Innovation activity and financing constraints: evidence from Italy during the recent crises.

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Innovation activity and financing constraints: evidence from Italy during the recent crises.

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Abstract

Financial frictions may represent a severe obstacle for firms' innovative activity. This paper shows the existence and quantifies the effect of binding financial constraints on the innovation propensity of Italian companies. Once provided a rich baseline specification for innovation, I analyze the impact of financial constraints by exploiting a survey-based direct measure, enriched with a credit-score-index estimated *ad hoc* on a representative sample of confidential local bank ratings. A recursive bivariate probit model is employed to estimate the probability of undertaking innovative projects conditional on the likelihood of facing financial constraints. This econometric strategy accounts for possible correlations between these two features. My results show firms that are more likely to suffer from financial problems to have a probability of innovation that is 34% lower than financially-sound companies. Furthermore, instrumenting innovation with R&D into the financial-status equation, I control for a feedback effect of the innovation propensity on the financial status. As predicted by economic theory, most dynamic firms are shown to suffer from greater financial problems. This in turn is reflected onto a stronger depressive effect of financial constraints on innovation (-42%). This impact is shown to be sizable only for those firms with a higher *ex ante* probability to innovate, not being driven by a sub-group of most distressed companies. Finally, the last section deepens the role of firm size in alleviating the effects of financial frictions on a breakdown of three definitions of innovation. Relevant differences are found, especially for product and process–innovations.

JEL # O31; L25; G21. Keywords: Innovation; firm performance; financial constraints; banks; ratings.

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1 Introduction

Innovation represents a crucial strategy that characterizes the degree of dynamism of a company and creates competitive advantages capable of boosting firms' performances (Schumpeter 1934). However, a unique and consensual definition of innovation still does not exist (Baregheh et al. 2009): the OSLO Manual identifies only product and process-innovations while economic literature has sometimes considered also organizational and managerial-improvements. The last type of innovations is related to phenomena of learning by doing and learning by using that may be particularly relevant for Small and Medium Enterprises (SMEs).

The literature on financial constraints (hereinafter FC) highlights several reasons why financial frictions should be particularly severe for innovative firms. Main argumentations are based on the higher asymmetric informational problems, the scarcity of tangible assets to pledge as collateral and the greater difficulty for banks in evaluating projects with high technological-content. However, since the FC status is something non directly observable, very few works provide robust results on this issue.

This paper analyzes the role of financial constraints as depressive factors for innovation activity. Preliminary results show traditional approaches, based on indirect proxies of FC or that ignore endogeneity issues, are not capable of properly capturing the impact of FC on innovation. Instead, a simultaneous estimation and the use of a direct measure of financial constraints combined with a credit-score estimated *ad hoc* on Italian firms' bank ratings, allow to shed light on the strong depressive effect of FC.

The Italian economy is an ideal laboratory to study this topic. The great dominance of 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. Within a framework of non-substitutability of bank debt, the effect of financial frictions should in principle be higher.

The contributions to the existing literature are numerous. This is the first paper employing Italian data to infer a causal relationship between FC and innovation. Moreover, this is the only work explicitly taking into account the behavior of micro-sized firms. Thanks to a unique, newly-available dataset (the MET survey on Italian industrial firms), I have information also on family-companies and partnerships with less than 10 employees. The quality of the dataset allows this work to be original along several other dimensions. First of all, the innovation variable employed is not proxied by the presence of R&D activity while it is actually based on the introduction of innovations. Furthermore, a breakdown of the type of innovation adopted, helps me in highlighting heterogeneous effects across different innovations.

A further asset of the analysis is related to the generality of the FC indicator. The fact that my variable of financial status is not referred to the specific innovation propensity but instead it is linked to the overall investment, allows me to have a more precise *ceteris paribus* interpretation and to avoid selection bias problems. Moreover, this is the first paper trying to quantify the feedback effect on the financial status without imposing any restriction on the signs of the parameters.

Another contribution of the paper is the way I estimate the probability of facing financial constraints. At best of my knowledge this is the very first work estimating an *ad hoc* credit-score on the basis of confidential bank ratings. The specificity of the estimation permits to have a more reliable measure of firm creditworthiness and to model the FC equation with variables linked to both credit demand and supply.

The timing of the survey waves (2008, 2009 and 2011) allows for quantifying this depressive effect during a period of deep turmoil, when the issue of innovation may represent a key strategy to relaunch firms' performances. Finally, the baseline specification for innovation is extremely rich and provides evidences on the role played by R&D, size, market power, future market expectations as well as presence and complexity of firm networks and of international activity.

The remainder of the paper is organized as follows: Section 2 is devoted to a review of economic literature on FC, including theoretical argumentations and traditional empirical strategies. Section 3 provides a description of the dataset exploited and a detailed explanation of the empirical strategy. Section 4 shows the main results and section 5 provides concluding remarks.

2 The theoretical background

Over the years, economic literature provided several argumentations why financial constraints should be particularly severe for innovative firms. Common explanations are mostly based on problems of asymmetric information and on the nature of the investment to be carried on. In a contest of inapplicability of the celebrated Modigliani-Miller theorem (Modigliani and Miller 1958), all frictions from asymmetric informational problems are more severe for dynamic firms. Stiglitz and Weiss (1981) and Jensen and Meckling (1976), show that adverse selection and moral hazard problems can produce a disproportional increase in the cost of financing leading, in extreme cases, to phenomena of credit rationing. This issue is even more relevant in absence of an adequate stock of tangible assets to use as collateral (Berger and Udell 1990), a crucial characteristics to identify financially constrained firms (Almeida and Campello 2007). In this spirit, financial frictions should have stronger impact on innovative firms and companies that perform R&D because of their high share of intangible assets and the low amount of collateral to pledge. This increases firms' cost of funding and/or limits their borrowing capabilities (possibly at zero).

A further element that can increase financial frictions for innovative firms is related to banks' difficulty in evaluating expected future profits of projects with high scientific and technological-content. Even with a full disclosure of information between the two agents, proper analytical tools are required in order to have a correct evaluation on the quality of the project to be financed. The need of highly qualified consultants would then raise the cost of bank screening and monitoring, leading either to increases in the firm cost of borrowing or to phenomena of credit rationing. All these frictions may also be amplified by a sub-optimal information transmission due to strategic issues (Leland and Pyle 1977, Kihlstrom and Mattheus 1984, Bhattacharya and Ritter 1985). Following this strand of the literature, firms would face a trade-off in transferring information on the project to be financed. On the one hand, an increase in the quality of the signal may produce a reduction in the cost of financing (thanks to the decrease of bank monitoring costs). On the other hand, a full disclosure of the project technological content may reduce its flow of future expected profits. In line with new-shumpeterian models of "creative destruction", revealing all the project technical features may increase the likelihood of being replaced on the monopolistic market generated by the innovation. This argument is linked to the non-excludability of the knowledge-capital.

Finally, all these issues are worsened by the peculiar nature of investments in R&D and innovation. While expenditures in physical capital occur usually 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.

From an empirical point of view, analyses to test presence and impact of FC are not easy to perform. The main difficulty relies in the deep nature of this phenomenon: since credit demand and supply are not observable, financial constraints that affect firms' investments are something non directly detectable. 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 costs of funds". Even if this definition is definitely too broad, it sheds lights on how difficult is, in practice, to classify a firm as financially constrained.

When direct indicators of financial constraints were not available, economic literature tried to infer the financial status by exploiting indirect measures. The strand of excess-sensitivity is the first and most adopted approach to study the effects of FC. Fazzari, Hubbard and Petersen (1988) is the first work explicitly modeling the excess sensitivity. In a framework with imperfect capital markets they construct a model exploiting the concept of hierarchical scale of financing (pecking order theory, Myers and Majluf 1984). The idea is that, in absence of financial frictions, cash flows should not directly influence investment decisions. They then exploit the distribution of dividends to classify firms into sub-groups with a priori different FC probability and show the higher investment-to-cash flow sensitivity for more financially constrained companies. Following this paper, several works added over-identifying restrictions to an equation that models the investment path, such as a flexible accelerator model or a Euler equation (Kashyap et al. 1994, Korajczyk and Levy 2003, Whited and Wu 2006). The common strategy is to exploit the distribution of indirect proxies to rank firms on their FC status and to show heterogeneous cash-flow sensitivity among firms' classes (depending on financial leverage, availability of tangible assets, interest coverage, existence of a bond rating, dividends, etc.).

Although these approaches are widespread, they have been deeply criticized. Moyen (2004) and Hennessy and Whited (2007) highlight the instability of the results on the choice of the FC proxy. They conclude that this "choice-sensitivity" of the results makes these strategies extremely difficult to interpret and not very reliable. On the other hand, Kaplan and Zingales (1997, 2000) debate about the nature of the relationship between financial constraints and investment-to-cash flow sensitivity, criticizing the idea of a monotonic relationship between the two. If the Tobin's Q is not completely capable of capturing firm's investment opportunity (Poterba 1988), cash flows may reflect part of this channel. In their view, the higher investment-to-cash-flow sensitivity would not be due to the presence of financing constraints but, instead, it would be a sign of sensitivity to future expected returns on investments. Moreover, the possibility of "empire-building managers" (i.e. managers with personal incentives to increase the size of their firm) would provide a further alternative explanation on the higher sensitivity associated to smaller companies.

Finally, other papers exploit the properties of indicators like the Kaplan and Zingales "K-Z score" or the Altman Z-score to rank firms on the basis of their creditworthiness and probability of default (Lamont et al. 2001). The weakness of these strategies is the application of "universal" fixed coefficients on peculiar industrial systems. In order to have general validity, universal credit-scores are computed on broad characteristics that may not be appropriate in correctly classifying firms within a certain country. The cross-country heterogeneity in the industrial structure may lead to an incorrect ranking of firm probability of FC. Moreover, the inclusion of variables linked to the issue of shares, makes these measures difficult to apply to the Italian case[1]. Simply excluding the share-related variables from the K-Z or Z-score, may provide an inadequate measure of firm creditworthiness.

[1]The Altman Z-score considers the Tobin's Q while in the K-Z 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 substitutes these variables with a measure of leverage that is independent by the possibility of issuing shares. The version in Altman, Donavi and Fallini (2013) is used as a robustness check.

The inapplicability or generality of standard scores, the difficulty in the interpretation of the effect of cash flows, and the instability of results highlight the need of more direct measures of FC: either based on rare datasets exploiting bank-level data or derived from survey data at firm-level. Although bank-level data on loan-applications provide great opportunities to investigate the effects of a crisis (see for example Carbó-Valverde, Degryse and Rodriguez-Fernandez 2011), these kind of analyses may suffer from relevant selection bias problems. Inferring financial constraints only on the basis of documented, rejected loans neglects a relevant part of the total phenomenon. On the one side, all firms who receive an undocumented refuse of the loan are excluded from the sample. On the other, all companies that did not ask for loans are classified as non-financially constrained, even if they didn't apply because they knew their application would have been rejected. Performing studies neglecting these aspects may underestimate the overall effects.

These issues led several studies to exploit survey data that enable to directly detect the presence of FC at firm-level. On the Italian economy, Becchetti, Castelli and Hasan (2008) match firms' balance-sheet data with direct qualitative information (from the Capitalia survey) to deepen the relationship between investment-to-cash flow sensitivity and the financial and credit-constrained status. More recently, Presbitero, Udell and Zazzaro (2012) exploit the ISAE-ISTAT survey data. They investigate loan-applications and lending decisions to identify the credit crunch in Italy during the Lehman crisis.

3 The empirical strategy

The identification strategy of this paper differs from previous analyses because of a combined approach that takes into account both direct and indirect measures of FC.

My main variable is a binary measure from the MET survey. In particular, firms are asked to answer whether the lack of financial sources prevented the realization of projects with positive net present-value (i.e. led to a sub-optimal level of investment). This measure is included into a simultaneous-equations model that contains a credit-score specifically calibrated on the Italian economy. The empirical analysis is able to estimate firm's likelihood of being FC by taking into account components of credit demand and a measure that proxies for bank perception on firm creditworthiness (which is potentially able to capture an important factor of the supply side).

Estimated ratings have all those features considered as crucial for a good measure of FC (Cleary 1999 and 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 it is built on the basis of variables that vary over time, also credit ratings change period-by-period capturing the dynamic of the financial constraint status. 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" (Crouhy et al. 2001). 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.

The approach I employ should be potentially immune from selection bias critiques that affect analyses on bank-level data. First of all, my direct variable is 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[2], then the use of estimated coefficients will produce a score that penalizes this kind of firms. A lower value of the score would be able to identify as unsound, all those firms which were incorrectly classified as non-FC in a bank-level dataset.

3.1 The dataset

The dataset used for the estimation is the result of alignments and transformations of several data. The main source of data is the MET survey on Italian firms (Brancati 2012). It consists of a three-waves-survey performed in 2008, 2009 and 2011. The timing of these waves is extremely interesting since it captures firm behaviors, performances and strategies in three crucial points in time: pre-Lehman, post financial crisis boom and the first period of the sovereign debt crisis. The sample has been selected and stratified in order to guarantee representativeness at size, geographical region and industry levels. These surveys have unique features and embed a huge amount of potential information on Italian firms. Among many others: R&D, international activity, innovation, existence and degree of inter-firm relationships (i.e. networks), self-perceptions about financing constraints, performance indicators and limiting factors to investments. The numerosity is about 25,000 firms in 2008, 22,000 in 2009 and 25,000 in 2011 and, differently from other surveys, it allows to have information also on very small firms (even partnerships with just one employee). Observations refers to both of manufacturing firms (60% of the sample) and to service industries (40%).

[2]For example, an excessive financial level of leverage greatly reduces firm's likelihood to obtain a loan. This pre-existing risky financial position may in turn discourage firms' applications for new loans, even in presence of profitable projects to be financed.

The sample of credit rating comes from a confidential dataset provided by Fiditoscana[3] and it consists in a vector of about 3,000 bank credit ratings assigned by several Italian banks to local firms. The universe of balance-sheet data from 2006 to 2011 comes from CRIBIS D&B.

All the quantitative variables have been winsorized in order to reduce the influence of outliers. The numerosity of the final sample of estimation is about 13,500 firms.

3.2 Variable Definition

3.2.1 A direct indicator of financial constraints

The measure employed to classify financially constrained firms is a dichotomous variable extracted directly from a question into the MET survey: "Have there been potentially profitable projects not carried-on by the firm due to a lack of financial sources?". In other words firms are considered FC if the overall investments would have been higher in absence of financial frictions (i.e. there were projects with positive net present-value, non undertaken for lack of financial means). Notice that the definition of FC is related to the overall investments and it is thus independent from the actual innovation propensity. The data do not reveal whether the constraints have damaged investments in innovation or simply reduced other kinds of expenditures. The ability to evaluate the average depressive effect on innovation is achieved only through a simultaneous estimation of both likelihoods. If one had data on limitations in financing 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, the variable I employ is the ideal device.

Finally, the way in which the question is administrated, clears all the problems linked to the timing between the two variables. In practice, since the question already embeds a lag in the timing of FC, I can compare data on FC and on innovation related to the same wave of the survey, without caring on timing issues. As a robustness check, I also adopt another definition of financial constraints based on the difficulties encountered in accessing to credit. Results are quantitatively unchanged.

3.2.2 What kind of innovation?

Innovation is widely recognized as one of the main determinants of the firms' degree of dynamism, capable of fostering economic growth, stimulating firms' performances and generating new markets. However, several

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

definition problems still exist. Economic literature often works in line with the OSLO Manual, focusing only on product and process-innovations. Product-innovations are related to the introduction of new or improved products that differ from the ones of previous generation: they can be innovation both for the market (creating a totally new segment) or just for the firm (i.e. an already existent product that wasn't produced by the firm). On the other hand, all significantly improved methods of production belong to the class of process-innovations.

A few papers also take into account organizational and managerial-improvements as a further source of innovation. They are defined as "the implementation of a new organizational or managerial method in the firm's business practices, workplace organization or external relations". Organizational-innovations represent a relevant source of improvement in a system dominated by SMEs. Even though their definition is broader, the lost in specificity from using a more general measure may be more than offset by possibility of considering effects of learning by doing and leaning by using, embedded in the organizational and managerial-innovations, and not considered by standard definitions.

In the light of all this, even though I also provide disaggregate results, the main specification within this paper is a broad definition of innovation. If is not differently specified, innovation is a binary variable that takes value 1 independently of the fact that the firm undertakes a product, process or organizational and managerial-innovation.

3.3 The econometric approach

An econometric analysis that wants to provide conclusions about the effect of FC on innovation activity must deal with the issue of endogeneity between the two variables. On the one hand financial problems lower the likelihood of introducing innovations, on the other hand the propensity to innovate may itself increase the probability of being FC through the worsening of asymmetric informational problems and the increasing riskiness of the projects.

In presence of potential endogeneity, traditional limited dependent variable (LDV) models produce biased and inconsistent results that may lead to wrong and counter-intuitive conclusions about the causal nexuses. In order to provide a correct answer to the research question of this work it is crucial to identify those firms for which financial constraints represent an actual obstacle to the innovation activity: those firms which were actually willing to innovate but did not succeed because of a lack of financial means. Indeed, even in presence of relevant FC that limits the total amount of investment (that implies a constrained firm in my definition), a company cannot be considered as having "binding financial constraints" for innovation if it hasn't scheduled innovative projects. In absence of detailed information on firms' plans, a simultaneous equation model helps overcoming this problem. Following the basic specification of Savignac (2006), I employ a bivariate probit model to simultaneously estimate the probability of innovation, conditional on the likelihood of facing FC. A general bivariate probit model can be written as:

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

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

Where 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} represent vectors of exogenous parameters for each equation of the model, θ and φ are the two interaction coefficients. In the case of a bivariate probit, the error terms $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ are assumed to be independently and identically distributed as a bivariate normal with unitary variance and correlation coefficient equals to $\rho = corr(\varepsilon_{1,i},\, \varepsilon_{2,i})$:

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

hence, the vector of parameters to be estimated is given by $\Lambda = (\beta_1', \beta_2', \theta, \varphi, \sigma_1^2, \sigma_2^2, \rho)$
However, once one allows for both the possibility of a direct effect of FC on innovation and for a reverse effect of innovation on the probability of being financially constrained, a coherency condition problem arises. The works of Gouriroux et al. (1980) and Maddala (1983) prove this model is inconsistent and needs prior parameter restrictions in order to be logically consistent. The standard coherency condition in the literature consists in imposing $\theta\varphi = 0$, that is, either $\theta = 0$ or $\varphi = 0$. This simplifies the previous system of equations into a recursive bivariate model.

With the aim to investigate the impact of FC on innovation, I am mainly interested in sign, magnitude and significance of θ. The only logical restriction left requires to impose $\varphi = 0$; that is, no feedback-effect is allowed. Since parameter restrictions to make the estimation feasible exclude any possible reverse-effect of innovation on FC, I also provide specifications in which innovation in the financial constraint equation is instrumented by the R&D intensity. Even though R&D and innovation are two different activities that cannot be confused, they share several common characteristics and their leading causes of encountering financing constraints are very similar (Hall 2002). Although financial frictions are presumably more relevant for innovative firms (at least in case of radical product and process-innovations), controlling for the presence of R&D in the FC equation allows for catching at least part of the channel and permits to check for variations in the overall magnitude and significance of the effect of FC on innovation.

Finally, it is useful to notice that the correlation coefficient between the two 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 being financially-constrained. 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. On the other hand, if $\hat{\rho}$ is significantly different from zero, the estimates of two separate probit models are inconsistent and a joint estimation is required.

From an operative point of view, the estimation is performed *via* a pooled bivariate probit. 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. In the light of all this, the employed empirical strategy consists in a pooled bivariate probit estimator that controls for several firm-specific characteristics and corrects for clustering of the standard errors. The latter takes into account the non-independence of observations within the same firm, allowing to catch at least part of the unobserved heterogeneity.

3.4 The determinants of innovation and financial constraints

A correct specification of the FC and innovation equations is a critical issue for minimizing omitted variable problems.

The identification strategy for the existence of binding FC takes into account several aspects of the credit channel, including variables linked to both supply and demand for credit. Firm's probability of being financially constrained is mainly influenced by its composition of financing, economic performance and bank perception on its creditworthiness. To control for dependence from external funds, the FC equation contains the share of investments covered though self-financing and though bank debt. In principle, those firms that are more dependent upon external finance should have a higher likelihood of facing financial problems during periods of crisis. Economic performances are measured by the gross operating profit margin ratio; firms with low past profit margin should face higher difficulties in raising funds on the credit market to finance innovative projects.

Finally, bank perception on firm's creditworthiness is measured with a credit-score estimated *ad hoc* on a vector of credit ratings assigned by several Italian banks to a group of local firms. This variable should capture a component of the credit supply and should heavily affect the likelihood of being FC (i.e. higher creditworthiness is associated to less constraints). The credit-score is lagged once in order to avoid time-mismatches with the direct measure of FC.

Firm's innovative propensity may be influenced by several characteristics: firm market power, perceived customers' demand as well as behavioral and environmental factors. Market power is proxied by the ratio between firm's output and the median output of the belonging industry.

A further main determinant of innovation is whether the firm performs research and development activity or not. R&D eases the production process of new knowledge and the assimilation of existing information from outside sources. R&D intensity is a variable defined as the share of employees devoted to R&D over the total number of employees.

Strategic and environmental characteristics may also influence firm's innovative attitude. Network organizational structures and international environments that promote competition may represent features 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 be transformed through the innovative process.

Traditional approaches on the Italian industrial system focus on the positive externalities of "industrial districts". The MET survey provides a more accurate measurement of local networks avoiding strict definitions based only on territorial borders. Although the requirements for a network connection are strictly listed in the survey, it is left to the firm the interpretation of what "local" means. On this regard, the classification allows to group firms as: "stand alone" (if there isn't any significant and prolonged inter-firm relationship) and belonging to "simple networks" (whether a stable commercial relationship exists) or "complex networks" (when firms have more sophisticated relationships such as cooperation, common R&D projects, joint venture, common services and commercialization). Since this classification does not rely on rigid geographical frontiers the resulting definitions are much less stiff and, in principle, are better able to capture the positive externalities of a network structure. Indeed, both structured relationships like connections with the scientific world or R&D-oriented links, and informal (simple) networks may provide the right environment for creation and circulation of new knowledge. The empirical analysis includes two dummy variables to capture the effect of simple and complex networks.

In the same vein, firm's international activity is summarized by two different variables. The first one refers to the degree of presence on the international markets and it is measured as the share of total sales abroad on total sales. In principle, exporting firms may need to innovate to survive the highly competitive pressure in the 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 international interactions. In order to catch this channel a further binary variable called "multinational" is introduced to capture advanced forms of internationalization such as FDI, international cooperation, inter-firms international agreements, and the presence of commercial branches abroad.

The innovation equation also contains two dummy indicating firm's positive or negative expected, future market performances. This allows for taking into account perceived future customers' demand.

Finally, structural controls are considered in both equations: size (log of employees), age (log of age), industry (2-digit), regional and time dummies.

Table 1 summarizes descriptive statistics and expected signs of all variables used in the Innovation and FC equations.

4 The results

4.1 Credit-Score estimation

The empirical analysis starts with the estimation of the credit-score used as a proxy for firm creditworthiness. The purpose of this section is to develop an approach of "reverse engineering" to reproduce the way banks assign credit ratings on the reliability of Italian firms. Neglecting all the components linked to soft-information, firm "perceived creditworthiness" is considered to be a function of a set of balance-sheet ratios considered as relevant by the literature on bank-firm relationship. Exploiting a sample of about 3,000 credit ratings assigned by several Italian banks to local firms I estimate a score in the spirit of Altman (1968). The advantages of such an approach arise both from the specificity of the estimation and from the fact that I

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-process inn.	Dummy	0.20	0.40	0.00	1.00		+
Org-Man inn.	Dummy	0.19	0.39	0.00	1.00		+
FC	Dummy	0.13	0.34	0.00	1.00	-	
R&D	Bounded	0.02	0.22	0.00	50.0	+	+
Size	Scalar	2.45	1.43	0.70	10.7	+	-
Age	Scalar	2.94	0.80	0.00	6.81	+/-	-
Market power	Scalar	0.86	0.91	0.00	8.76	+	
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	+	
Positive exp.	Dummy	0.42	0.49	0.00	1.00	+	
Negative exp.	Dummy	0.30	0.46	0.00	1.00	-	
% self-financing	Bounded	0.01	0.02	0.00	1.00		-
% bank debt	Bounded	0.01	0.01	0.00	1.00		+
Credit score	Bounded	1.55	0.50	0.00	2.00		-
Profitability	Scalar	3.40	1.06	0.00	4.66		-

Notes: variable definition. *Innovation* defines a dummy variable that takes value of 1 if the firm undertook at least one type of innovation. *Product-process inn* and *Org-Man inn* are related (respectively) to the introduction of product-process or organizational-managerial innovations. *FC* is a dummy variable that takes value of 1 if the firm is financially constrained. *R&D* is a measure of intensity of the research and development activity. It is defined as the share of employees devoted to R&D over the total amount of employees. *Size* is defined as the (log of) the number of employees. *Age* is the log of age. *Market power* is the ratio between firm's output and the median output of the industry where the company belongs. *Simple* and *advanced networks* are dummy variables expressing the presence of simple or complex forms of network. Simple network if the prolonged inter-firm relationship is based exclusively on 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 turnover deriving from export activity. *Multinational* defines a dummy equal to 1 if the firm performs complex forms of internationalization (FDI, international cooperation, inter-firm international agreements or has commercial branches abroad). *Positive exp* and *Negative exp* are two dummies expressing (respectively) positive or negative firm's expectations on future customers' demand. *% self-financing* is the share of the overall expenditure in investment covered through internally-generated funds. *% bank debt* is the share of the overall expenditure in investment covered through bank debt. *Credit score* is the credit-score measure estimated in section 4.1. It takes bounded values between 0 and 2 and it is increasing in firm creditworthiness. *Profitability* is the gross operating profit margin ratio (Ebitda to value-added ratio).

explicitly take into account a structural break in the post-financial crisis period. Estimates performed only on Italian firms have the merit to overcome several problems. First of all, they allow to clear inaccurate approximations due to possible cross-country heterogeneity in the rating assignment (due to differences in the applied weights and/or in the peculiar composition of the industrial structure). Furthermore, they permit to catch potential differences in bank judgments between the pre and post-Lehman Brothers collapse. This approach should be able to provide a more reliable approximation of firm's specific creditworthiness than the application of a universal score.

The overall procedure performs a generalized ordered logit model and estimates the coefficients (weights) on a set of firm balance-sheet ratios used to discriminate the soundness of a company. Once the weights are recovered, they are applied out-of-sample on all the firms in the MET survey[4]. The resulting state-probabilities are then aggregated to obtain a credit-score that is increasing in the degree of firm creditworthiness.

Within this section, firm-specific rating-class is the dependent variable I'm interested to explain. Since it can assume only discrete values, the choice of the econometric estimation is restricted to non-linear models.

Rating classes are explained through a vector of covariates that includes: an index of financial independence (firm's own sources to total debt ratio), returns on equity (ROE), returns on investment (ROI), net sales to invested capital ratio, floating-capital to invested-capital ratio and a dummy variable that indicates whether the firm has been evaluated in the pre or post-Lehman period.

Table 2 shows the results of the estimation. The first benchmark (column 1) is an ordered logit model. 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. Before proceeding with the analysis, it is crucial to test for the validity of this "proportional odds assumption". The high significance of the likelihood ratio 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 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.

Columns 2 and 3 of Table 2 show the results. Column 2 contains the estimates applied in the state transition between low and medium rating classes (state 0 and 1 of the LDV) while column 3 refers to the transition from state 1 to state 2 (i.e. from medium to highly reliable firms). All variables are strongly significant and signs of the estimates reflect a priori assumptions. Interestingly, the impact of ROE would

[4]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.

seem 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 during the post-financial crisis. This effect should not be due to a worsening in the economic conditions of the firms. If this was the case, the lower rating level should come from worse firm-specific indicators rather than structural breaks in the parameter estimates. Further evidence on this phenomenon is found once the sample is split in the two periods (not reported). Results are coherent with those in Table 2 and highlight a significant reduction in the coefficients of the last column, sign that, *ceteris paribus*, banks are on average less willing to assign very good credit ratings during the post-crisis period. The overall model is able to correctly classify more than 80% of the firms in the rating sample[5].

However, the purpose of all this approach is to replicate bank rating assignment procedure in order to create a proxy of creditworthiness for all the firms in my original sample. Once computed the out-of-sample probability of being in each rating class, the credit-score is obtained by multiplying the probability in each state by the order of the state itself and by aggregating across all the possible outcomes. The resulting variable "score" is a continuous variable with support (0,2) that is increasing in firm's creditworthiness.

Interesting considerations can be derived from the match between the estimated score, and the FC and innovation variables. Figure 1 plots the empirical cumulative distribution functions of different types of firms on the estimated score. As expected, the distribution of non-financially constrained firms is always characterized by higher values of the score with respect to FC companies. Moreover, innovations seem to be more frequent for more creditworthy companies. This may be a sign of the depressive effect of FC on the innovation propensity of Italian firms.

All in all, these cross-checks enable me to be reasonably sure about the goodness of the credit-score in capturing the actual firm's creditworthiness perceived by the banks. This is particularly important when standard proxies are not directly applicable or are constructed in order to have general validity.

4.2 Innovation and financial constraints: main results

As a benchmark, Table 3, column 1, shows the results of simple logit models on the main determinants of the innovative activity. In line with economic literature, structural characteristics play a critical role in determining firm's propensity to innovate. First of all, thanks to the better ability in diversifying embedded-risk and the higher availability of internally-generated funds, bigger firms are more prone to introduce innovations. On the contrary, firm age does not seem to play any role in fostering innovative activity.

[5]The accuracy in the rating assignment is performed out-of-sample with a bootstrap procedure in order to avoid standard problems related to over-fitting in the in-sample tests.

Table 2: Credit score estimation.

	Ordered logit	Generalized ordered logit	
		0	1
Degree of financial independence	5.69***	3.31***	6.45***
	(0.37)	(0.49)	(0.40)
ROE	-0.005	0.60***	-0.19
	(0.06)	(0.13)	(0.12)
$\frac{Net\,sales}{Invested\,capital}$	1.51***	0.97***	1.76***
	(0.09)	(0.1)	(0.1)
$\frac{Ebitda}{Invested\,capital}$	17.11	16.83***	16.83***
	(1.16)	(0.49)	(0.49)
$\frac{Floating\,capital}{Invested\,capital}$	1.85***	1.1***	2.34***
	(0.24)	(0.35)	(0.27)
Crisis	-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	–	-3.5
	(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: This table reports the results from Ologit and Gologit models on the credit-score. The dependent variable is firm rating class, an ordinal variable between 0 to 2 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 firm's own sources and firm total debt. *Crisis* is a dummy variable that takes value of 1 if the rating was assigned after the Leman collapse. The other covariates correspond to the ratios listed in the table. Estimates refer either to ordered logit (column 1) and to generalized ordered logit (columns 2 and 3) models. *, **, *** denote respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

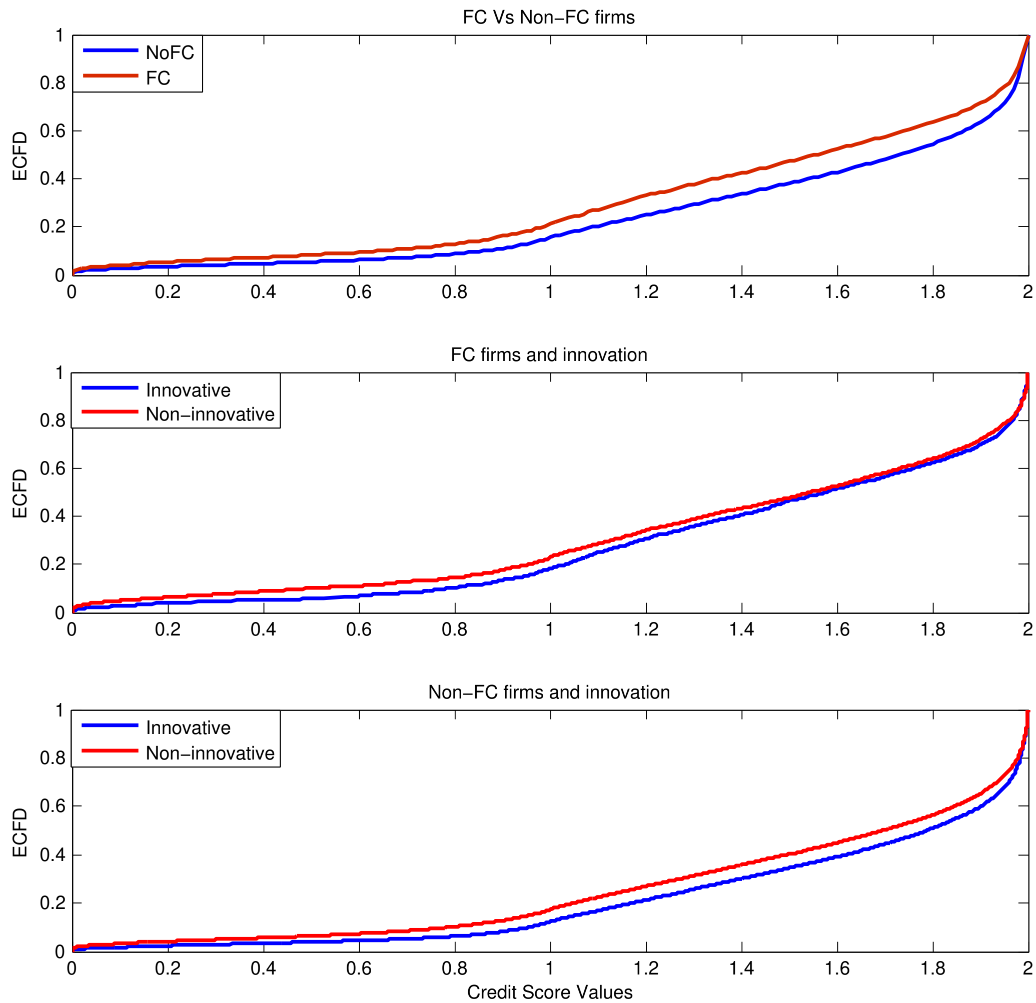

Figure 1: Empirical cumulative distribution functions: credit-score. by FC and innovation.
Notes: This figure plots the empirical cumulative distribution function (ECDF) of the credit-score for several classes of firms. The first panel matches financially constrained and unconstrained firms. The second plot compares innovative and non-innovative financially constrained companies. The last panel compares innovative and non-innovative non-financially constrained firms.

The analysis on behavioral and strategic characteristics is extremely interesting. Coherently with a priori expectations, R&D intensity is an extremely relevant factor in fostering innovative processes. *Ceteris paribus*, undertaking R&D projects raises the ability of generating or assimilating knowledge and increases the probability of introducing innovations up to 60%.

A surprisingly important role is played by environmental factors. Market power is a positive and stable determinant of innovation, especially for inventions of new products. Even though the empirical evidence provided by the economic literature is very mixed, a positive effect seems to prevail in the Italian case[6]. As expected, both belonging to a network and undertaking international activities increase the probability of introducing innovations. Interestingly, the positive effect seems to be increasing in the degree of complexity of the activity undertaken. In other words, belonging to advanced networks and performing complex forms of internationalization generate a further raise in the likelihood of innovation with respect to the affiliation with simple networks or the mere export business on international markets.

Finally, good expectations on future customers' demand have a strong positive impact while negative expectations are associated to a negative, even though not always significant, estimate.

In order to limit omitted variable issues, this rich specification is adopted across all the regressions within this paper. Traditional studies on the relationship between FC and innovation, include indirect proxies of financing constraints to a basic specification of innovation propensity. To highlight the problems of these approaches, Table 3, column 2, adds indirect measures of FC to my baseline regression. Wile profitability measures do not seem to affect the innovation propensity, a positive association is found for banking debt and the share of tangible assets. However, it is not easy to infer a direct relationship between FC and innovation, especially looking at the share of investment financed through bank debt. On the one hand the higher banking debt may be associated with low FC that allowed an extension of credit. On the other hand, if the banking debt was preexistent to the investment, a higher exposure may reduce bank willingness to provide additional loans, increasing in this way the likelihood of constraints. Moreover, even if results on the share of tangible assets are coherent with the conclusion of Campello and Almeida (2007), it is hard to say whether this impact is due to the higher capitalization *per se* or to its effect on bank propensity to grant credit.

[6] It is worth it to stress the potential immunity to endogeneity problems. Although market power may be influenced by the introduction of new innovations, it is reasonable to assume a delayed effect in time. Indeed, in order to have an actual problem of endogeneity, the innovation should produce a flow of wealth that is large enough to modify the distribution of turnover within a sector. This is unlikely to happen within just one year. Moreover, this hypothesis is particularly realistic when innovations are not introduced at the very beginning of the period while instead they are spanned over the whole fiscal year. However, to eliminate every doubt on the validity of the interpretation, a robustness check is performed by repeating the analysis with the one-period lagged market power. The nexus between innovation and firm's market power remains unchanged both in significance and magnitude.

Table 3: Baseline specification: probability of innovation and FC.

Innovation Equation			
	Logit model		
	(1)	(2)	(3)
FC			0.31***
			(0.04)
R&D	4.9***	4.9***	4.88***
	(0.28)	(0.33)	(0.28)
Size	0.21***	0.19***	0.22***
	(0.01)	(0.01)	(0.01)
Age	-0.03	-0.02	-0.03
	(0.02)	(0.01)	(0.02)
Market power	0.08***	0.05***	0.08***
	(0.02)	(0.02)	(0.02)
Simple network	0.19***	0.2***	0.19***
	(0.03)	(0.03)	(0.03)
Advanced network	0.44***	0.41***	0.43***
	(0.03)	(0.04)	(0.03)
Export share	0.03***	0.03***	0.03***
	(0.002)	(0.002)	(0.002)
Multinational	0.42***	0.40***	0.41***
	(0.06)	(0.06)	(0.06)
Positive exp.	0.17***	0.18***	0.19***
	(0.03)	(0.03)	(0.03)
Negative exp.	-0.04	-0.07*	-0.06*
	(0.03)	(0.04)	(0.03)
% bank debt		0.04***	
		(0.002)	
Profitability		0.006	
		(0.007)	
Collateral		0.02***	
		(0.006)	
Constant	-1.02***	-1.62***	-1.1***
	(0.11)	(0.17)	(0.11)
Industry dummies	yes	yes	yes
Regional dummies	yes	yes	yes
Time dummies	yes	yes	yes
# obs.	36917	29777	36917
Pseudo R^2	0.1434	0.1465	0.1448
Logliklihood	-20959	-17139	-20923
Wald χ^2	5234***	4322***	5269***

Notes: This table reports the results from logistic regressions on the probability of innovating. The dependent variable is the general measure of innovation (Innovation). All the other variables are defined as in Table 1. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level.
Robust standard errors in parentheses.

4.2.1 A simultaneous estimation

Problems in the interpretation of the results justify the use of a direct measure of the financial status. However, once firm perception on FC is inserted into the logit specification, regression estimates are positive and very significant (Table 3, column 3). An approach that ignores the endogeneity of FC and the simultaneity problem, may lead to incorrectly infer a causal nexus that is at least counter-intuitive and difficult to justify: the presence of FC has a strong positive impact on the probability of innovation.

This result clearly shows the inadequacy of standard LDV model in presence of qualitative endogenous explanatory variables: the positive association between innovative activity and FC highlighted in the literature, doesn't uncover the depressive impact of financial constraints.

The decision to undertake innovative projects and the probability of facing financing constraints are both affected by unobservable heterogeneity. Thus, following Gatchev et al. (2010) and the work of Savignac (2006) I model the FC variable as endogenous in the innovation equation. The resulting bivariate probit model allows for a simultaneous estimation of both the probability of FC and the likelihood of introducing innovations. In this setup, each variable affects each other, that is: FC can reduce the probability of undertaking innovative projects and the innovation behavior can at the same time worsen the financial status. Unfortunately, the coherency condition needed to obtain consistent estimates, requires proceeding with a recursive model not allowing for a feedback impact of innovation on the FC variable.

However, once the two equations are simultaneously estimated (Table 4, column 1), the impact of FC on innovation becomes very negative and significant (while the other coefficients stay unchanged in sign and significance). This sudden change represents a proof of the importance of unobserved elements that affect both the existence of financial constraints and the innovation attitude. Keeping all rest constant at mean level, the presence of FC reduces the probability of innovation of about 34% (-17 percentage points). A close examination of the FC equation may also be worth it. First of all, the data highlight higher financial problems for lower-sized firms. This is perfectly justifiable with their limited possibility to switch among different sources of finance, their lower capitalization and their higher likelihood of default in the short-term horizon.

Coefficients on the composition among different sources of finance are extremely sensible. Firms that are characterized, by lower pre-existent levels of banking debt and higher percentages of self-financing have on average a lower probability of facing financial problems. Moreover, profitable companies are associated to a higher capability to finance their own projects. The last effect might be either due to an increase in the self-financing possibilities or to the increased bank willingness to grant loans.

The credit-score variable, estimated to capture credit supply, is particularly relevant. Coherently with the expectations, the score enters with negative and very significant sign, highlighting the negative association between high creditworthiness and the firm rationing status[7]. It is worth it to stress the independence of this variable with the specific investment to be financed. First of all, the "true" bank rating assignment is (almost) always independent by the specific project to be financed, 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 "score" cannot be interpreted as bank negative valuations on the innovative project.

Finally, the significance of the correlation coefficient ($\hat{\rho}$) represents an indicator of the importance of "simultaneously neglected third-party effects". Restricting the residual correlation of the model to zero (which is imposed when two separated probit models are estimated) may result in biased and inconsistent estimations due to endogeneity problems (Lollivier 2001). This is a further validation of the need of a simultaneous equations model.

Although parameter restrictions enabled to get coherent results, a further point is still undiscussed: the feedback-effect of innovation on the probability of being FC. Given the impossibility of eluding coherency conditions on innovation, I try to capture at least part of the phenomenon by instrumenting with R&D intensity the innovation in the FC equation. R&D and innovation are affine strategies and, more importantly, share the leading causes of encountering financial constraints. This exercise should be able to quantify (at least part of) the variation in the overall impact of financial constraints on the likelihood of innovation, showing at the same time the direction of the feedback effect.

In support of traditional arguments, Table 4, column 2, shows the positive association between R&D activity and the probability of being FC. This in turn is reflected onto a larger effect of FC on innovation. All estimates remain almost unchanged except for the impact of FC on innovation that increases both in magnitude and significance: financial problems reduce the probability of introducing innovation of about 42% (-22 percentage points, -5 percentage points with respect to the previous specification).

All in all, the instrumentation highlights a further link between innovation and FC. The direct effect of the financial status on the probability of introducing innovations is amplified by the consequences that the choice to innovate itself has on the likelihood of facing constraints. If innovation is even riskier than R&D, then the "actual" reverse effect of innovation on FC may lead to an even stronger, depressive effect of FC

[7] As robustness check the analysis is repeated with a traditional Altman Z-score and a modified version for emerging countries. Even though the impact of FC on innovation is still strong and significant, the new score is much less capable to explain the probability of FC. This provides comforting evidence on the goodness of the approach adopted within the paper.

on the innovative activity.

A further exercise wants to rule-out the possibility that the results were driven by the behavior of a group of less sound firms with low-quality projects. Given the absence of a "true control group" I identify the pool of (more) innovative companies by choosing arbitrary thresholds on firm unconditional likelihood to innovate. After a logit model on the structural determinants of the innovative activity (without taking into account any financial feature as in Table 3, column 1) I compute the unconditional predicted probabilities of innovation and use several cutoff points to identify the group of most innovative firms. Table 5 presents the results obtained splitting the sample respectively by the median and the 75^{th} percentile of the distribution of the estimated likelihood of innovation. In both cases, the negative impact of FC is strong and significant only for the subgroup of innovative firms. This is a reassuring evidence that the overall results are not driven exclusively by a subset of more fragile companies.

4.2.2 Financial constraints, innovation type and firm size

The purpose of this section is to provide details on the effect across several definitions of innovation and different levels of firm size. Table 6 reports the results obtained by splitting the dependent variable into product-process (column 1) and organizational and managerial-innovations (column 2). Interestingly, the effect of FC doesn't seem to differ across innovation types. Both magnitude and significance of the two coefficients are totally comparable.

On the other hand, strong differences are found for the other explanatory variables. Sensibly, both R&D and the share of exports seem to be more important for product and process-innovation than for organizational and managerial ones[8]. The same heterogeneity is found for the affiliation to firm-networks[9].

As a final exercise I test whether the positive effect of firm size on innovation is the result of a triple-acting: a direct effect due to the greater propensity to innovate (simply due to a scale-effect), an indirect impact though the lower probability of financial problems and a further relaxing action once FC occurs. While the first two channels have been widely analyzed in the previous sections, the last issue deserves a deeper examination.

To investigate this additional channel, an interaction term between size and FC is inserted into the previous equation. Table 7 shows the results. The effects of firm size on the probability of innovation are multiple. Not only through a direct positive effect on innovation and an indirect effect on the financial

[8] The stronger effect of the export activity on product-innovations provides evidences on possible "demand-pull" effects from the international markets.

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

Table 4: Probability of innovation and FC: simultaneous estimation.

Innovation Equation	Bivariate Probit (no feedback effect)		Bivariate Probit (feedback effect)	
FC	-0.45**	(0.22)	-0.56***	(0.20)
R&D	2.16***	(0.34)	2.2***	(0.34)
Size	0.08***	(0.01)	0.08***	(0.01)
Age	0.002	(0.02)	0.003	(0.02)
Market power	0.03**	(0.02)	0.03**	(0.02)
Simple network	0.16***	(0.03)	0.16***	(0.03)
Advanced network	0.24***	(0.03)	0.23***	(0.03)
Export share	0.02***	(0.01)	0.01***	(0.01)
Multinational	0.32***	(0.05)	0.32***	(0.05)
Positive exp.	0.11***	(0.03)	0.11***	(0.03)
Negative exp.	0.011	(0.03)	0.01	(0.03)
Constant	-0.46***	(0.13)	-0.43***	(0.13)
Industry dummies	yes		yes	
Regional dummies	yes		yes	
Time dummies	yes		yes	
FC Equation				
R&D			0.4**	(0.19)
Credit score	-0.16***	(0.03)	-0.16***	(0.03)
% self-financing	-0.16***	(0.04)	-0.16***	(0.04)
% bank debt	0.08*	(0.05)	0.07*	(0.05)
Profitability	-0.03**	(0.02)	-0.03**	(0.01)
Size	-0.07***	(0.01)	-0.06***	(0.01)
Age	0.02	(0.02)	0.03	(0.02)
Constant	-0.31***	(0.14)	-0.26*	(0.14)
Industry dummies	yes		yes	
Regional dummies	yes		yes	
Time dummies	yes		yes	
$\hat{\rho}$	0.33***	(0.13)	0.39***	(0.12)
# obs.	13476		13476	
Logliklihood Bivariate	-13117		-13114	

Notes: This table reports the results from recursive bivariate probit models on the probability of innovating and of facing financial constraints. The dependent variables are the general measure of innovation (Innovation) and FC. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other variables 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 5: Probability of innovation and FC: simultaneous estimation. Innovative vs. non-innovative firms.

Innovation Equation	Innovative (median)		Non-innovative (median)		Innovative (75^{th} perc.)		Non-innovative (75^{th} perc.)	
FC	-0.91***	(0.32)	-0.36	(0.31)	-1.52***	(0.34)	-0.39	(0.31)
R&D	1.79***	(0.30)	8.5***	(1.12)	1.29***	(0.31)	5.77***	(0.49)
Size	0.08***	(0.02)	0.06**	(0.03)	0.06***	(0.02)	0.08***	(0.02)
Age	0.01	(0.02)	-0.03	(0.04)	-0.01	(0.03)	0.01	(0.04)
Market power	-0.009	(0.02)	0.06*	(0.04)	-0.007	(0.02)	0.06***	(0.02)
Simple network	0.22***	(0.03)	0.001	(0.03)	0.18***	(0.04)	0.14***	(0.03)
Advanced network	0.2***	(0.03)	0.34***	(0.03)	0.18***	(0.04)	0.27***	(0.04)
Export share	0.008***	(0.00)	0.02***	(0.004)	0.002	(0.00)	0.02***	(0.00)
Multinational	0.33***	(0.05)	0.18	(0.05)	0.36***	(0.06)	0.15	(0.11)
Positive exp.	0.09***	(0.03)	0.06	(0.05)	0.08*	(0.04)	0.11***	(0.04)
Negative exp.	-0.04	(0.04)	0.01	(0.06)	0.03	(0.05)	-0.004	(0.04)
Constant	-0.5***	(0.17)	-0.26	(0.25)	-0.43*	(0.27)	-0.33**	(0.16)
Industry dummies	yes		yes		yes		yes	
Regional dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
FC Equation								
R&D	0.43**	(0.22)	0.99	(1.31)	0.52*	(0.31)	1.11**	(0.52)
Credit score	-0.17***	(0.04)	-0.14***	(0.05)	-0.18***	(0.05)	-0.16***	(0.05)
% self-financing	-0.12***	(0.04)	-0.29***	(0.08)	-0.08	(0.06)	-0.22***	(0.05)
% bank debt	-0.04	(0.06)	0.29***	(0.09)	-0.05 (0.06)	0.14**	(0.06)	
Profitability	-0.04**	(0.02)	-0.02	(0.03)	-0.03	(0.02)	-0.03	(0.02)
Size	-0.04***	(0.01)	-0.12***	(0.03)	-0.05**	(0.02)	-0.06***	(0.02)
Age	0.02	(0.03)	0.05	(0.04)	0.04	(0.03)	0.02	(0.03)
Constant	-0.49**	(0.12)	-0.03	(0.29)	-0.34	(0.31)	-0.17	(0.17)
Industry dummies	yes		yes		yes		yes	
Regional dummies	yes		yes		yes		yes	
Time dummies	yes		yes		yes		yes	
$\hat{\rho}$	0.6***	(0.21)	0.31*	(0.19)	0.79***	(0.14)	0.31*	(0.19)
# obs.	9703		3773		5782		7694	
Loglik. Bivariate	-9407		-3543		-5253		-7714	

Notes: This table reports the results from recursive bivariate probit models on the probability of innovating and of facing financial constraints. The dependent variables are the general measure of innovation (Innovation) and FC. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other variables 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) and (3) reports the estimates on the subset of most innovative firms (respectively divided on the basis of the median (column 1) or the 75th percentile (column 3) of the unconditional innovation likelihood distribution. as in Table 2. column 1). Column (2) and (4) report the same coefficients for the subsample of non-innovative firms. *, **, *** denote, respectively, significance at 10%, 5%, and 1% level. Robust standard errors in parentheses.

status. Big firms are also better able to overcome the limiting effect on innovation once credit constraints occur. Interestingly, this additional effect is significant and positive only for product and process-innovations. Figure 2 highlights this heterogeneity by plotting the predicted probability for the breakdown of innovation definitions. Once imposed the other variables to be at their mean values, the figure show the innovation-specific likelihoods for several levels of firm size and FC. The effects greatly vary across innovation types. The overall negative impact of FC on innovation is inferred from the vertical distance between the blue and the green line. In accordance with the regression results, the predicted innovation probability of financially constrained firms always lies on lower levels than the one of sound firms. However, this negative effect tends to disappear moving towards higher levels of firm size. On average, the depressive impact of FC on innovation is much stronger for small firms than bigger companies. Even in presence of financial difficulties, big firms are better able to raise funds in order to undertake potentially profitable investments, while small firms are heavily damaged by FC. Interestingly, the dynamic of organizational-managerial innovation is very different and firm size does not seem to play any role in overcoming financial problems. On the one hand, this might be due to the nature of this broad definition of innovation (which embeds a great variety of different improvements and is often adopted by very small firms). On the other hand, the result might also hide firm valuations on the different expected returns among the projects. A big firm that faces problems in raising external funds, is more willing to find different sources of finance (internal or external) to introduce structural improvements (product or process) where potential returns are much higher than organizational and managerial-innovations.

4.3 Robustness

Results are robust to:

- Different specifications of the logit model on the innovation propensity.
- Different specifications of the bivariate probit model that simultaneously estimates both the likelihood to innovate and the probability to be financially constrained.
- A different definition of financial constraints based on the difficulties encountered in accessing the credit market (instead of a measure on investment limiting factors).
- A different definition of R&D. Using a dummy variable instead of a measure of intensity of research and development.

Table 6: Probability of innovation and FC: simultaneous estimation (details).

	Innovation type			
Innovation Equation	Product-Process		Organizational-Managerial	
FC	-0.5***	(0.20)	-0.58**	(0.27)
R&D	2.33***	(0.31)	1.27***	(0.18)
Size	0.05***	(0.01)	0.1***	(0.01)
Age	0.02	(0.02)	-0.04	(0.02)
Market power	0.05***	(0.02)	-0.0008	(0.02)
Simple network	0.16***	(0.03)	0.06**	(0.03)
Advanced network	0.15***	(0.03)	0.26***	(0.03)
Export share	0.02***	(0.01)	0.004**	(0.01)
Multinational	0.29***	(0.05)	0.33***	(0.05)
Positive exp.	0.09***	(0.03)	0.05*	(0.03)
Negative exp.	0.01	(0.03)	-0.02	(0.03)
Constant	-0.81***	(0.13)	-0.59***	(0.15)
Industry dummies	yes		yes	
Regional dummies	yes		yes	
Time dummies	yes		yes	
FC Equation				
R&D	0.39**	(0.17)	0.34**	(0.17)
Credit score	-0.16***	(0.03)	-0.16***	(0.03)
% self-financing	-0.15***	(0.04)	-0.15***	(0.04)
% bank debt	0.08*	(0.04)	0.09**	(0.04)
Profitability	-0.3**	(0.01)	-0.03**	(0.01)
Size	-0.07***	(0.01)	-0.06***	(0.01)
Age	0.02	(0.02)	0.02	(0.02)
Constant	-0.23***	(0.14)	-0.27*	(0.14)
Industry dummies	yes		yes	
Regional dummies	yes		yes	
Time dummies	yes		yes	
$\hat{\rho}$	0.38***	(0.12)	0.32*	(0.17)
# obs.	13476		13476	
Logliklihood Bivariate	-13135		-12835	

Notes: This table reports the results from recursive bivariate probit models on the probability of innovating and of facing financial constraints. The dependent variables are FC and either the introduction of product-process innovation (column 1) or the introduction of organizational-managerial innovations (column 2). $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other variables 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 7: Probability of innovation and FC: simultaneous estimation (details).

	Innovation type					
Innovation Equation	Total		Product-Process		Organizational-Managerial	
FC	-0.45**	(0.21)	-0.41**	(0.22)	-0.53**	(0.21)
Interaction: FC*size	0.05*	(0.03)	0.05**	(0.03)	-0.005	(0.03)
R&D	2.19***	(0.34)	2.3***	(0.31)	1.22***	(0.34)
Size	0.08***	(0.01)	0.04***	(0.01)	0.1***	(0.01)
Age	0.002	(0.01)	0.02	(0.02)	-0.04**	(0.01)
Market power	0.04**	(0.02)	0.05***	(0.02)	-0.001	(0.02)
Simple network	0.17***	(0.03)	0.16***	(0.03)	0.06**	(0.03)
Advanced network	0.24***	(0.03)	0.15***	(0.03)	0.26***	(0.03)
Export share	0.01***	(0.002)	0.18***	(0.002)	0.004**	(0.002)
Multinational	0.32***	(0.05)	0.29***	(0.05)	0.33***	(0.05)
Positive exp.	0.11***	(0.03)	0.1***	(0.03)	0.05*	(0.03)
Negative exp.	0.01	(0.03)	0.01	(0.03)	-0.02	(0.03)
Constant	-0.48***	-0.13	-0.87***	(0.14)	-0.61***	(0.15)
Industry dummies	yes		yes		yes	
Regional dummies	yes		yes		yes	
Time dummies	yes		yes		yes	
FC Equation						
Credit score	-0.16***	(0.03)	-0.17***	(0.03)	-0.16***	(0.03)
% self-financing	-0.15***	(0.04)	-0.15***	(0.04)	-0.15***	(0.04)
% bank debt	0.09*	(0.05)	0.09**	(0.05)	0.09**	(0.05)
Profitability	-0.03*	(0.02)	-0.03**	(0.02)	-0.03**	(0.02)
Size	-0.06***	(0.01)	-0.06***	(0.01)	-0.06***	(0.01)
Age	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)
Constant	-0.24*	(0.14)	-0.23*	(0.14)	-0.25*	(0.14)
Industry dummies	yes		yes		yes	
Regional dummies	yes		yes		yes	
Time dummies	yes		yes		yes	
$\hat{\rho}$	0.23*	(0.13)	0.23*	(0.14)	0.3*	(0.18)
# obs.	13476		13476		13476	
Loglik. Bivariate	-13116		-13136		-12837	

Notes: This table reports the results from recursive bivariate probit models on the probability of innovating and of facing financial constraints. The dependent variables are FC and either the introduction of any type (Total, column 1), product-process (column 2) or organizational-managerial innovation (column 3). Interaction: FC*size is the interaction term obtained multiplying Size by FC. $\hat{\rho}$ is the estimated correlation coefficient between the error terms of the two equations. All the other variables 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.

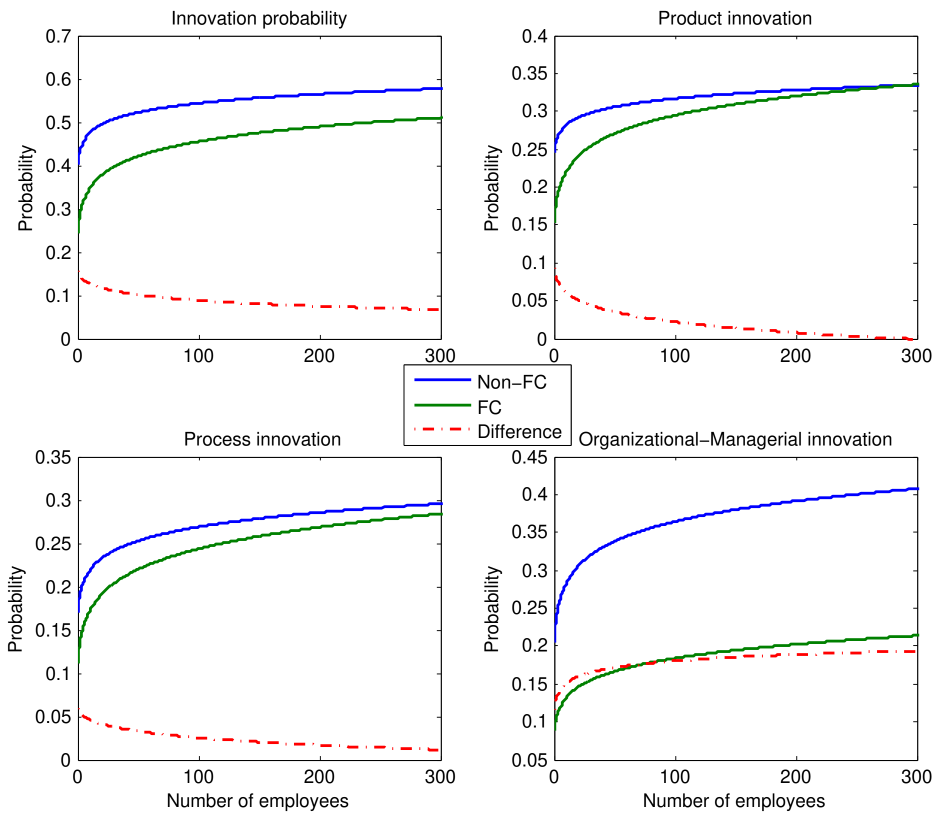

Figure 2: Probability of innovation. financial constraints and firm size.
Notes: This figure plots the innovation predicted probabilities as a function of firm FC status and size. Predicted probabilities are computed imposing all the other covariates at their mean value.

- Different measures of firm creditworthiness. Replacing the estimated rating score with the more traditional Altman Z-score. The latter is computed in two ways. The first one employs the standard version of the Z-score: $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$. Where X_1 to X_5 represents 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 non-quoted firms) and sales to total assets. The second way exploits the version of Altman Donavi and Fallini (2013), specifically calibrated 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 (at the limit of 10%).

5 Concluding remarks

The paper establishes the existence and the impact of binding financial constraints on the innovation activity of Italian firms. Differently from most studies on FC, a rich baseline specification for both innovation and financial constraints is provided. On the one hand, considering structural, behavioral, strategic and environmental characteristics as determinants of the innovative propensity. On the other hand, modeling the FC equation with variables linked to both credit supply and demand. With this regard, a big role is played by a credit-score estimated *ad hoc* on a sample of 3,000 confidential bank ratings. The score allows to control for firm perceived creditworthiness and to take into account part of the credit supply channel.

Thanks to a direct measure of financial constraints, I am able to overcome standard interpretative problems linked to the use of indirect proxies. I employ a recursive bivariate probit model to simultaneously estimate the probability of innovation and the likelihood of facing binding financial constraints, controlling for the possible correlation between the two. Results show the deep negative effect of FC on innovation. Keeping all rest equal, the presence of financial problems reduces the probability of introducing innovations of about 34%. This effect is even stronger (42%) when I partially allow for a feedback effect of innovation on the FC status.

Detailed data about the type of innovation enable to analyze the presence of possible heterogeneity in all the effects. While the impact of financial problems does not seem to vary across innovation classes, the effects of networks, internationalization and R&D is much stronger for product and process-innovations. Finally, I investigate the role of firm size in fostering innovative activity. The positive effect does not boil down to a direct positive effect on innovation and an indirect effect on the financial status. Big firms are also better able to overcome the limiting effect on innovation once credit constraints occur. This is true only for projects with higher potential returns.

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