Università della Calabria

Dipartimento Economia, Statistica e Finanza

Gruppo CALCOM

EXTERNAL FINANCE, INTERNAL FINANCE AND INNOVATION: EVIDENCE FROM ITALIAN MANUFACTURING FIRMS

G. Damiana Costanzo
Damiano B. Silipo
Marianna Succurro

Marzo 2013

External Finance, Internal Finance and Innovation: evidence from Italian manufacturing firms

Abstract

This paper studies the impact of different sources of finance on innovation, by focusing on Italian manufacturing firms over the 2003-2010 period. By using a dynamic econometric model based on an original measure of R&D expenditure, we get surprising results compared to previous findings. The effects of finance on innovation can be heterogeneous depending on firms' relative size, geographic location and technological intensity of the sector. In the Centre-North, where access to financial markets is easier, firms rely on external funding to undertake R&D. By contrast, in Southern regions, where access to external finance is harder, firms do R&D by substituting external funds with internal resources. The different role played by financial institutions in Mezzogiorno and Centre-North of Italy also emerges by comparing large companies and SMEs. Empirical evidence shows that external finance plays a crucial role in spurring innovation of high-tech firms, independently from their size. For patent probability, on the contrary, internal funding seems economically more relevant than external funding.

JEL Classification: D22, G20, G30, O30

Keywords: External Finance, Internal Finance, Innovation, R&D

1 INTRODUCTION

Innovation projects require, like any investment, financial resources but, as it is known, the source of financing is particularly important for investments in the creation of knowledge (Arrow, 1962; Nelson, 1959). R&D is characterized by high firm specific investment costs, on the one hand, and low collateral value, on the other hand. Although innovative activity may provide high rewards, it is characterised by technological, strategic and market uncertainty (Encaoua *et al.* 2000). Firms that undertake R&D do not know whether they will succeed or not and, even if they succeed, they do not know whether they will be the first in the patent race. Indeed, innovation projects are very often a race to be the first, and the value to be second in the race may be the same than not succeeding at all. Given the nature of innovative activity, it is relevant for the firm to share the risk of innovation with other investors searching for high yields. So, it is reasonable to assume that the higher is the opportunity for the firm to share the risk of innovation with outside investors, the greater will be the incentive to innovate. However, both positive externalities and capital market imperfections may lead to financing constraints with a consequent sub-optimal investment in R&D. Besides information asymmetries, the intangibility of the potential asset may make raising funds externally more costly for innovation than for other types of investments (EIB, 2009).

In principle, there are two sources for financing innovation projects: external financial sources, such as bank loans or other debt contracts, and internal sources, such as cash flow (Czarnitzi and Hottenrott, 2011; Himmelberg and Petersen, 1994; Hall, 1992). Previous works highlighted the role of banking loans on innovative activity (Guiso et al. 2004, Herrera and Minetti, 2005, Benfratello et al. 2008). By contrast, Giudici and Paleari (2000), Ughetto (2007), Muller and Zimmermann (2009), Brown et al. (2009) stressed the importance of cash-flow and equity finance for R&D. External and internal finance channels are not independent since serving debt requires a stable cash flow which makes financing of innovation projects by external sources more difficult because most of innovation projects do not immediately lead to success (Czarnitzi and Hottenrott, 2011). In addition, serving debt reduces cash flow for future investments (Hall, 2002; Hall, 1990). In this context, the extent to which financial constraints are binding depends on the firms' ability to raise external or internal funds.

Recent empirical evidence based on micro-data shows that banks play an important role in the financing of innovation (Amore *et al*., 2013; Chava *et al*., 2013; Berger, 2010; Nanda and Nicholas, 2012, Cetorelli and Strahan, 2006; Berger and Udell,1998). This is particularly true for Italy where the growth of venture capital is limited and the bank loans represent the most important source of external finance (Benfratello et al. 2008). However, it is reasonable to assume that, in making investments, firms take account of all the sources of funding. For this reason, our research analyses the impact of different firms' financial sources on innovation. We first build up a measure of innovative activity, external finance and internal finance. Then, we investigate to what extent finance explains firms' innovative activity by focusing on Italian manufacturing firms over the 2003-2010 period.

Our paper has several elements of strength. First, we propose an original measure of R&D expenditure which, despite its relative simplicity, has a great potential for future applied research on innovation. This measure of R&D expenditure, based on accounting data, allows us to collect data for several years and implement a dynamic analysis which controls for endogeneity. Second, while previous empirical studies focus only on large listed companies or on small firms, our analysis includes a very large sample of both large firms and small and medium enterprises (SMEs). Third, while previous empirical studies focus on internal funding or external funding, we consider both financial channels simultaneously and evaluate their impact on both firms' R&D expenditure and innovation output probability. However, we do not consider other financial factors external to the firm - such as sector or public incentives.

The paper is organized as follows. Section 2 specifies the relevant variables for our empirical investigation and illustrates some descriptive statistics. Section 3 and Section 4 present respectively the econometric specification and the empirical evidence on the impact of finance on R&D expenditure. Section 5 investigates the impact of finance on innovation output probability. Section 6 provides some concluding remarks.

2 EXTERNAL FINANCE, INTERNAL FINANCE and INNOVATION

2.1 Preliminary definitions and estimates

This study is mainly based on firms' accounting data taken from the Amadeus database, published by *Bureau van Dijk*. It is a European financial database which includes more than 4 million firms' accounting data in a standardized balance sheet format. The database includes both SMEs and large companies operating in all industries.

This section of the research aims at reducing the general lack of tools for rightly evaluating R&D investments from intangibles (Lev, 2001). A preliminary step in the analysis of the effects of finance on innovation deals with the definition of firms' innovative activity. Since innovations typically result from investment in research and development, we focus on this innovation input and build up the ratio between firms' estimated R&D expenditure and Total Fixed Assets. We use Intangible Fixed Assets as proxy variable for the intangible production factors. These include R&D expenditures, patents, copyrights, software, employees training, trademarks and other similar items (Marrocu et al., 2011). In order to evaluate the firm's R&D expenditure, not automatically available in the Amadeus database, we correct the data on the Intangible Fixed Assets by considering the Italian companies' average R&D expenditure by sector, region and size as reported in the Istat database[1] (Source: Istat, *NoiItalia* and *I.Stat*). Specifically, as a first step, we estimate the R&D expenditure of firm *i* operating in the sector *s* in the following way:

$$R\&D_i^s = IA_i * \frac{\overline{R\&D_s} * N}{IA_s}$$

where IA_i indicates total intangibles of firm *i* taken from Amadeus, $\overline{R\&D_s}$ is the average research and development expenditure of the companies in the sector *S* (*S=10....32*, NACE Rev.2 primary codes) taken from the Istat database, *N* is the total number of companies taken from Amadeus, and IA_s indicates total Intangible Fixed Assets of the sector taken from Amadeus. See Table A.1 in the Appendix for a list of the industrial sectors.
As a second step, we estimate the R&D expenditure of firm *i* operating in the region *R* in the following way:

$$R\&D_i^R = IA_i * \frac{\overline{R\&D_R} * N}{IA_R}$$

where IA_i indicates total intangibles of firm *i* taken from Amadeus, $\overline{R\&D_R}$ is the average research and development expenditure of the companies in the region *R* (*R=1....20*) taken from the Istat database, *N* is the total number of companies taken from Amadeus, and IA_R indicates total Intangible Fixed Assets of the region taken from Amadeus.
As a third step, we estimate the R&D expenditure of firm *i* on the base of its relative size in the following way:

$$R\&D_i^D = IA_i * \frac{\overline{R\&D_D} * N}{IA_D}$$

where IA_i indicates total intangibles of firm *i*, $\overline{R\&D_D}$ is the average research and development expenditure of the companies by size (dimension *D*, *D*=1....4), taken from the Istat database, *N* is the total number of companies taken from Amadeus, and IA_D indicates the total Intangible Fixed Assets of the firms in the same size group. *D* is measured according to the European Union classification[2]. In particular, we initially consider four groups of firms on the base of their relative size: micro firms (turnover<2mln euros); small firms (2mln euros<turnover<10mln euros); medium firms (10mln euros<turnover<50mln euros); large firms (turnover>50 mln euros). For the reasons explained below (section 2.2), we then implement our empirical analysis only on small, medium and large companies.
Finally, we compute the mean value of the previous three estimates of R&D of firm *i* in order to obtain a more accurate estimate of R&D for each firm:

$$R\&D_i = \overline{R\&D_i} = mean\ (R\&D_i^s;\ R\&D_i^R;\ R\&D_i^D)$$

$R\&D_i$, divided by firms' total assets is the measure of firms' innovative activity used in our analysis.

[1] Data on the companies' R&D expenditure by sector, region and size are obtained by combining data from the *NoiItalia* database (*La Ricerca e Sviluppo in Italia, Tav.5, Tav.6, Tav.10*) and data from the *I.Stat* database (*Unità economiche dell'industria e dei servizi*).
[2] Commission Recommendation 96/280/EC, updated in 2003/361/EC of May 6, 2003.

Note that our measure of research and development spending is an estimate of the real value of firms' R&D expenditure. In order to verify the quality of our measure of firms' innovative activity, we implement a statistical validation of our estimated $R\&D_i$ explained afterwards.
For 367 firms we have the real values of R&D expenditure available for 2010. This hand-collected information has been taken from the additional note reported, in pdf format, at the end of each firm' balance sheet. It is a an optical reading procedure supplied by Bureau van Dijk that allows to search for specific keywords.
Therefore, for these 367 firms, we have both the real R&D expenditure value and our estimated R&D expenditure. Table 1 compares relevant statistical findings for this group of firms with available real data. More specifically, we consider: a) the Pearson Correlation coefficient; b) the paired samples *t*-test which typically consists of a sample of matched pairs of similar units.
The correlation coefficient between our estimated R&D and the real R&D is very high, being equal to 0.926, at a high significance level. At the same time, the *p*-value=0.016 of the t-paired test indicates that, at the standard significance level α=0.01, we do not reject the null hypothesis that there are no differences between the two sources of data, the estimated R&D values and the R&D expenditures taken from the balance sheets' additional note. Note that the t-test is an highly sensitive statistical test. Hence, the whole consideration of the previous statistical results is encouraging in using our measure of firms' innovative activity in the following steps of our analysis.

Table 1 Statistical validation of R&D estimates

Pearson Correlation Coefficient								
Estimated R&D and Real R&D	Sig. (two tails)							
0.926	0.000							
t-paired test	Mean	Std. Dev.	SE	Conf. Int. 95%		t	df	Sig.(two tails)
				Low	Upper			
Estimated R&D – Real R&D	595.953	4716.093	246.178	111.852	1080.054	2.421	366	0.016

Source: own elaborations on Amadeus Database

Therefore, the next step of our research deals with the definition of access to external and internal finance. R&D activity and innovation strongly depend on the availability of financial resources (Czarnitzi and Hottenrott, 2011; Brown *et al*. 2009; Benfratello *et al*. 2008; Sarno 2008; Sarno, 2007; Ughetto, 2008; Guiso *et al.* 2004; Giudici and Paleari, 2000; Himmelberg and Petersen, 1994; Hall, 1992; Hall, 1990). In presence of strong external financial constraints, internal sources of finance become an important channel for innovation activity. Indeed, in principle, there are two sources for financing innovation projects: external financial sources, such as bank loans or other debt contracts, and internal sources, such as cash flow.
Thus, in the following empirical analysis, we consider both firms' external and internal funds and evaluate their impact on innovation. So, we need an appropriate empirical measure of access to external and internal finance.
By external financing we mean funds not generated internally (not self financing). More specifically, we measure external finance (*EXTF*) as the ratio between bank loans and long term debt to total assets. Despite previous indirect measures of external finance based on aggregate county-level bank deposits used as a proxy of bank loans (Butler and Cornaggia, 2011; Becker, 2007), our analysis has the advantage of using micro-data on bank loans and additional external resources reported in the balance sheets.
We measure the availability of internal funds (*INTF*) as the ratio between cash flow and total assets. Some empirical studies underline the different role played by internal and external funds on different types of innovation. While the availability of internal funds can allow greater risk of radical innovations, external funds are usually connected with incremental innovation (Galende and de la Fuente, 2003). Our database does not allow us to distinguish among different types of

innovation, but this is not the specific aim of our analysis. Our objective is to evaluate the impact of both internal and external finance on research and development expenditure (innovation input) and on innovation output probability as a whole by focusing on different geographic location, size of the firms and sectors.

2.2 Some descriptive statistics

Table 2 illustrates some descriptive statistics for R&D expenditure by firms' size, while Table 3 illustrates some descriptive statistics on intangibles and R&D to total assets, estimated as illustrated in section 2.1. Data show that more than the 90% of R&D expenditure is made by large (46.47%), medium (22.41%) and small (21.07%) companies. Moreover, notice that R&D to total assets is very low for micro firms, so we exclude this category from our empirical analysis.
Table 3 illustrates the main variables and their descriptive statistics for all the manufacturing firms included in the analysis.

Table 2 R&D by firms' size, (thousands euros, 2003-2010, average values)

Firms' Size	Mean	Std. Dev.	Min	Max	N	% on total R&D
Micro	5.117	20.223	0	3395.77	83930	9.84
Small	23.759	54.051	0	6766.45	38668	21.07
Medium	86.384	205.617	0	6940.07	11315	22.41
Large	1105.621	5465.578	0	243987.31	1841	46.67
					112398	*100*

Source: own elaborations on Amadeus Database

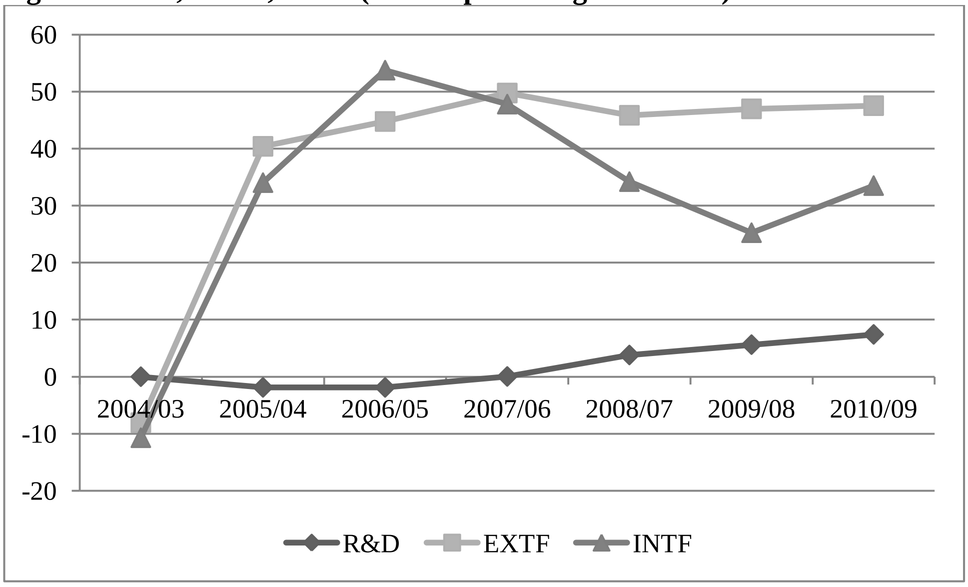
Table 3 Description of variables and summary statistics, all firms (2003-2010, average values)

Variable	Description	Mean	Std. Dev.	Min	Max	Obs
IA	Intangibles to total assets	0.0181	0.0291	0	0.3310	234576
R&D	Research and development spending to total assets	0.0064	0.0086	0	0.0491	234576
EXTF	External financial resources to total assets	0.1794	0.1677	0	0.5491	234576
INTF	Internal financial resources to total assets	0.0553	0.0452	-0.0593	0.1914	234576

Source: own elaborations on Amadeus Database

Figure 1 shows the annual percentage variation of the considered ratios over the 2003-2010 period. The ratio between external funds and total assets increases by 50.35% over the 2004-2005 period and by 10% over the 2005-2007 years, then it declines registering the highest negative percentage variation (-7.68%) in the year following the international financial crisis. In the two years following the financial crisis, the ratio between cash flow and total assets decreases at a higher rate (-18.65%). Nevertheless, R&D over total assets shows a restrained positive trend.

Figure 1 *R&D, EXTF, INTF* (annual percentage variation)



Source: own elaborations on Amadeus Database

Table 4 illustrates R&D expenditure over total assets and both external and internal financial resources to total assets by region.

Data on innovative activity and internal funds show some homogeneity among the Italian regions even if, on average, firms operating in the Centre-North of the country show some higher cash flow availability (5.2%) compared to the companies operating in the South of Italy (4.8%). By contrast, when we look at the external finance, data show higher heterogeneity among the Italian regions. On average, Southern Italian manufacturing firms face higher difficulties in accessing external finance compared to firms operating in the Centre-North of the country. Moreover, *EXTF* may vary a lot across the regions belonging to the same geographical area. In the South, indeed, it varies between the 16.21% of Basilicata and the 19.62% of Sardinia region, while in the Centre-North it varies between the 16% of Lazio and the 22% of Umbria.

Table 4 R&D and Financial Resources by region (2003-2010, av. % values)

	R&D	*EXTF*	*INTF*
SOUTH	***1.02***	***16.59***	***4.83***
Basilicata	0.96	16.21	4.91
Calabria	0.32	16.97	5.22
Campania	1.54	16.88	4.79
Puglia	1.01	17.88	4.77
Sardegna	0.96	19.62	4.61
Sicilia	1.34	17.96	4.72
CENTRE-NORTH	***1.18***	***18.32***	***5.21***
Abruzzo	0.59	18.32	4.67
Emilia Romagna	1.34	17.48	5.43
Friuli V.G.	1.21	21.23	5.43
Lazio	1.6	15.98	5.08
Liguria	1.79	17.62	5.5
Lombardia	1.98	17.41	5.41
Marche	0.96	18.59	5.19
Molise	0.64	16.43	4.79

Piemonte	1.29	18.45	5.44
Toscana	0.9	18.3	4.75
Trentino	1.43	17.99	5.89
Umbria	0.78	22.11	4.91
Valle d'Aosta	0.97	19.08	4.89
Veneto	1	18.44	5.57

Source: own elaborations on Amadeus Database

As preliminary investigation, we analyze the correlation between innovation and finance by considering the mentioned ratios for all the Italian manufacturing firms as a whole (Table 5). The correlation coefficient between external finance and R&D expenditure is generally positive and significant at 1% level, but it is relatively higher in the Centre-North than in the South of the country. Also the correlation coefficient between internal funds and R&D expenditure is positive and statistically significant at 1% level, but in this case it assumes an higher value for the South of the country.
Finally, external and internal funds show a negative and significant correlation in both geographical areas. As mentioned in the introduction, the two finance channels are not independent since serving debt requires a stable cash flow which makes financing of innovation projects by external sources more difficult because most of innovation projects do not immediately lead to success (Czarnitzi and Hottenrott, 2009). In addition, serving debt reduces cash flow for future investments (Hall, 1990; Hall, 2002).

Table 5 Correlation between R&D and Financial Resources

	Centre-North		
	R&D	*EXTF*	*INTF*
R&D	1.0000		
EXTF	0.0850***	1.0000	
INTF	0.0289***	-0.1542***	1.0000
	South		
	R&D	*EXTF*	*INTF*
R&D	1.0000		
EXTF	0.0387***	1.0000	
INTF	0.0609***	-0.1012***	1.0000

Pairwise correlations significante levels: *10%; **5%; ***1%
Source: own elaborations on Amadeus Database

3 ECONOMETRIC SPECIFICATION

The econometric analysis is based on the estimation of the following model:

$$R\&D_{it} = \beta_0 + \beta_1 EXTF_{it} + \beta_2 INTF_{it} + \beta_3 Size_{it} + \beta_4 Age_{it} + \beta_5 C_{4_{it}} + \beta_6 W_{it} + \gamma_t + u_i + \varepsilon_{it} \quad (1)$$

where *i* indicates firms, observed over the 2003-2010 period;
γ_t indicates time effects, u_i indicates firms' effects and ε_{it} are the stochastic residuals.
The dependent variable *R&D* indicates the firms' innovative activity and it is given by the ratio between research and development expenditure to total assets, as explained in section 2.
The variables *EXTF* and *INTF* indicate firms' external and internal financial resources respectively. As mentioned before, *EXTF* is built up as the ratio between long term debt and loans to total assets

and it indicates external financing; *INTF*, which indicates internal funds, is given by the ratio between cash flow and total assets.
The additional explanatory variables include firm-level, industry-level and region-level variables. Specifically:
Size of the firm, measured in terms of annual turnover;
Age, measured as the difference between the last available year and the foundation year of the company;
C_4 is 4-firms concentration rate for each manufacturing sector.
Finally, our model includes the W matrix which considers relevant regional-level controls[3]:
TK which is a measure of technological capital, computed as 3 years patents stock (source: *Ufficio Italiano Brevetti e Marchi*) over 1000 population (source: Istat);
HK as a measure of human capital, calculated as the number of people with a scientific degree over 1000 residents aged 20-29 (source: Istat);
Firm Density, computed as the average number of firms over 1000 inhabitants (source: Istat), is a significant indicator of competition but also an indicator of technological externality among firms.
GDP is per-capita gross domestic product (source: Istat);
Infr is a proxy of public infrastructures computed as kilometers of highway network in each region (over 1000 km^2 of regional territory) (source: Istat);
Criminality is a proxy of social cohesion. It is computed as the number of people denounced for crimes over 100000 inhabitants (source: Istat).
Table A.2 in the Appendix illustrates some descriptive statistics for all the explanatory variables used in the empirical analysis distinguishing, for firm-level variables, patenting and non-patenting firms. The following analysis, however, is based on the sample as a whole and not only on firms with patents which, given the nature of the innovation projects, would not be the correct measure of the innovative activity (Lanjouw and Schankerman, 2004).

4 EMPIRICAL EVIDENCE

In this paragraph, we present our main empirical results for Italy as a whole (Table 6), for the Centre-North (Table 7) and the Southern part of the country (Table 8). Moreover, we report empirical findings separately for all firms, large companies and SMEs.
Note that we drop observations with missing values in the explanatory variables and, in order to correct for significant outliers, we eliminate all observations in the lowest and in the highest 5% percentiles.
To evaluate statistical significance of our model, we consider several statistical tests. F-tests estimates the overall (global) fit of the linear regression model. As it is shown, although the descriptive measure of the goodness of fit of the models (R^2) is relatively low, the F test null hypothesis that all the coefficients are jointly equal to zero is always rejected at 1% level.
The pooled cross-section specification might generate biased and inconsistent results, since it does not take into account unobserved heterogeneity among firms like managerial ability, degree of risk-aversion, ownership structure, etc. In all the relevant specifications, indeed, the Breusch-Pagan test indicates that pooled cross-section is not the correct specification of the model since there are significant differences across firms. Individual shocks should be taken into account with a panel data estimation.
The Hausman specification test is then performed to investigate the correlation between the unobserved individual effect and the observed explanatory variables. As reported in all the tables,

[3] The regional controls have been used as alternative to time-invariant regional dummies which, besides sector dummies, have been included in the random effects model but dropped in a (successive) fixed effects model (see section 4 for technicalities).

we always reject the null hypothesis; therefore, the correct specification of our model - in a static context and without dealing with the endogeneity problem - would be a Fixed Effect specification.
Moreover, the F test on the time dummies variables allows us to reject the hypothesis that all the coefficients are jointly equal to zero; therefore, also time fixed effects are explicitly considered in our FE model specification.
The majority of previous empirical studies on finance and innovation focus on a static fixed effects model. That is why, for completeness, we report also Fixed Effect estimation results in each table.
However, as it is known, fixed effects in panel data model allow us to solve the omitted variable problem by controlling for the unobservable individual effect but the endogeneity problem is still present. Endogeneity could be produced by several factors like systematic shocks (period effects), omitted variables (unobserved heterogeneity), simultaneity, measurement error. Here, because of potential simultaneity, one could think that also the innovative activity determines firms' access to finance. More specifically, the firms' external and internal finance, as well as the other potential endogenous explanatory variables, could be determined jointly with the dependent variable. Under endogeneity, the FE-estimator will be biased. The traditional approach to solve the endogeneity problem consists in instrumental variables regression with external instruments and fixed or random effects estimators. An alternative approach to tackle the endogeneity issue uses internal instruments by exploiting panel data structure. More specifically, we use a Generalized Method of Moment (GMM) estimator (Arellano and Bond 1991; Blundell and Bond 1998) treating all explanatory variables as potentially endogenous. Thus, we rewrite Eq.1 in dynamics terms, as follows:

$$R\&D_{it} = \beta_0 + \beta_1 R\&D_{i,t-1} + \beta_2 EXTF_{it} + \beta_3 INTF_{it} + \beta_4 Size_{it} + \beta_5 Age_{it} + \beta_6 C_{4_{it}} + \beta_7 W_{it} + \gamma_t + u_i + \varepsilon_{it} \quad (2)$$

Equation 2 is a dynamic panel model with fixed effects (u_i) and a lagged dependent variable which allows us to take into account the dynamic nature of the innovative activity.
It can be properly estimated through the first differences GMM (GMM-DIFF) estimator proposed by Arellano and Bond (1991) which uses all the available lags of each independent variable in levels as instruments. However, the levels are poor instruments when variables exhibit strong persistence, as in the analyzed model (weak instruments). For this reason, we employ the estimation of the system of equations (GMM-SYS) implemented by Blundell and Bond (1998). It combines the first differenced regression used in GMM-DIFF and the Eq.2 in levels, whose instruments are the lagged differences of the endogenous variables.
A dynamic GMM-System specification of the model could give different empirical evidence from the static Fixed Effects specification, as it is shown afterwards.
Note that the coefficient of the lagged dependent variable is always significant with a positive sign, showing the opportunity of the dynamic specification of the model.
All the following tables show the empirical results and some specification tests. We report the results of the tests proposed by Arellano and Bond (1991) to detect first and second-order serial correlation in the residuals[4]. As it is shown, the absence of second-order serial correlation, which is a necessary condition for the validity of the instruments, is satisfied in our analysis.
A second specification test is a test of overidentifying restrictions. Since p>0.05, the null that the population moment conditions are correct is not rejected, therefore overidentifying restrictions are valid.
To sum up, our test statistics hint at a proper specification of our model allowing us to interpret and comment single coefficients of each model specification.
Given all the previous considerations, the following comments are mainly based on GMM-System estimates underlying, where necessary, significant differences with the FE model results.

[4] If ε_{it} are not serially correlated, the differenced residuals should show autocorrelation of first-order and absence of second-order serial correlation.

General results on a large sample of Italian manufacturing firms show that, controlling for fixed effects, both internal and external finance affect R&D activity (Table 6, column 1). However, when we control for endogeneity as well, the availability of external funds seems to be the relevant factor affecting R&D activity (Table 6, column 2).

Specifically, external finance enters at 1% level of significance with the expected positive sign (Table 6, column 2) suggesting that, in a bank-based economy like the Italian one, bank loans and other forms of debt play a crucial role in explaining firms' innovative activity. When we consider the Italian manufacturing firms as a whole, without distinguishing between large companies and SMEs, we unexpectedly find that internal funds are not statistically significant in explaining firms' R&D expenditure to total assets (Table 6, column 2). As mentioned before, it is well established in the literature (Czarnitzi and Hottenrott, 2011; Bougheas *et al*., 2003; Himmelberg and Petersen, 1994; Hall, 1992; Hall, 1990) that, due to the high risk of R&D activity, financial institutions are less prone to finance innovation, and firms rely first on internal funding to undertake R&D, and then they recur to external finance. So, we would expect internal funding to be more significant in determining firms' R&D activity than external finance. However, we also expect innovation is spurred by easier access to external finance, due to the possibility to share the risk of innovation with other investors. These first findings need additional investigation, as reported afterwards.

Moreover, we find that the incentive to innovate is higher among young and small firms than among the other firms.

With reference to the size of the firms, previous empirical studies find contrasting results. On the one hand, smaller firms should be more likely to face financing constraints as they usually cannot provide overall collateral value compared to larger, more capital intensive firms. Therefore, one would expect a positive effect of size on R&D activities. On the other hand, the fast growth of the knowledge economy has been accompanied by a fast growth of innovative start-ups. This evidence, which is in line with our empirical findings, can be related to the propensity for higher innovation in small firms as opposed to large ones (Pederzoli et al. 2013; Arora et al. 2001; Harhoff, 1996). Our empirical evidence, indeed, shows that size is a significant determinant of innovation and, for all Italian manufacturing firms as a whole, it enters the function with a negative sign.

Previous empirical findings on the relationship between age and R&D activities are ambiguous as well. Some authors find lower R&D investments for younger firms due to stronger financial constraints (Savignac, 2008; Schneider and Veugelers 2010; Canepa and Stoneman, 2002), while recent empirical evidence finds that small and young firms tend to innovate more radically, create new technologies, products and markets (Baumol, 2002). Also recently, Hottenrott and Peters (2009) use the concept of innovation capacity which should not depend on size or age *per se*. Our empirical findings show that age enters at 1% level with a negative sign suggesting that the innovative activity decreases with age, it may be because younger firms invest an higher percentage of financial resources in R&D than older and more established firms. In this context, younger Italian manufacturing firms, like start-up ones, would show higher innovation capacity.

The coefficient of concentration rate, on the contrary, is not significant when we consider the entire sample of the Italian manufacturing firms.

Table 6 also reports the GMM system results for large firms and SMEs separately (Table 6, column 4, column 6). Both financial channels are significant in explaining innovation activity, but the level of significance of external finance is relatively higher for small and medium enterprises than for large firms. Additional differences arise with respect to the firms' size, which is significant at 1% level with negative sign only for SMEs, and age, which enters significantly with negative sign only for large firms. The industry concentration rate is significant only for large firms.

The empirical findings on the additional control variables, not reported to save space but available on request, indicate that they are almost significant, at 5% or 1% level, with the expected sign.

Table 6 Finance and Innovation, Italy (2003-2010)

Dependent variable: $R\&D_{it}$						
	All Firms		LARGE		SMEs	
	Fixed Effects	GMM System	Fixed Effects	GMM System	Fixed Effects	GMM System
	(1)	(2)	(3)	(4)	(5)	(6)
$R\&D_{it-1}$		0.9153***		1.053***		0.912***
		(0.007)		(0.030)		(0.007)
$EXTF_{it}$	0.056***	0.059***	0.048***	0.047*	0.057***	0.061***
	(0.003)	(0.015)	(0.011)	(0.027)	(0.004)	(0.016)
$INTF_{it}$	0.038***	-0.016	-0.025	0.087*	0.041***	0.015*
	(0.005)	(0.031)	(0.026)	(0.092)	(0.005)	(0.030)
$Size_{it}$	-0.155***	-0.264***	0.274***	0.020	-0.221***	-0.343***
	(0.016)	(0.039)	(0.091)	(0.123)	(0.018)	(0.040)
Age_{it}	-0.038*	-0.07**	-0.013*	-0.176*	-0.021*	0.081
	(0.025)	(0.055)	(0.065)	(0.079)	(0.023)	(0.056)
C_4	0.029	0.017	-0.165	0.033***	0.087***	-0.015
	(0.275)	(0.078)	(0.128)	(0.947)	(0.029)	(0.041)
Regional controls	included	included	included	included	included	included
constant	-14.50***	-5.60*	2.59	-6.85	-14.40***	-3.77
	(3.719)	(2.916)	(5.37)	(8.55)	(3.83)	(3.00)
F test[a]	46.01***	18754.15***	6.98***	1480.61***	47.54***	18037.48***
Firm effects (F test)	10.66***		14.25***		10.36***	
Time effects (F test)	25.94***		9.15***		22.71***	
Hausman test	376.72***		31.92***		367.56***	
Breusch-Pagan test	1.4e+05***		7551.41***		1.3e+05***	
Sargan test (p value)		0.098		0.479		0.078
AR (1) (p value)		0.000		0.000		0.000
AR (2) (p value)		0.242		0.274		0.110
N obs.	147793	90728	6784	3578	141009	85633
R^2	0.03	0.15	0.06	0.16	0.05	0.15

All variables are considered in log. WC-Robust standard errors in parenthesis.
Time dummies included but not reported. Significance levels: *10%; **5%; ***1%.
[a] It refers to Wald test when GMM-System is considered.

As it is known, the Centre-North and the South of the country differ along several lines, the first being the different degree of economic growth between the two geographic areas, with the Centre-North characterized by more developed and industrialized regions than the South. Moreover, it is common place that firms located in Southern regions are riskier, more subject to credit constraints and have lower access to the capital market than firms located in the Centre-North (Iazzolino and Succurro, 2012; Sarno, 2008; Sarno, 2007). For this reason, and to get more insight on previous empirical results, we split the sample by both geographic area and size of the firms.
The econometric results, indeed, show that the effects of external and internal finance on innovation can be very different in the two areas of the country.
First, while in the Centre-North external funding is the relevant channel explaining innovation for all firms (Table 7, column 2), in the South of the country only self-financing is economically significant in explaining R&D expenditures (Table 8, column 2). Likely due to external financial constraints, southern firms tend to substitute external sources with internal sources. It seems that where access to financial markets is easier (Centre-North) firms rely on external finance to

undertake R&D. By contrast, where financial constraints are stronger because of harder access to external finance, firms do R&D by substituting external finance with internal funding.
Second, differently from the Centre-North, in the South of Italy the coefficient associated to internal finance is always higher than that associated to external funding.
We also illustrate empirical findings for large firms and SMEs separately. Empirical evidence for large firms mainly confirms the results obtained for the sample as a whole both for the Centre-North (Table 7, column 4) and the South (Table 8, column 4).
The different role played by financial institutions in Mezzogiorno and Centre-North of Italy emerges from the behavior of small and medium enterprises with respect to R&D activity.
SMEs located in Centre-North regions rely on both internal and external finance for R&D activity (Table 7, column 6). Because of higher difficulties to access external funding for small firms, also in the Centre-North SMEs use internal resources to finance innovation. By contrast and surprisingly, neither internal nor external finance seem to be significant in determining R&D activity of small and medium firms located in Southern regions (Table 8, column 6). In other words, although internal finance has a week significance in determining R&D activity of large Southern firms, both sources of finance are not significant in determining the R&D activity of Southern SMEs. In turn, the latter result raises the question whether other sources than private finance are relevant in determining R&D activity of Southern firms or whether credit constraints in South Italy may induce SMEs to not undertake R&D activity.
By contrast, size enters positively and significantly at 5% level for large firms in the Centre-North. Note that the impact of size on R&D is positive provided that firms can also exert some degree of market power. Indeed, the coefficient of concentration rate is significant at 5% level with a positive sign (Table 7, column 4). Moreover, innovation may be used as a barrier to entry in a market characterized by a relatively high monopolistic power.
Size enters negatively and significantly at 1% level for SMEs, both in Centre-North and South Italy. At the same time, the concentration rate is not significant for SMEs.
With respect to firms' age, we find very different results in the two areas of the country. Indeed, age is significant with negative sign for all firms located in the Centre-North of the country and independently from their relative size, suggesting that younger firms show an higher innovation capacity (Table 7, column 2, column 4, column 6). On the contrary, in South Italy, age is significant with positive sign for large companies (Table 8, column 4), while it is not significant for SMEs (Table 8, column 6). In the South of the country, problems of asymmetric information may be less severe for older firms that have established a long and stable relationship with their bank. Young firms, on the other hand, have not yet built such a relationship (Petersen and Rajan, 1995; Berger and Udell, 2002). This is particularly true for southern Italian regions.
In summary, empirical evidence on the relationship between external funding, internal funding and innovation shows heterogeneous results depending on the location of the firm and its relative size. Note that some of the previous, somehow unexpected, results would not have been obtained without the opportunity to build up a large and long panel dataset controlling for endogeneity.

Table 7 Finance and Innovation, Centre-North – all sectors (2003-2010)

Dependent variable: $R\&D_{it}$						
	All Firms		LARGE		SMESs	
	Fixed Effects	GMM System	Fixed Effects	GMM System	Fixed Effects	GMM System
	(1)	(2)	(3)	(4)	(5)	(6)
$R\&D_{it-1}$		0.912***		1.048***		0.906***
		(0.007)		(0.032)		(0.078)
$EXTF_{it}$	0.057***	0.047***	0.052***	0.087***	0.056***	0.049***
	(0.004)	(0.014)	(0.011)	(0.029)	(0.004)	(0.017)
$INTF_{it}$	0.035***	0.033	-0.037	0.016	0.039***	0.095***
	(0.005)	(0.030)	(0.027)	(0.097)	(0.005)	(0.034)
$Size_{it}$	-0.146***	-0.232***	0.321***	0.309**	-0.223***	-0.317***

	(0.017)	(0.038)	(0.092)	(0.141)	(0.018)	(0.041)
Age_{it}	-0.060**	-0.098*	-0.391*	-0.402**	-0.045*	-0.111**
	(0.026)	(0.054)	(0.202)	(0.202)	(0.027)	(0.056)
C_4	0.077***	-0.004	-0.091	0.035**	0.076**	-0.034
	(0.029)	(0.041)	(0.128)	(0.078)	(0.030)	(0.042)
Regional controls	included	included	included	included	included	included
constant		-10.07***	-0.118	-7.752	-15.96***	-8.819***
		(3.126)	(16.861)	(9.467)	(4.398)	(3.275)
F test[a]	43.32***	15514.75***	7.30***	1256.76***	44.23***	15304.96***
Firm effects (F test)	10.75***		14.28***		10.43***	
Time effects (F test)	23.77***		9.75***		20.12***	
Hausman test	343.58***		29.59***		336.00***	
Breusch-Pagan test	1.3e+05***		7137.04***		1.1e+05***	
Sargan test (*p* value)		0.122		0.445		0.100
AR (1) (*p* value)		0.000		0.000		0.000
AR (2) (*p* value)		0.133		0.334		0.121
N obs.	134282	81512	6461	3449	127821	78063
R^2	0.04	0.19	0.05	0.20	0.06	0.21

All variables are considered in log. WC-Robust standard errors in parenthesis.
Time dummies included but not reported. Significance levels: *10%; **5%; ***1%.
[a] It refers to Wald test when GMM-System is considered.

Table 8 Finance and Innovation, South – all sectors (2003-2010)

Dependent variable: $R\&D_{it}$						
	All Firms		**LARGE**		**SMESs**	
	Fixed Effects	GMM System	Fixed Effects	GMM System	Fixed Effects	GMM System
	(1)	(2)	(3)	(4)	(5)	(6)
$R\&D_{it-1}$		0.982***		0.964***		0.980***
		(0.017)		(0.330)		(0.078)
$EXTF_{it}$	0.047***	0.026	-0.125	-0.048	0.057***	0.046
	(0.013)	(0.042)	(0.121)	(0.732)	(0.013)	(0.051)
$INTF_{it}$	0.098***	0.054*	0.417**	0.092*	0.062***	0.041
	(0.021)	(0.020)	(0.166)	(0.997)	(0.022)	(0.126)
$Size_{it}$	-0.198***	-0.470***	-0.442*	-0.117	-0.196***	-0.501***
	(0.053)	(0.111)	(0.371)	(0.312)	(0.054)	(0.119)
Age_{it}	0.193**	0.025	0.781*	0.755***	0.217**	-0.034
	(0.089)	(0.190)	(0.198)	(0.230)	(0.090)	(0.193)
C_4	0.188*	0.008	-0.471	0.471***	0.236**	-0.000
	(0.112)	(0.138)	(0.373)	(0.851)	(0.113)	(0.149)
Regional controls	included	included	included	included	included	included
constant	-21.06**	-16.25	-7.220	-4.589	-24.57**	-16.664
	(11.62)	(10.43)	(4.809)	(11.529)	(12.812)	(11.232)
F test[a]	4.75***	2677.85***	2.17**	155.22***	5.17***	2158.70***
Firm effects (F test)	9.69***		14.28***		9.58***	
Time effects (F test)	3.54***		3.01**		3.87***	
Hausman test	343.58***		13.29***		23.84***	
Breusch-Pagan test	12713.95***		378.78***		12236.33***	
Sargan test (*p* value)		0.151		0.941		0.077
AR (1) (*p* value)		0.000		0.000		0.000
AR (2) (*p* value)		0.873		0.199		0.529
N obs.	13511	7699	286	129	13225	7570
R^2	0.08	0.22	0.06	0.24	0.10	0.23

All variables are considered in log. WC-Robust standard errors in parenthesis.
Time dummies included but not reported. Significance levels: *10%; **5%; ***1%.
[a] It refers to Wald test when GMM-System is considered.

4.1 Finance and Innovation in HIGH-TECH sectors

In this paragraph we focus on the relationship between finance and innovation in high-tech sectors[5]. Extensive literature stresses that innovative firms face stronger financial constraints, independently of their size (Hall and Lerner, 2010; Brown et al. 2009; Carpenter and Petersen, 2002; Hall, 2002; Harhoff and Korting, 1998), and financial constraints are even stronger for dynamic start-ups in high-tech industries (EIB, 2009). The problem of access to finance for innovative firms is even more pronounced in Italy because venture capital, considered to be the most appropriate form of financing for firms in high-tech sectors, is not sufficiently developed as in other countries like UK, Switzerland, USA, Canada (Bottazzi *et al*., 2008; Bottazzi and Da Rin, 2002). In this context, since we expect that R&D activity in high-tech sectors is more intense, we assume that high-tech firms need more finance. In addition, high tech firms bear more risk, and therefore they are more willing to share the risk with financial institutions. So, we expect both effects increase the role of external finance in R&D activity of high-tech firms.

The econometric results, indeed, confirm that external finance spurs innovation of the high-tech firms, both for large companies and SMEs (Table 9, column 4, column 6). The coefficient associated to external funding, as expected, is slightly higher for SMEs than for large companies.

Internal finance, on the contrary, is not significant in determining R&D activity for firms in high-tech sectors. This empirical finding could have several explanations. It could be explained by the fact that firms in high-tech sectors do not have enough internal funds to finance demanding innovation projects or by the existence of moral hazard behavior of the high-tech firms in sharing the risk of R&D with other investors. The reason why high-tech firms do not use internal finance to do R&D would deserve further investigation.

Moreover, the U-shaped relationship between size and innovation arising from the results reported in Table 9 suggests that, the incentive to innovate is higher both for large high-tech firms and SMEs, provided they can also exert some degree of market power. Indeed, the industry concentration rate enters positively and significantly for both categories of firms. Also firms' density rate, not reported in Table 9 but available on request, is significant at 1% level with positive sign. So, by contrast to some previous studies, our econometric investigation does not support the view that promoting the growth of small firm is naturally conducive to an increase in R&D activity. Our results suggest that what is more relevant for R&D is the access to external finance and the possibility for small firms to be located in an area where there is a greater density of high tech firms. So, external funding and agglomeration economies seem to be more relevant than internal growth in determining R&D activity of Italian high-tech firms.

Table 9 Finance and Innovation, HIGH-TECH sectors (2003-2010)

Dependent variable: $R\&D_{it}$						
	All Firms		**LARGE**		**SMESs**	
	Fixed Effects	GMM System	Fixed Effects	GMM System	Fixed Effects	GMM System
	(1)	(2)	(3)	(4)	(5)	(6)
$R\&D_{it-1}$		0.897***		0.925***		0.896***
		(0.012)		(0.045)		(0.013)
$EXTF_{it}$	0.054***	0.028**	0.039**	0.046***	0.053***	0.087**
	(0.006)	(0.019)	(0.017)	(0.029)	(0.006)	(0.051)
$INTF_{it}$	0.054 ***	-0.103	-0.004	0.035	0.056***	-0.090
	(0.010)	(0.057)	(0.043)	(0.096)	(0.010)	(0.059)
$Size_{it}$	-0.146***	-0.135**	0.456***	0.309**	-0.224***	-0.197***
	(0.155)	(0.058)	(0.155)	(0.143)	(0.031)	(0.071)
Age_{it}	-0.007	0.165**	-0.344*	0.367**	0.016	0.103
	(0.048)	(0.082)	(0.200)	(0.204)	(0.050)	(0.096)

[5] For a list of the high-tech sectors, see Table A.1 in the Appendix. All the methodological considerations reported in the previous sections hold for high-tech sectors as well.

C_4	0.011	0.566***	0.438	0.245***	0.023	0.482*
	(0.110)	(0.112)	(0.397)	(0.931)	(0.119)	(0.768)
Regional controls	included	included	included	included	included	included
constant	-21.124***	-11.401**	22.969	-12.213	-23.28***	-11.341**
	(6.841)	(4.860)	(28.220)	(11.124)	(7.09)	(5.008)
F test[a]	16.71***	5951.49***	6.63**	575.72***	16.56***	5589.44***
Firm effects (F test)	9.56***		11.46***		9.32***	
Time effects (F test)	10.96***		5.74***		9.24***	
Hausman test	193.36***		32.61***		193.75***	
Breusch-Pagan test	37082.09***		2507.16***		33734.92***	
Sargan test (*p* value)		0.101		0.142		0.086
AR (1) (*p* value)		0.000		0.000		0.000
AR (2) (*p* value)		0.148		0.351		0.095
N obs.	44566	27403	2477	1313	42089	25583
R^2	0.05	0.30	0.08	0.32	0.12	0.36

All variables are considered in log. WC-Robust standard errors in parenthesis.
Time dummies included but not reported. Significance levels: *10%; **5%; ***1%.
[a] It refers to Wald test when GMM-System is considered.

5 Finance and Patent Probability

This last section somehow contributes to a recent literature that, also motivated by the international financial crisis, investigates if different access to different sources of finance affects innovative performance (Amore *et al*., 2013, Campello *et al*., 2010, Duchin *et al*., 2010; Leary, 2009; Lemmon and Roberts, 2010). Innovative performance is not directly observable or easily predictable given the complexity of the technological knowledge capital which makes difficult to identify the main results of the technological innovation activities (Nelson, 2003; Lanjouw and Schankerman, 2004). However, an increasing number of studies use patent counts and/or other patent-related indicators to measure innovative performance (Chava *et al*., 2013; Amore *et al*., 2013; Pederzoli *et al*., 2013; Motohashi, 2011; Benfratello *et al*., 2008; Griliches, 1990).
For this reason, this part of the research explicitly aims at analyzing the relationship between external and internal financing and firms' patent probability. In particular, the analysis considers all the manufacturing companies with successful patent applications over the 2003-2010 period. Patenting firms have been extracted from the Bureau van Dijk's ORBIS database and patents are those filed at the European Patent Office (EPO). The identification of patenting firms, not available in the Amadeus database, has been kindly supplied by the Bureau van Dijk. Patent data have been matched with the Bureau van Dijk's Amadeus accounting data through the companies' *BvD ID Number* which guarantees high precision of the match by avoiding the necessity to harmonize firms' names. The matching procedure, indeed, has shown a good accuracy score (87,13%) since 11478 firms over 13173 companies with patents have been perfectly matched.
Table 10 shows the percentage composition of patenting firms by technological intensity of the cluster[6], size and geographic location. The share of patenting firms varies considerably across regions, led by Lombardia (33.18%) and followed by Veneto (16.66), Emilia Romagna (14.86%) and Piemonte (9.28%). In general, data show that patenting firms are essentially located in the Centre-North of the country while differences in size are less pronounced.
Statistics show that firms in high-tech sectors perform on average 36.34% of all patenting activity. Medium-high-technology manufacturing firms seldom contribute around the 9.7% of patent filings. Non-patenting firms are essentially active in low-tech (40.12%) and medium-low-tech sectors (34.21%).
See Table A.2 in the appendix for other descriptive statistics.

[6] See Table A.1 in the Appendix for a description of the technological clusters.

Table 10 Patenting Firms by technological clusters, size and location (% values)

	Patenting Firms	Non-Patenting Firms
High-tech sectors	36.34	19.60
Medium-High-tech sectors	9.69	6.07
Medium-Low-tech sectors	31.10	34.21
Low-tech sectors	22.87	40.12
	100	*100*
LARGE	42.2	44.7
SMEs	57.8	55.3
	100	*100*
Centre-North	95%	89.3%
South	5%	10.7%
	100	*100*
	Obs. 11478	Obs. 33225

Source: elaborations on Amadeus and Orbis data

In the following empirical analysis we aim at estimating, through a logistic regression model, the firms' patent probability as a function of R&D expenditure as well as of different degree of access to both internal and external financial resources.

Under the logistic specification, the dependent variable is dichotomous and it takes the value 1 for all the firms with successful patent applications over the 2003-2010 period, 0 otherwise.

In formal terms:

$$p_i = \Pr(PATENTS_i = 1) = F(x_i\, \beta)$$

where p_i is the probability that the dependent variable $PATENTS$=1 for individual i, $F(\cdot)$ is the logistic cumulative distribution function, x_i is the set of explanatory variables thought to affect p_i, β_0 is the intercept and β are the regression coefficients. The predictors include R&D expenditure to total assets – computed as explained in section 2 - and the explanatory variables used in section 3, that is internal and external resources to total assets, age, size, industry concentration. Moreover, we add sector and regional dummies[7]. All the explanatory variables enter the function with their firm-level average values computed over the 2003-2010 period.

Table 11 shows the estimation results of the logistic regression, expressed in its exponential form, for all the Italian manufacturing firms. Since the parameters of the logistic regression are not directly interpretable as marginal effects, these have been explicitly calculated. Moreover, given the non-linearity of the first-order conditions with respect to parameters, a solution of numerical approximation is adopted that reaches the convergence after 17 reiterations. The maximised value of the log-likelihood function is -8106.74.

LR chi-square (49) is the asymptotic version of the F-test for zero slopes. The p-value allows the rejection of the null hypothesis that all the model coefficients are simultaneously equal to zero. Therefore, the model as a whole is statistically significant. To avoid the risk of multicollinearity among variables, the computed bivariate correlation test has been carried out. It does not reveal any linear relation among variables. To further corroborate this result we computed the *tolerance*, an indicator of how much collinearity a regression analysis can tolerate, and the *VIF* (variance inflation factor), an indicator of how much of the inflation of the standard error could be caused by collinearity. Both measures were close to 1 for the considered variables, therefore we can exclude any multicollinearity.

[7] Instead of regional controls we use regional dummies, as well as sector dummies, because time-invariant variables do not constitute a difficulty here. Moreover, note that, as in section 3, size is measured in terms of turnover, but here100,000 euros is used as unit of measure for scaling reasons.

Turning to the analysis of the estimates (Table 11), as expected R&D is strongly significant with an economically relevant marginal effect. Our empirical investigation shows some interesting findings on the impact of financial channels and other variables on patenting probability.
Both internal and external financial resources are statistically significant at the 1% level with the expected positive sign, but internal funding enters the function with a relatively higher coefficient. More specifically, an increase in external finance by 1% rises the patent probability by 0.07% while an increase in internal financial resources by 1% rises the probability of successful patents applications by 0.29%. In terms of the odds ratios, rising internal finance by 1% (a unit) increases the odds ($p_i/1-p_i$) - of patenting- by 284% [(3.84-1)*100], holding the other variables constant. In other words, firms with higher internal financial resources are 3.84 times ($e^{1.347}$) likely to increase patenting than firms with limited internal financial resources. Analogously, firms with higher access to external finance are 1.39 times ($e^{0.333}$) likely to patent than firms characterised by strong external financial constraints. Therefore, access to finance is strongly significant in affecting the innovative performance, but internal finance seems economically more relevant for successful patents' applications.
As far as the other explanatory variables are concerned, age is significant at the 1% level with a positive sign likely indicating, for innovative performance, the importance of experience and, to some extent, the presence of learning economies. For an age increase equal to 1 (a unit measure in our analysis) the odds ($p_i/1-p_i$) - of patenting- increases by 3% [(1.03-1)*100]. Age-squared, included to capture non-linear effects, is significant with negative sign, therefore indicating decreasing returns to scale.
Firms' size is significant with a positive marginal effect. In terms of the odds ratios, for a turnover increase by 100,000 Euros (a unit) the odds of patenting increases by 14%, holding the other variables constant.
The industry concentration rate is significant at 5% level in explaining successful patents applications. Sector and regional dummies are almost significant at 1% level.
The logistic regression has been also estimated without R&D expenditure as explanatory variable. The empirical findings, available on request, are very similar to those reported here, at least for the sign and the level of significance associated to the predictors. However, without R&D expenditure, the coefficient associated to internal finance is even higher (2.281) than the coefficient estimated including R&D as regressor (1.347).

Table 11 Econometric Estimates - Logistic Regression, All Firms

Dependent variable: Patents$_i$			
	Coefficient β	**Marginal effects dy/dx**	**Odds ratio e^{β}**
R&D	4.402*** (0.439)	0.946*** (0.094)	81.65***
EXTF	0.333*** (0.126)	0.071*** (0.027)	1.39***
INTF	1.347*** (0.400)	0.289*** (0.086)	3.84***
Size	0.131*** (0.021)	0.028*** (0.004)	1.14***
Age	0.029*** (0.004)	0.006*** (0.000)	1.03***
Age-squared	-0.000*** (0.000)	-0.000*** (0.000)	0.99***
C_4	0.101** (0.087)	0.036** (0.002)	1.10**
Sector Dummies	included	included	
Regional Dummies	included	included	
constant	8.855*** (0.870)		

Log-likelihood: -8106.74 Pseudo R^2 = 0.10 LR chi-square(49)= 1611.33 Prob > chi-square= 0.000 N = 14011

Robust Standard Errors in parenthesis. Significance levels: *10%; **5%; ***1%.
Sector and Regional Dummy variables significant at 1% level.

To evaluate the model we computed the percentage of correct classifications, which gives us the percentage of correct predictions of our model. Table 12 shows that positive responses were predicted for 2214 observations, of which 1281 were correctly classified because the observed response was positive (PATENTS=1), while the other 933 were incorrectly classified because the observed response was negative. Likewise, negative responses were predicted for 11797 observations, of which 8416 were correctly classified because the observed response was negative (PATENTS=0). Overall, around 70% of predicted probability is correctly classified.
We have further assessed the model's ability to accurately classify observations using a receiver operating characteristic (ROC) curve (Figure A.1 in Appendix), which suggests that our model fits the data well. Indeed, a model with a high area under the ROC curve suggests that the model can accurately predict the value of an observation's response. The model provides outstanding discrimination since the area is larger than 0.7.
Finally, we have checked for the presence of any specification error using the linktest (Table A.3 in the Appendix), which suggests that our model is not misspecified[8].

Table 12 Prediction of the model

Classified	D	~D	Total
+	1281	933	2214
-	3381	8416	11797
Total	4662	9349	14011
Correctly classified			69.21%

Classified + if predicted Pr(D) >= 0.5

Further differences arise when we consider large and SMEs separately[9] (Table 13), even if the whole analysis would confirm the presence of some learning economies for successful patents' applications.
With respect to large firms, a different impact of financial channels on innovation emerges when we consider their patent probability instead of investment in R&D. Indeed, while external finance is significant in explaining large firms' R&D expenditure (section 4), it is not significant in explaining their patenting activity. Internal finance and size seem to be the most relevant predictors of patent probability. In particular, rising internal finance by 1% (a unit) increases the odds ($p_i/1\text{-}p_i$) - of large firms patenting activity- by 160% [(17.06-1)*100], holding the other variables constant. As reported by Cohen *et al*. (2000) and Lanjouw and Schankerman (2004), the international patent protection requires additional and sometimes significant filling costs. Therefore, the decision to apply by the owner would signal both the availability of internal funds and an high expectation of economic value related to the invention. In addition, while the R&D activity is typically risky, therefore

[8] The idea behind linktest is that if the model is properly specified, one should not be able to find any statistically significant additional predictors, except by chance. The linktest uses the linear predicted value (_hat) and linear predicted value squared (_hatsq) as the predictors to rebuild the model. Since the variable _hat is a statistically significant predictor, the model is not misspecified. On the other hand, if our model is properly specified, variable _hatsq should not have much predictive power except by chance. Since, _hatsq is not significant, we have not omitted relevant variables and our equation is correctly specified.

[9] We do not report estimates separately for Centre-North and South Italy here since the 95% of patenting firms are located in the Centre-North of the country. However, the logistic estimates for the South of Italy, available on request, show that none of the explanatory variables is significant in explaining firms' patenting activity.

requiring risk-sharing and external funding, applying for a patent, obtaining and enforcing patents, even if expensive, is less uncertain. In this contest, the availability of internal resources and R&D specialized workers, more likely in firms of larger size, would be relatively more important than the other factors.

The empirical findings on SMEs confirm that both internal and external financial resources are statistically significant at the 1 % level with the expected positive sign, but also in this case internal finance is relatively more important than external finance both in the coefficient and level of significance. While an increase in external finance by 1% rises the patent probability by 0.06%, an increase in internal financial resources by 1% rises the probability of successful patents applications by 0.24%. In terms of the odds ratios, rising internal finance by 1% (a unit) increases the odds ($p_i/1-p_i$) - of SMEs patenting- by 238% [(3.38-1)*100], holding the other variables constant. Therefore, SMEs with higher internal financial resources are 3.38 times more likely to increase patenting than small and medium firms with limited internal financial resources. Analogously, SMEs with higher access to external finance are 1.38 times likely to patent than firms characterised by strong external financial constraints.

In brief, internal funding is strongly significant in affecting the Italian manufacturing firms' patent probability. For large firms, it is the only financial channel explaining successful patents' applications; for SMEs, both external and internal resources are significant, but self-financing is anyway more important than having access to external funds.

With respect to the other explanatory variables, while size is significant in explaining firms' patenting activity both for large and SMEs, indicating the likely presence of skilled labour in patenting activity, age is significant only for small and medium enterprises. The industry concentration rate, on the contrary, is significant only for large firms.

Finally, sector and regional dummy variables are significant at 1% level.

Overall, around 65.6% of predicted patent probability is correctly classified for large firms and 72.2% is correctly classified for SMEs. Moreover, we have checked for the presence of any specification error (Table A.3 in the Appendix), which suggests that our model is not misspecified also when we implement the analysis for large firms and SMEs separately.

Table 13 Econometric Estimates - Logistic Regression, Large Firms and SMEs

Dependent variable: Patents$_i$						
	LARGE			**SMEs**		
	Coefficient β	**Marginal effects dy/dx**	**Odds ratio e^{β}**	**Coefficient β**	**Marginal effects dy/dx**	**Odds ratio e^{β}**
R&D	2.844*** (1.037)	0.707*** (0.257)	17.19***	4.594*** (0.513)	0.914*** (0.102)	98.89***
EXTF	0.438 (0.393)	0.108 (0.097)	1.54	0.321** (0.136)	0.064** (0.028)	1.38**
INTF	2.836** (1.191)	0.705** (0.293)	17.06**	1.219*** (0.461)	0.242*** (0.091)	3.38***
Size	0.037** (0.015)	0.009** (0.004)	1.04**	3.551*** (0.199)	0.708*** (0.039)	35.08***
Age	0.017 (0.011)	0.004 (0.002)	1.01	0.030*** (0.004)	0.006*** (0.000)	1.03***
Age-squared	-0.000 (0.000)	-0.000 (0.000)	0.99	-0.000*** (0.000)	-0.000*** (0.000)	0.99***
C_4	0.082** (0.023)	0.019** (0.008)	1.08**	0.035 (0.021)	0.008 (0.006)	1.03
dfgbhfgjkSector Dummies	included	included		included	included	
Regional Dummies	included	included		included	included	
constant	8.64*** (1.670)			8.225*** (0.982)		

	Log-likelihood: -880.379 Pseudo R^2 = 0.11 LR chi-square(49)= 227.48 Prob > chi-square= 0.000 N = 1429	Log-likelihood: -6625.476 Pseudo R^2 = 0.11 LR chi-square(49)= 1642.73 Prob > chi-square= 0.000 N = 12119

Robust Standard Errors in parenthesis. Significance levels: *10%; **5%; ***1%.
Sector and Regional Dummy variables significant at 1% level.

We have also estimated the patent probability associated to the average values of the predictors both for large firms and SMEs by assuming similar conditions to 2003-2010 years. The predicted probability that the representative Italian manufacturing firm successfully applies for patents in the future is p_i=0.52 for large firms and p_i=0.31 for small and medium enterprises.
The predicted patent probability is computed under the assumption of no major changes compared to the past. However, if financial constraints will be reduced, the expected effect should be an increase in the patenting activity in the future, at least if no other factor pushes in the opposite direction.

6 Conclusions

This paper studies the impact of different sources of finance on innovation based on an original measure of R&D expenditure, with a great potential for future applied research based on firms' accounting data. The analysis focuses on the Italian manufacturing firms over the 2003-2010 period.
The empirical findings show heterogeneous and interesting results.
First, econometric estimates as a whole suggest that while external funding is the relevant factor explaining R&D expenditure (innovation input), self-financing is the relevant factor explaining the probability of successful patents' applications (innovation output).
Second, the effects of finance on innovation differ in the two areas of the country. It seems that in the Centre-North, where access to financial markets is easier, firms rely on external finance to undertake R&D. By contrast, in Southern regions, where access to external finance is harder, firms do R&D by substituting external finance with internal funding. The different role played by financial institutions in Mezzogiorno and Centre-North of Italy emerges also from the comparison of large companies and SMEs.
Third, external finance spurs innovation of the high-tech firms, independently from their size, while internal finance is not significant in determining R&D activity. The reason why high-tech firms do not use internal finance to do R&D deserves further investigation.
In overall, even though the empirical evidence shows that both types of financial channels are important for innovation, our results do not support the view that internal finance is always more relevant for innovation, or the contrary. The role of external versus internal funding depends on the size of the firm, geographic location of the firm and technological intensity of the sector. Moreover, macro factors such as the financial market system play a crucial role. Firms in bank-based economies, like the Italian one, generally rely to a larger extent on bank financing compared to firms operating in market-based economies. Therefore, it seems that in Southern regions, where financing constraints are stronger, firms rely more on internal funds to finance R&D activity.
This research suggests avenues for future studies. First, we need to assess whether some unexpected results are due to the influence of other financial factors, external to the firm - such as sector or public incentives. Public incentives and structural EU funds could be a relevant financial channel, especially for firms operating in Southern Italian regions, and they should be explicitly considered in future analysis. Second, it would be interesting to evaluate the impact of external and internal funding on firms' innovative performance distinguishing between the quantity of innovation– based on patents' portfolio- and the quality of innovation – based on the value of the innovative output.

Finally, a comparison among European countries would be an additional and interesting development of this research.

Acknowledgements

For useful suggestions we thank Professor Alessandro Sembenelli, Workshop on innovation, Productivity and Growth in Italy (University of Calabria, 15-16 March 2013), SIE 2013, Marco Marozzi, Professor ……………….., Roger Meservey, Regione Calabria Funds…... We are particularly grateful to Armando Benincasa, Bureau van Dijk. Without his help and technical support, the last section of the research would not have been possible.

APPENDIX

Table A.1 List of the sectors in the sample (NACE Rev.2 primary codes)

10	Manufacture of food products (LT)
11	Manufacture of beverages (LT)
12	Manufacture of tobacco products (LT)
13	Manufacture of textiles (LT)
14	Manufacture of wearing apparel (LT)
15	Manufacture of leather and related products (LT)
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials (LT)
17	Manufacture of paper and paper products (LT)
18	Printing and reproduction of recorded media (LT)
19	Manufacture of coke and refined petroleum products (MLT)
20	Manufacture of chemicals and chemical products (HT)
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations (HT)
22	Manufacture of rubber and plastic products (MLT)
23	Manufacture of other non-metallic mineral products (MLT)
24	Manufacture of basic metals (MLT)
25	Manufacture of fabricated metal products, except machinery and equipment(MLT)
26	Manufacture of computer, electronic and optical products (HT)
27	Manufacture of electrical equipment (MHT)
28	Manufacture of machinery and equipment nec (HT)
29	Manufacture of motor vehicles, trailers and semi-trailers (MHT)
30	Manufacture of other transport equipment (HT)
31	Manufacture of furniture (LT)
32	Other manufacturing (LT)

Following Archibugi (2001), HT indicates high-tech sectors; MHT indicates medium-high-tech sectors; MLT indicates medium-low-tech sectors and LT indicates low-tech sectors.

Table A.2 Some descriptive statistics

Variable |	Obs	Mean	Std. Dev.	Min	Max
Patenting Firms					
R&D	6246	0.029	0.049	0	0.754
INTF	6246	0.058	0.052	-0.771	0.403
EXTF	4460	0.227	0.167	0	1.684
Age	10310	24.997	16.431	0	112

Turnover	10203	39281.27	270498.9	2000.33	1.77e+07
Non-Patenting Firms					
R&D	17750	0.217	0.039	0	0.645
INTF	17752	0.055	0.049	-0.426	0.563
EXTF	9142	0.237	0.1704	-0.129	1.084
Age	31881	21.190	15.355	0	111
Turnover	17773	15509.67	107319.6	2000	7984961
Additional Control Variables					
C_4	234576	0.119	0.097	0.04	0.97
TK	234539	5986.199	14488.66	0	57282.92
HK	234576	13.180	3.106	0.08	18.95
Firm Density	234576	71.217	7.939	46.14	84.93
GDP	234576	27521.86	4501.814	14838.54	33546.66
Infr	232845	25.291	6.730	2.9	69.24
Criminality	234576	842.653	203.129	553	1530.25

Source: elaborations on Amadeus database

Figure A1 ROC Curve – All firms

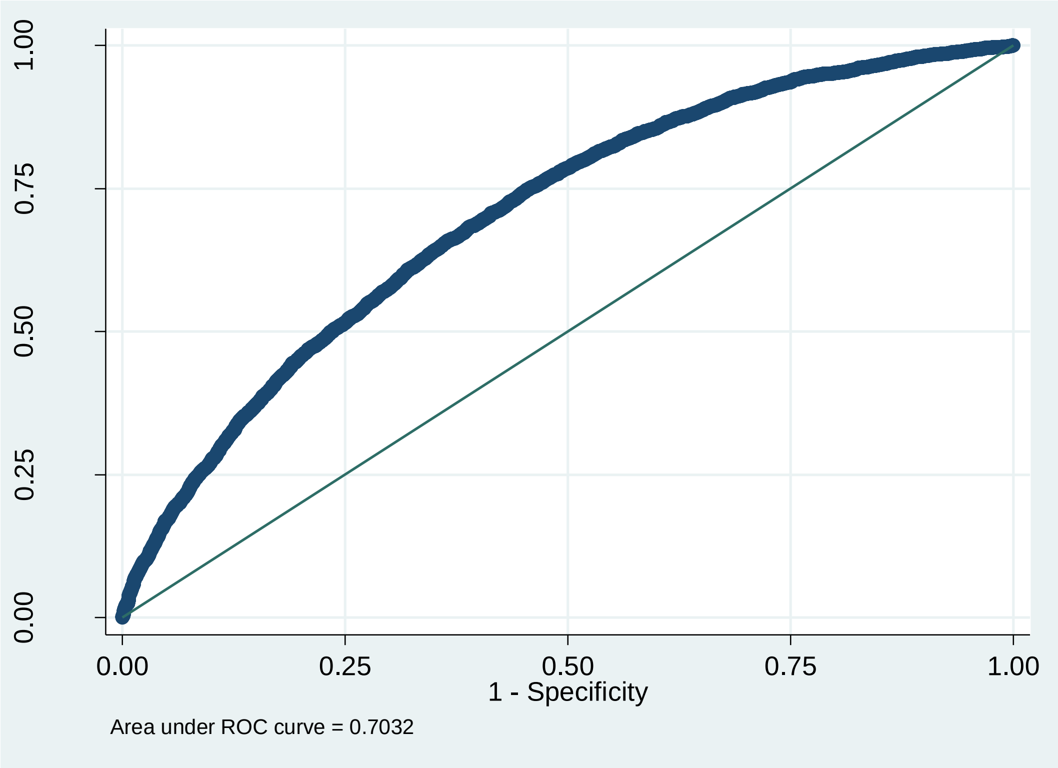


Table A3 Specification error test

patents	Coef.	Std. Err.	z	P>z
		All firms		
_hat	0.948	0.026	35.56	0.000
_hatsq	-0.038	0.042	-1.68	0.067
_cons	0.011	0.025	0.05	0.963
		Large Firms		
_hat	0.998	0.078	12.71	0.000
_hatsq	0.067	0.069	0.98	0.329

_cons	-0.037	0.070	-0.53	0.597
		SMEs		
_hat	1.044	0.049	21.12	0.000
_hatsq	0.026	0.024	1.09	0.274
_cons	0.002	0.028	0.08	0.936

REFERENCES

Amore, M., Schneider, C., Zaldokas, A., 2013. Credit supply and corporate innovation. Journal of Financial Economics 109, 835-855.

Archibugi, D., 2001. Pavitt's taxonomy sixteen years on: a review article. Economics of Innovation and New Technology 10, 415-425.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277–297.

Arora, A., Fosfuri, A., Gambardella, A., 2001. Markets for technology: The economics of innovation and corporate strategy. MIT press, Cambridge, MA.

Arrow, K., 1962. Economic Welfare and the Allocation of Resources for Invention. In: Nelson, R. (Ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors. UMI, pp.609-626.

Becker, B., 2007. Geographical segmentation of US capital markets. Journal of Financial Economics 85, 151–178.

Benfratello, L., Schiantarelli, F., Sembenelli, A., 2008. Banks and innovation: microeconometric evidence on Italian firms. Journal of Financial Economics 90, 197-217.

Berger, A., 2010. Small business lending. In: Berger, A., Molyneux, P., Wilson, J.(Ed.), The Oxford Handbook of Banking, Oxford University Press, NY,pp.531–549.

Berger, A., Udell, G., 2002. Small business credit availability and relationship lending: the importance of bank organizational structure. Economic Journal 112, 32-53.

Berger, A., Udell, G., 1998. The economics of small business finance: the roles of private equity and debt markets in the financial growth cycle. Journal of Banking Finance 22, 613–673.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115–143.

Bottazzi, L., Da Rin, M., Hellmann, T., 2008. Who are the active investors? Evidence from venture capital. Journal of Financial Economics 89, 488-512.

Bottazzi, L., Da Rin, M., 2002. Venture capital in Europe: Euro.nm and the financing of European innovative firms. Economic Policy 17, 229-269.

Bougheas, S., Görg, H., Strobl, E., 2003. Is R&D financially constrained? Theory and evidence from Irish manufacturing. Review of Industrial Organization 22, 159-174.

Brown, J., Fazzari, S., Petersen, B., 2009. Financing innovation and growth: cash flow, external equity, and the 1990s R&D boom. Journal of Finance 64, 151-186.

Butler, A., Cornaggia, J., (2011). Does access to external finance improve productivity? Evidence from a natural experiment. Journal of Financial Economics 99, 184-203.

Campello, M., Graham, J., Harvey, C., 2010. The real effects of financial constraints: evidence from a financial crisis. Journal of Financial Economics 97, 470-487.

Canepa, A., Stoneman, P., 2002. Financial constraints on innovation: a European cross-country study. Unpublished working paper. University of Warwick, UK.

Carpenter, R., Petersen, B., 2002. Capital market imperfections, high-tech investment, and new equity financing. The Economic Journal 112, 54-72.

Cetorelli, N., Strahan, P., 2006. Finance as a barrier to entry : bank competition and industry structure in local U.S. markets. Journal of Finance 61, 437–461.

Chava, S., Oettl, A., Subramanian, A., Subramanian, K., 2013. Banking deregulation and innovation. Journal of Financial Economics 109, 759-774.
Cohen, W., Nelson, R., Walsh, J., 2000. Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not). Unpublished working paper, NBER.
Czarnitzki, D., Hottenrott, H., 2011. R&D investment and financing constraints of small and medium-sized firms. Small Business Economics 36, 65-83.
Duchin, R., Ozbas, O., Sensoy, B., 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. Journal of Financial Economics 97, 418-435.
EIB, 2009. R&D and the financing of innovation in Europe. European Investment Bank 14.
Encaoua, D., Laisney, F., Hall, B., Mairesse, J., 2000. Economics and Econometrics of Innovation. Springer.
Galende, J., de la Fuente, J., 2003. Internal factors determining a firm's innovative behavior. Research Policy 32, 715-736.
Giudici, G., Paleari, S., 2000. The provision of finance to innovation: a survey conducted among Italian technology-based small firms. Small Business Economics 14, 37-53.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. Journal of Economic Literature 28, 1661-1707.
Guiso, L., Sapienza, P., Zingales, L., 2004. Does local financial development matter?. Quarterly Journal of Economics 119, 929–969.
Hall, B., 1990. The impact of corporate restructuring on industrial research and development. Brooking Papers on Economic Activity 1, 85-136.
Hall, B., 1992. Investment and research and development at the firm level: does the source of financing matter?. Unpublished working paper, NBER.
Hall, B., 2002. The financing of research and development. Oxford Review of Economic Policy 18, 35-51.
Hall, B., Lerner, J., 2010. Financing R&D and innovation. In: Hall, B., Rosenberg, N. (Ed.), The Handbook of the Economics of Innovation. Elsevier, Amsterdam, pp.610-638.
Harhoff, D., 1996. Strategic spillovers and incentives for research and development. Management Science 42, 907-925.
Harhoff, D., Korting, T., 1998. Lending relationship in Germany: empirical results from survey data. Journal of Banking and Finance 22, 1317-1353.
Herrera, A., Minetti, R., 2007. Informed finance and technological change: evidence from credit relationships. Journal of Financial Economics 83, 223–269.
Himmelberg, C. , Peterson, B., 1994. R&D and internal finance: a panel study of small Firms in high-tech industries. Review of Economics and Statistics 76, 38-51.
Hottenrott, H., Peters, B., 2009. More Money, More Innovation? Innovation Capacity and Financing Constraints for Innovation. mimeo, Leuven, Mannheim.
Iazzolino, G., Succurro, M., 2012. L'affidabilità finanziaria delle imprese del Mezzogiorno: un'analisi strutturale su micro dati. Rivista Economica del Mezzogiorno 26, 463-489.
Lanjouw, J., Schankerman, M., 2004. Patent quality and research productivity: measuring innovation with multiple indicators. Economic Journal 114, 441-465.
Leary, M., 2009. Bank loan supply, lender choice, and corporate capital structure. Journal of Finance 64, 1143-1185.
Lemmon, M., Roberts, M., 2010. The response of corporate financing and investment to changes in the supply of credit. Journal of Financial and Quantitative Analysis, 45, 555-587.
Lev, B., 2001. Intangibles: Management, Measurement, and Reporting. Brookings Institution Press, Washington.
Marrocu, E., Paci, R., Pontis, M., 2011. Intangible capital and firms' productivity. Industrial and Corporate Change 21, 377-402.

Motohashi, K., 2011. Innovation and entrepreneurship: a first look at linkage data of Japanese patent and enterprise census. Unpublished working paper, Research Institute of Economy, Trade and Industry.
Muller, E., Zimmermann, V., 2009. The importance of equity finance for R&D activity. Small Business Economics 33, 303–318.
Nanda, R., Nicholas, T., 2012. Did Bank Distress Stifle Innovation During the Great Depression? Unpublished Working Paper, Harvard Business School.
Nelson, R., 1959. The simple economics of basic scientific research. Journal of Political Economy 49, 297-306.
Nelson, R., 2003. On the uneven evolution of human know-how. Research Policy 32, 909-922.
Pederzoli, C., Thoma, G., Torricelli, C., 2013. Modelling credit risk for innovative SMEs: the role of innovation measures. Journal of Financial Services Research 44, 111-129.
Petersen, M., Rajan R., 1995. The effect of credit market competition on lending relationships: evidence from small business data. Journal of Finance 49, 3-37.
Sarno, D., 2008. Capital structure and growth of the firms in the backward regions of the south Italy. Applied Financial Economics 18, 821-833.
Sarno, D., 2007. Status finanziario delle imprese e struttura industriale: il caso del Mezzogiorno. Rivista Economica del Mezzogiorno 21, 751-777.
Savignac, F., 2008. Impact of financial constraints on innovation: what can be learned from a direct measure?. Economics of Innovation and New Technology 17, 553-569.
Schneider, C., Veugelers, R., 2010. On young highly innovative companies: why they matter and how (not) to policy support them. Industrial and corporate change 19, 969-1007.
Ughetto, E., 2008. Does internal finance matter for R&D? New evidence from a panel of Italian Firms, Cambridge Journal of Economics 32, 907-925.