1 x_{i1} + \varepsilon_{i1}$, $y_{i1} = 1$ if $y^*_{i1} > 0$, 0 otherwise

$y^*_{i2} = \beta'_2 x_{i2} + \varepsilon_{i2}$, $y_{i2} = 1$ if $y^*_{i2} > 0$, 0 otherwise

$(\varepsilon_1, \varepsilon_2) \sim \text{BVN}(0,0,1,1,\rho)$

(y_{i1}, x_{i1}) is observed only when $y_{i2} = 1$

The likelihood function is:

$$(2)\ L_{ss} = \prod_{y_1=1,y_2=1} \Phi_2\left[\beta'_1 x_{i1}, \beta'_2 x_{i2}, \rho\right] \prod_{y_1=0,y_2=1} \Phi_2\left[\beta'_1 x_{i1}, \beta'_2 x_{i2}, -\rho\right] \prod_{y_2=0} \Phi\left[\beta'_2 x_{i2}\right]$$

where Φ_2 denotes the bivariate normal cumulative distribution function with $\rho = \text{Cov}[\varepsilon_1, \varepsilon_2]$. Eq. (2) is maximized with respect to parameters β_1, β_2 and ρ. Thus, the methodology does not use the two-stage Heckit procedure due to Heckman (1979) but, instead, a maximum likelihood estimation (MLE) approach where the robust Huber/White estimator of the variance is used in place of the conventional one.[11] For more about this methodology and its applications, see Greene (1998) and Piga and Vivarelli (2003 and 2004). Here we limit the discussion to recalling that when $\rho=0$, it is possible to estimate the model using independent Probit equations. In this case, the sample selection problem could be tackled by simply running a single Probit model using the sub sample of firms with MORECREDIT=1. However, from a methodological point of view, it is always necessary to start the analysis using a two-equation approach to determine the significance of ρ. Furthermore, the use of a Hausman's test can be used to compare the consistent Bivariate Probit estimates with those obtained from a single Probit approach.

In addition to the advantage of studying the credit constrained status using only the sub sample of firms wishing more credit, using a two-equation methodology enables to determine a variable's differential effect on the two dependent variables. Consider, for instance, the role of internal financial resources. It reduces the probability that a firm needs credit but it also enhances the chances of a successful application. Thus, the effect on the former does not have to be confounded with that on the

[11] The regressors' vectors in the two equations may coincide. Indeed, there is no issue of identifiability or estimability in the Bivariate Probit model, as it allows for unrestricted variable lists including identical ones (see Greene, 2002, pp. E17-3 and E17-4). However, we dropped some explanatory variables from the DENIED regression after noting that they were highly insignificant. Their exclusion did not change the estimates for the other variables.

latter. This is even more striking when R&D expenditures are concerned. Indeed, Hall (2002) observes that the long-term nature of R&D activity forces firms to make sure that they have secured enough financial resources before engaging in any innovative project. Thus firms currently involved in R&D activities should be less likely to need extra credit. However, the fact that they are carrying out R&D project may adversely affect their application for extra credit, due to the reasons indicated in the Introduction.

4. Results

Table 3 reports the results of the Bivariate Probit with sample selection estimation from four models, which differ only in the measure of R&D used. The four R&D sets of regressors are not jointly used to avoid obvious collinearity problems. We first focus on the statistical evaluation of the econometric procedure, and then comment on the results.

+++++++++++Table 3 here=========

The penultimate row reports the Hausman's test that compares the estimates from the Bivariate probit with Sample Selection model with those obtained from single, univariate Probit models on MORECREDIT and DENIED, noting that the latter is estimated only on the 442 firms for which MORECREDIT=1. The test clearly suggests that, at least as far as the estimates of the MORECREDIT model are concerned, no significant difference exists in the two sets of estimates. However, the Hausman's test rejects, for all the models, the hypothesis that the analysis of DENIED can be adequately carried out using a single equation approach. Further support in this sense is provided by the last row of the table, where it is shown that the disturbances of the two equations in all the models are significantly correlated. Thus, even if the estimated coefficients do not differ in one case, statistical inference in the one-equation setting is likely to be biased. Both sets of tests indicate the appropriateness of the approach used here and therefore cast serious doubts on the general validity of findings based on a one-equation framework.

As far as the impact of R&D activity is concerned, a striking difference can be noted between model 1 and models 2, 3 and 4. The former considers total R&D expenditures without differentiating between levels of R&D investment. The coefficient from model 1 suggests no relationship between R&D activity and the probability of demanding credit or being constrained. However, a clear pattern emerges, for all the measures of R&D taken into account, when the High-R&D firms are distinguished from the Low-R&D ones. This latter group seems to be the one that is less likely to wish more credit: such an effect is statistically significant when Self Financed R&D and Internal R&D Expenditures are used as regressors. Quite interestingly, R&D spending for High-R&D firms tends to be positively associated with the probability to wish more credit, although not in a statistically significant manner. Because in practice a great proportion of R&D spending corresponds to wages to R&D personnel, and firms want to avoid having to lay off knowledge workers, firms will set up R&D facilities only when they have secured sufficient financial funds (Hall, 2002).

However, our findings reveal that when the Low-R&D firms applied for credit, their applications were more likely to be rejected. Indeed the estimates show that the probability of being denied credit is positively associated with R&D spending, although this holds only for the low-R&D group.[12] This finding is further confirmed in Table 4, which reports the marginal effects for all the regressors used in the models. The estimates show that when the variable "Total R&D on total assets: the first 9 deciles" moves from zero to its mean value, the probability to be denied credit increases by 4.4 times. This impact reduces and loses significance when Self Financed R&D is used, but increases sharply in magnitude and significance when Internal R&D outlays are considered (see model 2, 3 and 4 in Tables 2 and 3). These results, pertaining to the other measures of R&D activity here used, are consistent with prior hypotheses. Indeed, self-financing of risky activities works as a credible signal used by lenders to separate good from bad borrowers. Furthermore, lenders do not look favourably at large in-house R&D activities on the borrower's side as they entail a greater proportion of intangible assets and provide a stronger incentive to resort to secrecy, thereby exacerbating the informational asymmetry between the parties. The results for Self-Financed and Internal R&D activity indicate the need, when investigating the factors leading to credit constraint in innovative firms, to differentiate between different types of R&D strategies, as total R&D may not reflect accurately the nature of the problems responsible for credit constraint. Indeed, a firm spending its entire R&D budget in extramural activities is unlikely to exhibit those characteristics that may lead to the failure of the lender-borrower relationship.

+++++++++++Table 4 here=========

More importantly, our estimates in Table 3 and 4 indicate that no significant relationship seems to emerge between High-R&D activity, captured by the R&D expenditures in the Top decile, and the probability to be credit constrained. That is, the typical hypothesis linking credit rationing and High-R&D firm is not supported by our data, even when we study this relationship within the sample of firms wishing more credit. Taken together, the two differing results concerning Low- and High-R&D groups suggest the possibility of an inverse U-shaped relationship between R&D investment and the probability to be credit constrained: the latter increases until R&D investment reaches a level beyond which the lenders begin to consider the investing firms more favourably. This may reflect the fact that high levels of R&D activity is

[12] Such a result thus partly reconciles our study with the findings in Guiso (1998).

likely to be accompanied by positive reputation effects due to the number of successful innovative projects completed in the past.

We now briefly comment on the estimates of the other explanatory variables. EBIT and Inventories have opposite impacts on MORECRED: profitability reduces the need of external finances while these may be requested to finance shortages in liquidity when a great proportion of working capital is immobilized in inventories. Neither of these regressors is significant in the DENIED equation, although EBIT has a large and significant marginal effect (Table 4). Conversely, Net Hiring - in models 2 and 4 of Table 3- reduces the probability of rejection, but it does not significantly increase the need of extra credit. Because a firm's decision to hire is forward looking, given the associated adjustment costs, banks seem to consider an increase in the number of employees as "good news" because it signals about a firm' s future profitability (Guiso, 1998).

The impact of Debt is particularly interesting, especially if compared with the simple Probit model. Guiso (1998) reports a positive and significant coefficient for this variable, i.e., debt has a very significant effect on the probability of being liquidity-constrained. Our results reveal that short term debt has a very significant positive effect on the need for additional credit - maybe because firms want funds to service existing debts - but not on a bank's decision to deny credit. However, both studies are reconciled when we look at the marginal effects of Short Term Debt on the probability of being liquidity-constrained (Table 4), although this study shows that the effect of this variable is mediated by its impact on MORECREDIT.

Firms located in the North-Centre Italy are less likely to need extra funds, but when they do, the probability of being denied credit is significantly higher than that of firms in other areas. This is consistent with banks in the North-Centre being more skilled at screening (Guiso, 1998). Firm size is not significant in the lending decision, while it has a negative impact on the probability of requiring additional funds, suggesting that small firms find it more difficult to access the credit market (Hall, 2002). The hypothesis that an ISO9000 quality certification should reduce the probability of rejection is also partly supported by the data. A firm owned by a bank is less likely to need extra credit; the opposite result holds for exporting firms. Having access to equity-based forms of financing does not seem to affect significantly both the decision to apply for credit or to reject an application.

Furthermore, we find a positive relationship between concentration of insider ownership and the likelihood to apply for more funds, although we should also expect such a concentration to be a major reason for denying credit. However, this regressor was highly insignificant in the DENIED equation, and was then dropped without affecting the other estimates.[13] Finally, as expected, our measure of non-debt Tax Shield reduces the probability of applying for more credit.

[13] These are available on request.

4. Conclusions

While the reasons why financing constraints may be more widespread in the High-Tech sector have been extensively discussed in the literature (Carpenter and Petersen, 2002; Hall, 2002), very few articles have attempted to investigate such an issue from an empirical viewpoint (Berkowitz and White, 2004; Carpenter and Petersen, 2002; Guiso, 1998; Himmelberg and Petersen, 1994). This paper uses an extensive dataset of Italian manufacturing firms to investigate the factors affecting a firm's probability of being credit-constrained, after controlling for the determinants of its antecedent decision to request additional credit. An important methodological contribution of this paper is to emphasize the relevance of such a sample selection issue that has been largely overlooked in previous studies on the relationship between innovative activity and credit constraints. Econometric tests support the methodological approach adopted in this study.

As far as its empirical findings are concerned, the Low-R&D firms are less likely to request extra funds but when they do, we observe a higher probability of their application being rejected. Conversely, firms with high levels of R&D expenditures do not seem to be evaluated unfavourably by lenders. Thus, our findings lend support to the arguments of credit constraints being particularly severe only for non R&D-intensive firms, that is, those that in our sample invest less than 4.6% of their total asset in R&D activities, but rather negligible for High-R&D firms. These combined results suggest an inverse-U shaped relationship between R&D activity and the probability to be liquidity-constrained. Overall, such a probability is somewhat reduced when firms have a high proportion of Self-Financed R&D investments and/or when a significant amount of their R&D budget is spent in extramural activities. Thus, our findings reveal that total R&D expenditures may not accurately reflect the nature of the problems leading to potential credit market failure, and that a more diverse set of measures of R&D activities, such as Self-Financed and Internal R&D, should be used to shed more light on the presence of credit constraints in innovative firms.

References

Arrow, Kenneth J., (1962), Economic Welfare and the Allocation of Resources for Invention, in R.R. Nelson (ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton University Press, 609-625.

Atzeni, Gianfranco E., and Oliviero A. Carboni, (2004), ICT productivity and human capital: the Italian North-South duality, *International Review of Economics and Business*, 51, 265-284.

Bagella, Michele, Luigi Becchetti, and Antonio Caggese, (2000), Financial constraints on investment: A three-pillar approach, *Research in Economics*, 55, 219-254.

Bayona, Cristina, Teresa García-Marco, and Emilio Huerta, (2001), Firms' motivations for cooperative R&D: an empirical analysis of Spanish firms, *Research Policy,* 30, 1289-1307.

Bhattacharya, Sudipto and Jay R. Ritter, (1985), Innovation and Communication: Signalling with Partial Disclosure, *Review of Economic Studies*, L, 331-46.

Berkowitz, Jeremy, and Michelle J. White, (2004), Bankruptcy and small firms' access to credit, *Rand Journal of Economics,* 35 (1), 69-84.

Bester, Helmut, (1985), Screening vs Rationing in Credit Markets with Imperfect Information, *American Economic Review*, 75 (4), 850-855.

Blass, Asher A. and Oved Yosha, (2003), Financing R&D in Mature Companies: An Empirical Analysis, *Economics of Innovation and New Technology*, 12(5), 425-447.

Boadway, Robin, and Michael Keen, (2004), Financing New Investments under Asymmetric Information: a General Approach, CIRPÉE Working Paper 04-07.

Bougheas Spiros, Holger Görg and Eric Strobl, (2003), Is R&D financially constrained? Theory and Evidence from Irish Manufacturing, *Review of Industrial Organization,* 22(2), 159-174.

Carpenter, Robert E., and Bruce C. Petersen, (2002), Capital market imperfections, high-tech investment, and new equity financing, *The Economic Journal*, 112, F54-F72.

De Fraja, Gianni and Claudio A. Piga (2004), Strategic Debt in Vertical Relationships: Theory and Evidence", *Research in Economics,* 58 (2), 103-123.

Diamond, Douglas, (1991), Monitoring and Reputation: The Choice between Banks Loans and Directly Placed Debt, *Journal of Political Economy*, 99 (4), 689-721.

Evangelista, Rinaldo, Simona Iammarino, Valeria Mastrostefano and Alberto Silvani (2001), Measuring the regional dimension of innovation. Lessons from the Italian Innovation Survey, *Technovation*, 21, 733-745.

Filatotchev, Igor, Claudio A. Piga, and Natalya Dyomina, (2003), Network positioning and R&D activity: a study of Italian groups, *R&D Management*, 33, 37–48.

Freixas, Xavier, and Jean Rochet, (1997), *Microeconomics of Banking*, Mit Press, Cambridge, MA.

Greene, William H. (1998). Sample Selection in credit-scoring models, *Japan and the World Economy,* 10, 299—316.

Greene, William H. (2003). *Econometric Analysis*. Prentice Hall, Upper Saddle River, NJ, 5th edition.

Guiso, Luigi (1998). High-tech firms and credit rationing. *Journal of Economic Behaviour and Organization,* 35, 39–59.

Hall, Bronwyn H. (2002), The Financing of Research and Development, *Oxford Review of Economic Policy*, 18(1), 35-51.

Heckman, James (1979), Sample Selection Bias as a Specification Error, *Econometrica,* 47:153–161.

Hellmann, Thomas, and Joseph Stiglitz, (2000), Credit and equity rationing in markets with adverse selection, *European Economic Review*, 44, 281-304.

Himmelberg, Charles P., and Bruce C. Petersen, (1994), R&D and Internal Finance: a panel study of small firms in high-tech industries, *Review of Economics and Statistics,* 76, 38-51.

Jensen, Michael C., and William H. Meckling, (1976), Theory of the firm: Managerial Behaviour, Agency Costs and Ownership Structure, *Journal of Financial Economics*, 3, 305-360.

Jensen Richard, and Dean Showalter (2004), Strategic Debt and patent races, *International Journal of Industrial Organization*, 22, 887-915.

Leland, Hayne E., and David H. Pyle, (1977), Information Asymmetries, Financial Structure and Financial Intermediaries, *Journal of Finance*, 32, 371-387.

de Meza, David, and David Webb (1987), Too Much Investment: A Problem of Asymmetric Information, *Quarterly Journal of Economics* 102, 281–92.

de Meza, David, and David Webb, (2000), Does credit rationing imply insufficient lending?, *Journal of Public Economics*, 78, 215-234.

Močnik, Dijana, (2001), Asset specificit and a firm's borrowing ability: an empirical analysis of manufacturing firms, *Journal of Economics Behavior and Organization,* 45, 69:81.

Pavitt, Keith (1984). Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory, *Research Policy,* 3, 343-373

Piga, Claudio A. (2002), Debt and Firms' Relationship: the Italian Evidence, *Review of Industrial Organization,* 20, 267—282.

Piga, Claudio A., and Marco Vivarelli, (2003), Sample Selection in estimating the determinants of cooperative R&D, *Applied Economics Letters,* 10, 243-246.

Piga, Claudio A., and Marco Vivarelli, (2004), Internal and External R&D: a Sample Selection Approach, *Oxford Bulletin of Economics and Statistics,* 66(4), 457-482.

Showalter, Dean M. (1999), Strategic Debt: Evidence in Manufacturing, *International Journal of Industrial Organization*, 17, 319-333.

Stiglitz, Joseph, and Andrew Weiss (1981), Credit Rationing in Markets with Imperfect Information, *American Economic Review*, 71, 393–410.

Tether, Bruce, (2002), Who cooperates for innovation and why – An empirical analysis. *Research Policy*, 31, 947-967.

Veugelers, Reinhilde and Bruno Cassiman, (1999), Make and Buy in innovation strategies: evidence from Belgian manufacturing firms, *Research Policy,* 28, 63-80.

Table 1 – Dependent variables and regressors

	1	2	3	4	5	6	7	8	9	10
1	Description : Dependent Variables	Mean N=3144	Min N=3144	Max N=3144	R&D=0 N=2225	R&D>0 N=919	"R&D: first 9 deciles" group N=3052	"R&D: Top decile" group N=92	North-Centre Italy N=2626	South Italy N=518
2	MORECREDIT dummy=1 if firm wanted more credit or was willing to pay a higher interest rate in 1997	0.140	0	1	0.141	0.139	0.138	0.207	0.118	0.255
3	DENIED dummy=1 if firm applied for credit but it has been denied in 1997	0.031	0	1	0.028	0.036	0.030	0.033	0.0247	0.060
4					Expected sign on		Mean Values			
5	Regressors				DENIED	MORE-CREDIT	MORECRED No (N=2702)	 Yes (N=442)	DENIED (if MORECRED=1) No (N=346)	 Yes (N=96)
6	EBIT on total assets (mean 1995-96)	0.088	-0.089	0.685	-	-	0.091	0.072	0.078	0.053
7	Inventories on current assets (mean 1995-96)	0.267	0.000	0.719	-	+	0.261	0.305	0.300	0.324
8	Net Hirings over total employees (mean 1995-96)	0.020	-0.197	0.505	-	+	0.020	0.023	0.026	0.013
9	R&D on total assets (mean 1995-96)	0.0057	0.000	0.398	+	+/-	0.0057	0.0054	0.0055	0.0050
10	R&D on total assets (mean 1995-96): first 9 deciles	0.0031	0.000	0.046	+	+/-	0.0032	0.0023	0.0022	0.0029
11	R&D on total assets (mean 1995-96): Top decile	0.0025	0.000	0.398	+	+/-	0.0024	0.0030	0.0033	0.0021
12	Self Financed R&D on total assets (mean 1995-96): first 9 deciles	0.0026	0.000	0.044	+	+/-	0.0027	0.0017	0.0017	0.0018
13	Self Financed R&D on total assets (mean 1995-96): Top decile	0.0017	0.000	0.233	+	+/-	0.0016	0.0020	0.0023	0.0012
14	Internal R&D outlays on total assets (mean 1995-96): first 9 deciles	0.0025	0.000	0.046	+	+/-	0.0026	0.0017	0.0015	0.0023
15	Internal R&D outlays on total assets (mean 1995-96): Top decile	0.002	0.000	0.233	+	+/-	0.0020	0.0021	0.0024	0.0010
16	Short term debt on total assets (mean 1995-96)	0.145	0.000	0.597	+	+	0.141	0.169	0.158	0.210
17	Dummy=1 if Access to equity-based forms of financing	0.039	0	1	-	-	0.039	0.043	0.035	0.073
18	Dummy=1 if a firm is owned by a Bank	0.052	0.000	1.000		-	0.056	0.032	0.032	0.031
19	Dummy=1 if firm has Exported	0.73	0.000	1.000		+	0.731	0.717	0.711	0.740
20	Herfindhal index of insider ownership	59.50	0.000	100.00		+	59.34	60.47	60.02	62.13
21	Dummy=1 if firm has obtained ISO 9000 certification	0.302	0.000	1.000	-		0.307	0.274	0.301	0.177
22	Dummy=1 if firms is located in the North-Centre of Italy	0.830	0.000	1.000	+/-	+/-	0.857	0.701	0.708	0.677
23	Tax Shield (mean 1995-96): Depreciation of tangible assets over total assets	0.119	0.000	0.396		-	0.121	0.104	0.108	0.091
24	Nat. Log of total Sales (mean 1995-96)	9.500	6.577	14.815	+/-	-	9.54	9.26	9.28	9.19

Table 2 – Percentile values of “R&D expenditures over total assets” by Pavitt industry classification.

	Full sample				R&D>0			
	75centile	90centile	99centile	N	75centile	90centile	99centile	N
Traditional	0	0.0093	0.048	1327	0.0185	0.0319	0.110	300
Scale intensive	0.002	0.0144	0.074	821	0.0201	0.0424	0.094	232
Specialized Suppliers	0.007	0.0233	0.106	847	0.0247	0.0518	0.1258	318
Science-Based	0.018	0.043	0.233	149	0.0415	0.106	0.3626	69
Total	0.0025	0.016	0.086	3144	0.022	0.046	0.1258	919

Table 3 – Bivariate Probit with Sample Selection estimation results†.

	Model 1		Model 2		Model 3		Model 4	
	DENIED N=442	MORECRED N=3144	DENIED N=442	MORECRED N=3144	DENIED N=442	MORECRED N=3144	DENIED N=442	MORECRED N=3144
Total R&D on total assets	.845	.513						
	(.28)	(.36)						
Total R&D on total assets: first 9 deciles			16.09	-5.62				
			(1.93)[a]	(1.32)				
Total R&D on total assets: Top decile			-1.45	1.24				
			(.44)	(.88)				
Self Financed R&D on total assets: first 9 deciles					15.08	-9.39		
					(1.68)[a]	(1.82)[a]		
Self Financed R&D on total assets: Top decile					-2.99	2.01		
					(.61)	(.93)		
Internal R&D outlays on total assets: first 9 deciles							24.8	-9.58
							(2.48)[b]	(1.88)[a]
Internal R&D outlays on total assets: Top decile							-2.45	.816
							(.47)	(.42)
EBIT on total assets	-2.38	-1.409	-2.41	-1.41	-2.38	-1.41	-2.44	-1.41
	(1.42)	(3.17)[c]	(1.42)	(3.18)[c]	(1.41)	(3.2)[c]	(1.45)	(3.18)[c]
Inventories on current assets	-.412	.733	-.400	.734	-.40	.734	-.404	.737
	(1.14)	(4.04)[c]	(1.07)	(4.1)[c]	(1.07)	(4.1)[c]	(1.08)	(4.1)[c]
Net hirings over total employees	-1.05	.530	-1.11	.537	-1.07	.535	-1.13	.550
	(1.57)	(1.27)	(1.65)[a]	(1.28)	(1.59)	(1.27)	(1.65)[a]	(1.31)
Short term debt on total assets	.412	.734	.446	.724	.436	.721	.455	.723
	(.73)	(3.74)[c]	(.79)	(3.7)c	(.77)	(3.66)[c]	(.81)	(3.68)[c]
North-Centre Italy (0,1)	.343	-.503	.329	-.500	.337	-.499	.328	-.498
	(2.42)[b]	(7.07)[c]	(2.25)[b]	(7.0)[c]	(2.38)[b]	(7.0)[c]	(2.27)[b]	(7.0)[c]
Log Sales	.024	-.156	.012	-.150	.016	-.15	.006	-.148
	(.32)	(5.78)[c]	(0.16)	(5.5)[c]	(.21)	(5.5)[c]	(.1)	(5.43)[c]
Access to other forms of financing (0,1)	.289	.031	.274	.037	.279	.037	.278	.037
	(1.16)	(.22)	(1.08)	(.26)	(1.11)	(.27)	(1.10)	(.26)
ISO 9000 (0,1)	-.262		-.292		-.276		-.296	
	(1.89)[a]		(1.97)[b]		(1.96)[b]		(2.02)[b]	
Owned by a bank (0,1)		-.251		-.251		-.252		-.250
		(1.84)[a]		(1.84)[a]		(1.83)[a]		(1.84)[a]
Export (0,1)		.099		.104		.106		.11
		(1.67)[a]		(1.69)[a]		(1.72)[a]		(1.73)[a]
Herfindhal index of insider ownership		.002		.002		.002		.002
		(2.82)[c]		(2.85)		(2.88)c		(2.90)[c]
Tax shield		-.87		-.867		-.861		-.847
		(2.16)[b]		(2.14)[b]		(2.13)[b]		(2.09)[c]
Constant	.48	.45	.558	.405	.528	.398	.60	.382
	(.95)	(1.81)[a]	(1.09)	(1.61)	(1.05)	(1.59)	(1.17)	(1.52)
Hausman Test[d]	$\chi^2(10)=$ 45.9[c]	$\chi^2(13)=$ 3.50	$\chi^2(11)=$ 46.8[c]	$\chi^2(14)=$ 4.1	$\chi^2(11)=$ 45.7[c]	$\chi^2(14)=$ 4.26	$\chi^2(11)=$ 46.6[c]	$\chi^2(14)=$ 4.9
Equations' residuals correlation ρ	-.818[b]		-.813[b]		-.815[b]		-.809[b]	

†Robust z-statistics in parentheses. [a,b,c:] Significant at the 10%, 5% and 1% level, respectively.

[d] Test of significance of the outcome equation of DENIED relative to the same model estimated using a standard Probit technique.

Table 4 - Marginal effects *(dY/dX)*, with *Y=Pr(DENIED=1|MORECREDIT=1),* from the Bivariate Probit models in Table 3, calculated at the regressors' mean values†.

	Model 1		Model 2		Model 3		Model 4	
Total R&D on total assets	.445	(.47)						
Total R&D on total assets: first 9 deciles			4.39	(1.75)[a]				
Total R&D on total assets: top decile			-.204	(.18)				
Self Financed R&D on total assets: first 9 deciles					3.03	(1.09)		
Self Financed R&D on total assets: Top decile					-.57	(.34)		
Internal R&D outlays on total assets: first 9 deciles							6.54	(2.22)[b]
Internal R&D outlays on total assets: Top decile							-.68	(.39)
EBIT on total assets	-1.24	(3.69)[c]	-1.24	(3.68)[c]	-1.243	(3.67)[c]	-1.25	(3.68)[c]
Inventories on current assets	.042	(.43)	.045	(.45)	.047	(.47)	.043	(.43)
Net hirings over total employees	-.246	(1.14)	-.265	(1.21)	-.253	(1.16)	-.271	(1.22)
Short term debt on total assets	.344	(3.15)[c]	.35	(3.15)[c]	.349	(3.15)[c]	.352	(3.16)[c]
North Centre Italy (0,1)	-.005	(.14)	-.008	(.23)	-.005	(.15)	-.007	(.20)
Log Sales	-.032	(1.70)[a]	-.035	(1.81)[a]	-.034	(1.75)[a]	-.036	(1.86)[a]
Access to other forms of financing (0,1)	-.139	(1.34)	.132	(1.26)	.136	(1.31)	.133	(1.27)
ISO 9000 (0,1)	-.089	(2.61)[c]	-.097	(2.82)[c]	-.092	(2.67)[c]	-.098	(2.84)[c]
Owned by a bank (0,1)	-.06	(1.56)	-.058	(1.53)	-.06	(1.58)	-.06	(1.52)
Export (0,1)	.025	(1.1)	.027	(1.1)	.027	(1.12)	.027	(1.14)
Herfindhal index of insider ownership	.001	(1.54)	.001	(1.52)	.001	(1.53)	.001	(1.51)
Tax shield	-.230	(1.50)	-.225	(1.5)	-.226	(1.52)	-.219	(1.54)

†Robust z-statistics in parentheses. [a,b,c:] Significant at the 10%, 5% and 1% level, respectively.