Innovation, financial constraints and relationship lending: evidence from Italy during the recent crises

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Abstract

Financial frictions may 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 companies. Employing direct measures of financial constraints and a credit-score estimated *ad hoc*, I find firms that suffer from financial problems to have a probability of innovating that is significantly lower than sound companies (-30%). The paper also documents the existence of a feedback-effect of innovation on firms' financial position. Results suggest that the innovative propensity of a company is further affected by the consequences that the choice to innovate has on the likelihood of facing constraints. This in turn is reflected onto a stronger depressive effect of financial constraints on innovation (-34%). Finally, the paper also provides evidence on the role of soft information in mitigating financial obstacles for innovative companies. Relationship lending is found to improve the financial condition of more opaque (small) borrowers and to reduce the overall effect of financial constraints on innovation.

JEL # O31; L25; G21.

Keywords: Innovation; financial constraints; relationship lending; ratings.

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1 Introduction

Innovative activity and creation of new knowledge, are commonly considered to be 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 topic in the literature of finance and growth. According to King and Levine (1993a, 1993b), 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, taking also into account the "feedback-effect" that the decision to innovate itself has on firms' financial condition. The work also contributes to the 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 that is 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 essentially 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 are worth emphasizing. First, I make use of a newly-available dataset (the MET survey on the Italian industry) that includes also micro-sized firms (family-companies and partnerships) 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 also permits to control for a rich set of determinants of firms' innovativeness, including R&D, market power, presence and complexity of firm networks and degree of internationalization.

The empirical analysis takes advantage of simultaneous-equations models (recursive bivariate probit) to estimate firms' probability of innovation, conditionally on the likelihood of facing financial constraints (hereinafter FC).

The specification of the FC equation is one distinctive feature of this work. In addition to a large set of controls —structural characteristics and proxies of firms' demand for credit— the model includes a credit-score index that is estimated *ad hoc* on a sample of confidential bank ratings. 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).

The main results of the paper are easily summarized. Once accounted for the simultaneity of the two equations, financial constraints are found to strongly hamper firms' probability of introducing innovations (-30%). This impact is even larger (-34%) once accounted for the feedback effect of firms' innovativeness on their financial condition. Overall, my results suggest that the propensity to innovate of a company is also affected by the consequences that the choice to innovate itself has on its probability of FC. This is the first paper documenting this additional link without imposing any restriction on the signs of the parameters.

The analysis on relationship lending provides interesting results. Exploiting the identification of the firm-bank relationship in the last wave of the survey, I'm able to match banks' characteristics with firm-level data and to use the number of banking relationships, the size of the lender banks and their geographical distance from the firms, as inverse proxies of relationship lending (in the FC equation). Results confirm the critical role plaid by the accumulation of soft information in influencing the banks' decisions on whether and at what conditions to extend credit. Interestingly, this effect is found to be highly nonlinear and decreasing with the transparency of the borrower (proxied by its size), 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.

Finally, the analysis documents several dimensions of heterogeneity, based on the type of innovation introduced, the size of the firm and the technological intensity of the belonging sector.

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.

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 their innovations.

First of all, frictions from informational asymmetries are likely to be particularly severe because innovative firms usually invest in high-risk-high-return projects, whose expected returns are extremely difficult to evaluate.[1] This issue is even more relevant in presence of firms' strategic behaviors that lead to sub-optimal transmission of the information to the bank. This is motivated by the trade-off faced by innovative firms in transferring the scientific and technological content of their projects (Leland and Pyle, 1977; Kihlstrom and Mattheus, 1984; Bhattacharya and Ritter, 1985). On the one hand, better signals reduce informational asymmetries and lower firms' costs of funding. On the other, in line with new-shumpeterian 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.

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 (possibly at zero).

Finally, the peculiar nature of the investments in R&D and innovation is likely to further worsen firms' financial position. While expenditures in physical capital usually occur once in a while, investments for research and development tend to be smoothed over time. 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.

Although extensively studied from a theoretical perspective, empirical analyses testing the direct 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 that affect firms' investments are non directly detectable as well. Quoting Kaplan and Zingales (1997): "The most precise (but also the broadest) definition classifies firms as financially constrained if they face a wedge between internal and external cost of funds".[2] Even though this definition is definitely too broad, it sheds light on how difficult is, in practice, to correctly identify financially constrained firms.

When direct indicators were not available, economic literature deduced the presence of financial obstacles from indirect measures. Following Fazzari, Hubbard and Petersen (1988), several papers exploited the investment-to-cash-flow sensitivity to classify firms by their FC status (Kashyap et al., 1994; Korajczyk and

[1] Indeed, past experience can offer little guidance in assessing the prospects of truly new projects; rather, it is likely that the entrepreneur undertaking the innovative project has, if not more knowledge, at least a better perception of its likelihood of success (Guiso, 1998).

[2] Kaplan and Zingales (1997), p. 172.

Levy, 2003; Whited and Wu, 2006).[3] However, despite its diffusion, their 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).[4] 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 specific surveys at firm-level.[5]

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 et al., 2001; Bond et al., 2003, among others). More recently, Savignac (2008), Hajivassiliou and Savignac (2011), and Blanchard et al. (2012) focus on direct indicators of FC to prove the negative effect of financial obstacles on the innovative activity of French and European firms. Similarly, Mohnen et al. (2008) and Segarra, García-Quevedo, and Teruel (2013) find that financial barriers increase the likelihood of failure (or abandonment) of innovative projects.[6]

The literature on the Italian system mainly focuses on the effects of relationship lending or on indirect proxies of financial distress. Exploiting the Capitalia survey, Benfratello, Schiantarelli, and Sembenelli (2007) find evidence that local banking development has a significant effect on firms' process innovation and no relevant impact on the implementation of new products. Herrera and Minetti (2007) test the effects of the duration of the credit relationship on firms' innovativeness. They show that the amount of information accumulated by the main bank has a positive and significant role in promoting firms' innovations. Alessandrini, Presbitero, and Zazzaro (2009) study the effect of bank "functional distance". They provide compelling evidence that SMEs located in provinces where the local banking system is distant, have a lower propensity to introduce process and product innovations. Finally, Giannetti (2009) shows that relationship lending has negligible impact on the innovative activity of SMEs while plays an important role for firms operating in

[3]They usually add over-identifying restrictions to equations that model the investment path (such as flexible accelerator models or Euler equations) and exploit the distribution of indirect proxies (financial leverage, availability of tangible assets, interest coverage, existence of a bond rating, dividends, etc.) to rank firms by their probability of FC and to show heterogeneous sensitivities among firms' classes.

[4]Other works exploit the properties of the Kaplan and Zingales KZ-score or the Altman Z-score to rank firms by their creditworthiness and probability of default (Lamont et al., 2001). These approaches are often unable to correctly classify firms by their FC status because of the generality and the inapplicability of "universal scores" to specific economies. Indeed, in order to have general validity, universal credit scores are computed on broad characteristics that may not be suitable to sort firms within a certain country (with a specific industrial composition). Moreover, the inclusion of variables linked to the issue of shares, makes these measures difficult to apply to bank-based economies (Italy included). Simply excluding these variables from the KZ or Z-score, may provide inadequate measures of firm creditworthiness (the Altman Z-score considers the Tobin's Q while in the KZ score three out of the eight firm-specific characteristics considered, are related to issue of shares: Tobin's Q, dividends over physical capital and dividends restricted). To overcome this problem, the Altman Z"-score estimated for emerging countries replaces them with measures of leverage. The version in Altman, Hartzell and Peck (1995) is used as robustness check.

[5]Notice however the potential selection bias affecting bank-level data. Inferring FC only from documented, rejected loans neglects a relevant part of the total phenomenon. On the one side, all firms receiving undocumented refuses are excluded from the sample. On the other, all companies not asking for loans are classified as non-financially constrained, even if they didn't apply only because they knew their application would have been rejected. As a result, measures from loan-application data may lead to an underestimation of the overall effects of financial constraints.

[6]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 US firms.

high-tech industries.[7]

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 final dataset is the result of alignments and transformations of several kinds of information. 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 (true) representativeness at size, geographical region and industry levels (see Table 2 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 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%).

The estimation of the credit score is based on a confidential dataset provided by Fiditoscana[8], consisting in 3,000 credit ratings assigned by several Italian banks to local firms. Finally, the universe of firms' balance sheets comes from CRIBIS D&B, banks' data are from Bankscope Bureau van Dijk while measures of distance are hand-collected from Google maps.

From the original dataset the application of selection-filters produces a relevant contraction in the size of the sample. The major reduction comes from the focus (for econometric issues) on companies with multiple-interviews and with balance-sheet information. 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

[7] For other examples on relationship lending in Italy see also Ferri and Messori (2000), De Mitri et al. (2010), and Frazzoni et al. (2011).

[8] Fiditoscana is a credit-warranty structure operating on market basis and in the allowance of warranties based on public funds.

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. The second definition (FC_2) is directly based on firms' borrowing possibilities and identifies the existence of "grave difficulties" in accessing external credit.[9] Although highly correlated, the two variables are far from containing the exact same information (the correlation coefficient is 0.59). As a consequence, their alternative use allows for an actual robustness check of the results.

It is worth reminding that both measures are independent from firms' propensity to innovate. The negative impact on innovation is recovered only through a simultaneous estimation of both likelihoods. Notice also that, if one had data on specific limitations to innovative projects, the selection bias (i.e. only innovative firms would be potential candidates to be FC) would complicate the analysis because of the impossibility of a *ceteris paribus* interpretation. In order to quantify the depressive impact of FC on the innovation activity, independent measures are ideal devices.

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 et al., 2009): the OSLO Manual (OECD–Eurostat, 2005) identifies only product and process innovations while some papers also consider softer forms of improvements as the organizational and managerial ones. The latter are defined as "the implementation of new organizational or managerial methods in the firms' business practices, workplace organization or external relationships". Softer forms of innovation may be crucial in a system dominated by SMEs. Although their definition is broad and sometimes ambiguous, organizational and managerial innovations allow to account for effects of learning by doing and leaning by using not embedded in the standard definitions.

To this purpose, even though I always provide disaggregated results, the baseline specification adopts a comprehensive measure of innovation that does not distinguish among innovation types (product, process and

[9] 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.

organizational and managerial). This should be better able to capture firms' actual degree of innovativeness in the case of very small companies.

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:

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

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

where Inn_i and FC_i represent the observed dependent variables (innovation and financial constraints), Inn_i^* and FC_i^* are latent variables associated respectively to Inn_i and FC_i, X_{1i} and X_{2i} are vectors of exogenous parameters, while θ and φ 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 $\rho = corr(\varepsilon_{1,i}, \varepsilon_{2,i})$:

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} = \Phi_2 \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

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 (Gouriroux et al., 1980; Maddala, 1983). Imposing $\varphi = 0$ simplifies the previous system of equations 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 instrument the 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). Thus, although financial frictions are presumably more relevant for innovative firms (at least in case of radical product and process-innovations), the instrumentation should allow to catch (at least part of) this additional channel.

Finally, it is useful to notice that the correlation coefficient between the error terms (ρ) accounts for all possible omitted or unobservable factors that drive at the same time both the probability of innovation and the likelihood of FC. In a way, the significance of $\hat{\rho}$ represents a proof of the goodness of this approach. In other words, if $\hat{\rho}$ is not significantly different from zero, the error terms are not correlated and the model boils down to the estimation of two separate probit models.[10]

The 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).[11]

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 a proper econometric model. The full set of controls is given by:

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

where, coherently with equations 1 and 2, $X_{1,i}$ and $X_{2,i}$ refer, respectively, to the innovation and the financial-constraints 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

[10] *Vice versa*, if $\hat{\rho}$ is significantly different from zero, the estimates of two separate probit models are inconsistent and a joint estimation is required.

[11] 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 on the persistence of innovation are mainly based on effects linked to 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 1983) and on innovation smoothing strategies.

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.

Firm's dominant position is proxied by *Market power*, 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 groups of firms (taken into account with the inclusion of *Group*), I explicitly consider other kind of informal networks. While traditional approaches on the Italian economy focus on the positive externalities of "industrial districts", this work avoids strict definitions based on territorial borders and provides a more accurate measurement of local networks. Although the requirements for a network connection are strictly listed in the survey, the interpretation of what "local" means, is left to the firm. The classification distinguishes "stand alone" companies (if there isn't any significant and prolonged inter-firm relationship) and firms belonging to "*Simple network*" (whether a stable commercial relationship exists) or "*Advanced network*" (in the case of more sophisticated relationships such as cooperation, common R&D projects, joint venture, common services and commercialization). The independence from rigid geographical frontiers should guarantee a definition of networks that is better able to capture the positive externalities from inter-firm connections. To this purpose, the analysis includes two dummy variables identifying simple and complex networks.

In the same spirit, firms' international activity is summarized by two different variables. *Export share*, refers to the presence on the international markets and it is measured as the share of foreign sales. In principle, exporting firms are more prone to innovate because of the highly-competitive pressure on international markets. It is however possible that such a positive effect does not blow over with the simple export activity, while it may be strengthen by positive externalities deriving from more complex forms of internationalization. In order to account for this additional effect, a further binary variable (*Multinational*) captures 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 and measures for credit supply and demand.

Tangibles is the share of tangible to total assets. It is a measure of capability to pledge collateral and should negatively affect the probability of FC. *Roll over* is the short-term to total debt ratio and is a proxy for firms' need of rolling-over. A debt-maturity structure skewed toward short-term horizons may worsen firms' financial position because of their difficulties in rolling-over the debt. This issue is particularly relevant if the maturity coincides with times of credit crunch (see for instance, Ivashina and Scharfstein, 2010). *Profitability* captures firms' economic performance and is measured as operating profit to total assets ratio. Firms realizing low-profit margins are less capable to internally fund investment projects and are more likely to be credit rationed.

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. This variable captures a relevant component of the credit supply and should heavily affect the likelihood of FC (higher creditworthiness induces lower constraints). Estimated ratings have all those features considered as crucial for a good measure of FC (Cleary, 1999; Lamont et al., 2001). First of all, credit ratings are the result of a multivariate score that embeds several financial and non-financial firm-specific features. This allows for capturing a wider gamma of characteristics that may potentially influence bank willingness to lend. Moreover, since they are built from variables that vary over time, also credit ratings are time-varying following the dynamic of firms' financial condition. Third, they capture the actual investors' propensity to grant credit, since "credit ratings represent the opinion (of the markets) on future obligor's capacity to meet its financial obligations".[12] Finally, credit ratings provided by banks have the further advantage of not being associated to a single loan or credit line but instead to the overall creditworthiness of the firm.[13]

Some specifications also account for persistency of firms' innovativeness and for the feedback effect of innovation on FC. To this purpose, lagged innovation ($Inn_{i,t-1}$) and R&D ($R\&D_{i,t-1}$) are included into equations 1 and 2, respectively.

Analyses on relationship lending also consider inverse proxies for soft information. *Number of bank rel* is the total number of banks each firm borrows from, *Bank size* is the size of the financial institution defined as (the log of) total assets, while *Distance* is the physical distance between the firm and the headquarter of the lender bank (in log(km)).[14]

[12] Crouhy, Galai, and Mark (2001), pag. 51.

[13] Moreover, this approach should be immune from critiques of selection bias affecting measures based on loan-applications. First of all, the direct variables are available for any firm selected in the sampling procedure, independently by the actual application for a loan. Moreover, also the credit score variable should be capable to correctly classify the creditworthiness of any firm who provides balance-sheet data, independently by its applications or the actual existence of a banking rating. If the financial ratios used in the estimation are able to capture the reason why a firm didn't apply for a loan even though it would have needed, it then the use of estimated coefficients will provide a score that penalizes this kind of firms. A lower value would be able to identify as unsound, all those firms which were incorrectly classified as non-FC in a bank-level dataset.

[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.

Finally, structural controls are considered in both equations. *Size* and *Age* are defined as the log of (one plus) firm's number of employees and age, while α_t, α_{ind} and α_{reg} are, respectively, time-controls, 2-digit industry controls (12 dummies) and region controls (20 dummies).

All regressors are lagged once or more to avoid simultaneity bias and endogeneity problems.

4 Results

4.1 Descriptive results

Descriptive statistics are presented in Tables 1–4. Table 1 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 the high heterogeneity of 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 stronger for the implementation of new products. Interestingly, Table 3 also documents a positive association between firms' innovativeness and the existence of financial barriers. This evidence is also confirmed by the conditional propensities in Table 4. However, it is worth reminding 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 deep link highlights the necessity of a simultaneous estimation in order to correctly take into account all unobserved channels that drive both innovation and financial constraints.

4.2 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 considered 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). 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 may guarantee 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 5 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 (Williams, 2006).[15]

All variables are strongly significant and the signs of the estimates reflect *a priori* expectations. Interestingly, 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 2 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.[16]

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.[17] 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.[18] A further check on its sensibility comes from the empirical-cumulative distribution function of *Credit score* in Figure 1.

[15]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.

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

[17]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.

[18]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.

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.

All considered, these cross-checks reassure on the capability of *Credit score* in capturing a component of firms' creditworthiness. This is particularly important when standard proxies are not directly applicable or are designed to have general validity.

4.3 Innovations and financial constraints

As a benchmark, Table 6 presents results from standard logit models on the main determinants of firms' innovativeness. In line with 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 in fostering firms' innovative activity.

Also in line with the economic literature, my results document unclear effects of market power on firm propensity to innovate: even if the baseline effect is positive, the magnitude and the significance of the impact are not robust along the different specifications throughout the paper.[19]

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 degree of 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 complexity of the internationalization.

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 6, 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.[20]

[19] On the one hand, higher market power may be associated to consistent flow of funds that stimulates innovations (Shumpeter, 1942). On the other, the incentives to innovate might be greater in competitive markets relative to monopoly conditions because of the higher expected incremental returns from innovation (Arrow, 1962). On this point, Aghion et al. (2005) provide evidences on an inverted U-shaped relationship between competition and innovation.

[20] 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.

4.3.1 Simultaneous estimation

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 of financial constraints on innovation (Table 6, column 3). Approaches that ignore the endogeneity of the financial status and 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.

This result clearly shows the inadequacy of standard limited-dependent-variable models in presence of qualitative endogenous explanatory variables. 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. Following Gatchev et al. (2010) and Savignac (2008) I employ a bivariate probit to simultaneously estimate the probability of FC and the likelihood of introducing innovations. In so doing, the two variables are allowed to affect each other: FC can reduce the probability of undertaking innovative projects and the innovative behaviors can at the same time worsen the financial status. Unfortunately, the coherency condition needed to obtain consistent estimates, requires to fall back on a recursive model that does not leave room for any feedback impact of innovation on FC.

Nevertheless, once the two equations are simultaneously estimated (Table 7, column 1), the impact of FC on innovation appears to be very negative and significant. The switching sign is a proof of the importance of unobserved elements affecting both the existence of financial constraints and firms' innovativeness. Keeping all rest constant at mean level, the presence of FC reduces the probability of innovation of about 30%.

Results of the FC equation are also very sensible. First of all, smaller companies suffer from severe financial problems because of their limited possibility to switch among sources of finance, their lower capitalization and their higher likelihood of default in the short-term.

As expected, both the availability of tangible assets and consistent flows of profits reduce the probability of financial constraints by increasing firms' possibility to pledge collateral and to self-finance their own projects. Similarly, higher shares of debt maturing in the short-term increase firms' need of rolling-over and worsen their financial conditions.

The strong relevance of the estimated credit score justifies the effort in the construction of this *ad hoc* measures. In line with prior expectations, *Credit score* enters with very significant and negative sign, highlighting the negative association between firms' creditworthiness and rationing status.[21]

Finally, the significance of the correlation coefficient ($\hat{\rho}$) is an indicator of simultaneously neglected third-party effects. Indeed, 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. This is a further validation of the need of simultaneous estimations.

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 7 instruments the innovation propensity in the FC equation (equation 2) with lagged values of R&D intensity. Since R&D and innovation share the leading causes of encountering financial constraints, the instrumentation should allow to quantify the variation in the overall impact of FC, showing at the same time the direction of the feedback effect.

In support of traditional arguments, results show a positive association between R&D activity and the probability of FC. This in turn is reflected onto a stronger effect of FC: financial problems reduce the probability of innovation of about 34% (-4 percentage points with respect to the previous specification).

Overall, the instrumentation 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.

These results are robust to an alternative definition of financial constraints. Table 8 presents the estimation with a direct measure of credit accessibility (FC_2). Apart from changes in the magnitude of the coefficients, the main findings are totally comparable.[22]

One opened issue is whether these 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 6, column 1) to identify the subset of (more) innovative companies. Table 9 presents the estimations obtained by splitting the sample into "Innovative" and "Non-innovative" firms.[23] In both cases results continue to hold even if, as expected, the relevance of financial frictions increases with firms' innovativeness. This evidence suggests that my results are not driven by a subset of more fragile companies.

Although lagged covariates clear problems of simultaneity bias, the persistence of relevant attitudes (like

[21] It is worth stressing the independence of *Credit score* by the specific investment to be financed. Indeed,"true" bank ratings are (almost) always independent by the specific project, being instead related to the overall firm creditworthiness. Moreover, the score adopted in the estimation is itself computed ruling-out every issue linked to soft-information and to the investment to be undertaken. Thus, the negative coefficient of *Credit score* cannot be interpreted as a bank's negative valuations on the innovative project.

[22] 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.

[23] Firms are divided in the two groups depending on the median value their unconditional likelihood to innovate. As a robustness check, the estimation is repeated choosing a different threshold (75^{th} percentile). Results are qualitatively unchanged.

innovation, export, R&D, etc.) may leave residual endogeneity into the estimation. To control for this possibility, the 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. On this point, Table 10 shows the high persistence of innovation. However, the stability of the other coefficients suggests that my results are not driven by endogeneity problems produced by "sticky behaviors".

4.3.2 Heterogeneities: innovation type, industry and firm size

Table 11 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.[25] The same pattern emerges for the affiliation to simple networks,[26] while advanced forms of connections seem to have a greater effects on marginal forms of improvements.

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

Firms belonging to high-tech industries typically suffer from greater problems of asymmetric information. They usually invest in high-risk-high-return innovations that are unlikely to be undertaken elsewhere. As a result, their innovative projects are more difficult to evaluate since "past experience or observed past realizations can offer little guidance in assessing the prospects of truly new projects; rather, it is likely that the entrepreneur undertaking the innovative project has, if not more knowledge, at least a better perception of its likelihood of success" (Guiso, 1998).[27] This issue is even more relevant in presence of strategic behaviors leading to suboptimal information transmission to the bank (particularly important for high-tech firms developing new products and processes).

Table 12 presents the results once the effect of FC is allowed to be industry-type-specific. As expected, the impact of financial frictions on innovation is stronger for companies that operate in high-tech sectors.[28]

[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.

[25] The greater impact of export on product innovations may be related to effects of "demand-pull" from international markets.

[26] Indeed, a close commercial relationship between two or more firms may incentivize the production of *ad hoc* products to satisfy specific requests of customer companies.

[27] Guiso (1998, p. 40).

[28] Given the way the interaction term in computed, the overall effect of FC on the innovation activity of firms operating

Interestingly, the industry-specific additional effect 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).

Finally, I test firm size as an additional source of heterogeneity. In practice I examine whether the effect of size 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. Table 13 shows the results.

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 2 plots the predicted probability from Table 13 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.[29] 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.

4.3.3 Proxing for soft-information

Although previous sections proved 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.

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. Economic literature provides compelling evidence on the crucial role of relationship lending in reducing asymmetric-informational problems. Long-term commitments reduce firm cost of credit (Diamond, 1991; D'Auria, Foglia, and Reedtz,

in technologically intensive sectors is given by $(\beta_{FC} + \beta_{FC\times hightech})$ (the baseline coefficient $-\beta_{FC}-$ is augmented with the additional, partial effect $\beta_{FC\times hightech}$).

[29] 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.

1999) and the amount of collateral requested by the bank (Berger and Udell, 1995; Harhoff and Körting, 1998; Degryse and Van Cayseele, 2000).[30] This in turn lowers firms' likelihood of facing financial constraints (Petersen and Rajan, 1994), reducing bank willingness to support borrowers over the short-run in the expectation of future earnings.

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 several proxies of relationship lending.

The 2011-wave of the MET survey provides useful information on the identification of the bank-firm relationships. This allows to exploit the number of banking relationships, the size of the lender banks and their geographical distance from the firm, as inverse proxies of relationship lending.[31]

A relevant strand of the literature studies the effects of banks' degree of hierarchization in financing more opaque firms. "Highly hierarchicized institutions allocate few resources to activity absorbing a lot of soft information such as small-business lending or innovation financing" (Alessandrini, Presbitero, and Zazzaro, 2010). Indeed, the information gathered from delocalized branches cannot be transmitted costless to the upper levels. As a result, higher complexity of hierarchical organizations and the unobservability of the investment in information collection, give rise to incentive problems and lead to suboptimal investments in opaque firms.

Hierarchy is related to the specific bank-firm relationship, and not to the bank itself. The degree of hierarchization is associated to the "informational distance" between the lender and the borrower, which is likely to be associated to the physical distance between the lending branch, where information on borrowers are collected, and the decisional centers of the bank (Hauswald and Marquez, 2000). In the same spirit, bank complexity and hierarchization, are likely to increase together with the size of the financial institution, reducing the likelihood of relationship loans (see for instance Cole, Goldberg, and White, 2004).

To proxy for bank hierarchization I employ two measures commonly used in the literature. *Distance* is the physical distance between the firm and the headquarter of the lender bank (in log(km)) while *Bank size* is the size of the financial institution defined as (the log of) total assets. Differently from most of the previous studies, these variables have the additional advantage not to be computed as aggregated-local measures (typically at province level).[32] Instead, they allow to infer the effect of the actual hierarchization

[30] They all find a positive effect that dominates the so called hold-up problem. "Hold-up" is a situation in which banks can exploit their monopolistic condition charging higher interest rates on "captive firms". On the contrary, their findings would suggest that, adding a credit relationship with a new bank, can result in a coordination problem of monitoring and bargaining costs in bankruptcy. The raise in bank costs would then be translated onto higher interest rates charged to the firm.

[31] The survey does not contain information about the length of the relationship or the share of the main bank on total banking debt. These measures are traditionally used as proxies for the ties between the bank and the firm, and are likely to affect the amount of private information accumulated over time.

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

of the lender bank on the credit condition of the specific client firm.[33]

The number of banking relationships is used as additional proxy of relationship lending. The exclusivity of bank relationship can be thought as an indicator of close ties between the lender and the borrower. As a result, the amount of private information gathered by the bank should be negatively correlated with the number of relationships. This is likely to affect the probability of FC, especially of small and more opaque firms.

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.[34]

Tables 14, 15, and 16 show the results. For comparison, column 1 reports the coefficients of the baseline specification re-estimated for the new sample.

Both physical distance and bank size do not have any significant effect on firms' financial status (column 2). However, the inclusion of a further interaction term with firm size uncovers a highly non-linear effect. Columns 3 of Tables 14, 15, and 16 document the positive and significant impact of bank hierarchization (and the number of relationships) on the FC status of small —and more opaque— firms. Sign and significance of the interaction term denote effects that are decreasing with the size —and the transparency— of the borrower.[35,36] Moreover, the inclusion of controls for soft information alleviates the overall impact of FC on innovation (between -9% and -6%).

Overall, these results 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.

[33]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.

[34]Since the question on the lender identification has been introduced only in the last wave, I restrict the analysis to firms interviewed in 2011, exploiting also observations in the previous waves where a 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).

[35]This result is in contrast with the findings in Giannetti (2009).

[36]Notice that, differently from the other specifications, the number of banking relationships is interacted with *Small firms* instead of a continuous measure of size. *Small firms* is also included as a further control (not reported). The interaction with the continuous measure of firm size does not provide any significant result. This is probably due to the low cross sectional heterogeneity of the number of relationships or to the presence of non-monotonic effects.

4.4 Robustness

Selected list of robustness checks:

- Alternative definition of financial constraints (FC_2): employing a measure based on the difficulties encountered in accessing the credit market produce similar results from a qualitative point of view. However, the magnitude of the effect is less stable than the impact of *FC* documented throughout the paper.

- Alternative definitions of R&D (dummy), export (dummy) and size (log of assets): do not affect the results.

- Controls for the legal form of the firm (3 dummies: partnerships, cooperatives and enterprises): the main results are unchanged. Their direct effects, *viceversa*, are never significant.

- Alternative measures of firm creditworthiness: using the more traditional Altman score instead of *Credit score*. Two different versions are considered. The first one is based on the standard Z-score: $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$. Where X_1 to X_5 represent the following ratios: working capital to total assets, retained earnings to total assets, operating income after depreciation to total assets, market value of equity to total liabilities (imposed equal to zero for all unquoted firms) and sales to total assets. The second version is based on Altman, Hartzell, and Peck (1995), who propose a specifical calibration for emerging countries (and in general, countries with underdeveloped stock markets). The main results are unchanged, but the effect of firm creditworthiness on the probability of facing FC is much less significant (non significant for the general version and significant at the limit of 10% the one in Altman, Hartzell, and Peck (1995).

- Direct inclusion in the FC equation of the ratios composing *Credit score*: main findings still hold, even though ROE is no longer significant in explaining FC.

- Alternative econometric model: robustness of the results is tested using the share of sales from innovative products as an alternative measure of innovation. The logistic model that estimates FC is performed simultaneously to a tobit regression that models the innovation equation. While the effect of FC on innovation is still negative and very significant, coefficients of the other controls are very unstable.

- Further lags of balance sheet variables (lag=2): their own significance is strongly reduced (because of low power) while the main results are unchanged.

- Alternative proxy for bank degree of hierarchization (bank number of branches): the main results are consistent but there is no direct effect of branches on firms' probability of FC (not even when interacted with firms' size).
- Alternative clustering of the standard errors (12 industries, 20 regions or 4 bank-size classes): the main variables have similar significance. Some differences are found for some of the other controls.

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 firms. The dataset contains detailed information on the type of the innovations introduced and allows to control for structural, behavioral, strategic and environmental 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. Firms' financial status is explained by a rich set of variables linked to supply and demand of credit, including a credit score specifically calibrated on the Italian economy.

Once the two equations are simultaneously estimated, I find firms that suffer from financial problems to have a probability of innovating that is significantly lower than sound companies (-30%). Moreover, proxing innovation with (lagged) R&D, I document the existence of a feedback effect of innovation on the probability of financial constraints. Results suggest 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 to test several kinds of heterogeneity. While the impact of financial distress does not seem to vary across innovation types, the effect of financial constraints is much stronger for smaller firms and companies operating in technologically-intensive industries, above all for the introduction of new products.

Finally, the paper documents the role of relationship lending in mitigating financial barriers to innovation. Specific data on the lender-borrower relationship allow to control for components of soft information. Firm's number of lenders, the size of the banks and their distance from the company are used as inverse proxies of relationship lending and are found to significantly affect the probability of financial constraints. Interestingly, this effect is highly nonlinear and decreasing with the transparency of the borrower (proxied by its size), 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, provides further evidence on the role of relationship lending as a device to reduce the effect of financial constraints on innovation.

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Main Tables

Table 1: Summary statistics and expected signs

	Type	Mean	Std. Dev.	Min	Max	Expected sign Inn eq.	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 power	Scalar	0.02	0.03	0.00	0.38	+/-	
Group	Dummy	0.14	0.34	0.00	1.00	+	
Simple network	Dummy	0.37	0.48	0.00	1.00	+	
Advanced network	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		+
Number of bank rel.	Ordinal	1.02	0.42	0.00	7.00		+
Size	Scalar	2.45	1.43	0.70	10.7	+	-
Age	Scalar	2.94	0.80	0.00	6.81	+/-	-

Notes: variable definition. *Innovation* defines 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 power* is the share of firm's output within the belonging industry. *Group* is a dummy identifying the affiliation to groups of firms. *Simple network* and *Advanced network* are dummies for simple or complex forms of network. Simple network if the prolonged inter-firm relationship is exclusively for commercial purposes. Complex network if firms have more advanced 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 for further details). *Credit score* is the credit score measure estimated in section 4.2. 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). *Number of bank rel.* is the number of banks each firm borrows from. 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 2: 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, 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 R. Brancati (2012).

Table 3: Innovation and financial constraints: industry details

Industry:	Innovation	Product inn.	Process inn.	Org-man inn.	FC
Food	28.3%	18.6%	14.5%	15.0%	11.9%
Textiles, clothing and leather	34.1%	23.2%	17.4%	17.8%	11.9%
Wood, pieces of furniture	30.4%	20.0%	15.4%	17.0%	14.0%
Publishing, printing, reproduction	27.3%	16.9%	13.9%	14.8%	16.6%
Chemicals, plastic and chemical	42.8%	29.6%	23.7%	24.3%	13.4%
Metal products, machinery and equipment	33.2%	20.0%	17.6%	17.4%	12.8%
Means of transportation	44.3%	28.4%	23.7%	26.0%	14.9%
Engineering	38.2%	26.0%	19.2%	22.0%	11.6%
Electric and electronic equipment	35.1%	23.7%	17.7%	20.1%	12.2%
Mineral extraction and others	33.4%	20.7%	17.4%	17.4%	13.4%
Transport and telecommunications	22.9%	10.4%	9.30%	16.4%	13.3%
Services to firms	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: 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.

Table 6: Probability of innovation and financial constraints: benchmark regressions

Innovation 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 power$_{t-1}$	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 network$_{t-1}$	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)
Advanced network$_{t-1}$	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 effects (12)	yes	yes	yes
Region effects (20)	yes	yes	yes
Time effects	yes	yes	yes
# obs.	34010	27638	34010
Pseudo R^2	0.16	0.17	0.17
Logliklihood	-19002	-15652	-18979
LR chi2(.)	7464***	6207***	7509***

Notes: marginal effects from logit model. The dependent variable is *Innovation*. All the other measures are defined as in Table 1. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 7: Probability of innovation and financial constraints: simultaneous estimation

	(no feedback effect)		(feedback effect)	
Innovation Equation				
FC	-0.30***	(0.07)	-0.34***	(0.07)
R&D$_{t-1}$	0.30***	(0.01)	0.30***	(0.01)
Market power$_{t-1}$	0.01	(0.00)	0.01	(0.00)
Group$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)
Simple network$_{t-1}$	0.08***	(0.01)	0.08***	(0.01)
Advanced network$_{t-1}$	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 effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
FC Equation				
R&D$_{t-1}$			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 effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
$\hat{\rho}$	0.49***	(0.09)	0.52***	(0.09)
# obs.	13278		13278	
Log pseudolikelihood	-12634		-12630	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 8: Probability of innovation and financial constraints: alternative definition (access to credit)

	(no feedback effect)		(feedback effect)	
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 $power_{t-1}$	0.01	(0.00)	0.01	(0.00)
$Group_{t-1}$	-0.01	(0.01)	-0.01	(0.01)
Simple $network_{t-1}$	0.07***	(0.01)	0.07***	(0.01)
Advanced $network_{t-1}$	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 effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
FC Equation (FC_2)				
$R\&D_{t-1}$			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)
$Roll\text{-}over_{t-1}$	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 effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
$\hat{\rho}$	0.64***	(0.11)	0.66***	(0.10)
# obs.	13278		13278	
Log pseudolikelihood	-15285		-15275	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 9: Probability of innovation and financial constraints: innovative vs. non-innovative firms

	Innovative		Non-innovative	
Innovation Equation				
FC	-0.40***	(0.08)	-0.26**	(0.13)
R&D$_{t-1}$	0.27***	(0.01)	0.28***	(0.03)
Market power$_{t-1}$	-0.01	(0.01)	0.01	(0.01)
Group$_{t-1}$	-0.03	(0.05)	0.07***	(0.02)
Simple network$_{t-1}$	0.10***	(0.01)	0.01	(0.02)
Advanced network$_{t-1}$	0.06***	(0.01)	0.11***	(0.02)
Export share$_{t-1}$	0.01	(0.01)	0.08***	(0.02)
Multinational$_{t-1}$	0.12***	(0.02)	0.14*	(0.08)
Output growth$_{t-1}$	-0.01	(0.01)	0.01	(0.01)
Size$_{t-1}$	0.02***	(0.00)	0.01	(0.01)
Age$_t$	0.01	(0.01)	-0.01	(0.01)
Constant (coeff.)	0.24**	(0.11)	-0.28	(0.25)
Industry effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
FC Equation				
R&D$_{t-1}$	0.04***	(0.02)	0.18	(0.22)
Credit score$_{t-1}$	-0.02***	(0.01)	-0.02*	(0.01)
Tangibles$_{t-1}$	-0.03***	(0.01)	-0.01	(0.01)
Roll-over$_{t-1}$	0.01	(0.01)	0.11***	(0.02)
Profitability$_{t-1}$	-0.01**	(0.00)	-0.01	(0.01)
Size$_{t-1}$	-0.01***	(0.00)	-0.02***	(0.01)
Age$_t$	0.01	(0.01)	0.01	(0.01)
Constant (coeff.)	-0.27	(0.18)	-0.81**	(0.41)
Industry effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
$\hat{\rho}$	0.62***	(0.10)	0.52***	(0.21)
# obs.	9639		3639	
Log pseudolikelihood	-9110		-3391	

Notes: marginal effects from recursive 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 1. The upper panel reports the estimates for the innovation equation. The lower panel refers to the FC equation. Column 1 reports the marginal effects on the subset of most innovative firms (above the median of the unconditional innovation likelihood distribution. as in Table 6, column 1). Column 2 reports the same effects for the subsample of non-innovative firms. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 10: Probability of innovation and financial constraints: controlling for persistence

	(no feedback effect)		(feedback effect)	
Innovation Equation				
FC	-0.10***	(0.03)	-0.12***	(0.03)
Innovation$_{t-1}$	0.88***	(0.02)	0.89***	(0.02)
R&D$_{t-1}$	0.08***	(0.00)	0.08***	(0.00)
Market power$_{t-1}$	0.01	(0.01)	0.01	(0.01)
Group$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)
Simple network$_{t-1}$	0.02***	(0.00)	0.02***	(0.00)
Advanced network$_{t-1}$	0.02***	(0.00)	0.02***	(0.00)
Export share$_{t-1}$	0.01***	(0.00)	0.01***	(0.00)
Multinational$_{t-1}$	0.05***	(0.01)	0.05***	(0.01)
Output growth$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)
Size$_{t-1}$	0.01***	(0.00)	0.01***	(0.00)
Age$_{t}$	-0.01	(0.01)	-0.01	(0.01)
Constant (coeff.)	-0.15	(0.13)	-0,14	(0.12)
Industry effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
FC Equation				
R&D$_{t-1}$			0.05***	(0.02)
Credit score$_{t-1}$	-0.03***	(0.01)	-0.03***	(0.01)
Tangibles$_{t-1}$	-0.02**	(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	(0.00)	0.01	(0.00)
Constant (coeff.)	-0.42***	(0.16)	-0.43***	(0.16)
Industry effects (12)	yes		yes	
Region effects (20)	yes		yes	
Time effects	yes		yes	
$\hat{\rho}$	0.47***	(0.13)	0.51***	(0.12)
# obs.	13278		13278	
Log pseudolikelihood	-10930		-10926	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 11: Probability of innovation and financial constraints: details

	Innovation type					
Innovation 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 power$_{t-1}$	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 network$_{t-1}$	0.05***	(0.01)	0.02***	(0.01)	0.03***	(0.01)
Advanced network$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
FC Equation						
R&D$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
$\hat{\rho}$	0.48***	(0.13)	0.41**	(0.16)	0.49***	(0.14)
# obs.	13278		13278		13278	
Log pseudolikelihood	-12168		-11127		-12546	

The dependent variables are *Innovation* and . *Notes:* marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 12: Probability of innovation and financial constraints: industrial heterogeneity

	Innovation type							
Innovation Equation	All		Product		Process		Org-man	
FC	-0.34***	(0.05)	-0.27***	(0.09)	-0.19***	(0.26)	-0.32***	(0.18)
FC × 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 power$_{t-1}$	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 network$_{t-1}$	0.08***	(0.01)	0.05***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
Advanced network$_{t-1}$	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 effects (12)	yes		yes		yes		yes	
Region effects (20)	yes		yes		yes		yes	
Time effects	yes		yes		yes		yes	
FC Equation								
R&D$_{t-1}$	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 effects (12)	yes		yes		yes		yes	
Region effects (20)	yes		yes		yes		yes	
Time effects	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 pseudolikelihood	-12630		-12167		-12032		-12546	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 13: Probability of innovation and financial constraints: size heterogeneity

	Innovation type							
Innovation Equation	All		Product		Process		Org-man	
FC	-0.33***	(0.09)	-0.25***	(0.09)	-0.19***	(0.07)	-0.33***	(0.06)
FC × Size$_{t-1}$	0.01*	(0.01)	0.01**	(0.01)	0.01*	(0.1)	-0.01	(0.02)
R&D$_{t-1}$	0.30***	(0.02)	0.32***	(0.02)	0.14***	(0.01)	0.15***	(0.01)
Market power$_{t-1}$	0.01	(0.01)	0.01	(0.01)	-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 network$_{t-1}$	0.08***	(0.01)	0.05***	(0.01)	0.02***	(0.01)	0.03***	(0.01)
Advanced network$_{t-1}$	0.08***	(0.01)	0.03***	(0.01)	0.01	(0.01)	0.08***	(0.01)
Export share$_{t-1}$	0.03***	(0.01)	0.07***	(0.01)	0.01	(0.01)	0.01	(0.01)
Multinational$_{t-1}$	0.15***	(0.03)	0.16***	(0.02)	0.12***	(0.01)	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$_{t-1}$	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)	0.03***	(0.00)
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 effects (12)	yes		yes		yes		yes	
Region effects (20)	yes		yes		yes		yes	
Time effects	yes		yes		yes		yes	
FC Equation								
R&D$_{t-1}$	0.04***	(0.01)	0.04***	(0.01)	0.04***	(0.01)	0.04***	(0.01)
Credit score$_{t-1}$	-0.02***	(0.01)	-0.03***	(0.01)	-0.02***	(0.01)	-0.02***	(0.01)
Tangibles$_{t-1}$	-0.01**	(0.01)	-0.01	(0.01)	-0.01**	(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	(0.00)	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 effects (12)	yes		yes		yes		yes	
Region effects (20)	yes		yes		yes		yes	
Time effects	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 pseudolikelihood	-12630		-12167		-11127		-12545	

Notes: marginal effects from recursive 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 1. 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.

Table 14: Probability of innovation and financial constraints: bank distance as inverse proxy of relationship lending

Innovation 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 power$_{t-1}$	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 network$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.02)
Advanced network$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
FC Equation						
Distance			-0.00	(0.00)	0.01***	(0.00)
Distance × Size$_{t-1}$					-0.004***	(0.00)
R&D$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
$\hat{\rho}$	0.59***	(0.06)	0.51***	(0.11)	0.45***	(0.11)
# obs.	9935		9935		9935	
Log pseudolikelihood	-8648		-8627		-8620	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 15: Probability of innovation and financial constraints: bank size as inverse proxy of relationship lending

Innovation 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 power$_{t-1}$	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 network$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.02)
Advanced network$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
FC Equation						
Bank size			-0.00	(0.00)	0.02**	(0.01)
Bank size × Size$_{t-1}$					-0.005***	(0.00)
R&D$_{t-1}$	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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
$\hat{\rho}$	0.59***	(0.06)	0.51***	(0.11)	0.45***	(0.11)
# obs.	9935		9935		9935	
Log pseudolikelihood	-8648		-8627		-8620	

Notes: marginal effects from recursive 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 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Table 16: Probability of innovation and financial constraints: number of banking relationships as inverse proxy of relationship lending

Innovation Equation						
FC	-0.36***	(0.04)	-0.35***	(0.04)	-0.30***	(0.04)
R&D$_{t-1}$	0.29***	(0.03)	0.28***	(0.02)	0.29***	(0.03)
Market power$_{t-1}$	0.01	(0.01)	0.01	(0.01)	0.01	(0.01)
Group$_{t-1}$	0.06***	(0.02)	0.06***	(0.02)	0.07***	(0.02)
Simple network$_{t-1}$	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.02)
Advanced network$_{t-1}$	0.09***	(0.02)	0.09***	(0.02)	0.09***	(0.02)
Export share$_{t-1}$	0.08***	(0.02)	0.08***	(0.02)	0.09***	(0.02)
Multinational$_{t-1}$	0.21***	(0.04)	0.22***	(0.04)	0.21***	(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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
FC Equation						
Number of bank rel.			0.00	(0.00)	0.09***	(0.01)
Number of bank rel. × Small firms						(0.01)
R&D$_{t-1}$	0.05*	(0.03)	0.05*	(0.03)	0.06*	(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)	-0.01	(0.01)	-0.01	(0.01)
Roll-over$_{t-1}$	0.08***	(0.02)	0.08***	(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 effects (12)	yes		yes		yes	
Region effects (20)	yes		yes		yes	
Time effects	yes		yes		yes	
$\hat{\rho}$	0.59***	(0.06)	0.51***	(0.11)	0.45***	(0.11)
# obs.	9935		9935		9935	
Log pseudolikelihood	-8648		-8627		-8620	

Notes: marginal effects from recursive bivariate probit models. The dependent variables are *Innovation* and *FC*. *Small firms* is included as a further control (not reported). $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other measures are defined as in Table 1. 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 intensity of R&D. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

Figures

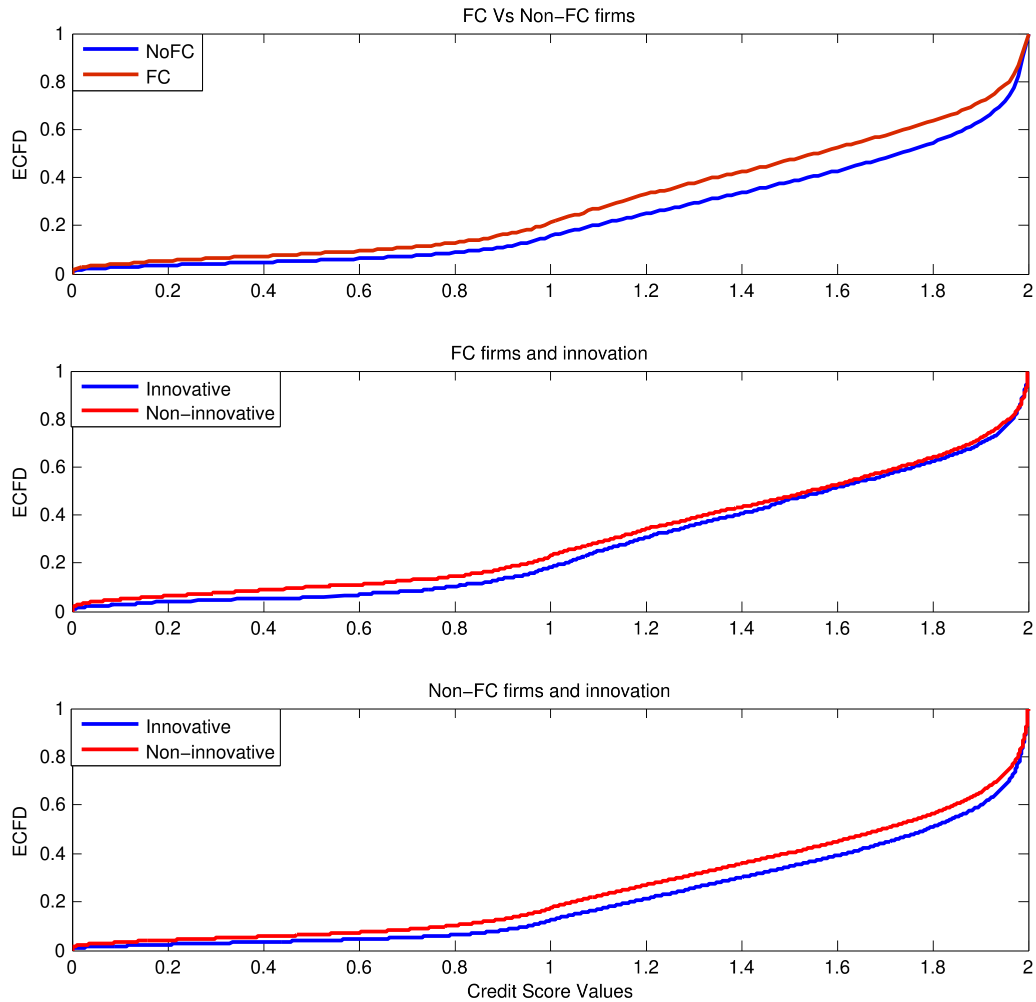

Figure 1: Empirical cumulative distribution functions: credit score. by FC and innovation.

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.

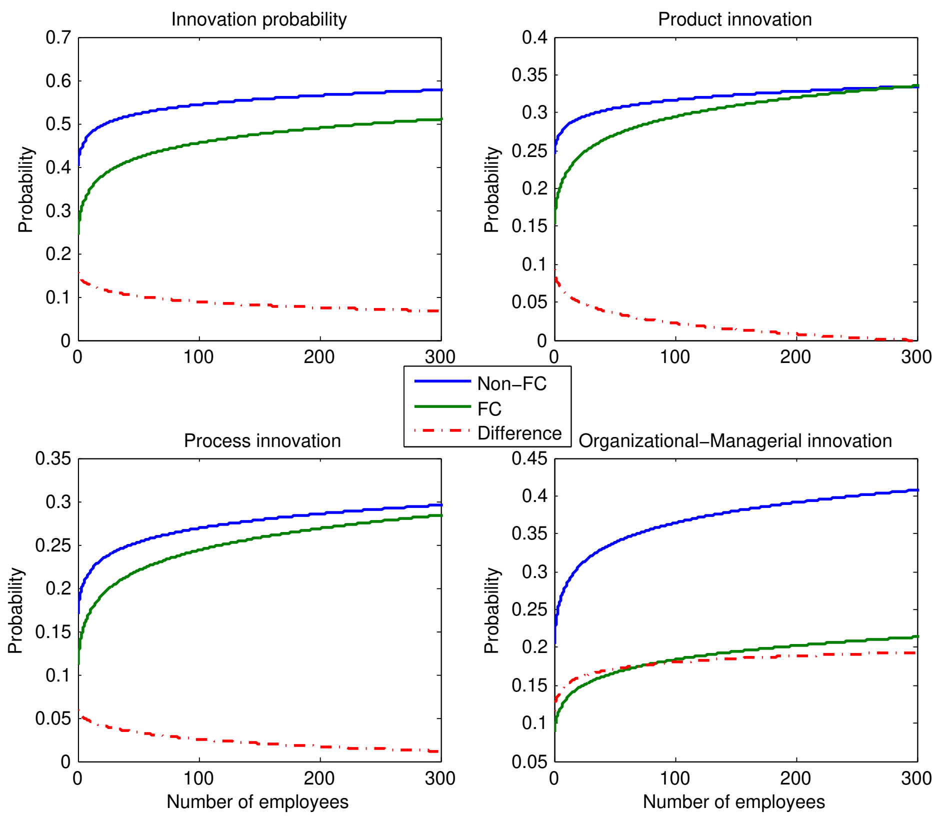

Figure 2: Probability of innovation. financial constraints and firm size.

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.

Appendix: 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 power	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 network	Dummy variable = 1 if the company has stable commercial relationships with other firms.
Advanced network	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 shared commercialization).
Export share	Share of firm's sales from exported products over firm's total sales.
Multinational	Dummy variable = 1 if the company undertakes more complex forms of internationalization (FDI, international cooperation, inter-firm international agreements, and presence of commercial branches abroad).
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.

Variable name	Definition
Distance	log of distance (in Km) between the province each firm belongs to, and the headquarter of the bank each company has relationship with.
Bank size	size (log of total assets) of the bank each company has relationship with.[a]
Number of bank rel.	number of banks each firm borrows from (as of 2011).
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).
Small firms	Dummy variable identifying firms below the 33^{th} percentile of the size distribution.
Time controls	Dummy variables identifying the three years of the waves.
Region controls	Dummy variables identifying 20 geographical regions.
Industry controls	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.