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## INNOVATION, FINANCIAL CONSTRAINTS AND RELATIONSHIP LENDING: FIRM-LEVEL EVIDENCE IN TIMES OF CRISIS

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# Innovation, financial constraints and relationship lending: firm-level evidence in times of crisis

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ABSTRACT

Financial frictions represent a severe obstacle to firms' innovativeness. This paper shows the existence and quantifies the effects of financial barriers to the innovation propensity of Italian SMEs. Employing direct measures of financial constraints and a credit-score estimated *ad hoc*, I find financially-constrained firms have a probability of innovating that is significantly lower than sound companies (-30%). Results document the existence of a feedback-effect of innovation on firms' financial position, resulting into an additional reduction in firms' propensity to innovate. The paper also highlights the role of soft information in mitigating financial obstacles to innovation by improving the financial condition of more opaque (small) borrowers.

**JEL classification:** O31; L25; G21.

**Keywords:** Innovation, financial constraints, relationship lending, SMEs.

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# 1 Introduction

Innovative activity and creation of new knowledge are commonly thought as the main engine for economic growth, capable of originating new markets and producing competitive advantages that foster firms' performances (Schumpeter, 1934).

The financing of innovative projects is a crucial issue in the literature of finance and growth. According to King and Levine (1993a,b), the ability of a financial system to direct funds toward projects with high returns is the key channel through which GDP growth is affected. However, the efficient allocation of funds can be severely jeopardized by the presence of informational asymmetries.

By their very own nature, innovative firms are more likely to suffer from financial problems. Because of their informational opaqueness, their little tangible assets to pledge as collateral, and the riskiness of their strategies, most potentially-innovative firms are credit-rationed and face relevant obstacles in financing their projects.

This paper contributes to the literature on financial constraints and innovation. The analysis quantifies the impact of financial distress on firms' innovativeness, also taking into account the "feedback-effect" that the decision to innovate has on firms' financial condition. The work also contributes to studies on relationship lending by documenting the role of soft information in mitigating financial barriers to innovation.

The experimental framework of the paper is the Italian economy, an ideal laboratory to analyze the real consequences of financial constraints. The dominance of small and medium enterprises (hereinafter SMEs), together with a financial system characterized by low-developed stock and bond markets, ensures that firms that are constrained by banks lack access to alternative sources of financing. The absence of substitutability among external funds makes the Italian system a perfect case study to document the effects of financial frictions on firms' behaviors.

There are several features of the analysis that is worth emphasizing. First, I make use of a newly-available dataset, the MET survey on the Italian industry, that includes also micro-sized firms with less than ten employees. The survey contains detailed data on product, process and organizational-managerial innovations, as well as two direct measures of financial constraints. The dataset permits to control for a rich set of determinants of firms' innovativeness, including R&D, market share, presence and complexity of firm networks and internationalization.

The empirical analysis takes advantage of simultaneous-equations models to estimate firms' probability of innovation, conditionally on the likelihood of facing financial constraints (hereinafter FC). The specification of the FC equation includes, in addition to a large set of controls, a credit-score index that is estimated *ad hoc* on a sample of confidential bank ratings.[1]

The main results of the paper are easily summarized. Once accounted for the simultaneity of the two phenomena, financial constraints are found to strongly hamper firms' probability of introducing innovations (-30%). This impact is even larger (-34%) once allowed for the existence of a feedback effect of firms' innovativeness on their credit condition. The negative impact of innovation on the external perceived riskiness of the company worsens firms' access to credit, and results into an additional negative effect of FC on firms' innovativeness. This is the first paper documenting this kind of links without imposing any restriction on the signs of the parameters.

The analysis also presents several dimensions of heterogeneity, based on the type of innovation introduced, on firm size, and on the technological intensity of firms' belonging sector.

The second part of the paper focuses on the effects of relationship lending. Exploiting the identification of the firm-bank relationship in the MET survey, I match banks' characteristics with firm-level data to test how soft information affects firms' financial status and, indirectly, their probability to innovate. Results highlight a critical role for relationship lending; its effect is found to be highly nonlinear and decreasing with the transparency of the borrower (proxied by its size). This evidence is a sign that very small firms can gain disproportional benefits from banks' accumulation of soft information, resulting into a weakened effect of FC on innovation.

The remainder of the paper is organized as follows: Section 2 discusses the literature on financial constraints and innovation, including theoretical argumentations and empirical approaches. Section 3 introduces the dataset and provides detail on the econometric strategy. Section 4 presents the results and Section 5 concludes the paper.

[1]Since the data on banks' valuations refer to the Italian system during the recent crises, the specificity of the estimation furnishes a measure of firms' creditworthiness that is more reliable than universal scores (as the Altman Z-score or the Kaplan and Zingales KZ-score).

## 2 Theoretical background

Because of its critical role in promoting long-run growth, the financing of innovative projects has been at the center of the economic debate for years. Due to the very nature of their investments, dynamic firms suffer from relevant financial obstacles in developing innovations.

Innovative firms usually invest in high-risk-high-return projects, whose expected returns are difficult to evaluate. In this regard, past experience can offer little guidance in assessing the prospects of truly new projects; rather, it is likely that the innovative entrepreneur has, if not more knowledge, at least a better perception of its likelihood of success (Guiso, 1998). This worsens informational asymmetries and may result into rationing phenomena for more dynamic companies. This issue is even more relevant in presence of firms' strategic behaviors leading to suboptimal information transmission (Brealey, Leland, and Pyle, 1977; Kihlstrom and Matthews, 1990; Bhattacharya and Ritter, 1983).[2]

Moreover, frictions from informational asymmetries are not even reduced by the availability of consistent guarantees. The financial condition of innovative firms is typically worsened by high shares of intangible assets that cannot be pledged as collateral (Berger and Udell, 1990; Almeida and Campello, 2007). Furthermore, also the few investments in physical capital, designed to embody the results of R&D activities, are firm-specific and have, therefore, little collateral value (Carpenter and Petersen, 2002). All this increases firms' cost of funding and/or limits their borrowing opportunities.

Finally, the peculiar nature of the investments in R&D and innovation is likely to further exacerbate firms' financial position. While expenditures in physical capital usually occur once in a while, investments in R&D tend to be smoothed over time because of relevant sunk costs.[3]

Although extensively studied from a theoretical perspective, empirical analyses testing the impact of financial constraints often suffer from problems of identification and interpretability. The main difficulty relies in the very nature of this phenomenon: since credit demand and supply are not observable, financial constraints affecting firms' investments are hard to identify.

[2] Suboptimal information transmission can arise from the trade-off in transferring the scientific and technological content of innovative projects. On the one hand, better signals reduce informational asymmetries and lower firms' costs of funding. On the other, in line with neo-schumpeterian models of creative destruction, a full disclosure of the project may increase the likelihood of being replaced on the monopolistic market generated by the innovation, reducing its flow of future expected returns. This argumentation is linked to the non-excludability of the knowledge-capital.

[3] Dynamic firms face sunk costs linked to skilled workers, researchers, engineers and scientists who cannot be fired and hired without a consistent loss in human capital and accumulated knowledge.

When direct indicators were not available, economic literature deduced the presence of financial obstacles from indirect measures. Following Fazzari and Petersen (1988), several papers exploited the investment to cash flow sensitivity to classify firms by their FC status (Kashyap, Lamont, and Stein, 1994; Korajczyk and Levy, 2003; Whited and Wu, 2006). However, despite its diffusion, this approach has been greatly criticized for its ambiguous interpretation (Poterba, 1988; Kaplan and Zingales, 1997, 2000) and for the instability of results to the choice of the indirect proxy of FC (Moyen, 2004; Hennessy and Whited, 2007). This explains why a growing and growing strand of the literature moved the attention toward more direct measures of FC, either from loan-application data or from surveys at the firm-level.

The empirical literature on finance and innovation is extremely rich but far from being conclusive. A large number of papers provided mixed and counterintuitive evidence on the relationship between financial constraints and innovations (Mulkay, Hall, and Mairesse, 2001; Bond, Harhoff, and Van Reenen, 1999, among others). More recently, Savignac (2008), Hajivassiliou and Savignac (2011), and Blanchard, Huiban, Musolesi, and Sevestre (2013) focus on direct indicators of FC to show the negative effect of financial obstacles on the innovative activity of French and European firms. Similarly, Mohnen, Palm, Van Der Loeff, and Tiwari (2008) and Segarra, García-Quevedo, and Teruel (2013) find that financial barriers increase the likelihood of failure or abandonment of innovative projects.[4]

The paper also relates to the literature on relationship lending. Gathering relevant information about the prospects and the creditworthiness of a borrower can greatly influence the lender's decisions on whether (and at what conditions) to extend credit. Long-term commitments reduce firm cost of credit (Diamond, 1991; D'Auria, Foglia, and Reedtz, 1999) and the amount of collateral requested by the bank (Berger and Udell, 1995; Harhoff and Körting, 1998; Degryse and Van Cayseele, 2000). This in turn lowers firms' likelihood of facing financial constraints (Petersen and Rajan, 1994), increasing bank willingness to support borrowers over the short-run in the expectation of future earnings.

A closely related strand of the literature puts the emphasis on the link between banks' degree of hierarchization and their willingness to finance more opaque borrowers. Since the information gathered from delocalized branches cannot be transmitted costless to the upper levels, "highly hierarchicized institutions

[4]Coherent results are also found by Atanassov, Nanda, and Seru (2007) who show the advantage of equity financing, relative to bank debt financing, in developing innovations for large and quoted U.S. firms.

allocate few resources to activity absorbing a lot of soft information such as small-business lending or innovation financing".[5] Among others, Hauswald and Marquez (2000), and Cole, Goldberg, and White (2004) exploit banks' size and the lender-borrower "informational distance" as proxies for banks' complexity.

The literature on the Italian system mainly focuses on indirect proxies of financial distress. Exploiting the Capitalia survey Benfratello, Schiantarelli, and Sembenelli (2008) find evidence that local banking development affects firms' innovation, while Herrera and Minetti (2007) test the effects of the duration of the credit relationship on firms' innovativeness.

Finally, Alessandrini, Presbitero, and Zazzaro (2010) study the effect of bank functional distance, showing that SMEs located in provinces with distant local banking system have a lower propensity to introduce process and product innovations.

# 3 Empirical strategy

The identification strategy of this paper differs from previous analyses because of a combined approach that accounts both for direct and indirect measures of FC. The direct indicators are then included into a simultaneous-equations model with a credit-score index specifically calibrated on the Italian economy and a set of inverse proxies of relationship lending. This methodology allows to overcome problems of interpretability of indirect measures, to quantify the effect on innovation, and to document the causes of financial barriers.

## 3.1 Data

The main source of data is the MET survey on Italian firms (R. Brancati, 2012), a three-waves survey performed in 2008, 2009 and 2011. The timing of the waves allows to capture firms' behaviors, performances and strategies in three crucial points in time: pre-Lehman, post financial crisis boom and the onset of the sovereign-debt crisis. The sample is selected and stratified in order to guarantee representativeness at size, geographical region and industry levels (see Table 1 for some details). As a result, the estimation sample is mainly composed by very small firms, even companies with less than 10 employees (about 54%). The

[5] Alessandrini, Presbitero, and Zazzaro (2010).

sampling numerosity is roughly 25,000 firms in 2008, 22,000 in 2009 and 25,000 in 2011 referring to both manufacturing (60%) and service industries (40%).

Other sources of data are CRIBIS D&B, for firms' balance sheets, Bankscope Bureau van Dijk, for banks' data, and Google maps for the geographical distance (hand-collected).

From the original dataset the application of selection-filters produces a relevant contraction in the sample size. The major reduction comes from the focus on multiply-interviewed companies and firms with complete balance-sheet information.[6] In addition, some observations are dropped because of unreasonable values (negative or nil assets, negative or nil sales or negative debts) or to reduce the influence of outliers (balance sheet variables are censored at 1%). Depending on the specification, the numerosity of the final sample ranges from 13,500 to 9,900 firms.

## 3.2 Main measures

### 3.2.1 Direct indicators of financial constraints

The direct measures of financial constraints come from two questions in the MET survey. The first one ($FC$) refers to the presence of potentially-profitable investment projects bypassed because of lack of financial means. In other words firms are considered FC if the overall investments would have been higher in absence of financial frictions. This measure recalls the spirit of the excess-sensitivity approach, without suffering from its aforementioned problems of interpretability.

The second definition ($FC_2$) is directly based on firms' borrowing possibilities and identifies the existence of "grave difficulties" in accessing external credit.[7] Although highly correlated, the two variables are far from containing the exact same information (the correlation coefficient is 0.59), allowing for an actual robustness check on the validity of the results.

It is worth reminding that both measures are not explicitly related to firms' propensity to innovate; the negative impact on innovation is recovered only through a simultaneous estimation of both likelihoods.

[6] About 40% of the sample in each wave.

[7] The original question asks to quantify firms' difficulties in accessing external credit on a scale from one to ten. The definition employed throughout the paper considers "grave difficulties" values (strictly) greater than seven. Results are robust to the choice of different thresholds.

### 3.2.2 What kind of innovation?

Innovation is widely recognized as one of the main determinants of firms' degree of dynamism, capable of fostering long-run growth, stimulating economic performances and generating new markets. However, a unique and consensual definition of innovation still does not exist (Baregheh, Rowley, and Sambrook, 2009): the OSLO Manual (OECD–Eurostat, 2005) identifies only product and process innovations while some papers also consider softer forms of improvements such as the organizational and managerial ones.[8]

Less radical forms of innovation may be crucial in a system dominated by SMEs. Although their definition is broader, organizational and managerial innovations arise from effects of learning by doing and leaning by using not explicitly embedded in standard definitions. To account for this additional channel, although I always provide disaggregate results, the baseline specification adopts a comprehensive measure that does not distinguish among innovation types (product, process and organizational and managerial).

## 3.3 Econometric model

The effect of financial constrains on innovation is recovered through a bivariate probit model that takes into account the simultaneity of the two phenomena. The estimation of firms' probability of innovation conditionally on firms' financial status allows to identify those companies whose innovative propensity is actually hampered by financial obstacles. Indeed, even in presence of relevant FC that limit total investments (that implies FC=1), a firm cannot be considered as having "binding" financial barriers to innovation if it hasn't scheduled any innovative project. In absence of detailed information on firms' investment plans, a simultaneous-equations model helps isolating this effect.

A general bivariate probit model can be written as:

$$\begin{cases} \text{Inn}_i = 1 \quad \text{if } \text{Inn}_i^* = X_{1i}'\beta_1 + \theta \text{FC}_i + \varepsilon_{1,i} > 0 \\ \text{Inn}_i = 0 \quad \text{if } \text{Inn}_i^* = X_{1i}'\beta_1 + \theta \text{FC}_i + \varepsilon_{1,i} \leq 0 \end{cases} \tag{1}$$

[8] The latter are defined as "the implementation of new organizational or managerial methods in the firms' business practices, workplace organization or external relationships".

$$\begin{cases} \mathrm{FC}_i = 1 \quad \text{if } \mathrm{FC}_i^* = X_{2i}'\beta_2 + \varphi \mathrm{Inn}_i + \varepsilon_{2,i} > 0 \\ \\ \mathrm{FC}_i = 0 \quad \text{if } \mathrm{FC}_i^* = X_{2i}'\beta_2 + \varphi \mathrm{Inn}_i + \varepsilon_{2,i} \leq 0 \end{cases} \tag{2}$$

where $\mathrm{Inn}_i$ and $\mathrm{FC}_i$ represent the observed dependent variables (innovation and financial constraints), $\mathrm{Inn}_i^*$ and $\mathrm{FC}_i^*$ are latent variables associated respectively to $\mathrm{Inn}_i$ and $\mathrm{FC}_i$, $X_{1i}$ and $X_{2i}$ are vectors of exogenous parameters, while $\theta$ and $\varphi$ are the two interaction coefficients. The error terms $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ are assumed to be i.i.d. as a bivariate normal with unitary variance and correlation coefficient equals to $\rho = corr(\varepsilon_{1,i}, \varepsilon_{2,i})$.

However, once allowed for both a direct effect of FC on firms' innovativeness and a reverse impact of innovation on the probability of financial constraints, the model requires prior parameter restrictions (typically $\theta\varphi = 0$) to be logically consistent (Maddala, 1986). Imposing $\varphi = 0$ would simplify the system into a recursive bivariate model that does not leave room for any feedback effect of innovation on the financial status.

To overcome this problem and to allow for a reverse effect that preserves the feasibility of the estimation, I proxy innovation in the financial constraint equation with (lagged) R&D intensity. Indeed, R&D and innovation share common characteristics and the leading causes of financing constraints (Hall, 2002), allowing to catch this additional channel. However, even if lagged R&D avoids problems of simultaneity bias, residual endogeneity can still exist.

In order to address this point and still allow for a feedback effect, firm's dynamic attitude in the FC equation is proxied by the "structural" R&D-probability of its belonging *stratum*. This measure, only based on structural characteristics, has the advantage of being positively correlated with firms' R&D activity and immune from potential endogeneity issues.

In particular, the structural propensity is computed as the predicted probability of the following probit model:

$$Pr(1R\&D_{i,t-1} = 1) = \phi\left(\omega_{s,p,\theta} + \lambda_{t-1}\right)$$

where $1R\&D$ is a dummy variable identifying R&D projects, $\lambda_{t-1}$ are time controls and $\omega_{s,p,i}$ are specific effects of firms' belonging stratum (identified by its size class, geographical province and industry, respectively

$s, p$ and $\theta$).[9]

The fitting property of this first-stage regression (pseudo-$R^2 = 0.16$) ensures a good power of the instrumenting set. Moreover, since the determinants of $\widehat{R\&D}_{i,t-1}$ are controlled for in the FC equation, $\varphi_{\widehat{R\&D}_{i,t-1}}$ should be correctly interpreted as the direction of the feedback effect of firms' dynamism on the financial status.

The final estimation is performed *via* pooled bivariate probit, controlling for time, industry and region effects and correcting for clustering of the standard errors (at individual, sector, region, or size level).[10]

### 3.4 Determinants of innovation and financial constraints

A correct specification of firms' innovation propensity and financial status is as important as the choice of the proper econometric model. The full set of controls is given by:

$$\begin{aligned}
X_{1,i} =& (R\&D_{i,t-1}\,,\, Market\,share_{i,t-1}\,,\, Group_{i,t-1}\,,\, Simple\,ntw_{i,t-1}\,,\, Advanced\,ntw_{i,t-1}\,,\\
& Export\,share_{i,t-1}\,,\, Multinational_{i,t-1}\,,\, Output\,growth_{i,t-1}\,,\, Size_{i,t-1}\,,\, Age_{i,t}\,,\, \alpha_t\,,\, \alpha_{ind}\,,\, \alpha_{reg})'\\
X_{2,i} =& ((\widehat{R\&D}_{i,t-1})\,,\, Credit\,score_{i,t-1}\,,\, Tangibles_{i,t-1}\,,\, Roll\text{-}over_{i,t-1}\,,\, Profitability_{i,t-1}\,,\\
& Size_{i,t-1}\,,\, Age_{i,t}\,,\, (Bank\,size_{i,t}\,,\, Distance_{i,t})\,,\, \nu_t\,,\, \nu_{ind}\,,\, \nu_{reg})'
\end{aligned}$$

where, coherently with Equations 1 and 2, $X_{1,i}$ and $X_{2,i}$ refer, respectively, to the innovation and the FC equations.

Firms' innovative activity is explained by a rich set of structural, environmental and behavioral characteristics. *R&D* proxies for the intensity of Research and Development, commonly accepted as the main

[9] Firms are grouped into four size classes (depending on $25^{th}$, median, and $75^{th}$ percentile of the size distribution), 110 provinces and 12 industries. As a result, $\omega_{s,p,\theta}$ is a set of $4 \times 110 \times 12 = 5,280$ dummy variables associated to the different strata in the sample.

[10] Although models that fully exploit the panel structure of the data have the great advantage to control for firm-specific idiosyncratic components, they require variation across time of the binary dependent variable. Given the high persistence and state-dependence of both the innovation propensity and the FC status, all these models produce an excessive reduction in the sample and lead to a selection bias due to the empirical approach itself. Explanations about the persistence of innovation are mainly based on the cumulative nature of learning processes (Rosenberg, 1976), "success-breeds-success" (according to which succeeding in innovation increases generated cash flows that may be devoted to finance further innovations, Stoneman and David, 1986) and on strategies of innovation smoothing. To this purpose, a robustness check accounts for firms' unobserved heterogeneity with the inclusion of regressors' mean in both equations. Results are qualitatively similar to the main specification.

driving force of a firm's innovativeness. Undertaking R&D projects eases the production of new knowledge and the assimilation of existing information from outside sources. *R&D* is defined as the share of employees devoted to activity of Research and Development.[11]

Firm's dominant position is proxied by *Market share*, constructed as the share of firms' output within the belonging sector. *Output growth* is the rate of growth of sales and controls for expected-future performances and customers' demand.

In addition to standard determinants of innovation, firms' innovative attitude may be affected by other strategic and environmental characteristics. Network organizational structures and international environments may be capable of influencing either the way firms interact with each other and the process of circulation and generation of new ideas. This increases the capability to elaborate, assimilate and accumulate new knowledge to transform through the innovative process.

Besides the affiliation to formal groups of firms (*Group*), the MET survey allows to investigate the effects of other kind of informal connections. Firms are classified into "stand alone" and belonging to networks, depending on the existence of prolonged and relevant relationships with other firms. "*Simple ntw*" identifies companies with stable commercial relationship, and "*Advanced ntw*" captures more sophisticated cooperations such as common R&D projects, joint ventures, services and commercialization.

In the same spirit, firms' international activity is summarized by two different variables: *Export share* and *Multinational*. While the former refers to the share of foreign sales, *Multinational* is a dummy variable capturing the additional positive externalities from more complex forms of internationalization (such as FDI, international cooperation, inter-firms international agreements, and the existence of commercial branches abroad).

The FC equation takes into account several aspects of the credit channel, including structural characteristics, credit supply and demand.

*Tangibles* is the share of tangible assets and measures firms' capability to pledge collateral. *Roll over* is the short-term to total debt ratio proxing for firms' need of rolling-over. A debt-maturity structure skewed toward the short-term may worsen firms' financial position because of the difficulty in rolling-over debt.

[11] R&D expenditure (as a share of total sales) and a dummy variable are also used as alternative measures.

This issue is particularly relevant if the debt expires in times of credit crunch (see for instance, Ivashina and Scharfstein, 2010). *Profitability* captures firms' economic performance (measured as the operating profits to total assets ratio) proxing for the capability to internally fund investment projects.

Banks' perception on firms' creditworthiness is measured with a *Credit score* estimated *ad hoc* on a vector of ratings assigned by several Italian banks to a group of local firms (see Appendix 2 for more details). This variable captures a relevant component of the credit supply and should heavily affect the likelihood of FC (higher creditworthiness induces lower constraints).

Most specifications also account for the feedback effect of innovation on FC (the predicted probability $\widehat{R\&D}_{i,t-1}$ as defined in Section 3.3). All estimations include a set of structural controls including firms' age, size, time-effects, region-effects, and industry-effects.[12] All regressors are lagged once or more to avoid simultaneity bias and endogeneity problems.

The last section of the paper tests for the role of relationship lending in reducing informational asymmetries and fostering innovation. Exploiting the lender-borrower identification in the 2011-wave of the MET survey, the FC equation is further enriched by a set of inverse proxies of soft information.[13] *Distance* is the physical distance between the firm and the headquarter of the lender bank, while *Bank size* is the size of the financial institution (log of total assets).[14] Differently from most previous studies, these variables have the additional advantage not to be computed as aggregated-local measures.[15] Instead, they are based on the actual firm-bank relationship allowing for greater accuracy and the inclusion of local controls.[16]

This set of measures is then included in the FC equation and interacted with firms' size to allow for non-linear effects along different degrees of borrowers' opaqueness. The effect of relationship lending on innovation is then obtained "indirectly" by observing changes in the magnitude of $\theta_{FC}$ with respect to the baseline specification.

[12] *Size* and *Age* are defined as the log of (one plus) firm's number of employees and age, while $\alpha_t$, $\alpha_{ind}$, and $\alpha_{reg}$ are, respectively, time-controls, 2-digit industry controls (12 dummies) and region controls (20 dummies).

[13] Unfortunately, the survey does not contain information about the length of the relationship or the share of the main bank on total banking debt, typically considered as alternative measures of relationship lending.

[14] The number of branches is also included as a further measure of bank size and hierarchization. Even though the main effect of FC on innovation stays unchanged, no striking result is found for its direct effect on the probability of financial constraints.

[15] Degryse and Ongena (2005) is one of the few examples using the actual distance between the firm and the lender bank.

[16] Only for computational reason, *Distance* is constructed as the distance between the province (110) each firm belongs to, and the actual headquarter of the specific-lender bank. Notice however that, as a result of the cross-sectional heterogeneity in the identification and the localization of the lender banks, *Distance* still turns out to be firm-specific.

The price to pay to include measures of soft information into the FC equation is a relevant reduction in the sample numerosity. Focusing on the available observations, the final estimation sample reduces to roughly 9900 firms.[17]

# 4 Results

## 4.1 Descriptive

Descriptive statistics are presented in Tables 2–4. Table 2 summarizes information about the nature of the innovation introduced. Overall, 32% of the companies in the sample developed at least one innovation, 19% introduced product innovations, 16% new production processes while 19% opted for less-radical forms of improvements (i.e. organizational-managerial innovations). Table 3 also documents high heterogeneity of the innovation propensity across industries. The greater diffusion of innovative firms in high-tech sectors is a stylized fact that is coherent across types of innovation, but is more evident for the implementation of new products. Interestingly, Table 3 also shows a positive association between firms' innovativeness and the existence of financial barriers. This evidence is confirmed by the conditional propensities in Table 4.

It is worth recalling that the positive correlation between innovation and FC doesn't imply any causal nexus. On the one hand, innovation represents a risky activity that raises the likelihood of FC. On the other, financial problems are an obstacle to the actual capability of undertaking innovative projects. This link highlights the necessity of a simultaneous estimation to take into account all unobserved channels driving both innovation and financial constraints.

[17]Since the question on the lender identification has been introduced only in the last wave of the survey, I restrict the analysis to firms interviewed in 2011, exploiting also observations in the previous waves when repeated interviews were available (this is done to avoid an excessive sample reduction). Notice that this approach requires the assumption of stability of the firm-bank relationships over time.

Several considerations support this hypothesis. First of all, in a system dominated by SMEs, firms do not usually have the reputation needed to get credit from a new financial institution and they have to rely on prolonged relationships (Diamond, 1991). This issue is even more relevant in times of crisis characterized by increased opaqueness of less structured companies. Moreover, evidence from Italy indicates that firms attempted to broaden the range of financial sources rather than substitute one bank with another (D'Auria, Foglia, and Reedtz, 1999). Given the low diffusion of multiple-banks in the sample (15%), the potential issue of "bank-switcher firms" should be negligible.

## 4.2 Innovations and financial constraints

As a benchmark, Table 5 presents results from logistic models on the main determinants of firms' innovativeness. In line with the economic literature, structural characteristics play a critical role in determining firms' propensity to innovate. First of all, thanks to the ability in diversifying embedded-risk and the higher availability of internally-generated funds, larger firms are more prone to introduce innovations (on the contrary, firm age does not seem to play any role).

Also consistently with previous evidence, my results document unclear effects of market share on firm propensity to innovate: even if the baseline effect is positive, the magnitude and significance of the impact are not robust along the different specifications throughout the paper.

The analysis on behavioral and strategic characteristics is extremely interesting. Coherently with a priori expectations, R&D intensity is a crucial factor in fostering innovative processes. The affiliation to groups of firms have a positive impact on firms' probability of innovating, but belonging to "informal networks" seems to play an even more important role. Moreover, the effect is increasing with the complexity of the inter-firm relationship (from simple to advanced forms of networks). Similarly, the presence on international markets is found to stimulate firms' innovativeness with an intensity that depends upon the sophistication of the international activity.

Finally, past sales growth as a proxy for firm future expectations (and availability of funds), have positive –even though not always significant– impact on innovation.

Table 5, column 2, includes a set of indirect measures of financial constraints to the baseline regression. While profitability does not affect firms' propensity to innovate, a positive association is found for banking debt and the share of tangible assets. It is however difficult to interpret these results as a direct relationship between FC and innovation.[18]

### 4.2.1 Simultaneous estimation and feedback effect

Direct indicators of financial constraints have the great advantage of being immediately interpretable. However, results from the inclusion of $FC$ into the previous specification show a positive and very significant effect

[18] On the one hand the higher banking debt may be associated with low FC that allowed an extension of credit. On the other, if the banking debt was preexistent to the investment, a higher exposure may reduce bank willingness to provide additional loans, increasing the likelihood of constraints.

of financial constraints on innovation (Table 5, column 3). Approaches that ignore problems of simultaneity of the two phenomena, may lead to incorrectly infer a causal nexus that is counter-intuitive and difficult to justify: the presence of FC has a strong and positive impact on the probability of innovation. Coefficients from logistic regressions document the same positive association shown in Table 4, without revealing any causal nexus between financial constraints and innovation.

Indeed, the decision to undertake innovative projects and the probability of facing financing constraints are both affected by unobservable heterogeneity. As in Gatchev, Pulvino, and Tarhan (2010) and Savignac (2008) I employ a bivariate probit model to simultaneously estimate the innovation and FC probabilities, accounting for third-party factors affecting both phenomena.

Once the two equations are simultaneously estimated (Table 6, column 1), the impact of FC appears to be very negative and significant, with a reduction in the probability of innovation that is quantifiable around 30%.

Results from the FC equation are also very sensible. Because of their lower capitalization, higher probability of default, and limited availability of internal funds, small firms are more likely to suffer from financial problems. Similarly, the availability of tangible assets, consistent flows of profits, and high shares of long-term funding reduce the probability of financial constraints.

The strong relevance of the estimated *Credit score* justifies the effort in the construction of this measure. Its economically and statistically significance confirms the inverse relationship between firm's creditworthiness a the rationing status of a company.

Finally, the estimated correlation coefficient ($\hat{\rho}$) provides a further validation of the use of simultaneous estimations, showing the relevance of neglected third-party factors.[19]

Although parameter restrictions enabled to get coherent results, the model still fails in accounting for the feedback effect of innovation on the probability of FC. To this purpose, column 2 of Table 6 proxies for the innovation propensity in the FC equation (Equation 2) with firms' structural probability of R&D ($\widehat{R\&D}$).

In support of traditional arguments, results show a positive association between innovative propensity and the probability of FC. This in turn is reflected onto a stronger effect of FC on innovation (-34%).

[19] In this regard, Lollivier (2001) showed that restricting the residuals' correlation to zero (which is imposed with two distinct probit models) yields to endogeneity problems and biased and inconsistent estimates.

Overall, the approach highlights an additional link between innovation and FC. The direct effect on firms' innovativeness is amplified by the consequences that the choice to innovate itself has on the likelihood of facing constraints. Moreover, if innovative activity is even riskier than R&D, then the "actual" reverse-effect may lead to an even stronger, depressive impact of FC on innovation.

This finding holds even if FC is replaced with a direct measure of credit accessibility ($FC_2$ in Table 7).[20] Results are also robust to alternative measures of firm creditworthiness (Altman score), the inclusion in the FC equation of the variables composing *Credit score*, the use of further lags for balance sheet measures (lag=2), alternative definitions of R&D (dummy or R&D expenditure to total sales ratio), export (dummy) and firms' size (log of assets), controls for the legal form of the company (partnerships, cooperatives and enterprises), or alternative clustering of the standard errors (industry or region).

Other robustness are performed on subsamples of firms,[21] specifications allowing AR(1) processes for innovation,[22] and the inclusion of regressors' mean to account for firms' unobserved heterogeneity.[23] In all cases results still hold.

#### 4.2.2 Heterogeneities: innovation type, industry and firm size

Table 8 presents the results for the breakdown of innovation types (product, process, and organizational-managerial innovations are presented in column 1, 2, and 3, respectively). Interestingly, the effect of FC doesn't significantly differ across definitions of innovation.[24] On the contrary, relevant heterogeneities are found for the other explanatory variables. Sensibly, the effects of R&D and exports are stronger for product and process innovation than for organizational-managerial ones. The same pattern emerges for the affiliation

[20] Even if the rest of the paper only focuses on the first definition of FC, every forthcoming result also holds for the alternative measure of financial constraints.

[21] One opened issue is whether results are driven by a subset of unsound firms with low-quality projects and reduced financial means. Given the absence of a control group, I exploit firms' unconditional-innovation likelihood (as in Table 5, column 1) to identify the subset of (more) innovative companies. The sample is then split into "Innovative" and "Non-innovative" firms depending on the median value (or $75^{th}$ percentile) of their unconditional likelihood to innovate. Results hold for both subsets, although they are stronger for more innovative firms.

[22] Although lagged covariates clear problems of simultaneity bias in the main equation, the persistence of relevant attitudes (like innovation, export, R&D, etc.) may leave residual endogeneity into the estimation. To control for this possibility, the baseline model is augmented with lagged values of innovation. Controlling for previous realizations allows to purge all the persistent behaviors already embedded in $Innovation_{t-1}$ and to focus on the "pure" effect of each regressor. Although innovation presents a high persistence, the other coefficients are very stable, suggesting that the main results are not affected by endogeneity problems generated by "sticky behaviors".

[23] This approach is justified by the non feasibility of id-fixed effects, and provides further support to the validity of the baseline regression

[24] Although the magnitude of the coefficient is higher for organizational-managerial improvements, an F-test on the difference of the coefficients does not detect any significant heterogeneity.

to simple networks, while advanced forms of connections seem to have a greater effects on marginal forms of improvements.

The homogeneity across different types of innovation raises the question whether other dimensions of heterogeneity exist. In particular, financial constraints can be critical for small firms and companies operating in technologically-intensive sectors (see for instance Canepa and Stoneman, 2008; Revest and Sapio, 2012).

Table 9 allows the effect of FC to be specific to the belonging industry. The impact of financial frictions on innovation is stronger for companies that operate in high-tech sectors, with an additional effect that is monotonically decreasing from product to process and organizational-managerial innovations (non significant). Since asymmetric informational problems are likely to be more severe for high-return projects, these findings provide support to the interpretation of Guiso (1998).

Table 10 presents heterogeneous effects depending on firms' size. In practice the model tests whether the effect of dimension on innovation is the result of a triple-acting: a direct effect due to the greater propensity to innovate (scale-effect), an indirect impact though the lower probability of financial problems and a further relaxing action once FC occurs. The last channel is examined with the inclusion of an additional interaction term between firm size and FC.

The effects of firm size are multiple. Not only through a direct positive effect on innovation and an indirect effect on firms' financial status. Large companies are also better able to carry on innovative projects once credit constraints occur. This additional effect is significant and positive only for product and process-innovations.

Figure ?? plots the predicted probability from Table 10 for different size levels and FC status. As it is clear from the figure, the impact of FC tends to decrease moving towards higher levels of firm size.[25] On the contrary, the dynamic of organizational-managerial innovations shows no positive role for firm dimension in alleviating the effects of financial problems. This discrepancy may be due to the very nature of these soft-forms of innovation, which embed a great variety of different improvements and are often adopted by very small companies. An alternative explanation can be found in the higher expected payoff of product and process innovations relative to organizational-managerial improvements.

[25] The negative effect of FC for each level of firm size can be inferred from the vertical distance between the blue and the green line.

#### 4.2.3 Proxing for soft-information

Although previous sections showed the importance of *Credit score* in determining firms' financial status, the analysis conducted so far neglects a relevant component of the credit channel. Indeed, capturing supply effects with hard information has the drawback to ignore all the benefits from relationship lending. An issue that can be critical for SMEs.

The accumulation of relevant information about the prospects and the creditworthiness of a borrower can greatly affect the lender's decisions on whether to extend credit and can lower firms' likelihood of facing financial constraints. Neglecting soft information may thus lead to an underestimation of firms' actual creditworthiness and to an overestimation of the final impact of FC on innovation. To test this hypothesis and to check the validity of previous results, the FC equation is augmented with the size of the lender banks and their geographical distance from the firm, as inverse proxies of relationship lending.

Tables 11 and 12 show the results (for comparison, column 1 reports the coefficients of the baseline specification re-estimated for the new –reduced– sample). When included in the specification, physical distance and bank size do not appear to significantly affect firms' probability of FC (column 2). This result seems to be in contradiction with the findings in Benfratello, Schiantarelli, and Sembenelli (2008), and Alessandrini, Presbitero, and Zazzaro (2010).

However, once the measures are interacted with firms' size, the estimation documents a strong and highly non-linear effect (columns 3 of Tables 11 and 12). Coherently with previous literature, my proxies of relationship lending greatly affect firms' probability of financial constraints, with a magnitude that depends upon the transparency of the borrower (here proxied by its size). This evidence suggests that small –and more opaque– firms, who suffer the most from financial problems, can gain a disproportional benefit from banks' accumulation of soft information. On the other side, the effect is never statistically significant for large firms with negligible problems in accessing external credit.

Moreover, the inclusion of controls for soft information alleviates the overall impact of FC on innovation (six to nine percentage points lower with respect to column 1).

Overall, the results of the paper document the negative effect of financial barriers to innovation, highlighting at the same time the critical role plaid by relationship lending. Bank's accumulation of soft information can be critical in determining the probability of financial constraints of very small firms and in mitigating the effect of financial frictions on firms' innovativeness.

## 5 Concluding remarks

The paper takes advantage of a newly-available survey to document the effect of financial barriers on the innovation activity of Italian SMEs. The dataset contains detailed information on the type of innovation introduced and allows to control for a rich set of firm characteristics.

The use of direct measures of financial constraints permits to overcome interpretational problems and to estimate firms' probability of innovating conditionally on the presence of financial barriers. Results show that firms suffering from financial problems have a probability of innovating that is significantly lower than sound companies (-30%). Moreover, an IV approach documents the existence of a feedback effect of innovation on the probability of financial constraints. The finding suggests that firms' propensity to innovate is further affected by the consequences that the choice to innovate itself has on the likelihood of facing constraints. This in turn is reflected onto a stronger hampering effect of financial barriers on innovation (-34%).

The detail of the dataset allows for testing several kinds of heterogeneity. While the impact of financial distress does not seem to vary across innovation types, the effect of financial constraints is significantly stronger for small firms and companies operating in technologically-intensive industries, especially for the introduction of new products.

Finally, the paper documents the role of relationship lending in mitigating financial barriers to innovation. Differently from previous approaches based on the direct inclusion of proxies into the innovation equation, this paper shows their indirect effect through the reduction in financial frictions. The size of the lender banks and their distance from the company are found to significantly affect the innovation activity of Italian companies by influencing firms' accessibility to the credit market. Interestingly, this effect is highly nonlinear and decreasing with the transparency of the borrower, sign that very small firms can gain disproportional benefits from relationship lending. Overall, the effect of FC on innovation is lowered once soft information is accounted for. This finding promotes relationship lending as an effective device to reduce the impact of financial constraints on the innovation activity of SMEs.

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Table 1: Sample composition of the MET surveys

| | 2008 | 2009 | 2011 |
|---|---|---|---|
| Micro (1-9) | 38.4% | 60.0% | 61.6% |
| Small (10-49) | 38.4% | 26.0% | 24.7% |
| Medium (50-249) | 19.5% | 10.4% | 10.6% |
| Large (>250) | 3.60% | 3.50% | 3.10% |
| North | 46.6% | 39.8% | 42.1% |
| Center | 32.0% | 33.7% | 31.8% |
| South | 21.4% | 26.5% | 26.1% |
| High-tech | 33.5% | 29.1% | 31.1% |
| Non high-tech | 66.5% | 70.9% | 68.9% |
| Numerosity | 24896 | 22340 | 25090 |

*Notes*: composition by firms' size classes (# of employees), geographical macro-regions and industrial macro-sectors. The original sample is mainly stratified along 12 industries (listed in Table 3), 20 regions and four size classes. The large numerosity is compatible with an oversampling of more innovative firms in the manufacturing sector, and of companies in certain geographical regions. The oversampling scheme is performed with Bayesian models exploiting the observed frequencies of previous waves. The survey is administrated *via* phone calls or *via* web with the assistance of a phone operator. The actual administration follows a preselection of the most suitable answerer. In the case of incoherent answers along the survey, firms are interviewed a second time as an additional control of validity. For further details about the sampling scheme, the administration methods, and the control procedures see Brancati (2012).

Table 2: Summary statistics and expected signs

| | Type | Mean | Std. Dev. | Min | Max | Expected sign Inn eq. | Expected sign FC eq. |
|---|---|---|---|---|---|---|---|
| Innovation | Dummy | 0.32 | 0.47 | 0.00 | 1.00 | | + |
| Product inn. | Dummy | 0.19 | 0.39 | 0.00 | 1.00 | | + |
| Process inn. | Dummy | 0.16 | 0.36 | 0.00 | 1.00 | | + |
| Org-Man inn. | Dummy | 0.19 | 0.39 | 0.00 | 1.00 | | + |
| R&D | Bounded | 0.02 | 0.22 | 0.00 | 50.0 | + | + |
| Market share | Scalar | 0.02 | 0.03 | 0.00 | 0.38 | +/- | |
| Group | Dummy | 0.14 | 0.34 | 0.00 | 1.00 | + | |
| Simple ntw | Dummy | 0.37 | 0.48 | 0.00 | 1.00 | + | |
| Advanced ntw | Dummy | 0.17 | 0.38 | 0.00 | 1.00 | + | |
| Export share | Bounded | 0.09 | 0.21 | 0.00 | 1.00 | + | |
| Multinational | Dummy | 0.03 | 0.18 | 0.00 | 1.00 | + | |
| Output growth | Scalar | 0.02 | 0.23 | -0.42 | 0.58 | + | |
| FC | Dummy | 0.13 | 0.34 | 0.00 | 1.00 | - | |
| $FC_2$ | Dummy | 0.31 | 0.46 | 0.00 | 1.00 | - | |
| Credit score | Bounded | 1.55 | 0.50 | 0.00 | 2.00 | | - |
| Tangible | Bounded | 0.22 | 0.19 | 0.01 | 0.66 | | - |
| Roll-over | Bounded | 0.69 | 0.32 | 0.00 | 1.00 | | + |
| Profitability | Scalar | 0.05 | 0.07 | -0.30 | 0.34 | | - |
| Distance | Scalar | 4.82 | 3.34 | 0.00 | 12.6 | | + |
| Bank size | Scalar | 19.4 | 1.26 | 13.1 | 20.7 | | + |
| Size | Scalar | 2.45 | 1.43 | 0.70 | 10.7 | + | - |
| Age | Scalar | 2.94 | 0.80 | 0.00 | 6.81 | +/- | - |

*Notes:* variable definition. *Innovation* is a dummy identifying innovative firms. *Product inn.*, *Process inn.* and *Org-Man inn* are related (respectively) to the introduction of product, process or organizational-managerial innovations. *R&D* is a measure of intensity of the research and development activity, defined as the share of employees devoted to R&D. *Market share* is the share of firm's output within the belonging industry. *Group* is a dummy identifying the affiliation to groups of firms. *Simple ntw* and *Advanced ntw* are dummies for simple or complex forms of network. Simple ntw if the prolonged inter-firm relationship is exclusively for commercial purposes. Advanced ntw if firms have more sophisticated forms of collaboration (cooperation, common R&D projects, joint venture, common services or commercialization). *Export share* is the share of sales from exported products. *Multinational* defines a dummy for complex forms of internationalization (FDI, international cooperation, inter-firm international agreements or has commercial branches abroad). *Output growth* is the rate of growth of sales between $t-1$ and $t$. *FC* and $FC_2$ are the two definitions of financial constraints. They both take value 1 if the firm is financially constrained and 0 otherwise. *FC* is related to the presence of potentially profitable investments bypassed because of lack of financial means. $FC_2$ is related to difficulties in accessing the credit market (see Appendix 1 for further details). *Credit score* is the credit score measure estimated in Appendix 2. It takes bounded values between 0 and 2 and it is increasing in firms' creditworthiness. *Tangible* is the share of tangible assets. *Roll-Over* is the short-term to total-debt ratio. *Profitability* is the Ebitda to total assets ratio. *Distance* is (the log of) the distance (in Km) between the headquarter of the lender bank(s) and the firm's belonging province. *Bank size* is (the log of) the size (in total assets) of the lender bank(s). In the case of multiple-banking relationships *Distance* and *Bank size* are computed as the equally-weighted average of each measure among the lender banks. *Size* is the log of (1+) the number of employees. *Age* is the log of (1+) age.

Table 3: Innovation and financial constraints: industrial details

| Industry: | Innovation | Product inn. | Process inn. | Org-man inn. | FC |
|---|---|---|---|---|---|
| Food | 28.3% | 18.6% | 14.5% | 15.0% | 11.9% |
| Textile | 34.1% | 23.2% | 17.4% | 17.8% | 11.9% |
| Furniture | 30.4% | 20.0% | 15.4% | 17.0% | 14.0% |
| Printing | 27.3% | 16.9% | 13.9% | 14.8% | 16.6% |
| Chemical | 42.8% | 29.6% | 23.7% | 24.3% | 13.4% |
| Machinery | 33.2% | 20.0% | 17.6% | 17.4% | 12.8% |
| Transportation | 44.3% | 28.4% | 23.7% | 26.0% | 14.9% |
| Engineering | 38.2% | 26.0% | 19.2% | 22.0% | 11.6% |
| Electric | 35.1% | 23.7% | 17.7% | 20.1% | 12.2% |
| Mineral | 33.4% | 20.7% | 17.4% | 17.4% | 13.4% |
| Transports | 22.9% | 10.4% | 9.30% | 16.4% | 13.3% |
| Services | 30.4% | 16.6% | 14.0% | 20.4% | 14.5% |
| High-tech | 41.0% | 27.7% | 21.7% | 23.6% | 14.9% |
| Non high-tech | 30.4% | 18.3% | 14.9% | 17.9% | 12.1% |

*Notes:* diffusion of innovations and financial constraints by firms' industry.

Table 4: Conditional propensities

| | Innovation | Product inn. | Process inn. | Org-man inn. |
|---|---|---|---|---|
| FC | 35.4% | 22.3% | 17.7% | 20.1% |
| Non-FC | 31.4% | 19.3% | 15.6% | 18.5% |

*Notes:* percentage of innovative firms, conditionally on their financial condition.

Table 5: Innovative propensity and financial constraints: benchmark regressions

| **Inn. Equation** | Logit model | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| FC | | | 0.06*** |
| | | | (0.01) |
| R&D$_{t-1}$ | 0.33*** | 0.34*** | 0.33*** |
| | (0.01) | (0.01) | (0.01) |
| Market share$_{t-1}$ | 0.01** | 0.01** | 0.01** |
| | (0.00) | (0.00) | (0.00) |
| Group$_{t-1}$ | 0.01* | 0.02* | 0.01* |
| | (0.01) | (0.01) | (0.01) |
| Simple ntw$_{t-1}$ | 0.05*** | 0.05*** | 0.05*** |
| | (0.01) | (0.01) | (0.01) |
| Advanced ntw$_{t-1}$ | 0.09*** | 0.09*** | 0.09*** |
| | (0.01) | (0.01) | (0.01) |
| Export share$_{t-1}$ | 0.07*** | 0.06*** | 0.07*** |
| | (0.01) | (0.01) | (0.01) |
| Multinational$_{t-1}$ | 0.15*** | 0.14*** | 0.15*** |
| | (0.02) | (0.02) | (0.02) |
| Output growth$_{t-1}$ | 0.01* | 0.01** | 0.01* |
| | (0.00) | (0.00) | (0.00) |
| Size$_{t-1}$ | 0.03*** | 0.03*** | 0.03*** |
| | (0.00) | (0.00) | (0.00) |
| Age$_t$ | -0.01 | -0.01 | -0.01 |
| | (0.00) | (0.00) | (0.00) |
| Tangibles$_{t-1}$ | | 0.06** | |
| | | (0.02) | |
| Profitability$_{t-1}$ | | 0.01 | |
| | | (0.03) | |
| Bank debt$_{t-1}$ | | 0.13*** | |
| | | (0.01) | |
| Constant (coeff.) | -0.66*** | -1.11*** | -0.71*** |
| | (0.11) | (0.17) | (0.11) |
| Industry (12) | yes | yes | yes |
| Region (20) | yes | yes | yes |
| Time | yes | yes | yes |
| # obs. | 13278 | 13278 | 13278 |
| Pseudo $R^2$ | 0.16 | 0.17 | 0.17 |
| Logliklihood | -19002 | -15652 | -18979 |
| LR chi2(.) | 7464*** | 6207*** | 7509*** |

*Notes:* marginal effects from logit models. The dependent variable is *Innovation*. All the other measures are defined as in Table 2.

*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.

Robust standard errors in parentheses.

Table 6: Innovative propensity and financial constraints: simultaneous estimation

| | | | | |
|---|---|---|---|---|
| **Innovation Equation** | | | | |
| FC | -0.30*** | (0.07) | -0.34*** | (0.07) |
| R&D$_{t-1}$ | 0.30*** | (0.01) | 0.30*** | (0.01) |
| Market share$_{t-1}$ | 0.01 | (0.00) | 0.01 | (0.00) |
| Group$_{t-1}$ | -0.01 | (0.01) | -0.01 | (0.01) |
| Simple ntw$_{t-1}$ | 0.08*** | (0.01) | 0.08*** | (0.01) |
| Advanced ntw$_{t-1}$ | 0.08*** | (0.01) | 0.08*** | (0.01) |
| Export share$_{t-1}$ | 0.03*** | (0.01) | 0.03*** | (0.01) |
| Multinational$_{t-1}$ | 0.15*** | (0.02) | 0.15*** | (0.02) |
| Output growth$_{t-1}$ | 0.01 | (0.00) | 0.01 | (0.00) |
| Size$_{t-1}$ | 0.02*** | (0.01) | 0.02*** | (0.01) |
| Age$_t$ | 0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | 0.07 | (0.11) | 0.08 | (0.10) |
| Industry (12) | yes | | yes | |
| Region (20) | yes | | yes | |
| Time | yes | | yes | |
| **FC Equation** | | | | |
| $\widehat{R\&D}_{i,t-1}$ | | | 0.05*** | (0.02) |
| Credit score$_{t-1}$ | -0.02*** | (0.01) | -0.02*** | (0.01) |
| Tangibles$_{t-1}$ | -0.01** | (0.01) | -0.01** | (0.01) |
| Roll-over$_{t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) |
| Profitability$_{t-1}$ | -0.01** | (0.00) | -0.01** | (0.00) |
| Size$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Age$_t$ | 0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | -0.42*** | (0.16) | -0.43*** | (0.16) |
| Industry (12) | yes | | yes | |
| Region (20) | yes | | yes | |
| Time | yes | | yes | |
| $\hat{\rho}$ | 0.49*** | (0.09) | 0.52*** | (0.09) |
| # obs. | 13278 | | 13278 | |
| Log ps-lik | -12634 | | -12630 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *Innovation* and *FC*. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Column 1 reports the estimates for the model without feedback effect. The regression in column 2 proxies the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.

*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.

Robust standard errors in parentheses.

Table 7: Innovative propensity and financial constraints: alternative definition (access to credit)

| | | | | |
|---|---|---|---|---|
| **Innovation Equation** | | | | |
| $FC_2$ | -0.41*** | (0.07) | -0.43*** | (0.07) |
| $R\&D_{t-1}$ | 0.28*** | (0.02) | 0.28*** | (0.01) |
| Market $share_{t-1}$ | 0.01 | (0.00) | 0.01 | (0.00) |
| $Group_{t-1}$ | -0.01 | (0.01) | -0.01 | (0.01) |
| Simple $ntw_{t-1}$ | 0.07*** | (0.01) | 0.07*** | (0.01) |
| Advanced $ntw_{t-1}$ | 0.07*** | (0.01) | 0.07*** | (0.01) |
| Export $share_{t-1}$ | 0.03*** | (0.01) | 0.03*** | (0.01) |
| $Multinational_{t-1}$ | 0.14*** | (0.02) | 0.14*** | (0.02) |
| Output $growth_{t-1}$ | 0.01 | (0.00) | 0.01 | (0.00) |
| $Size_{t-1}$ | 0.02*** | (0.01) | 0.02*** | (0.01) |
| $Age_t$ | -0.01 | (0.01) | -0.01 | (0.01) |
| Constant (coeff.) | 0.39*** | (0.12) | 0.08 | (0.10) |
| Industry (12) | yes | | yes | |
| Region (20) | yes | | yes | |
| Time | yes | | yes | |
| **FC Equation ($FC_2$)** | | | | |
| $\widehat{R\&D}_{i,t-1}$ | | | 0.14*** | (0.03) |
| Credit $score_{t-1}$ | -0.05*** | (0.01) | -0.05*** | (0.01) |
| $Tangibles_{t-1}$ | -0.02** | (0.01) | -0.02** | (0.01) |
| Roll-$over_{t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) |
| $Profitability_{t-1}$ | -0.01** | (0.00) | -0.01** | (0.00) |
| $Size_{t-1}$ | -0.02*** | (0.00) | -0.02*** | (0.00) |
| $Age_t$ | 0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | 0.34** | (0.15) | -0.31*** | (0.15) |
| Industry (12) | yes | | yes | |
| Region (20) | yes | | yes | |
| Time | yes | | yes | |
| $\hat{\rho}$ | 0.64*** | (0.11) | 0.66*** | (0.10) |
| # obs. | 13278 | | 13278 | |
| Log ps-lik | -15285 | | -15275 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *Innovation* and $FC_2$. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Column 1 reports the estimates for the model without feedback effect. The regression in column 2 instruments the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.

*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.

Robust standard errors in parentheses.

Table 8: Innovative propensity and financial constraints: details

| | Innovation type | | | | | |
|---|---|---|---|---|---|---|
| **Inn. Equation** | Product | | Process | | Org-Man | |
| FC | -0.27*** | (0.08) | -0.19** | (0.08) | -0.30*** | (0.09) |
| R&D$_{t-1}$ | 0.31*** | (0.01) | 0.14*** | (0.01) | 0.13*** | (0.01) |
| Market share$_{t-1}$ | 0.01** | (0.01) | -0.01 | (0.01) | -0.01 | (0.01) |
| Group$_{t-1}$ | -0.02 | (0.01) | -0.01 | (0.01) | 0.01 | (0.01) |
| Simple ntw$_{t-1}$ | 0.05*** | (0.01) | 0.02*** | (0.01) | 0.03*** | (0.01) |
| Advanced ntw$_{t-1}$ | 0.02*** | (0.01) | 0.01 | (0.01) | 0.08*** | (0.01) |
| Export share$_{t-1}$ | 0.07*** | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Multinational$_{t-1}$ | 0.16*** | (0.02) | 0.12*** | (0.01) | 0.11*** | (0.02) |
| Output growth$_{t-1}$ | 0.01 | (0.01) | 0.01** | (0.00) | 0.01 | (0.01) |
| Size$_{t-1}$ | 0.01*** | (0.00) | 0.01*** | (0.00) | 0.03*** | (0.01) |
| Age$_t$ | -0.01 | (0.01) | 0.01 | (0.01) | -0.01** | (0.00) |
| Constant (coeff.) | -0.36*** | (0.11) | -0.85*** | (0.13) | -0.67*** | (0.12) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| **FC Equation** | | | | | | |
| $\widehat{R\&D}_{i,t-1}$ | 0.04*** | (0.02) | 0.04*** | (0.02) | 0.04*** | (0.02) |
| Credit score$_{t-1}$ | -0.03*** | (0.01) | -0.02*** | (0.01) | -0.02*** | (0.01) |
| Tangibles$_{t-1}$ | -0.01** | (0.01) | -0.02*** | (0.01) | -0.02** | (0.01) |
| Roll-over$_{t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) |
| Profitability$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Size$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Age$_t$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | -0.42*** | (0.16) | -0.41** | (0.16) | -0.42*** | (0.16) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| $\hat{\rho}$ | 0.48*** | (0.13) | 0.41** | (0.16) | 0.49*** | (0.14) |
| # obs. | 13278 | | 13278 | | 13278 | |
| Log ps-lik | -12168 | | -11127 | | -12546 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *FC* and *Product inn* in column 1, *Process inn* in column 2, and *Org-Man inn* in column 3. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Both columns instrument the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.

*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.

Robust standard errors in parentheses.

Table 9: Innovative propensity and financial constraints: industrial heterogeneity

| | Innovation type | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Inn. Equation** | All | | Product | | Process | | Org-man | |
| FC | -0.34*** | (0.05) | -0.27*** | (0.09) | -0.19*** | (0.26) | -0.32*** | (0.18) |
| FC $\times$ hightech | -0.02* | (0.01) | -0.06*** | (0.01) | -0.02* | (0.01) | -0.01 | (0.06) |
| R&D$_{t-1}$ | 0.30*** | (0.02) | 0.31*** | (0.02) | 0.20*** | (0.02) | 0.16*** | (0.01) |
| Market share$_{t-1}$ | 0.01 | (0.01) | 0.01* | (0.00) | 0.01 | (0.01) | -0.01 | (0.01) |
| Group$_{t-1}$ | -0.01 | (0.02) | -0.02 | (0.02) | -0.02 | (0.02) | 0.01 | (0.02) |
| Simple ntw$_{t-1}$ | 0.08*** | (0.01) | 0.05*** | (0.01) | 0.04*** | (0.01) | 0.03*** | (0.01) |
| Advanced ntw$_{t-1}$ | 0.08*** | (0.01) | 0.02*** | (0.01) | 0.04*** | (0.01) | 0.08*** | (0.01) |
| Export share$_{t-1}$ | 0.03*** | (0.01) | 0.07*** | (0.01) | 0.02*** | (0.01) | 0.01 | (0.03) |
| Multinational$_{t-1}$ | 0.15*** | (0.03) | 0.16*** | (0.02) | 0.13*** | (0.02) | 0.11*** | (0.01) |
| Output growth$_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01* | (0.00) | 0.01 | (0.01) |
| Size$_{t-1}$ | 0.02*** | (0.01) | 0.02*** | (0.01) | 0.01** | (0.01) | 0.03*** | (0.01) |
| Age$_t$ | 0.01 | (0.01) | -0.01 | (0.01) | 0.01 | (0.01) | -0.01*** | (0.00) |
| Constant (coeff.) | 0.08 | (0.13) | -0.36*** | (0.11) | -0.68*** | (0.11) | -0.67*** | (0.12) |
| Industry (12) | yes | | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | | yes | |
| Time | yes | | yes | | yes | | yes | |
| **FC Equation** | | | | | | | | |
| $\widehat{R\&D}_{i,t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) |
| Credit score$_{t-1}$ | -0.03*** | (0.01) | -0.03*** | (0.01) | -0.03*** | (0.01) | -0.02*** | (0.01) |
| Tangibles$_{t-1}$ | -0.01 | (0.01) | -0.01 | (0.01) | -0.02** | (0.01) | -0.02** | (0.01) |
| Roll-over$_{t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) |
| Profitability$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Size$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Age$_t$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | -0.43*** | (0.16) | -0.42** | (0.16) | -0.42** | (0.17) | -0.42** | (0.17) |
| Industry (12) | yes | | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | | yes | |
| Time | yes | | yes | | yes | | yes | |
| $\hat{\rho}$ | 0.53*** | (0.11) | 0.50*** | (0.13) | 0.53*** | (0.10) | 0.49*** | (0.11) |
| # obs. | 13278 | | 13278 | | 13278 | | 13278 | |
| Log ps-lik | -12630 | | -12167 | | -12032 | | -12546 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *FC* and *Innovation* in column 1, *Product inn* in column 2, *Process inn* in column 3, and *Org-Man inn* in column 4. *Hightech* identifies firms operating in technologically intensive sectors (for a precise definition see the Appendix). $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Both columns instrument the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.
*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.
Robust standard errors in parentheses.

Table 10: Innovative propensity and financial constraints: size heterogeneity

| | **Innovation type** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Inn. Equation** | All | | Product | | Process | | Org-man | |
| FC | -0.33*** | (0.09) | -0.25*** | (0.09) | -0.19*** | (0.07) | -0.33*** | (0.06) |
| FC × $\text{Size}_{t-1}$ | 0.01* | (0.01) | 0.01** | (0.01) | 0.01* | (0.1) | -0.01 | (0.02) |
| $\text{R\&D}_{t-1}$ | 0.30*** | (0.02) | 0.32*** | (0.02) | 0.14*** | (0.01) | 0.15*** | (0.01) |
| Market $\text{share}_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | -0.01 | (0.01) | -0.01 | (0.01) |
| $\text{Group}_{t-1}$ | -0.01 | (0.02) | -0.02 | (0.02) | -0.02 | (0.02) | 0.01 | (0.02) |
| Simple $\text{ntw}_{t-1}$ | 0.08*** | (0.01) | 0.05*** | (0.01) | 0.02*** | (0.01) | 0.03*** | (0.01) |
| Advanced $\text{ntw}_{t-1}$ | 0.08*** | (0.01) | 0.03*** | (0.01) | 0.01 | (0.01) | 0.08*** | (0.01) |
| Export $\text{share}_{t-1}$ | 0.03*** | (0.01) | 0.07*** | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| $\text{Multinational}_{t-1}$ | 0.15*** | (0.03) | 0.16*** | (0.02) | 0.12*** | (0.01) | 0.11*** | (0.01) |
| Output $\text{growth}_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01*** | (0.00) | 0.01 | (0.01) |
| $\text{Size}_{t-1}$ | 0.01*** | (0.00) | 0.01*** | (0.00) | 0.01*** | (0.00) | 0.03*** | (0.00) |
| $\text{Age}_t$ | 0.01 | (0.01) | -0.01 | (0.01) | 0.01 | (0.01) | -0.01*** | (0.00) |
| Constant (coeff.) | 0.07 | (0.13) | -0.38*** | (0.11) | -0.86*** | (0.11) | -0.67*** | (0.12) |
| Industry (12) | yes | | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | | yes | |
| Time | yes | | yes | | yes | | yes | |
| **FC Equation** | | | | | | | | |
| $\widehat{R\&D}_{i,t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) |
| Credit $\text{score}_{t-1}$ | -0.02*** | (0.01) | -0.03*** | (0.01) | -0.02*** | (0.01) | -0.02*** | (0.01) |
| $\text{Tangibles}_{t-1}$ | -0.01** | (0.01) | -0.01 | (0.01) | -0.01** | (0.01) | -0.02*** | (0.01) |
| $\text{Roll-over}_{t-1}$ | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) | 0.04*** | (0.01) |
| $\text{Profitability}_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| $\text{Size}_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| $\text{Age}_t$ | 0.01 | (0.00) | 0.01 | (0.00) | 0.01 | (0.00) | 0.01 | (0.00) |
| Constant (coeff.) | -0.43*** | (0.17) | -0.41*** | (0.17) | -0.40** | (0.17) | -0.43*** | (0.16) |
| Industry (12) | yes | | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | | yes | |
| Time | yes | | yes | | yes | | yes | |
| $\hat{\rho}$ | 0.49*** | (0.05) | 0.39** | (0.15) | 0.39*** | (0.13) | 0.58*** | (0.09) |
| # obs. | 13278 | | 13278 | | 13278 | | 13278 | |
| Log ps-lik | -12630 | | -12167 | | -11127 | | -12545 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *FC* and *Innovation* in column 1, *Product inn* in column 2, *Process inn* in column 3, and *Org-Man inn* in column 4. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation.
*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.
Robust standard errors in parentheses.

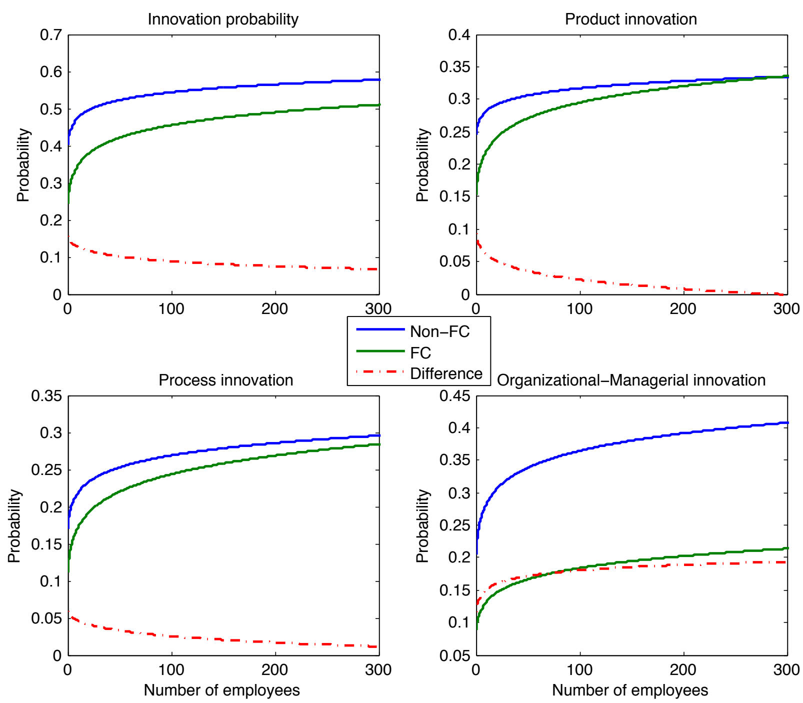


Figure 1: Probability of innovation, financial constraints and firm size.

*Notes*: predicted probabilities of innovation as a function of firm FC status and size. Predicted probabilities are computed imposing all the other covariates at their mean value.

Table 11: Innovative propensity and financial constraints: bank distance as inverse proxy of relationship lending

| | | | | | | |
|---|---|---|---|---|---|---|
| **Inn. Equation** | | | | | | |
| FC | -0.36*** | (0.04) | -0.32*** | (0.04) | -0.27*** | (0.04) |
| R&D$_{t-1}$ | 0.29*** | (0.03) | 0.30*** | (0.02) | 0.30*** | (0.02) |
| Market share$_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Group$_{t-1}$ | 0.06*** | (0.02) | 0.06*** | (0.02) | 0.06*** | (0.02) |
| Simple ntw$_{t-1}$ | -0.01 | (0.01) | -0.01 | (0.01) | -0.01 | (0.02) |
| Advanced ntw$_{t-1}$ | 0.09*** | (0.02) | 0.09*** | (0.02) | 0.09*** | (0.02) |
| Export share$_{t-1}$ | 0.08*** | (0.02) | 0.08*** | (0.02) | 0.08*** | (0.02) |
| Multinational$_{t-1}$ | 0.21*** | (0.04) | 0.21*** | (0.04) | 0.22*** | (0.05) |
| Output growth$_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Size$_{t-1}$ | 0.01*** | (0.00) | 0.01** | (0.01) | 0.02** | (0.01) |
| Age$_t$ | -0.01 | (0.01) | -0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | -0.93*** | (0.11) | -0.98*** | (0.09) | -0.99*** | (0.09) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| **FC Equation** | | | | | | |
| Distance | | | -0.00 | (0.00) | 0.01*** | (0.00) |
| Distance × Size$_{t-1}$ | | | | | -0.004*** | (0.00) |
| $\widehat{R\&D}_{i,t-1}$ | 0.05* | (0.03) | 0.04* | (0.03) | 0.05* | (0.03) |
| Credit score$_{t-1}$ | -0.03*** | (0.01) | -0.03*** | (0.01) | -0.03*** | (0.01) |
| Tangibles$_{t-1}$ | -0.01** | (0.00) | -0.00 | (0.00) | -0.01 | (0.01) |
| Roll-over$_{t-1}$ | 0.08*** | (0.02) | 0.10*** | (0.02) | 0.10*** | (0.02) |
| Profitability$_{t-1}$ | -0.01** | (0.00) | -0.01** | (0.00) | -0.01** | (0.00) |
| Size$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Age$_t$ | 0.01 | (0.02) | 0.01 | (0.02) | 0.01 | (0.02) |
| Constant (coeff.) | -0.92*** | (0.26) | -0.97** | (0.22) | -1.24*** | (0.23) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| $\hat{\rho}$ | 0.59*** | (0.06) | 0.51*** | (0.11) | 0.45*** | (0.11) |
| # obs. | 9935 | | 9935 | | 9935 | |
| Log ps-lik | -8648 | | -8627 | | -8620 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *Innovation* and *FC*. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Column 1 reports the estimates for the model without feedback effect. The regression in column 2 proxies the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.
*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.
Robust standard errors in parentheses.

Table 12: Innovative propensity and financial constraints: bank size as inverse proxy of relationship lending

| | | | | | | |
|---|---|---|---|---|---|---|
| **Inn. Equation** | | | | | | |
| FC | -0.36*** | (0.04) | -0.31*** | (0.04) | -0.29*** | (0.04) |
| R&D$_{t-1}$ | 0.29*** | (0.03) | 0.30*** | (0.02) | 0.30*** | (0.02) |
| Market share$_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Group$_{t-1}$ | 0.06*** | (0.02) | 0.06*** | (0.02) | 0.06*** | (0.02) |
| Simple ntw$_{t-1}$ | -0.01 | (0.01) | -0.01 | (0.01) | -0.01 | (0.02) |
| Advanced ntw$_{t-1}$ | 0.09*** | (0.02) | 0.09*** | (0.02) | 0.09*** | (0.02) |
| Export share$_{t-1}$ | 0.08*** | (0.02) | 0.08*** | (0.02) | 0.08*** | (0.02) |
| Multinational$_{t-1}$ | 0.21*** | (0.04) | 0.22*** | (0.04) | 0.22*** | (0.05) |
| Output growth$_{t-1}$ | 0.01 | (0.01) | 0.01 | (0.01) | 0.01 | (0.01) |
| Size$_{t-1}$ | 0.01*** | (0.00) | 0.01** | (0.01) | 0.02** | (0.01) |
| Age$_t$ | -0.01 | (0.01) | -0.01 | (0.01) | 0.01 | (0.01) |
| Constant (coeff.) | -0.93*** | (0.11) | -0.98*** | (0.09) | -0.99*** | (0.09) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| **FC Equation** | | | | | | |
| Bank size | | | -0.00 | (0.00) | 0.02** | (0.01) |
| Bank size × Size$_{t-1}$ | | | | | -0.005*** | (0.00) |
| $\widehat{R\&D}_{i,t-1}$ | 0.05* | (0.03) | 0.04* | (0.03) | 0.04* | (0.03) |
| Credit score$_{t-1}$ | -0.03*** | (0.01) | -0.03*** | (0.01) | -0.03*** | (0.01) |
| Tangibles$_{t-1}$ | -0.01** | (0.00) | -0.00 | (0.00) | -0.01 | (0.01) |
| Roll-over$_{t-1}$ | 0.08*** | (0.02) | 0.10*** | (0.02) | 0.10*** | (0.02) |
| Profitability$_{t-1}$ | -0.01** | (0.00) | -0.01** | (0.00) | -0.01** | (0.00) |
| Size$_{t-1}$ | -0.01*** | (0.00) | -0.01*** | (0.00) | -0.01*** | (0.00) |
| Age$_t$ | 0.01 | (0.02) | 0.01 | (0.02) | 0.01 | (0.02) |
| Constant (coeff.) | -0.92*** | (0.26) | -0.97** | (0.22) | -1.24*** | (0.23) |
| Industry (12) | yes | | yes | | yes | |
| Region (20) | yes | | yes | | yes | |
| Time | yes | | yes | | yes | |
| $\hat{\rho}$ | 0.59*** | (0.06) | 0.51*** | (0.11) | 0.45*** | (0.11) |
| # obs. | 9935 | | 9935 | | 9935 | |
| Log ps-lik | -8648 | | -8627 | | -8620 | |

*Notes:* marginal effects from bivariate probit models. The dependent variables are *Innovation* and *FC*. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 2. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Column 1 reports the estimates for the model without feedback effect. The regression in column 2 proxies the innovation variable in the FC equation with the predicted structural probability of R&D as defined in Section 3.3.

*, **, *** denote, respectively, significance at 10%, 5%, and 1% level.

Robust standard errors in parentheses.

# Appendix 1: variable definitions

| Variable name | Definition |
|---|---|
| Innovation | Dummy variable = 1 if the firm introduced at least one innovation (independently by the type). |
| Product inn | Dummy variable = 1 if the firm introduced at least one product innovation. |
| Process inn | Dummy variable = 1 if the firm introduced at least one process innovation. |
| Org-man inn | Dummy variable = 1 if the firm introduced at least one organizational-managerial innovation. |
| FC | Dummy variable = 1 if the firm declared to have bypassed potentially profitable investments because of a lack of funding. |
| $FC_2$ | Dummy variable = 1 if the firm declared to have had "grave difficulties in accessing the credit market". |
| R&D | Share of employees devoted to R&D activity over the total number of employees. |
| Market share | Share of firm's sales over the aggregated sales of the belonging industry. |
| Group | Dummy variable = 1 if the company belongs to a group of firms. |
| Simple ntw | Dummy variable = 1 if the company has stable commercial relationships with other firms. |
| Advanced ntw | Dummy variable = 1 if the company has more complex forms of collaborations with other firms (cooperation, common R&D projects, joint venture, common services and commercialization). |
| Export share | Share of firm's sales from exported products. |
| Multinational | Dummy variable = 1 if the company undertakes more complex forms of internationalization (FDI, international cooperation, inter-firm international agreements, and commercial branches). |
| Output growth | Rate of growth of firm's sales in the previous year. |
| Credit score | Estimated credit score recovered in Section 4.2. |
| Tangible | Firm's tangible-to-total-assets ratio. |
| Roll-over | Firm's short-term-to-total-debt ratio. |
| Profitability | Firm's operating-profit-to-total-assets ratio. |
| Distance | log of distance (in Km) between the province each firm belongs to, and the headquarter of the bank each company borrows from. |
| Bank size | size (log of total assets) of the lender bank.[a] |
| Size | (log of) firm's number of employees. |
| Age | (log of) firm's age. |
| Hightech | Dummy variable identifying high-tech industries (chemicals, plastic and chemical; means of transportation; engineering; electric and electronic equipment). |
| Time | Dummy variables identifying the three years of the waves. |
| Region | Dummy variables identifying 20 geographical regions. |
| Industry | Dummy variables identifying 12 (2-Digit) industries. |

[a] In the case of multiple-banking relationships *Distance* and *Bank size* are computed as the equally-weighted average of each measure among the lender banks.

# Appendix 2: Credit score estimation

This section estimates the credit score employed throughout the paper as a proxy for firms' creditworthiness. This approach of "reverse engineering" allows to reproduce the way banks assign credit ratings and to exploit a side-estimate to recover an indicator of reliability for all the firms in my sample (filling the consistent gaps of the actual ratings).

Neglecting all the components of soft-information, firm "perceived creditworthiness" is considered to be a function of a set of balance-sheet ratios (traditionally employed in the literature on credit scores). Exploiting a sample of about 3,000 credit ratings assigned by several Italian banks to a group of local firms I estimate a score in the spirit of Altman (1968).[26] The advantages of this approach come from the geographical and temporal specificity of the estimation. Estimates performed on the Italian system have the advantage to clear inaccurate approximations due to possible cross-country heterogeneity in the rating assignment. Furthermore, the timing of the data permits to catch potential changes in bank valuations in times of crisis (post Lehman Brothers). This approach guarantees an approximation of firms' specific creditworthiness that is more reliable than universal scores.

The estimation is performed through non-linear models. Firms' rating classes are explained through a vector of covariates that includes: an index of financial independence (firms' own sources to total debt ratio), returns on equity (ROE), returns on investment (ROI), Ebitda to invested capital ratio, floating-capital to invested capital ratio and a dummy variable that indicates whether the firm has been evaluated in times of crisis.

Table 13 shows the estimates from ordered logit and generalized ordered logit models. The likelihood-ratio (LR) test in column 1 documents the violation of the "proportional odds assumption" suggesting the adoption of generalized models.[27]

All variables are strongly significant and the signs of the estimates reflect *a priori* expectations. Inter-

[26]The estimation of the credit score is based on a confidential dataset provided by Fiditoscana (a credit-warranty structure operating on market basis and in the allowance of warranties based on public funds), consisting in 3,000 credit ratings assigned by several Italian banks to local firms.

[27]The proportional-odds model is based on a multi-equation estimation where coefficients are constrained to be the same across different states of the dependent variable. The high significance of the LR test suggests the violation of this hypothesis and requires switching to a generalized ordered logit model that allows for variations in the beta estimates across states. The advantage of using such a regression (with respect to standard multinomial logit models) is the possibility of imposing constancy for all the covariates that do not violate the proportional-odds assumption, having in such a way a more parsimonious model.

estingly, the impact of ROE seems to vanish once a medium level of creditworthiness is reached. Moreover, the strong significance of the crisis dummy suggests an increased severity of bank-rating assignment in the post-financial crisis. This effect is not due to a worsening in the economic conditions of the firms. If this was the case, lower ratings would come from worse balance-sheet ratios rather than structural breaks in the parameter estimates. Further evidence is found once the sample is split in the two sub-periods (not reported). Results are coherent with those in Table 13 and document a relevant reduction in the coefficients of the last column. This evidence suggests a significant contraction in bank willingness to assign high ratings after the Lehman collapse.[28]

Once provided a satisfactory specification, the estimates are applied out-of-sample to compute the state probabilities for all the companies in the MET survey.[29] The latter are then aggregated into *Credit score*, a measure that is increasing in firms' creditworthiness.

Overall, the estimation is able to correctly classify 80% of the firms in the rating sample.[30] A further check on its sensibility comes from the empirical-cumulative distribution function of *Credit score* in Figure 2. Not only the distribution of non-financially-constrained firms is always higher than FC companies; innovative firms are also the most creditworthy. This evidence highlights the possibility of relevant financial barriers to the innovation activity of Italian companies.

[28]This evidence may be explained by the higher informational asymmetries due to the increased opaqueness of SMEs in times of crisis.

[29]This is required by the absence of actual ratings for most of the companies in the original sample. Moreover, estimated ratings have the further advantage to provide a measure of creditworthiness also for those firms that didn't apply for a loan only because they already knew their application would have been rejected. Limiting in this way issues linked to selection bias.

[30]The accuracy of the model is tested out-of-sample with a bootstrap procedure to avoid standard problems related to over-fitting of in-sample tests.

Table 13: Credit score estimation

| | Ordered logit | Generalized ordered logit | |
|---|---|---|---|
| | | 0 | 1 |
| Degree of financial independence$_t$ | 5.69*** | 3.31*** | 6.45*** |
| | (0.37) | (0.49) | (0.40) |
| ROE$_t$ | -0.005 | 0.60*** | -0.19 |
| | (0.06) | (0.13) | (0.12) |
| ROI$_t$ | 1.51*** | 0.97*** | 1.76*** |
| | (0.09) | (0.10) | (0.10) |
| $\frac{Ebitda_t}{Invested\,capital_t}$ | 17.11*** | 16.83*** | 16.83*** |
| | (1.16) | (0.49) | (0.49) |
| $\frac{Floating\,capital_t}{Invested\,capital_t}$ | 1.85*** | 1.10*** | 2.34*** |
| | (0.24) | (0.35) | (0.27) |
| Crisis$_t$ | -0.32*** | -0.32*** | -0.32*** |
| | (0.11) | (0.11) | (0.11) |
| cut$_1$ | 0.18 | 0.91*** | – |
| | (0.17) | (0.19) | |
| cut$_2$ | 3.03 | – | -3.50*** |
| | (0.18) | | (0.19) |
| # obs. | 2864 | 2864 | |
| Pseudo $R^2$ | 0.28 | 0.31 | |
| Logliklihood | -1818 | -1687 | |
| LR test for proportional odds hp. | 700.14*** | – | |

*Notes:* coefficients from Ordered Logit (column 1) and Generalized Ordered Logit models (columns 2 and 3) on the credit score. The dependent variable is firms' rating class, an ordinal variable with increasing degree of creditworthiness (0 = C, CC, CCC; 1= B, BB, BBB; 2= A, AA, AAA). *Degree of financial independence* is the ratio between firms' own sources and total debt. *Crisis* is a dummy variable identifying whether the rating is assigned after the Leman collapse. The other covariates correspond to the ratios listed in the table. Column 2 and 3 refer, respectively, to the estimates applied in the state transition between low and medium and between medium and high rating classes.
*, **, *** denote respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

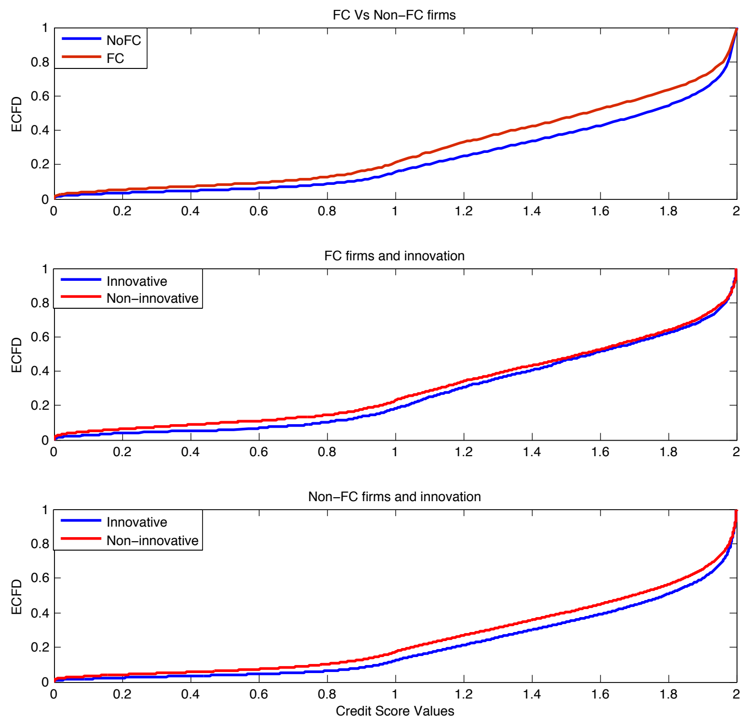


Figure 2: Empirical cumulative distribution functions: credit score. by FC and innovation.

*Notes*: empirical cumulative distribution function (ECDF) of the credit score for several classes of firms. The first panel matches financially constrained and unconstrained firms. The second plot compares innovative and non-innovative financially constrained companies. The last panel compares innovative and non-innovative non-financially constrained firms.