R&D and Credit Rationing in SMEs*

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Abstract

We study the effects of credit rationing on Research and Development (R&D) investment using survey and accounting data on a large representative sample of manufacturing small and medium size enterprises (SMEs). Our econometric model accounts for the endogeneity of our credit rationing indicator and employs an innovative theory based identification strategy. We find that credit rationing has a significantly negative effect on both the probability to set up R&D activities and on the level of R&D spending (conditioned on the R&D decision), but the overall estimated reduction in R&D spending is largely to be associated with the first effect.

Keywords: R&D, credit rationing, Whited and Wu index, bivariate probit, IV Tobit

JEL codes: G21, D82, O32, C35

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1. Introduction

Long-run economic growth and welfare resides on the production of new knowledge and its implementation into new or improved products or processes. For this reason, identification, evaluation and correction of the detrimental effects of potential under-investment in R&D activities have a prominent place in the policy agendas of all industrialized countries. This is particularly the case in Europe where, since the start of the recent economic crisis, the policy debate has been focussed on the role of capital market imperfections, as they increase the cost of R&D when firms do not have sufficient internal funds to finance it. The *credit crunch*, i.e. the lack of availability (or reduction in supply) of credit to businesses from traditional financial institutions, is said to reduce firms' investment in innovative activities and growth prospects. However, despite its theoretical appeal and in contrast with the proven sensitivity of fixed capital investment to financing constraints, evidence on the susceptibility of R&D investment to financial frictions and, in particular, to credit rationing is still mixed and inconclusive.

Three explanations have been put forward for the lack of robust evidence. First, it is claimed that the variety in the results reflects the contrast between theoretical explanations based on asymmetric information arguments (suggesting a sensitivity of R&D to financing constraints potentially higher than that of ordinary investment) and the characteristics of R&D as a long term investment with high adjustment costs (suggesting rather the opposite[1]). Second, existing evidence is based almost exclusively on the sensitivity of firm-level R&D spending to the availability of internal finance (typically measured through cash flow), which is however known to be problematic in its ability to proxy for financing constraints (Kaplan and Zingales, 1997 and 2000). Third, recent contributions have stressed the difficulty in identifying the role financing constraint using standard investment models when firms have access to multiple channels for raising external financial resources and managing buffer stocks of liquidity (Brown et al., 2011).

[1] See, for instance, Hall and Lerner (2010).

In this study, we measure the detrimental effect of credit rationing on R&D investment dealing with all the above specified issues . First, we claim that the ambiguity originated by information problems vs. the nature of R&D as a long term investment might be resolved if we distinguish between the probability of R&D investment (the *R&D participation decision*) and the size of R&D investment, once the decision to invest has been taken (*the amount of R&D spending decision*). We therefore study the effect of credit rationing on the decision to do R&D and on the amount of R&D investment: our hypothesis is that credit rationing displays a stronger effect on the first decision compared to the latter. While this expectation might seem obvious, to our knowledge econometric analyses on the topic have not yet addressed or proven the differential impact of credit rationing on the participation and amount decisions, respectively.

Second, we avoid indirect identification of credit rationing through internal liquidity and exploit direct qualitative information on limits to credit availability to obtain an indicator of credit rationing and allow it to be endogenously determined. Our identification strategy is grounded in the theoretical models by Stiglitz and Weiss (1981) and Bester (1985) and innovatively employs the Whited and Wu (2006) index (WW) – a recently established indicator of need of external finance – amongst the set of instruments for our direct indicator of credit rationing, along with collateral and a proxy for local banking development. We then employ recent econometric methods developed by Conley et al (2011) to deal with concerns on the instruments' exogeneity.

Third, our sample of Italian SMEs provides an ideal testing ground for studying the relationship between credit rationing and R&D investment since it significantly reduces the effects of confounding factors, primarily the availability of alternative sources of external finance. Pecking order theory (Myers and Majluf, 1984) predicts that firms would first prefer debt finance such as bank loans to equity financing when internal financial resources appear to be insufficient. However, the alternative approach emphasizing control rights (Aghion and Bolton, 1992) suggests rather the opposite. Identifying the effect of credit restrictions on R&D investment would thus require controlling for firm's equity financing availability and preferences over alternative sources of external finance. SMEs in Italy represent a good setting for our study since not only equity issues are rare events for such firms (which are mostly unlisted and often family led firms). Also, they traditionally and heavily rely on bank financing as stock markets and venture capital are significantly less developed in Italy compared to the United States.[2]

Finally, it should be emphasized that focussing on SMEs is worth doing for further several reasons. First, SMEs account for a large share of enterprises in most countries, constituting, on average, over 60% of total employment in manufacturing and even more so in countries like Italy, where their share of total employment is 80% (Ayyagari et al, 2007). Second, theoretical reasoning suggests that SMEs are likely to face higher costs of external finance and to be more constrained in their R&D investment decisions. Well established economic theory indeed predicts that, with fixed transaction costs and information asymmetries, SMEs will face higher costs of external financing because they typically demand smaller loans, they are less transparent and have less collateral to offer. These costs are supposedly higher for firms that are both small and young. Young firms may indeed face different conditions than established firms, which make them more likely to be credit constrained (e.g. low internal finance through cumulated past profits, high default risk, no long-term established relationship with local banks, etc.). However, such firms may also have a pivotal role in bringing radically new innovations to the market and in promoting growth. Therefore, it is important to assess the relevance of credit rationing on the R&D investment decision also for this particular group of firms.

Our data on R&D investment and credit constraints are from the fifth wave (2001-2003) of the Capitalia survey on a large number of firms in Italy. These data have been previously employed by other studies on related issues (see, for example, Angelini and Generale, 2008; Benfratello et al.,

[2] In 1999, for example, the stock market had a capitalization of 66.1% relative to GDP, compared with 180.8% in the United States (Herrera and Minetti, 2007). The capitalization of the stock exchange Nuovo Mercato for high-growth firms relative to the GDP was 0.64% in June 2002, versus 20.54% of Nasdaq (Federation of European Stock Exchanges Statistics Database, 2002). In 2000, the ratio of venture capital investment to GDP was 0.26% compared with 1.24% in the United States (European Venture Capital Association, 2002 Yearbook) and there were only 18 business angels and incubators, compared to more than 800 in the United States (see also Herrera and Minetti, 2007).

2008; Becchetti et al, 2009; Herrera and Minetti, 2007; Piga and Atzeni, 2007) and can be easily matched with accounting data.

Our analysis leads to three main results. First, we find that credit rationing significantly reduces both the likelihood to invest in R&D and the amount of resources invested in R&D. Second, the percentage reduction in R&D investment as a consequence of a firm being credit rationed is largely associated with the reduction in the likelihood to do R&D, rather than with a reduced amount of investment, conditioned on the investment decision. Finally, but importantly, we find that firms that are both young and small face additional difficulties in obtaining bank financing – even after controlling for both size and age – and display a higher probability of being credit rationed, ceteris paribus. This fully explains their reduced propensity and intensity of R&D investment, as we find no other direct effect associated with their young-small status. Our results thus confirm that that the emphasis attributed by European policy makers to the role of these companies in meeting the Barcelona target[3] is not ill posed and that appropriate policy measures should be directed towards alleviating their credit constraints in order to increase their R&D investment.

The paper is organized as follows. Section 2 reviews the main economic issues and empirical contributions on financing constraints and R&D investment. Section 3 describes the data and survey information used in the empirical analysis. Section 4 presents our theoretical and econometric model and discusses our instrumental variable strategy. Section 5 reports and comments the estimation results. Section 6 concludes.

2. Related literature

Over the past decades, a number of studies have extended conventional models of business fixed investment to explicitly incorporate and account for the influence of financing constraints, once

[3] The Barcelona European Council of 15-16 March 2002 announced targets for rasing R&D investment from 1.9% at that time, to close to 3% of GDP by 2010. The Council also stipulated that the private sector should provide two-thirds of the additional R&D investment. The 3% target was not met by 2010 in spite of a substantial increase of the overall EU R&D expenditure (+25% in real terms from 2000 to 2008) and progress achieved in a majority of Member States. Recognising that Europe's future growth relies to a large extent on research and innovation, the European Council reaffirmed in March 2010 that the overall R&D investment level should be increased to 3% of EU GDP as part of improving the conditions for research and development.

neglected in the neoclassical theory of investment. Theoretical models, departing from the conventional neoclassical assumptions, have provided foundations for the imperfect substitutability between external and internal funds and have thus justified the influence of financial factors on firm's investment decisions. These models have illustrated the effects of informational asymmetries on investment in a moral hazard or adverse selection setting, where private information on project risk or quality induce a substantial difference between the cost of new debt and equity and the opportunity cost of using internal finance generated through cash flow and retained earnings (e.g. Stiglitz and Weiss, 1981; Myers and Majluf, 1984). Hence information costs and the availability of internal resources influence the firm's shadow cost of external funds for fixed investment, holding underlying investment opportunities constant.

Recent studies have argued that R&D investment might be even more sensitive to financial factors than other types of investment.[4] This is because outsiders may find it more difficult to make accurate appraisals of the value and risk of investment in intangible assets and in innovation-based physical investment. In addition, even if firms could costlessly transmit information to outsiders, strategic considerations may induce them to actively maintain information asymmetries, so to avoid the leaking of information to rivals, which would reduce the prospective value of innovation. Finally, it has also been noted that adverse incentive and selection problems are compounded by the absence of collateral value for investments like R&D (Himmelberg and Petersen, 1994).

Although plausible, a high sensitivity of R&D investment to credit rationing and, more generally, financing constraints might not be observed. This might be the consequence of two key features of R&D investment: (i) establishing an R&D program involves significant sunk costs and (ii) large fluctuations in the level of spending in existing research programs are very costly, as a consequence of the expenditures in R&D being predominantly payments to highly trained scientists, engineers and other specialists. These workers are not perfectly elastic in supply: firing and hiring them in accordance with temporary changes in business conditions would be extremely costly because they require a great deal of firm-specific knowledge, because training new workers is expensive, and

[4] See Hall (2002) and Hall and Lerner (2010) for extended reviews.

because fired specialists are able to transmit valuable knowledge to competitors who hire them (Hall, 1992).

The existence of high adjustment costs for R&D might then imply that firms set the level of R&D investment in accordance with the permanent level of internal finance, so to minimize both current and future adjustment costs. Thus R&D should be relatively unresponsive to transitory movements in internal funds and credit rationing should then mostly affect the decision to set up R&D facilities (*the R&D participation decision*), rather than the decision about yearly level of spending in existing research programs (*the amount of R&D spending decision*).[5]

All the considerations presented above might prove to be particularly relevant for SMEs. These firms are indeed less transparent, have higher relative transaction costs and fewer assets that can be used as collateral. This should be even more the case for firms that are small *and* young, as they add to the above mentioned difficulties further ones as low cumulated past profits, no long-term established relationships with local banks and high default risk. As a consequence, small and young firms are more likely to be credit rationed, ceteris paribus.

Theoretical predictions on the role of size on financing constraints and investment have been confirmed by recent empirical evidence, suggesting that financing constraints in general are more severe for small-sized firms (Harhoff and Körting, 1998; Beck and Demirguc-Kunt, 2006; Benfratello et al., 2008; Czarnitzki, 2006; Czarnitzki and Hottenrott, 2011) and that smaller firms are more likely to face difficulties in conducting R&D and innovations projects because of lack of funding (see, for example, Himmelberg and Petersen, 1994; Hyytinen and Toivanen, 2005). Little evidence is instead available for young firms (Cincera, 2002; Savignac, 2008; Schneider and Veugelers, 2010).

The use of indirect measures of financing constraints has represented the prevailing methodology in the empirical literature on financing constraints and investment. The literature has suggested many possibilities, including investment–cash flow sensitivity (Fazzari et al. 1988), the well-known Kaplan and Zingales (KZ) index of constraints (Kaplan and Zingales, 1997), the more recent Whited and Wu

[5] See Bond et al (2003).

(WW) index of constraints (Whited and Wu, 2006), and a variety of different sorting criteria based on firm characteristics. The investment-cash flow sensitivity methodology relies on the estimation of a standard investment equation using either a neoclassical accelerator model or the Euler equation approach. A variable for the availability of internal finance is then added to the model (usually cash flow) and its significance (and correct sign) should signal the relevance of financing constraints in the firm's investment decisions. Econometric exercises have often relied on finding differential sensitivity to cash flow between sub-samples of firms that are thought of being differentially affected by financing constraints a priori.

This approach has three major drawbacks. First, the allocation of firms to "constrained" and "unconstrained" regimes is often based on outcomes which are at least partially chosen endogenously by firms (e.g. dividend payments, employment size, ...). Second, the results obtained within this line of research have been quite inconclusive.[6] Finally, and most importantly, a major problem exists with using cash flow as a proxy for financing constraints: the interpretation of cash flow is ambiguous because it contains information about expected future profitability, which may be relevant for investment decisions even with perfect capital markets. Hence, the sensitivity of investment to cash flow does not necessarily signal financing constraints (Kaplan and Zingales, 1997 and 2000).

For the reasons above, some recent contributions have exploited the availability of alternative direct indicators of financing constraints, which require appropriate treatment for their endogeneity (Aghion et al., 2010; Savignac, 2008; Hajivassiliou and Savignac, 2011; Tiwari et al., 2007). We also follow this approach, but differently from these studies we focus on a direct indicator of credit rationing, rather than on a broader definition of financing constraints, and we study its effects on

[6] Among the numerous studies, Himmelberg and Petersen (1994) find that internal finance is an important determinant of R&D expenditures. Harhoff (1998) finds strong or no the sensitivity of R&D to cash flow depending on the model specification adopted. Bond, Harhoff and Van Reenen (2003) show that financial constraints are significant in the UK economy while no effect is found for German firms, which can be explained by the institutional differences across the financial systems in the two countries. Cincera (2002) finds a positive impact of cash flow on the firms' investment decisions, although these effects appear to play a considerably more important role for investment in physical capital than for R&D investments. Mulkay, Hall and Mairesse (2001) show that cash flow appears to be more important in the US than in France for any type of investment.

R&D investment by separating its impact on the R&D participation decision and on the conditional R&D spending decision.

3. Data

Our data come from the Capitalia survey on Italian manufacturing firms undertaken in 2004 and covering the period 2001-2003. The sample of the survey is stratified according to industry, geographical location and size class for firms with 11 to 500 employees, while it includes all Italian firms with more than 500 employees. Here we will focus only on small and medium manufacturing enterprises, i.e. firms with less than 250 employees, which account for 90 percent of firms in the original sample, thus confirming their extremely relevant weight in Italy.

Table 1 – Firms' distribution by size classes

	Survey manufacturing sample		**Final sample**	
	Frequency	**Percentage**	**Frequency**	**Percentage**
11-20	816	27.28	569	26.54
21-50	1,057	35.34	775	36.15
51-250	1,118	37.38	800	37.31
Total	2,991	100.00	2,144	100.00

Table 2 - Firms' distribution by industry

	Survey manufacturing sample		**Final sample**	
	Frequency	**Percentage**	**Frequency**	**Percentage**
Food/Tobacco	334	11.17	246	11.47
Textiles	462	15.45	359	16.74
Wood/Paper/Print	259	8.66	188	8.77
Chemicals/Coke	156	5.22	113	5.27
Plastic/Rubber	160	5.35	97	4.52
Glass/Ceramics	181	6.05	138	6.44
Metals	565	18.89	381	17.77
Machinery	392	13.11	276	12.87
Electrical/Medicals	214	7.15	140	6.53
Veichles	59	1.97	42	1.96
Furnitures	209	6.99	164	7.65
Total	2,991	100	2144	100

The survey data is coupled with complete financial accounting data from AIDA[7] for each fiscal year from 2001 to 2003. Balance sheet data are not available for all the firms in the survey, hence our final sample of 2,144 SMEs[8] is smaller than the manufacturing sample of 2,991 SMEs firms included in the original Capitalia survey. Reducing the sample does not significantly alter the firms' distribution by size classes, industry and geographical location, as shown in Tables 1 to 3.

Table 3 - Firms' distribution by geographical area

	Survey manufacturing sample		**Final sample**	
	Frequency	**Percentage**	**Frequency**	**Percentage**
North-West	1,072	35.84	728	33.96
North-East	930	31.09	690	32.18
Centre	547	18.29	408	19.03
South	440	14.71	318	14.83
No response	2	0.07	-	-
Total	2,991	100	2,144	100

In the section on bank-customer relationships and investment financing decisions, the survey includes a question that allows us to directly identify the existence of credit rationing. The question refers to 2003 – i.e. the last year covered by the survey – and asks the respondent to indicate whether the firm desired additional bank financing at the interest rate agreed with the main partner bank. We classify the firm as being subject to credit rationing if the answer to the above question is positive and define our credit rationing indicator accordingly (*rationed* = 1). This indicator has been recently used by Angelini and Generale (2008) to study the effect of financing constraints on firm's growth and provides a direct measure of credit rationing given by the firms themselves.[9]

[7] AIDA is the country based version of AMADEUS for Italy. Data comes from the specialized information provider Honyvem BilancItalia, which purchases and revises balance sheets from the Italian Chambers of Commerce.
[8] These also exclude a few firms with unreliable balance sheet information, a few outliers and firms with missing values for the relevant variables of interest.
[9] Other recent related contributions using the same indicator are Piga and Atzeni (2007) and Becchetti et al. (2009).

Note that, while our indicator does not account for sources of external finance other than bank financing, we claim this does not significantly limit the scope of our analysis with reference to our sample. First of all, based on the result from a survey conducted on over 10,000 firms in more than 80 countries, Beck and Demirguc-Kunt (2006) find that the gap in bank financing of investment for small and medium firms vs. large firms is negative, significant and large, while the difference is much smaller or not significant in other formal sources of financing (equity, lease, supplier credit, development finance). Second, and most importantly, it should be noted that the financial system in Italy is strongly centred around banks, with other sources of firm financing being much less developed.[10] As a consequence, Italian firms heavily rely on bank financing, as recently shown by Beck et al. (2008). Using survey data from 48 countries and comparing financing patterns across them, the authors find that Italy is the country with the highest proportion of investment financed by banks, with a share equal to 49.67, which accounts for 64% of external finance.[11]

Table 4 - Firms' distribution by credit rationing and innovative status
(row percentage in parenthesis)

		R&D=No	**R&D=Yes**	**Total**
Survey Manufacturing Sample	**rationed=No**	1,537 (65.21)	820 (34.79)	2,357 (100)
	rationed=Yes	267 (64.49)	147 (35.51)	414 (100)
	Total	1,804 (65.10)	967 (34.90)	2,771 (100)
Final Sample	**rationed=No**	1,212 (65.94)	626 (34.06)	1,838 (100)
	rationed=Yes	197 (64.38)	109 (35.62)	306 (100)
	Total	1,409 (65.72)	735 (34.28)	2,144 (100)

[10] In Italy, bank debts account for about 75% of financial debts and while differences in the financial structures of firms located in other EU countries are not significant, those with the US are still large, especially for what concerns the bond market. Furthermore, the share of venture capital investment over GDP in Italy is extremely low, even compared to the European average (see Hall and Lerner, 2010).

[11] The corresponding figure for the US is 21.47 and accounts for about 45% of external financing.

Each firm participating to the survey is asked whether it has pursued any in-house R&D investment and, if so, to report the amount of money spent on such investment.[12] Table 4 reports frequencies of firms with R&D investment in 2003 for both the rationed and not rationed groups and interestingly shows that the relative share of R&D active firms is not significantly different in the two groups. If anything, the probability of doing R&D appears slightly higher in the group of firms subject to credit rationing. As we shall discuss in the next sections, this is suggestive of a key source of endogeneity originating from firms' self selection. Finally, Table 4 once again shows that the reduction in the sample due to balance sheet data availability does not induce any lack of representativeness.

4. Estimation strategy

Our self reported indicator of credit rationing is based on the firm's perceived shortage of bank debt financing with respect to its desired level at the agreed interest rate. As we discuss in Section 5, the main source of endogeneity for this indicator is self-selection driven by unobserved heterogeneity (Imbens and Angrist, 1994; Heckman et al., 2006) which may result in spurious positive correlation with R&D investment. This is mostly due to the presence of a large group of firms with little or no attitute towards innovation, which are consequently unlikely to perceive themselves as rationed.[13] Therefore, in this section we describe our estimation strategy, which is designed to account for the endogeneity of the credit rationing indicator and aimed at identifying its effect on R&D investment. We first present the theoretical framework and then describe the econometric model and the identification strategy. Finally, we discuss our instruments in the last subsection.

4.1 Investment opportunities and credit rationing: Theoretical framework

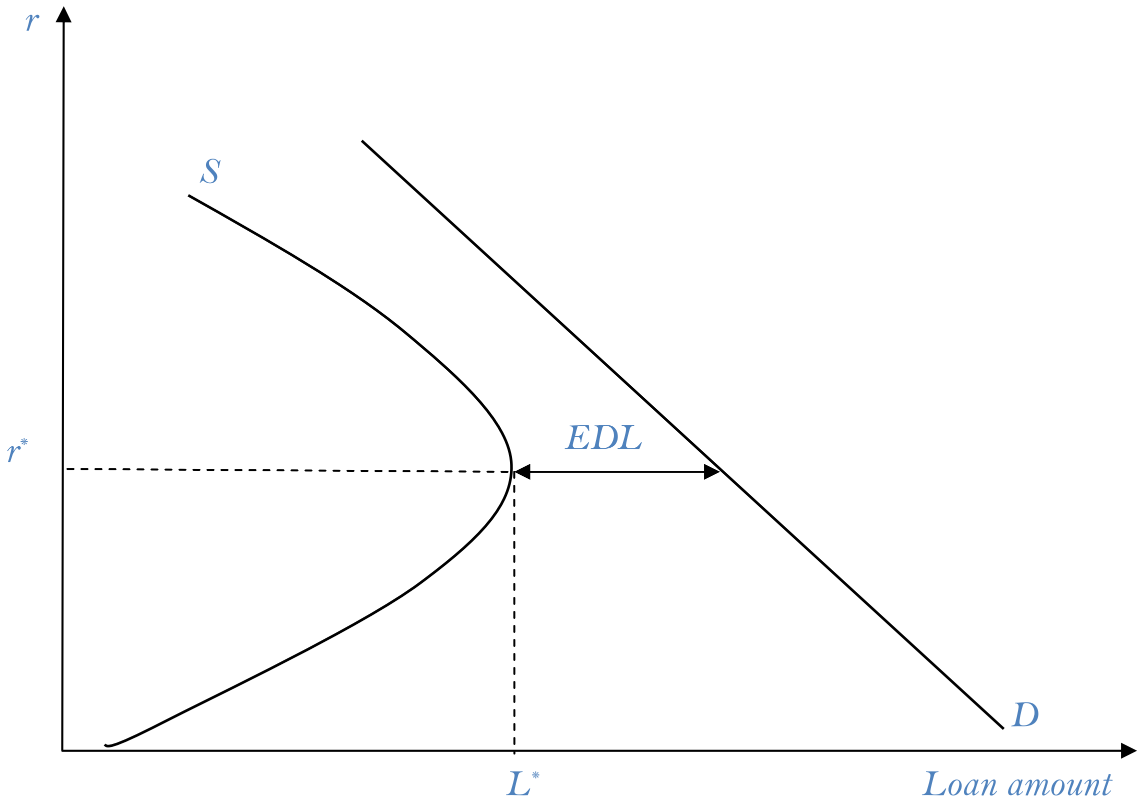
Our empirical strategy builds upon the theoretical models of Stiglitz and Weiss (1981) and Bester

[12] In order to check for consistency and to fill some missing values of the R&D expenditures figures in the Capitalia Survey we used additional information from another survey released yearly by the Italian Institute of Statistics (ISTAT) called "Ricerca e Sviluppo intra-muros (R&S) in Italia". This allowed us to replace 130 missing values in the original Capitalia R&D data.

[13] As shown in Table 4, more than half of our final sample of SMEs declare no R&D expenditures and a "non-rationed" status.

(1985). Stiglitz and Weiss (1981) show that rationing may arise in competitive credit markets because information asymmetries can cause the supply curve for loans to bend backward. The reason for this result is that the lender's expected return is not a monotonic increasing function of the interest rate r if the lender cannot discriminate between low risk (θ_L) and high risk (θ_H) projects ($\theta_H > \theta_L$). Thus a higher interest rate increases the revenues (if the bank gets repaid) on one side, but it also increases the proportion of applicants who are risky on the other side, thus the bank's expected return starts to decrease when the second effect dominates the first one.

Figure 1
Equilibrium credit rationing



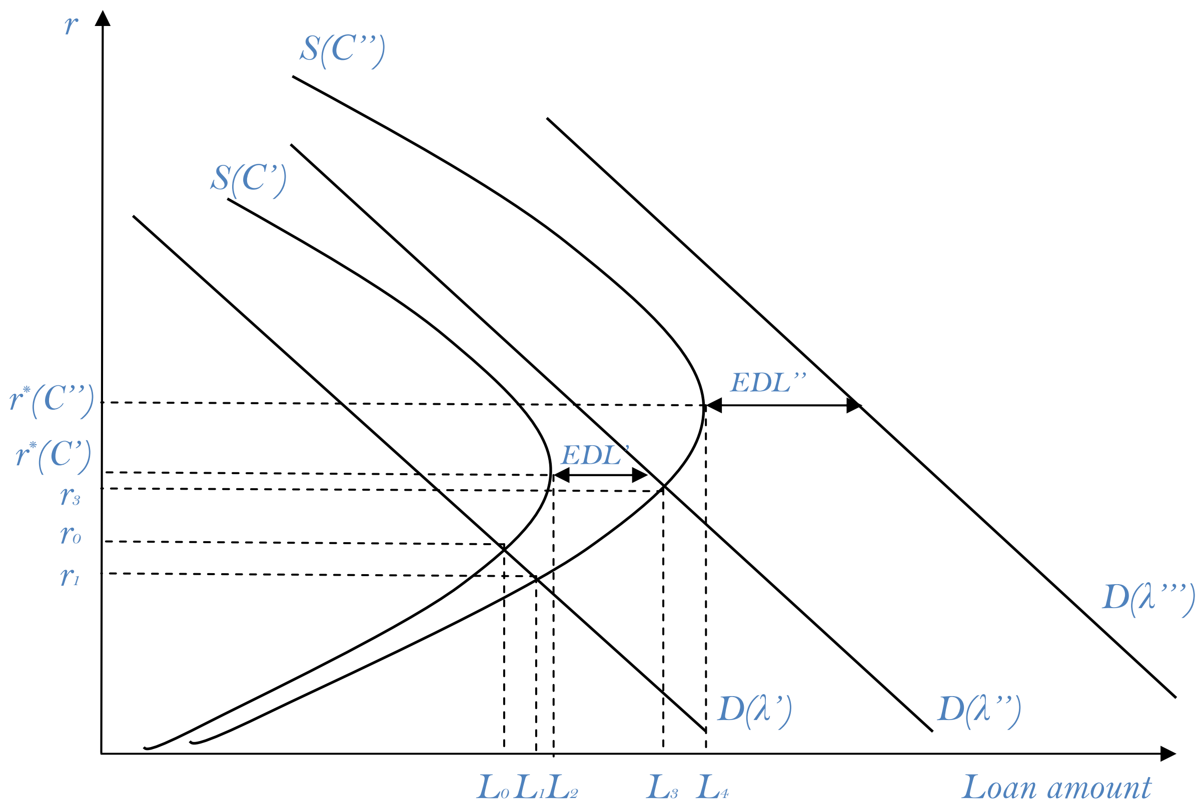
This is the well known problem of adverse selection: the less risky firms drop out of the market as the interest rate rises. The main consequence is that, without any information on borrower's quality, the bank maximizes its expected returns by setting the interest rate at the optimum level *r**, obtained by "averaging" the unobserved parameter θ from its distribution. The interest rate *r** can be lower than the market clearing interest rate that would have been set in the absence of information asymmetries, thus generating equilibrium credit rationing. This is illustrated in Figure 1 for the representative firm: when the demand for funds is sufficiently high, the supply (*S*) and demand (*D*) curves do not intersect, the equilibrium interest rate will be *r** at which there will be excess demand for loans (EDL).

Bester (1985) extended the Stiglitz and Weiss (1981) model and emphasized the role of collateral (*C*) as an instrument that banks can use to discriminate between high-risk and low-risk projects by offering contracts with different combinations of collateral and interest rate. Different contracts can thus serve as a signalling mechanism because borrowers with a low probability of bankruptcy (i.e. borrowers with low-risk projects) are more inclined to accept an increase in collateral requirements for a certain reduction in the interest rate than borrowers with a high probability of failure (i.e. borrowers with high-risk projects). This leads to a separating equilibrium in which contracts with low *r* and high *C* are preferred and chosen by low-risk borrowers while contracts with high *r* and low *C* are instead preferred by high-risk borrowers. The possibility of credit rationing here arises when low-risk entrepreneurs are unable to raise a sufficient amount of collateral to distinguish themselves from high-risk ones. Indeed, low collateral availability might be a particularly relevant cause of rationing for SMEs and, even more so, for small young firms. Hence we expect collateral (*C)* to be a relevant instrument in our setting.

Using this framework, but simplifying matters, assume that the bank offers loan contracts with two different levels of collateral requirements (*C''*>*C'*). A greater collateral requirement translates in a right-ward shift of the loan supply curve Figure 2): a higher level of collateral allows the bank to offer the same amount of loan at a lower interest rate or to offer larger loans at a given interest rate.

Looking at the borrower side, the firm can choose to finance its desired level of investment by either internal resources or external finance. The cost of the use of an additional unit of external finance is given by the interest rate r[14], while the cost of using an additional unit of internal resources is given by the latent shadow cost λ, which is assumed to depend on both the amount of internal liquidity available to the firm and on the expected profitability of alternative investment opportunities. The optimal financing mix for the firm is obtained at the margin when $r = \lambda$. Thus the demand for external finance $D(r, \lambda)$ will be decreasing with r (for a given λ) and increasing with λ (for a given r). This reasoning also justifies the use of (a measure for) λ as a relevant instrument.

Figure 2
The role of collateral (C) and of the opportunity cost of internal resources (λ) as "instruments" for detecting credit rationing



[14] We assume that the only available source of external finance is debt and that there is no pledging cost for collateral C. As we explained in Section 3, the assumption that debt financing is the only source of external finance for SMEs is consistent with our setting.

Figure 2 illustrates the role of both collateral (C) and of the opportunity cost of internal resources (λ) as "instruments" for detecting credit rationing situations. Consider three different representative firms facing three different opportunity cost of internal resources ($\lambda''' > \lambda'' > \lambda'$). The firm facing λ' can choose (according to the riskiness of its investment projects and collateral availability) either a loan of amount L_0 with interest rate r_0 and collateral C' or another one of amount L_1 interest r_1 and collateral C''. In none of these cases this firm will be credit rationed (*rationed* = 0). Firm facing λ'' will not be credit rationed if it can afford a collateral disposal of C'', obtaining a loan amount of L_3 and paying an interest rate of r_3, otherwise it will be able only to borrow L_2 paying an interest of $r^*(C')$. In the latter case the firm will be credit rationed (*rationed* = 1), with a desired extra amount of loan *EDL'* at the given interest rate $r^*(C')$. Finally, the firm facing λ''' can borrow a maximum amount of L_4 by offering a collateral C'' and paying an interest rate $r^*(C'')$. This type of firm with high need for external funds will always be rationed (*rationed* = 1), with a desired amount of unfulfilled loan equal to *EDL''*.

4.2 Econometric model

The model presented in the previous section drives our empirical strategy for estimating the marginal effect of being credit rationed on the decision to invest and on the amount of investment in R&D. In both cases the estimated model can be written as:

$$\begin{cases} y_i = f(\alpha \cdot rationed_i + \beta_1 X_i + u_i) \\ rationed_i = I(\beta_2 X_i + \gamma Z_i + v_i \geq 0) \end{cases} \tag{1}$$

where $Z = [C, \lambda]$, y is either the binary variable representing the decision to invest in R&D or the actual amount invested in R&D and $f(.)$will be specified in the next sections according to the nature of y.

As pointed out by Imbens and Angrist (1994) if the instruments affect the probability of being treated (i.e. being *rationed* in our case) in the same way for all the units (i.e. γ is constant across firms) then α can be interpreted as the average treatment effect (ATE). Otherwise, if the instruments affect differently the probability of being treated for different units (i.e. γ is individual-specific: $\gamma = \gamma_i$) because of some forms of unobserved heterogeneity (Heckman et al. 2006) then the IV estimate of α can be interpreted (with the further assumption of "monotonicity") as the local average treatment effect (LATE). In other words, it only identifies the average effect for the entities that are induced by a change in the instruments to change their *rationed* status (this subpopulation is called the "compliers").

In our case the IV estimates of α can be interpreted as the average effect of being credit rationed on R&D investments for the sub-population of firms for which a change in the amount of collateral or in the latent opportunity cost λ is likely to affect the *rationed* status. In other words, both the "never takers" (i.e. the firms who are likely to report themselves as being not credit rationed - *rationed* = 0 - regardless of their amount of collateral or their λ) and the "always takers" (i.e. those firms who are likely to report themselves as being always credit rationed - *rationed* =1) are excluded from the IV estimate of α. The so-called population of "defiers" is excluded by the monotonicity assumption.

In our framework, where firms can self-select themselves as being credit rationed, we can have some forms of "spurious" positive correlation between *y* and *rationed* due to either the presence of low innovative-oriented firms who are likely to be always not rationed regardless of the values of Z (never takers) or by the presence of some forms of credit-addicted innovative firms who will always report themselves as being rationed regardless of Z (always takers). Thus the IV-LATE estimator may help in solving this puzzle by focusing on the population of compliers only.

The appropriate estimation methods for the model outlined above and employed in the analysis of the R&D decision and of the amount of R&D spending will be briefly discussed in sections 5.2 and 5.3, respectively. We now turn to the presentation of our instruments and, in particular, to the more problematic measurement of the opportunity cost of internal funds, λ.

4.3 Instruments

Using the theoretical model of credit rationing presented in section 4.1, we can assume that, conditional on the set of observable covariates (X), our instruments Z can predict the credit rationing status (*rationed*). We further assume that the instruments are independent of potential outcomes (y), by adopting, for each firm i, the one-year lagged values of the level of collateral (C) and of our measure of the latent opportunity cost of internal resources (λ).

We therefore assume that:

(i) The set of instruments Z is mean independent of the error term u conditional on X, i.e. $E(u_i|X = x, Z = z) = 0, \forall(x, z)$.

(ii) The probability of treatment choice is a non-trivial function of the instrument Z conditional on X, i.e.: $\gamma \neq 0$.

We cannot possibly obtain the *pledged* level of collateral, but we can calculate the *available* level of collateral from balance sheet data as the ratio between net tangible assets and total liabilities. However, available collateral should be a preferred exogenous instrument for credit rationing than pledged collateral, since the latter is more likely to be associated to the unobserved project/borrower's risk (Steijvers and Voordeckers, 2009).

We then need to find a measure for λ and we propose to use the Whited-Wu (2006) index of external financing constraints (WW) for this purpose. The WW index was first introduced by Whited and Wu (2006) as an alternative and improved index of financing constraints to the well-known Kaplan and Zingales (1997) index.[15] It is obtained using structural investment model and estimated as:

[15] This has been recently confirmed by Hadlock and Pierce (2010), who find that the Kaplan and Zingales index is unlikely to be a useful measure of financial constraints, as the coefficients of most of its components flip sign across estimated models and in many cases turn out to be insignificant.

$$WW = -0.091*CF - 0.062*DIVPOS + 0.021*TLTD - 0.044*LNTA + 0.102*ISG - 0.035SG. \qquad (2)$$

CF is the cash flow to total assets ratio, DIVPOS is a dummy equal to one when the firm pays cash dividends, TLTD is the long term debt to total assets ratio, LNTA is the natural log of total assets, ISG is the firm's industry sales growth and SG is the firm sales growth, both calculated with respect to the previous year.

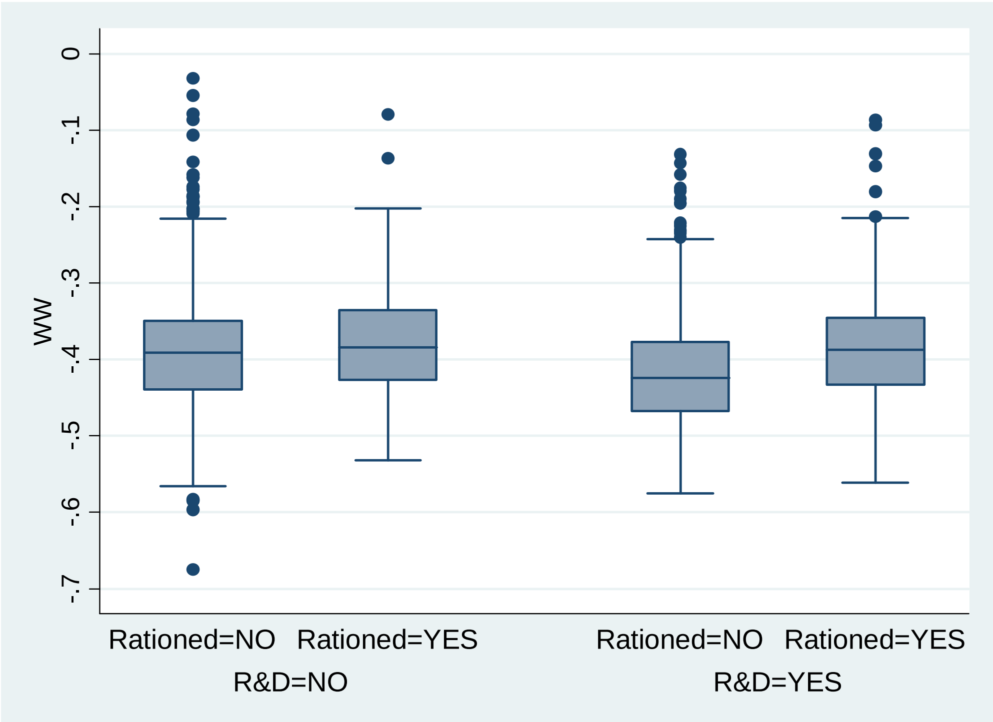
As the components of WW clearly suggest, higher values of the index can be associated to higher need for external capital (Hennessy and Whited, 2007), i.e. a demand function shifted to the right and a consequent higher likelihood of being subject to credit rationing.

Figure 3 shows the distribution of the WW index for 2002 (WW2002) in the final sample amongst *rationed* vs. *not rationed* firms for both firms with and without R&D investment.[16] The difference in the means of the index between rationed and not rationed firms is 0.0108 (statistically significant at the 5% level) for firms not performing R&D and is 0.0346 for firms with positive R&D (statistically significant at the 1% level). Thus a higher need of external financing and, hence, a higher likelihood of being credit rationed, as evidenced by the WW index, does translate in the firm's own perception of being credit rationed, significantly more so for R&D performing firms.

The evidence presented above suggests a positive relationship between our direct indicator of credit rationing and the WW index and thus increases our confidence in using the firm's desire for additional finance to identify firms subject to credit rationing. While this reassures us about the relevance of the potential instrument, there might still be doubts about its actual exogeneity. Indeed, some of the components of the WW index could be correlated to the firm's productivity (and, hence, R&D decision) even if we use predetermined values. We shall extensively deal with this issue in Section 5.3.

[16] In calculating the WW index, we do not observe directly whether a generic firm *i* actually paid cash dividend in a given year *t*, but we retrieve this information by assuming that cash dividends are paid if the firm had positive net profits in year *t* and if the amount of net assets at the end of year *t* is less than the sum of net profits in year *t* plus the amount of net assets in year *t-1*. All other firm level right-hand side variables can be obtained from balance sheet data. Finally, ISG is calculated at the SIC three-digit level from AIDA.

Figure 3
Distribution of the WW index amongst rationed (*rationed*) and R&D performing firms in the final sample



Finally, we employ a further (and arguably more confidently exogenous) instrument that is not accounted for in our theoretical framework, but that is established in the literature (e.g. Herrera and Minetti, 2007): the number of bank branches per 1,000 inhabitants in the province of residence of the firm in 2001 (branches2001). This is a measure of the level of development of local credit markets (Benfratello et al., 2008) and is obtained from the Statistical Bulletin of the Bank of Italy and the 2001 Census of the Italian National Statistics Office (ISTAT). We expect our branch density variable to be negatively related to the likelihood of credit rationing.

We should now emphasise that there might be other potential instruments for the *rationed* variable. In particular, there exist an extensive literature discussing the role of relationship lending in mitigating the information asymmetry between borrower and lender (Petersen and Rajan, 1994;

Boot, 2000; Berger and Udell, 2006). The proximity between borrower and lender allows the bank to better assess the quality of the firm and its investment projects, thus facilitating ex ante screening.

In our survey data we have a widely used measure of the strength of the relationship between borrower and lender: the duration of the relationship with the main bank. An alternative measure of the closeness of the bank-firm relationship in our data is a dummy variable for the participation of a bank into the firm's capital. None of these potential instruments is ever found relevant in our regressions. As a consequence, they will not be included and reported in our preferred specifications described in section 5.[17]

5. Empirical analysis

5.1 Covariates

In our set of covariates *X* we include traditional determinants of R&D investment, starting with firm size, measured as the logarithm of the firm's total number of employees (*logEMP*). As first suggested by Schumpeter (1942), firm size is likely to be a significant determinant of the decision to invest in R&D. One of the reasons is that R&D investment induces sunk costs. Large firms are therefore likely to be less reluctant to engage in R&D activities because they can spread such costs on more units of output (Cohen and Klepper, 1996). In addition, it may be easier for large firms to finance R&D investments as they are more likely to have internal financial resources and they may enjoy better and long established relations with external investors. Among others, Crépon et al. (1998) and also Bond et al. (2003) find a positive significant effect of firm size on the likelihood to undertake R&D.

The impact of market structure and market shares on R&D investment and innovation has also been largely emphasized in the literature, starting, once again, with Schumpeter (1942), who argues that a firm has higher incentives to engage in R&D activities if it enjoys a monopoly position. On the contrary, Arrow (1962) shows that under perfect ex-post appropriation, profit margins are larger in an ex-ante competitive industry. Blundell et al. (1999) also find a positive relationship between firms'

[17] We also choose not to employ the set of instruments used by Herrera and Minetti (2007), which are found weak in our setting. See section 5.3 for further details.

ex ante market share and innovation. We therefore include in our specification the variable *Mktshare*, which is calculated as the firm's share of the industry's turnover in 2002.

We also control for firm's age (*log(age)*) as firms' incentives to conduct R&D and its likelihood of incurring into credit rationing might differ with age. For example, successful R&D will be less valuable, ceteris paribus, for older firms with established products in the market and long-established relationship with banks might lower the cost of debt financing.

We further introduce a dummy variable which is equal to one if the firm is the head of a group (*grouphead*). Groups include both national and international groups and might pursue different R&D strategies, affecting the distribution of their R&D effort within the group: e.g. parent companies might prefer to retain full control of R&D activities and then transfer technology directly to subsidiaries and foreign affiliates. For similar reasons, we include a dummy which takes the value of one if there is foreign participation into firm's capital (*foreign*). Both the *group* and *foreign* dummies might also be expected to affect the likelihood of the firm facing credit rationing. Indeed, group membership accounts for the potentially relevant role of intra-group flows of resources as important option for funding R&D projects and multinational corporations also create an internal capital market, which facilitates their subsidiaries' access to external funds (Schiantarelli and Sembenelli, 2000).

We also introduce a measure of the intensity of investment in physical assets to account for the potential trade-off or complementarity between R&D and physical investments (*INV_EMP*). We also include a measure of firm's debt leverage equal to the ratio between firm's long term debts and firm's equity (*DEBT_EQUITY*). This is meant to account for the idea that a large debt burden can prevent a company from raising the funds to undertake new investment (Myers, 1977; Hart and Moore, 1995).

Finally, we introduce a dummy variable to identify small firms according to the standard European definition (i.e. firms with less than 50 employees), a dummy equal to one if the firm is less than 10 years of age, and their interaction. This set of dummies is meant to capture a potentially different propensity to do R&D by young and small companies. The same set of dummies will then be used to control for the additional difficulties that young and small companies are likely to face in obtaining sufficient bank financing to fund their R&D projects. Small companies are at a disadvantage because they cannot exploit scale economies and have fewer physical assets, and hence collateral, than more capital intensive firms. Young firms are similarly more likely to be financially constrained because they will usually have low cumulated past profits to finance their R&D investment internally, they cannot benefit from long-term established relationships with local banks and typically have high default risk. Firms that are both young and small would face all the difficulties mentioned above.

Table 5 – Variables definition

Variable	**Range**	**Description**
dumRD	dummy(0,1)	=1 if invested in R&D in 2003; 0=otherwise
logRD	continuous	log of firm's R&D expenditures in 2003 when dumRD2003=1.
rationed	dummy(0,1)	=1 if desired additional financing in 2003; 0=otherwise
*log*EMP	continuous	Log. of firm's total Employees in 2002
INV_EMP	continuous	Physical Investments /Total Employees in 2002
Mktshare	continuous	(Firm turnover/Sector turnover[18])*100 in 2002
DEBT_EQUITY	continuous	Long term debts /Firm's equity in 2002
North_East	dummy(0,1)	=1 if located in North-East Italy
Centre	dummy(0,1)	=1 if located in Centre Italy
South	dummy(0,1)	=1 if located in South Italy
Log(age)	continuous	=Log of firm's age in years
young	dummy(0,1)	=1 if the firm is less than 10 years of age
small	dummy(0,1)	=1 if the firm has less than 50 employees
grouphead	dummy(0,1)	=1 if is the leader of a group of firms
foreign	dummy(0,1)	=1 if foreign participation in firm's capital.
WW	continuous	Whited and Wu's index calculated in 2002
Collateral	continuous	Net Tangible Assets / Total liabilities in 2002
Branches	continuous	Number of branches per 1,000 inhabitants by province in 2001

In all specifications we control for the likely effect of firm's environment on its decision to undertake R&D investment through a complete set of industry dummies, which are primarily meant to capture the potentially relevant role of technological opportunities and appropriability conditions and the associated role of spillovers. We also include three geographical dummies, which identify firms

[18] Calculated at the ATECO 2002 (NACE rev. 1.1) 2 digits level.

located in the North-East (North_East), in the Centre (Centre) and in the South (South) of Italy, leaving regions located in the most industrialized North-West of Italy as the baseline. These dummies are thus particularly meant to account for the industrial divide in Italy between the industrialized northern regions vs. the less developed southern regions (which include some of the most disadvantaged regions in the EU).

The list of variables employed in the analysis and their definition is reported in Table 5. All continuous variables are predetermined and evaluated at 2002. Descriptive statistics are reported in the Appendix (Table A1).

5.2 Credit constraints and the R&D investment decision

In estimating the model presented in section 4.2 when studying the R&D decision, we follow the Full Information Maximum Likelihood approach proposed by Gouriéroux et al. (1980) and Maddala (1983) by estimating a recursive bivariate probit model. This approach has been proposed to model the endogeneity problem when both the dependent variable and the endogenous covariate are binary. Equation (1) is here specified as:

$$\begin{cases} dumRD_i = I(\alpha \cdot rationed_i + \beta_1 X_i + u_i \geq 0) \\ rationed_i = I(\beta_2 X_i + \gamma Z_i + v_i \geq 0) \end{cases} \tag{3}$$

where $dumRD_i$ here is equal to 1 if the firm undertakes R&D investment in 2003. The unobserved disturbances $(u_i,\, v_i)$ are assumed to be normally distributed according to the following bivariate normal density:

$$\binom{u_i}{v_i}\; iid\ \mathrm{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right) \tag{4}$$

where $\rho = Cov(u_i, v_i)$ measures the correlation between the unobservable terms and the variances of the error terms on the main diagonal are standardized to 1 for identification purposes (Greene, 2003). If $\rho = 0$ then the likelihood of the bivariate probit model is simply equal to the sum of the likelihoods of the two univarate probit models.[19]

Table 6, columns (2)-(4), report the estimated coefficients and marginal effects of the covariates included in equation (3) when considering the final sample of 2144 firms. In column (1) estimation results for the corresponding univariate probit model are reported for comparison.

[Table 6 about here]

With reference to the preferred bivariate probit model, we find that the estimated coefficient associated with the *rationed* variable is negative and significant: taking into account its endogenous nature, the credit rationing indicator negatively affects the decision to engage in R&D activities, by reducing its likelihood by 22.4%.

Looking at the other regressors listed in columns (2) and (4) we notice that the likelihood of performing R&D increases with firm's size and decreases when considering firms located in the south of Italy. This location effect reflects the well documented divide between the more advanced and industrialized northern regions in Italy vs. the other regions (especially the less developed southern regions). Firms located in northern regions are indeed characterized by higher average R&D intensity and innovative performance.

Physical investment intensity is positively correlated with the probability of performing R&D, suggesting the existence of a potential complementarity relationship between intangible investment and tangible investment. Finally, the coefficient of the variable *grouphead* is positive and significant, suggesting a prevailing centralization strategy for R&D activities.

[19] Note also that the exclusion of *dumRD* from the second equation in (3) implies that we meet coherency requirements and can estimate a partial-recursive bivariate probit model (see Gouriéroux et al., 1980; Lewbel, 1997; Hajivassiliou and Savignac, 2011).

With reference to the equation explaining the probability of being credit rationed, all instruments are highly significant. The WW index has the expected positive sign, while collateral negatively influences the probability of being credit rationed, thus suggesting its role as a means to reduce the informational asymmetries between borrower and lender and hence as a remedy for credit rationing. Finally, also the excluded branch density variable shows, as expected, a negative and significant effect on the likelihood of credit rationing.

Interestingly, while being young and small does not seem to affect the probability to conduct R&D directly, it significantly increases the chances to be credit rationed, and this is so after controlling for size, age, being young and being small. This implies that firms that are both young and small suffer an additional liability in finding sufficient resources to finance their R&D effort, which is therefore more likely to be discouraged.

A formal test for the endogeneity of the variable *rationed* is the statistical significance of the estimated parameter ρ. We indeed estimate a positive and significant correlation between the "unobservables" factors affecting both the probability of having positive R&D investments and the probability of being credit rationed. This can be interestingly related to the unexpected positive sign of the credit rationing indicator in the simple probit model, which is line with the results obtained in Savignac (2008) and Hajivassiliou and Savignac (2011) and might be the result of the positive correlation originated by the endogeneity bias associated with the credit rationing indicator.

The apparent positive impact of financing constraints on the firms' decision to invest in R&D when not controlling for endogeneity is likely to be generated by the important presence in the sample of firms not perceiving themselves as being subject to credit restrictions because they are not interested in innovation (either because of lack of entrepreneurial attitude or of promising technology and market opportunities) and hence do not wish to undertake R&D investment. The presence of these firms, representing a relatively large share of the sample, is a potential source of positive correlation between our credit rationing indicator and the R&D decision. This positive correlation may hide the negative impact of the first on the latter.

A way to verify the relevance of this selection problem and to dig into the sources of endogeneity is to study the effect of credit rationing on the decision to undertake R&D investment by focusing on a sample of firms potentially willing to do R&D, so to eliminate the source of the confounding positive correlation (Savignac, 2008). We do that by excluding from our final sample 655 firms that do not undertake any R&D investment (R&D = 0), do not desire additional financing (*rationed* = 0) and have not completed any innovative project in the recent past.[20] For this purpose, the survey includes a question asking whether in the previous three years the firm realized any (a) product innovation, (b) process innovation, (c) organizational or managerial innovation related to product or process innovations, (d) none of the above. Firms excluded from the sample have all selected the (d) option. We refer to the resulting reduced sample as including potentially "innovative firms".

The estimation results for the "potentially innovative" firms are reported in Table 7, where columns (2)-(4) report estimation results from the bivariate probit regression. Interestingly, the coefficient of the credit rationing indicator is now negative and statistically significant also in the simple probit regression (column (1)): potentially innovative firms facing credit rationing have a lower probability (of about -30%) to do R&D. The effects of the other variables are confirmed, with the exception of the physical investment intensity, which is no longer found significant. Indeed, the distribution of investment intensity of potentially innovative firms is slightly shifted to the right with respect to the whole sample, but it is fairly similar between the two groups of firms with and without R&D effort.

The parameter ρ, although still positive, is, as should be expected, smaller than previously estimated and, furthermore, it's no longer significant. By controlling for sample selection we therefore take care of most of the endogeneity bias, although the larger marginal effect of the "*rationed*" indicator in the bivariate probit regression (column (4)) compared to the simple probit regression (column (1)) suggests that other sources of endogeneity might not be irrelevant.

[Table 7 about here]

[20] Innovative activities are not necessarily associated with R&D investment in the survey, as they are treated in a different section.

The last columns in Tables 6 and 7 report the instrumental variable (IV) estimates of equation (3) obtained from the limited information maximum likelihood (LIML) procedure.[21] The results are robust with respect to the bivariate probit model and the larger coefficient and standard error of the *rationed* indicator in the IV approach with respect to the bivariate probit model estimates can be explained in the light of LATE interpretation of the IV coefficients (Imbens and Angrist, 1994) and the ATE interpretation that we should instead give to the bivariate probit marginal effects (Chiburis et al., 2010).

The Sargan test, reported in the last rows of column (6) in both Table 6 and Table 7, does not reject the null hypothesis of overidentifying restrictions, supporting the validity of our set of instruments. However Small (2007) discusses several cases in which the Sargan test has very low power versus many alternatives. Thus in the next section we perform a sensitivity analysis in order to corroborate our results.

5.3 Robustness and sensitivity analysis.

In this section we perform some robustness checks and a (semi-bayesian) sensitivity analysis in order to assess the validity of our set of instruments.

We first focus on the evaluation of two omitted factors that contribute to the determination of the WW index and can be potentially missing as control variables in both the equations of model (3): these are firm's productivity and firm's availability of internal financial resources. We then re-estimate model (2) using two additional control variables: the log of the ratio of net sales per employee in 2002 as a proxy for firm's productivity and the ratio of available internal cash flow over equity in 2002. Estimation results are not reported as they display no significant changes with

[21] Very similar results are obtained with a a two stage least squares (2SLS) procedure, which is therefore not reported.

respect the previous model specification.[22] In particular the coefficient associated with the variable *rationed* keeps the same sign and a very similar magnitude with respect to the former specification.

We next test the sensitivity of the effect of *rationed* on *dumRS2003* by relaxing the exclusion restriction concerning each of the instrumental variables involved in the estimation of model (2) by means of one of the approaches proposed by Conley et al. (2012). We thus deal with our earlier concern on the potential endogeneity of our set of instruments and, in particular, of the WW index.

We adopt the so-called "Local-to-Zero" approximation (using as reference model the IV-SLS specification estimated in Table 9, column 1) which treats θ as being local-to-zero in the following linear equation system:

$$\begin{cases} \widetilde{dumRD} = \alpha * \widetilde{rationed} + \theta\tilde{Z} + \nu \\ \widetilde{rationed} = \gamma\hat{Z} + \xi \end{cases} \tag{5}$$

which is obtained by linearizing model (2) and by setting $\widetilde{dumRD} = (I - P_X)dumRD$, $\widetilde{rationed} = (I - P_X)rationed$, $\tilde{Z} = (I - P_X)Z$ that is by defining the original dependent, treatment and instrumental variables as residuals from the projection upon the space defined by the set of exogenous regressors X.

The local-to-zero estimation approach involves the following approximation (see Conley et al., 2012):

$$\hat{\alpha} \xrightarrow{approx} \sim N(\alpha, V_{2SLS}) + A\theta \tag{6}$$

where

$$A = \left(\tilde{c}'\tilde{Z}\left(\tilde{Z}'\tilde{Z}\right)^{-1}\tilde{Z}'\tilde{c}\right)^{-1}\left(\tilde{c}'\tilde{Z}\right) \text{ and } \theta \backsim F \tag{7}$$

V_{2SLS} is the standard variance-covariance matrix of the 2SLS estimator. The bias term $A\theta$ is called "exogeneity error" and depends on the sample moments in matrix *A* and on the prior distribution *F*

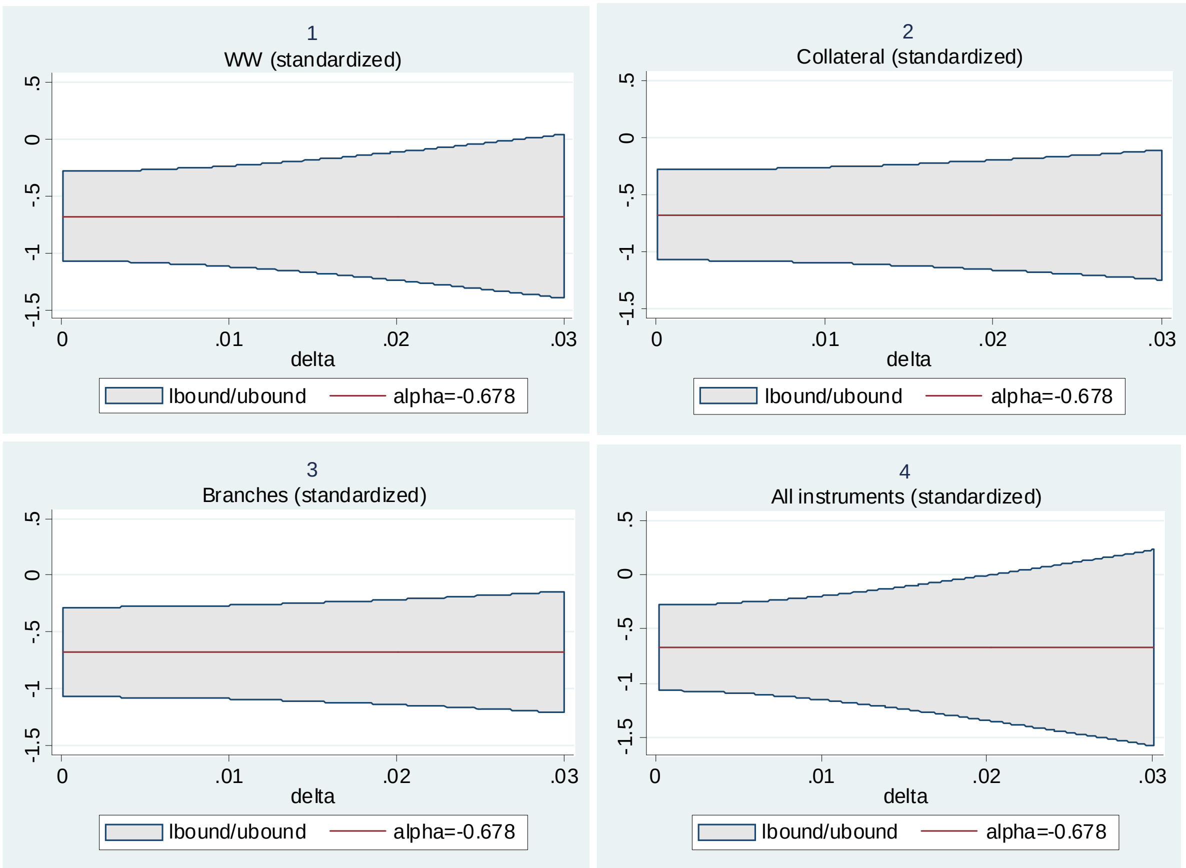
[22] They are however available from the authors upon request.

for θ, which reflects the deviations of $\hat{\alpha}$ from the asymptotic standard distribution of 2SLS estimators caused by violations of the "exclusion restriction" assumption.

As stressed by Conley et al. (2012), one of the advantages of this approach is that the relationship between strength of instruments and impact of exogeneity errors is transparent in equation (6): the size of A (which is inversely related to the strength of the instruments) determines how strongly exogeneity errors affect inference on α.

Figure 4

95% interval estimates for the effect of *rationed* on *dumRD* across various prior settings.



In our case we apply the simplest implementation of the Local-to-Zero approach by specifying a multivariate normal prior for θ, $\theta \sim N(0, \delta^2 I_3)$, and computing the 95% confidence intervals for α corresponding to different values of δ, after having standardized all variables in the instrument matrix Z. The 4 panels of Figure 4 show the computed 95% confidence intervals of α with respect to different prior settings. In the first panel we set $diag(I_3) = (1,0,0)$, i.e. we allow only the standard deviation of *WW* to vary and set to zero the variance of the parameters associated with the remaining instruments *collateral* and *branches*. In the second panel we set $diag(I_3) = (0,1,0)$, i.e. we allow only the standard deviation of *collateral* to vary, while in the third one we set $diag(I_3) = (0,0,1)$, i.e. we allow only the standard deviation of *branches* to vary. Finally, in the last panel we set $diag(I_3) = (1,1,1)$, thus allowing the standard deviation of all instruments to vary.

In order to evaluate whether the plotted intervals are informative or not we need a set of benchmark values for the "plausible" effect of the excluded instruments.[23] Therefore we estimate the plausible benchmark values for the effect of the excluded instruments on *dumRS* by using a 2SLS approach: Table 8 replicates the sequence of the quadrants of Figure 5 by including in the main R&D equation one of the instruments at a time (columns 2-4) and the whole set of instruments (column 5).

[Table 8 about here]

Before commenting the results we have to clarify that, since the 2SLS estimates of column 5 would be unfeasible without an "extra" set of instrumental variable, we used as additional set of instruments the ones adopted by Herrera and Minetti (2007). These instrumental variables are proxies for the structure of local baking market in Italy in 1936.[24] Their exclusion restriction can be plausibly justified in term of theoretical considerations but they have the disadvantage of being only weakly correlated with our treatment variable. Because of the potential dangers of using weak instruments (Bound et al. 1995) we restrict their use only in this section. The 2SLS regressions in Table 9 show that the estimated magnitude of the effects of the excluded instruments on the dependent variable are very small (and not significant): the 95% confidence interval for the effect of *WW* (which seems to be

[23] For instance, Conley et al (2012) adopt a set of plausible ranges for the direct effect of their instruments (quarter-of-birth) on the dependent variable (wage) provided by Bound at Jaeger (1996).
[24] See Herrera and Minetti (2007) for a more detailed description of the instrumental variables.

the less "plausible" exogenous instruments) is (-0.061, 0.01) according with the 2SLS estimates of column 2 and (-0.079, 0.029) according with the 2SLS estimates of column 5. By assuming a normal prior distribution with zero mean and standard deviation $\delta = 0.03$ we are considering a confidence interval for θ approximately equal to (-0.06, +0.06), which contains most of the range of the previously estimated effect. The plot of the local-to-zero estimator reported in the first quadrant of the Figure 5 shows that our treatment variable is still statistically significant (and negative) even when considering this level of uncertainty on the plausibility of the exclusion restriction of *WW*.

5.4 Credit rationing and the size of R&D investment

We now turn to the analysis of the effect of credit rationing on the size of R&D investment. We employ an instrumental variable Tobit (IV-Tobit) model, to account for the endogeneity of our credit rationing indicator. Model (1) is now specified as:

$$\begin{cases} logRD_i^* = \alpha \cdot rationed_i + \beta_1 X_i + u_i \\ rationed_i = I(\beta_2 X_i + \gamma Z_i + v_i \geq 0) \end{cases} \tag{8}$$

where $logRD_i^*$ is the logarithm of the firm's R&D expenditures in 2003 which is observed only when positive:

$$logRD_i = \begin{cases} logRD_i^* = \alpha \cdot rationed_i + \beta_1 X_i + u_i & if \quad logRD_i^* \geq 0 \\ 0 & if \quad logRD_i^* \leq 0 \end{cases} \tag{9}$$

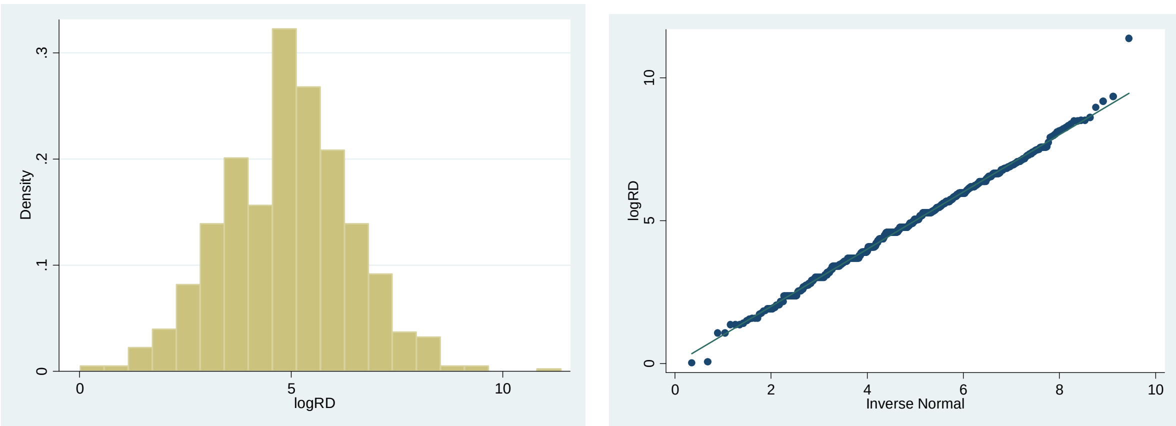
The endogeneity of *rationed* is treated both via the two-step Newey procedure, by inserting the fitted values of v_i into the first equation, and via full ML techniques, by specifying a full variance-covariance matrix of the error terms (u_i, v_i):

$$Var(u_i, v_i) = \Sigma = \begin{bmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{bmatrix} \tag{10}$$

The procedure applies to any kind of endogenous variables, including binary variables, as in our case.[25]

The two panels in Figure 5 report the distribution of the logarithm of R&D expenditures (over positive values) for the entire sample: the distribution is bell shaped and sufficiently close to Normal, thus justifying the use of the Tobit model.

Figure 5
Distribution of *logRD* in the final sample for fims with positive R&D (left panel) and quantile plot vs. Normal (right panel)



Note. N= 735; Mean= 4.90, Variance=2.32, Skewness= 0.039, Kurtosis = 3.3; Skewness/Kurtosis Normality test: 2.69; P>chi2(2): 0.260.

Table 9 reports the IV-Tobit estimation output for the final sample, using both the two-step (column (2)) and ML (columns (3) to (6)) procedures. The first column shows the output for the standard Tobit regression, which is reported for comparison, and confirms that ignoring endogeneity and sample selection induces a bias in the effect of credit rationing, which is found positive, although, differently from the probit setting, it is not significant in the final sample. Once again, controlling for endogeneity, the effect of credit rationing on the level of R&D is found significant and has the correct

[25] See Wooldridge, 2002 pp. 567-575.

sign. Among the other variables, the results confirm the complementarity between tangible and intangible investment and the positive effect of firm size and of the firm being the head of a group. Once again, firms located in the south of Italy show reduced investment expenditures in R&D, ceteris paribus.

The probability of being credit rationed is again positively related to the WW index and negatively to the size of collateral and to branch density. The additional liability of being both young and small is again confirmed.

The Wald test of exogeneity strongly rejects the null hypothesis of independence between the error terms of the two equations. Indeed we find a positive and strongly significant correlation between the errors in equation (5) (σ_{12}=9.08).

[Table 9 about here]

Table 10 reports similar estimation results for the subsample of potentially innovative firms. Analogously to the estimation results on the R&D decision for the same sample, credit rationing negatively and significantly affects the size of R&D investment also in the simple Tobit regression. The effects of the other variables are confirmed. Similarly to the bivariate probit model, we find a weaker correlation between the error terms of the two equations when considering the subsample of potentially innovative firms (σ_{12}=4.26). Differently from the bivariate probit model, however, the correlation here is still positive and significant, confirming our initial intuition that, some but not all of the endogeneity bias can be accounted for by excluding firms not interested in innovation from the sample.

[Table 10 about here]

Both in Tables 9 and 10, column (5) reports marginal effects of all the variables, and in particular of the credit rationing indicator, on the probability of doing R&D, while column (6) reports marginal effects on the expected value of *logRD* conditional on positive values. However, we're mostly interested in disentangling the negative effect of credit rationing on R&D into the reduction due to firms deciding not to pursue R&D effort and the reduction due to firms reducing their (positive) R&D effort. For this purpose we employ the decomposition proposed by McDonald-Moffitt (1980):

$$\frac{\partial E(y_i^*|\boldsymbol{x})}{\partial rationed} = \underbrace{\frac{\partial P(y_i^* > 0|\boldsymbol{x})}{\partial rationed} E(y_i^*|y_i^* > 0, \boldsymbol{x})}_{change\ in\ P(R\&D)} + \underbrace{P(y_i^* > 0|\boldsymbol{x}) \frac{\partial E(y_i^*|y_i^* > 0, \boldsymbol{x})}{\partial rationed}}_{change\ in\ existing\ R\&D} \tag{11}$$

where $y_i^* = logRD_i^*$.

The first component is the percentage reduction in R&D due to the reduced probability of pursuing R&D investment, while the second component is the percentage reduction in R&D due to the reduced amount of R&D investment, conditional on there being R&D investment in the first place. The two components are respectively -2.17 and -1.04 for the full sample and -1.81 and -1.04 for the sample of potentially innovative firms. This result confirms that, in relative terms, most of the negative effect of credit rationing on the observed level of R&D investment is due to firms deciding not to pursue R&D activities.

6. Conclusions

This paper aims at assessing the effect of credit rationing on R&D investment for SMEs. Our contribution to the existing literature is twofold. First, we show that the effect of credit rationing on the decision to invest in R&D and its effect on the size of the R&D investment (conditional on the investment decision) are different and, as a consequence, should be separately evaluated. Second, we innovatively use the WW index as one of the instruments for our direct indicator of rationing and provide a theory-based identification strategy. A sensitivity analysis based on the recent contribution by Conley et al. (2012) is then used to deal with potential concerns on instruments' exogeneity.

Our empirical findings support the assumption that credit rationing significantly reduces both the probability of doing R&D and the level of R&D investment. We further measure the percentage reduction in R&D investment as a consequence of the firm facing credit rationing and split it into its two components: the first is due to the reduction in the likelihood to do R&D (the R&D participation decision), and the second is due to a reduced level of investment, conditioned on the R&D decision. Our results show that most of the reduction is to be attributed to the first effect: credit rationing primarily affects the proportion of firms doing R&D (the *extensive margin*), rather than the expected level of R&D investment for firms already doing R&D (the *intensive margin*). This result implicitly suggests that credit rationing is more likely to discourage *new* R&D investment than to reduce investment expenses in *ongoing* R&D projects.

A further contribution of our work relates to the liability suffered by young and small firms in obtaining external financing. Their R&D effort is, ceteris paribus, more likely to be discouraged because it will be more difficult for them to obtain sufficient funds from external sources to finance it. Although we cannot verify it in our cross-sectional data and it might not necessarily be the case, however such R&D effort is more likely to be the *first* R&D effort for firms that are both young and small, than for either long established or large firms. As a consequence, credit rationing seriously hinders the post-entry growth of small young businesses, as discussed by Aghion et al (2007).

Furthermore, given the pivotal role that young and small innovative companies have in bringing radically new innovations to market (Veugelers, 2009), credit rationing also represents a serious obstacle to the process of creative destruction and to the realization of the social benefits from breakthrough innovations that small and young firms might introduce. Significant policy efforts should therefore be devoted to improving financial markets in bank-based systems, which do not provide satisfactory financial support to R&D investment for SMEs. Both private credit and stock market capitalization are important for promoting R&D and innovation by SMEs and, consequently, their growth and their direct and indirect benefits to society.

Table 6 – Estimation output – Final sample

	Probit	Bivariate Probit			IV-LIML
	(1)	(2)	(3)	(4)	(5)
Dependent variable	**dumRD**	**dumRD**	**rationed**	**dumRD**	**dumRD**
	Marg. Effects	**Coefficients**	**Coefficients**	**Marg. Effects**	**Coefficients**
rationed	0.0579*	-0.718**		-0.224***	-0.702***
	(0.0318)	(0.309)		(0.0801)	(0.263)
*log*EMP	0.0876***	0.213***	0.0457	0.0777***	0.0656***
	(0.0260)	(0.0651)	(0.0774)	(0.0236)	(0.0251)
INV_EMP	0.0008**	0.0021*	0.0005	0.0008*	0.000668
	(0.0004)	(0.0012)	(0.0013)	(0.0004)	(0.000430)
DEBT_EQUITY	0.0005	0.0026	0.0056	0.0009	0.00134
	(0.0012)	(0.0037)	(0.0035)	(0.0013)	(0.00134)
mktshare	0.260	0.492	-0.0637	0.179	0.0977
	(0.318)	(0.776)	(0.899)	(0.282)	(0.324)
North_east	-0.0270	-0.0540	0.222**	-0.0196	-0.0133
	(0.0260)	(0.0717)	(0.0954)	(0.0258)	(0.0285)
Centre	-0.0413	-0.0767	0.175*	-0.0276	-0.0115
	(0.0299)	(0.0872)	(0.104)	(0.0310)	(0.0346)
South	-0.123***	-0.235**	0.236	-0.0820**	-0.0335
	(0.0322)	(0.115)	(0.151)	(0.0380)	(0.0475)
Log(age)	0.0017	0.0112	0.0585	0.004	0.00748
	(0.0233)	(0.0634)	(0.0764)	(0.0231)	(0.0247)
young	-0.0472	-0.151	-0.315	-0.0533	-0.0771
	(0.0418)	(0.189)	(0.258)	(0.0646)	(0.0775)
small	-0.0449	-0.141	-0.0748	-0.0515	-0.0663
	(0.0806)	(0.106)	(0.128)	(0.0389)	(0.0422)
young*small	-0.0359	-0.0056	0.601**	-0.002	0.0556
	(0.0681)	(0.233)	(0.282)	(0.0847)	(0.0934)
grouphead	0.155***	0.350***	-0.238	0.134**	0.109**
	(0.0526)	(0.132)	(0.179)	(0.0522)	(0.0525)
foreign	0.0220	0.0823	0.132	0.0304	0.0442
	(0.0495)	(0.124)	(0.152)	(0.0463)	(0.0509)
WW			2.668***		
			(0.577)		
collateral			-0.226**		
			(0.108)		
branches			-1.190***		
			(0.386)		
Observations	2144	2144			2144
Rho		0.539**			
Shea Partial R-sq					0.015*** [0.00]
Under-identific. LM test					32.59*** [0.00]
Sargan stat					4.931[0.177]
C-stat (WW)					1.396 [0.238]
C-stat (collateral)					0.429 [0.513]
C-stat (comp)					0.526 [0.468]
Log Lik	-1233.9525	-2073.1291			

Robust standard errors in parentheses (Observed Information Matrix method). P-values in square brackets.
Constant and industry dummies included in all regressions.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 – Estimation output – Innovative firms

	Simple Probit	Bivariate Probit			IV-LIML
	(1)	(2)	(3)	(4)	(5)
Dependent variable	**dumRD**	**dumRD**	**rationed**	**dumRD**	**dumRD**
	Marg. Effects	**Coefficients**	**Coefficients**	**Marg. Effects**	**Coefficients**
rationed	-0.124***	-0.792**		-0.299**	-0.495**
	(0.0339)	(0.354)		(0.120)	(0.195)
*log*EMP	0.0757**	0.165**	-0.0156	0.0657**	0.0474*
	(0.0307)	(0.0762)	(0.0858)	(0.0304)	(0.0287)
INV_EMP	-0.0003	-0.001	-0.0017	-0.0004	-0.0005
	(0.0004)	(0.0013)	(0.0015)	(0.0005)	(0.0005)
DEBT_EQUITY	0.0002	0.0011	0.0053	0.0005	0.0006
	(0.0017)	(0.004)	(0.0037)	(0.0016)	(0.0015)
mktshare	0.297	0.607	-0.149	0.242	0.192
	(0.374)	(0.861)	(0.954)	(0.343)	(0.328)
North_east	-0.0188	-0.0301	0.272**	-0.0120	-0.0037
	(0.0340)	(0.0855)	(0.106)	(0.0341)	(0.0323)
Centre	-0.0575	-0.120	0.165	-0.0477	-0.0328
	(0.0395)	(0.103)	(0.116)	(0.0407)	(0.0388)
South	-0.153***	-0.300**	0.266	-0.118**	-0.0759
	(0.0455)	(0.137)	(0.170)	(0.0527)	(0.0537)
Log(age)	0.0068	0.0255	0.0883	0.0102	0.0140
	(0.0300)	(0.0759)	(0.0856)	(0.0303)	(0.0284)
young	-0.0355	0.0248	-0.179	0.0099	0.0110
	(0.0508)	(0.236)	(0.286)	(0.094)	(0.0885)
small	-0.143	-0.0937	-0.0378	-0.0374	-0.0427
	(0.106)	(0.124)	(0.142)	(0.0494)	(0.0468)
young*small	0.0189	-0.292	0.520*	-0.115	-0.0830
	(0.0965)	(0.284)	(0.316)	(0.108)	(0.106)
grouphead	0.163***	0.377**	-0.316	0.148**	0.107*
	(0.0581)	(0.158)	(0.195)	(0.0598)	(0.0562)
foreign	0.0551	0.156	0.175	0.0619	0.0682
	(0.0636)	(0.150)	(0.167)	(0.0593)	(0.0564)
WW			3.248***		
			(0.669)		
collateral			-0.283**		
			(0.129)		
branches			-1.445***		
			(0.441)		
Observations	1489	1489			1498
Rho		0.295			
Shea Partial R-sq					0.026***[0.00]
Under-identific. LM test					40.09*** [0.00]
Sargan stat					3.997 [0.262]
C-stat (WW)					1.806 [0.179]
C-stat (collateral)					0.023 [0.879]
C-stat (comp)					2.336 [0.126]
Log Lik	-918.00975	-1619.5739			

Robust standard errors in parentheses (Observed Information Matrix method). P-values in square brackets.
Constant and industry dummies included in all regressions.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8 – Sensitivity analysis – 2SLS-IV benchmark estimates - Final sample

	(1)	(2)	(3)	(4)	(5)
Dependent variable	**dumRD**	**dumRD**	**dumRD**	**dumRD**	**dumRD**
rationed	-0.678***	-0.374	-0.754***	-0.796***	-0.342
	(0.242)	(0.322)	(0.273)	(0.302)	(0.587)
WW (standardized)		-0.025			-0.0267
		(0.019)			(0.0264)
collateral (standardized)			-0.007		-0.0011
			(0.013)		(0.0138)
branches (standardized)				-0.015	0.0017
				(0.022)	(0.0270)
Instruments:					
WW (standardized)	Yes		Yes	Yes	
collateral (standardized)	Yes	Yes		Yes	
branches (standardized)	Yes	Yes	Yes		
Observations	2144	2144	2144	2144	2144
Shea Partial R-sq	0.0173**	0.008**	0.015***	0.012***	0.002
	[0.00]	[0.021]	[0.00]	[0.00]	[0.584]
Under-identific. LR test	37.43**	18.27**	31.83***	26.55***	4.76
	[0.00]	[0.019]	[0.00]	[0.00]	[0.575]
Sargan stat	5.573	4.730	5.002	4.72	4.784
	[0.695]	[0.693]	[0.66]	[0.694]	[0.443]
C-stat (WW)	1.531	0.056			0.086
	[0.216]	[0.813]			[0.769]
C-stat (collateral)	0.178		1.103		3.67**
	[0.673]		[0.293]		[0.055]
C-stat (branches)	0.031			1.46	1.450
	[0.861]			[0.227]	[0.228]

Robust standard errors in parentheses. P-values in squared brackets. All models include the full set of control variables as well as Herrera and Minetti (2007) instruments.

* significant at 10%; ** significant at 5%; *** significant at 1%

(1) These include: *log*EMP, INV_EMP, DEBT_EQUITY, mktshare, North_east, Centre, South, Log(age), young, small, young*small, grouphead, foreign.

Table 9 – Tobit Estimation output – Final sample

	Tobit ML	**Two-Step IV-Tobit**	**ML IV – Tobit**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable	**logRD**	**logRD**	**logRD**	**rationed**	**dumRD**	**E(logRD | logRD>0)**
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Marg. Effects**	**Marg. Effects**
rationed	0.605	-10.98***	-11.91***		-0.4538***	-2.6436***
	(0.388)	(3.827)	(4.207)		(0.0784)	(0.6742)
*log*EMP	1.479***	1.240***	1.225***	0.002	0.0695***	0.3775***
	(0.350)	(0.365)	(0.403)	(0.0178)	(0.0228)	(0.1242)
INV_EMP	0.0138***	0.0136**	0.0136**	0.0001	0.0007**	0.0042**
	(0.0047)	(0.0062)	(0.00548)	(0.0003)	(0.0003)	(0.0017)
DEBT_EQUITY	0.0034	0.0203	0.0217	0.0014	0.0012	0.0067
	(0.0163)	(0.0217)	(0.0273)	(0.0015)	(0.0015)	(0.0085)
mktshare	3.710	1.376	1.190	-0.0393	0.0675	.03667
	(3.944)	(4.489)	(3.945)	(0.335)	(0.2238)	(1.2161)
North_east	-0.412	-0.186	-0.169	0.0406**	-0.0096	-0.052
	(0.333)	(0.408)	(0.407)	(0.0197)	(0.0230)	(0.1247)
Centre	-0.494	-0.0904	-0.0587	0.0379*	-0.0033	-0.0181
	(0.407)	(0.503)	(0.510)	(0.0216)	(0.0289)	(0.1567)
South	-1.91***	-0.590	-0.488	0.0703**	-0.0275	-0.1481
	(0.509)	(0.710)	(0.757)	(0.0341)	(0.0421)	(0.2263)
Log(age)	0.001	0.0872	0.0943	0.0098	0.0053	0.0291
	(0.300)	(0.360)	(0.368)	(0.0168)	(0.0209)	(0.1135)
young	-0.658	-0.976	-1.030	-0.0627	-0.0572	-0.3052
	(0.548)	(1.088)	(1.065)	(0.0440)	(0.0576)	(0.3034)
small	-0.811	-0.909	-0.929	-0.0279	-0.0528	-0.2885
	(1.149)	(0.608)	(0.646)	(0.0278)	(0.0368)	(0.2022)
young*small	-0.299	0.618	0.729	0.128**	0.0418	0.2316
	(0.914)	(1.376)	(1.376)	(0.0577)	(0.0798)	(0.4503)
grouphead	1.886***	1.408*	1.373**	-0.0345	0.0794**	0.4474*
	(0.545)	(0.719)	(0.677)	(0.0284)	(0.0397)	(0.2332)
foreign	0.469	0.802	0.829	0.0262	0.0476	0.2642
	(0.599)	(0.704)	(0.757)	(0.0349)	(0.044)	(0.2495)
WW				0.608***		
				(0.121)		
collateral				-0.0285*		
				(0.0153)		
branches				-0.212**		
				(0.0829)		
Observations	2144	2144	2144			
Censored	1409	1409	1409			
Log Lik	-2971.2525		-3716.3634			
Wald test ($\sigma_{12}=0$)		13.35 ***	9.08 ***			

Robust standard errors in parentheses. Constant and industry dummies included in all regressions.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10 – Tobit Estimation output – Innovative firms

	Tobit ML	Two-Step IV-Tobit	ML IV – Tobit			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**logRD**	**logRD**	**logRD**	**rationed**	**dumRD**	**E(logRD| logRD>0)**
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Marg. Effects**	**Marg. Effects**
rationed	-1.277***	-5.391***	-5.842***		-0.4652***	-1.8806***
	(0.338)	(1.980)	(2.247)		(0.1429)	(0.5923)
*log*EMP	1.070***	0.877***	0.858***	-0.0091	0.0741***	0.3382***
	(0.293)	(0.291)	(0.317)	(0.0235)	(0.0274)	(0.1249)
INV_EMP	0.0017	-0.000706	-0.001	-0.0003	-0.0001	-0.0004
	(0.0052)	(0.00485)	(0.0058)	(0.0003)	(0.0005)	(0.0023)
DEBT_EQUITY	-0.0014	0.00544	0.0062	0.0015	0.0005	0.0024
	(0.0172)	(0.0167)	(0.0215)	(0.0019)	(0.0019)	(0.0085)
mktshare2002	2.925	1.931	1.828	-0.0416	0.1579	0.7205
	(3.316)	(3.275)	(2.690)	(0.386)	(0.2325)	(1.06)
North_east	-0.244	-0.111	-0.0968	0.0627**	-0.0084	-0.0381
	(0.293)	(0.323)	(0.320)	(0.0274)	(0.0277)	(0.1257)
Centre	-0.454	-0.275	-0.256	0.0448	-0.0222	-0.0999
	(0.364)	(0.393)	(0.402)	(0.0292)	(0.0348)	(0.1551)
South	-1.658***	-0.964*	-0.893	0.0957**	-0.0776	-0.3377
	(0.462)	(0.560)	(0.610)	(0.0487)	(0.0531)	(0.2213)
Log(age)	0.0480	0.125	0.134	0.0211	0.0116	0.0527
	(0.266)	(0.288)	(0.290)	(0.0231)	(0.025)	(0.1142)
young	-0.410	0.187	0.168	-0.0458	0.0145	0.0669
	(0.468)	(0.863)	(0.832)	(0.0653)	(0.0715)	(0.3341)
small	-1.570	-0.472	-0.480	-0.0202	-0.0415	-0.1899
	(1.021)	(0.472)	(0.492)	(0.0368)	(0.0424)	(0.1951)
young*small	0.367	-0.972	-0.911	0.146*	-0.0792	-0.3401
	(0.796)	(1.088)	(1.083)	(0.0831)	(0.0943)	(0.3828)
grouphead	1.499***	1.230**	1.203**	-0.0532	0.1014**	0.5081**
	(0.459)	(0.546)	(0.503)	(0.0337)	(0.041)	(0.2269)
foreign	0.691	0.861	0.881	0.0411	0.0749	0.3655
	(0.519)	(0.548)	(0.564)	(0.0461)	(0.0469)	(0.2459)
WW				0.910***		
				(0.171)		
collateral				-0.0572*		
				(0.0295)		
branches				-0.341***		
				(0.127)		
Observations	1489	1489	1489			
Censored	754	754	754			
Log Lik	-2606.6562		-3312.8941			
Wald test ($\sigma_{12}=0$)		5.08 **	4.26 **			

Robust standard errors in parentheses. Constant and industry dummies included in all regressions.
* significant at 10%; ** significant at 5%; *** significant at 1%

References

Aghion P., Askenazy P. Berman N., Cette G. and Eymard L. (2008), "Credit Constraint and the Cyclicality of R&D Investment: Evidence from France", *Journal of the European Economic Association* (forthcoming).

Aghion P., Fally T. and Scarpetta S. (2007), "Credit Constraints as a Barrier to the Entry and Post-Entry Growth of Firms", *Economic Policy*, 22 (52), 731-779.Aghion, P and P. Bolton (1992), "An incomplete contracts approach to financial contracting", *Review of Economic Studies*, 59, 473-494.

Angelini P. and Generale A. (2008), "On the Evolution of Firm Size Distribution", *American Economic Review*, 98(1), 426-38.

Arrow K.J. (1962), "EconomicWelfare and the Allocation of Resources for Invention", in Nelson, R.R. (ed.) The Rate and Direction of Inventive Activity. Princeton University Press.

Ayyagari M., Thorsten B. and Demiurguk-Kunt A. (2007), "Small and Medium Emterprises Across the Globe", *Small Business Economics*, 29(4), 415-434.

Becchetti L., Castelli A. and Hasan I. (2010), "Investment–Cash Flow Sensitivities, Credit Rationing and Financing Constraints in Small and Medium-Sized Firms", *Small Business Economics*, 35, 467-497.

Beck T. and Demirguc-Kunt A. (2006), "Small and Medium-size Entrerprises: Access to Finance as a Growth Constraint", *Journal of Banking and Finance* 30, 2931-2943.

Beck T., Demirguc-Kunt A. and Maksimovic V. (2008), "Financing Patterns Around the World: Are Small Firms Different?", *Journal of Financial Economics* 89, 467-487.

Benfratello L., Schiantarelli F. and Sembenelli A. (2008), "Banks and Innovation: Microeconometric Evidence on Italian Firms", *Journal of Financial Economics* 90(2), 197-217.

Berger A. and Udell G. (2006) "A more complete conceptual framework for SME finance", *Journal of Banking & Finance*, 30, 2945-2966.

Bester H. (1985), "Screening and Rationing in Credit Markets with Imperfect Information", The American Economic Review 75(4), 850-855.

Blundell R., Griffith R. and Van Reenen J. (1999), "Market Share, Market value and Innovation in a Panel of British Manufacturing Firms", *Review of Economic Studies* 66, 529–554.

Bond S., Harhoff D. and Van Reenen J. (2005), "Investment, R&D and Financial Constraints in Britain and Germany", *Annales d'Economie et de Statistique.*, N.79/80.

Boot A. (2000), "Relationship Banking: What Do We Know?", *Journal of Financial Intermediation* 9(1): 7-25.

Bound J., David A.J. and Baker R.M. (1995), "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak", *Journal of the American Statistical Association*, 90(430), 443- 450.

Bound J. and Jaeger D.A. (1996), "On the validity of season of birth as an instrument in wage equations: A comment on Angrist and Krueger's 'Does compulsory school attendance affect schooling and earnings?'", NBER Working Paper No. 5835.

Brown J.R., Martinsson G. and Petersen B.C. (2011), "Do Financing Constraints Matter for R&D?", mimeo.

Chiburis R, Das J. and Lokshin M. (2010), "A practical comparison of the Bivariate Probit and Linear IV Estimators", mimeo.

Cincera M. (2002), “Financing constraints, fixed capital and R&D investment decisions of Belgian firms”, NBB Working Paper No. 32.

CohenW.M. and Klepper S. (1996), “A Reprise of Size and R&D”, *The Economic Journal*, 106(437), 925–951.

Conley T.G., Hansen C.B. and Rossi P.E. (2012), “Plausibly Exogenous,” *Review of Economics and Statistics*, 94(1), 260-272.

Crépon B., Duguet E. and Mairesse J. (1998), “Research, Innovation and Productivity: An Econometric Analysis at the Firm Level”, *Economics of Innovation and New Technology*, 7(2), 115–158.

Czarnitzki D. (2006), “Research and development in small- and medium-sized enterprises: The role of financial constraints and public funding”, *Scottish Journal of Political Economy*, 53(3), 257–335.

Czarnitzki D. and Hottenrott H. (2011), “R&D investment and financing constraints of small and medium_sized firms”, *Small Business Economics*, 36(1), 65-83.

Gouriéroux C., Laffont J.J., Monfort A. (1980), “Coherency conditions in Simultaneous Linear Equation Models with Endogenous Switching Regime”, *Econometrica*, 29(4), 975-696.

Greene W.G. (2003), “Econometric Analysis”, 5th edition, Prentice Hall (NJ).

Hadlock J.H. and J.R. Pierce (2010), “New Evidence on Measuring Financing Constraints: Moving Beyond the KZ Index”, *The Review of Financial Studies*, 23(5), 1909-1940.

Hall B.H (1992), “Research and Development Investment at the Firm Level: Does the Source of Financing Matter?”, NBER Working Paper No. 4096.

Hall B.H (2002), “The financing of research and development”, *Oxford Review of Economic Policy*, 18 (1), 35-51.

Hall, B.H and Lerner J. (2010), “The Financing of R&D and Innovation” in Hall, B. H. and N. Rosenberg (eds.), Handbook of the Economics of Innovation, Elsevier-North Holland.

Hajivassiliou V. and Savignac F. (2011), “Novel Approaches to Coherency Conditions in LDV Models with an Application to Interactions between Financing Constraints and a Firms Decision and Ability to Innovate”, mimeo.

Harhoff D. (1998), “Are There Financing Constraints for R&D and Investment in German Manufacturing Firms?”, *Annales d'Economie et de Statistique*, 49-50, 421-56.

Harhoff D. and Körting T. (1998), “Lending Relationships in Germany: Empirical Results from Survey Data”, *Journal of Banking and Finance*, 22 (10-11), 1317-1354.

Hart O. and Moore J. (1995), “Property Rights and the Nature of the Firm”, *The Journal of Political Economy* 98(6), 1119-1158.

Heckman J.J., Urzua S. and Vytlacil E. (2006) “Understanding Instrumental Variables in Models with Essential Heterogeneity”, *Review of Economics and Statistics*, 88(3), 380-432.

Hennessy C.A. and Whited T.M. (2007), “How Costly is External Financing? Evidence from a Structural Estimation”, *The Journal of Finance* 62(4), 1705-1745.

Herrera A. M. and Minetti R. (2007) “Informed Finance and technological change: Evidence from credit relationships”, *Journal of Financial Economics*, 83, 223-269.

Himmelberg C.P. and Petersen B.C. (1994), “R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries”, *Review of Economics and Statistics* 76, 38-51.

Hyytinen A. and Toivanen O. (2005), “Do Financial Constraints Hold Back Innovation and growth? Evidence on the Role of Public Policy”, *Research Policy* 34 (9), 1385-1403.

Kaplan S. and Zingales L. (1997), “Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?”, *Quarterly Journal of Economics*, 112(1), 169-215.

Kaplan S. and Zingales L. (2000), “Investment-Cash Flow Sensitivities Are Not Valid Measures of Fi-nancing Constraints”, *Quartely Journal of Economics*, 115, 707-712.

Imbens G.W. and Angrist J.D. (1994) ‘Identification and Estimation of Local Average Treatment Effects’, Econometrica 62(2): 467–75.

Lewbel A. (1997), “Coherency and Completeness of Structural models Containing a dummy endogenous variable”, Boston College Working Papers in Economics, n. 442, rev. Sept 2006.

Maddala G.S. (1983), “Limited-dependent and Qualitative Variables in Econometrics”, Cambridge University Press (UK).

McDonald J.F. and Moffit R.A. (1980), "The Uses of Tobit Analysis", *The Review of Economics and Statistics*, 62, 318-321.

Mulkay B., Hall B.H. and Mairesse J. (2001), “Investment and R&D in France and in the United States,” in Deutsche Bundesbank (ed.), Investing Today for the World of Tomorrow. Springer Verlag.

Myers S.C. (1977), “Determinants of Corporate Borrowing”, *Journal of Financial Economics* 5(2): 147-175.

Myers S.C. and Majluf, N. (1984), “Corporate Financing and Investment Decisions When Firms Have Informations That Investors Do Not Have”, *Journal of Financial Economics* 13(2): 187-221.

Petersen M. and Rajan R. (1994). “The Benefits of Firm-Creditor Relationships: Evidence from Small Business Data”, *Journal of Finance*, 49 (1), 3-37.

Piga C.A. and Atzeni G. (2007), “R&D investment, Credit Rationing and Sample Selection”, *Bulletin of Economic Research*, 59(2), 149-178.

Savignac F. (2008), “Impact of Financial Constraints on Innovation: What Can Be Learned from a Direct Measure?”, *Economics of Innovation and New Technology*, 17(6), 553-69.

Schiantarelli F. and Sembenelli A. (2000), “Form of Ownership and Financial Constraints: Panel Data Evidence From Flow of Funds and Investment Equations”, *Empirica*, 27(2), 175-192.

Schneider C. and Veugelers R. (2010), “On Young Innovative Companies: Why They Matter and How (not) to Policy Support Them”, *Industrial and Corporate Change*, 19(4), 969-1007.

Schumpeter J.A. (1942), “Capitalism, Socialism, and Democracy”, NewYork: Harper.

Small D.S. (2007), “Sensitivity Analysis for Instrumental Variables Regression With Overidentifying Restrictions”, *Journal of the American Statistical Association* 102 (479), 1049-1058.

Steijvers T. and Voordeckers W. (2009) “Collateral and Credit Rationing: A Review of Recent Empirical Studies as a Guide for Future Research”, *Journal of Economic Surveys*, 23(5), 925-946.

Stiglitz J. and Weiss A. (1981) “Credit rationing in markets with imperfect information”. *American Economic Review*, 71:393–410.

Tiwari A.K., Mohnen P., Palm F.C. and Van der Loeff S.S. (2007), “Financial Constraints and R&D Investment: Evidence from CIS”, UNU-MERIT Working Paper No. 11.

Veugelers R. (2009), "A Lifeline for Europe's Young Radical Innovators", Bruegel Policy Brief.

Whited T.M. and Wu G. (2006), "Financial Constraints Risk", *Review of Financial Studies*, 19(2), 531-559.

Wooldridge J.M. (2002), "Econometric Analysis of Cross-section and Panel Data", The MIT Press.

Appendix A: further tables.

Table A1 – Descriptive statistics

	Final Sample (2144 obs.)				Innovative Firms (1489 obs.)			
Variable	**Mean**	**St. dev.**	**Min**	**Max.**	**Mean**	**St. dev.**	**Min**	**Max.**
dumRSin	0.343	0.475	0	1	0.494	0.500	0	1
rationed	0.143	0.350	0	1	0.206	0.404	0	1
lEMP	3.745	0.882	0	6.492	3.846	0.894	0	6.492
INV_EMP	12.519	26.273	0	553.042	14.432	28.772	0	553.042
DEBT_EQUITY	1.282	8.671	-195.47	180.873	1.471	8.703	-195	180.873
Mktshare	0.021	0.041	0	0.901	0.023	0.046	0	0.901
grouphead	0.051	0.220	0	1	0.058	0.235	0	1
foreign	0.054	0.226	0	1	0.057	0.232	0	1
WW	-0.398	0.073	-0.675	-0.032	-0.403	0.073	-0.59	-0.054
collateral	0.643	0.388	0.013	7.445	0.643	0.327	0.037	3.956
branches	0.592	0.143	0.218	1.010	0.595	0.141	0.218	1.010

Table A2 – Correlation matrix for continuous indicators (Final sample)

	lEMP	INV_EMP	DEBT_EQUITY	Mktshare	log(age)	WW	collateral	comp
lEMP	1							
INV_EMP	0.0315	1						
DEBT_EQUITY	0.0649	-0.0033	1					
Mktshare	0.3905	0.0836	0.0194	1				
Log(age)	0.1552	0.0530	0.0096	0.0577	1			
WW	-0.4939	-0.1347	-0.0309	-0.3654	-0.1035	1		
collateral	0.0439	0.0987	-0.0287	0.0079	0.1478	-0.1066	1	
branches	0.0955	-0.0316	0.0689	0.0611	0.0544	-0.0003	-0.0841	1

Table A3 – Correlation matrix for continuous indicators (Innovative Firms)

	lEMP	INV_EMP	DEBT_EQUITY	Mktshare	Log(age)	WW	collateral	comp
lEMP	1							
INV_EMP	0.0315	1						
DEBT_EQUITY	0.0649	-0.0033	1					
Mktshare	0.3905	0.0836	0.0194	1				
Log(age)	0.1552	0.0530	0.0096	0.0577	1			
WW	-0.4939	-0.1347	-0.0309	-0.3654	-0.1035	1		
collateral	0.0439	0.0987	-0.0287	0.0079	0.1478	-0.1066	1	
branches	0.1092	-0.0287	0.0752	0.0664	0.0453	-0.0104	-0.0989	1