Public R&D support in Italy. Evidence from a new firm-level patent dataset

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Abstract. This paper evaluates the impact of public support to private R&D on the innovation activities of a sample of manufacturing SMEs. Unlike most of the literature, we look at the effect of incentives on innovation output rather than on innovation input. The innovation output is measured by firm patenting activity. By using a new dataset obtained by combining information from EPO records and the Capitalia dataset on Italian corporations, we find that R&D policy increases the probability to patent. However, that publicly and privately funded R&D have a similar positive effect on patenting activity.

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1. Introduction

There are two main arguments to explain the low level of private R&D investments. The first refers to the appropriability of basic research. If technology is a quasi-public good then the incentive to invest will be reduced because each firm will try to take advantages from the innovative efforts made by others. The final outcome is a level of innovative activities which is lower than that desirable at an aggregate level (Arrow 1962). The second element influencing R&D investments relates to capital-market imperfections. The risk of research leads investors to increase the cost of financing innovation and, as a consequence tends to reduce the amount of research made by the private sector. This is particularly true for Italy, a country with a low propensity to innovate due to specific characteristics of its industrial sector which is dominated by small firms and by firms operating in low-tech sectors.

These considerations help to understand state intervention in favor of innovation. Any policy is aimed at making up for the difference between social and private returns on R&D innovations and ensuring financial facilities to innovators, particularly in the first stage of the innovation process. While the initial objective of R&D policy is to increase the amount of innovative activity, the general scope of any research and innovation policy is to strengthen the position of each country among the leading knowledge and competence-based countries. In other words, public support for private R&D is a good policy option *per se* because increasing technological potential through sizeable investments should lead to innovation and, ultimately, growth in an economy. This is basically the mission of many R&D programs, such as, for example, Europe 2020 which is part of the EU's growth strategy to promote a more competitive economy in the coming years. With regards to the theme of this paper, it is of value to point out that, among many other objectives, Europe 2020 fixes at 3% the proportion of the EU's GDP to be invested in R&D up to 2020. According to the EU commission, this is a pre-requisite to have a smart-growth which is based on more effective investments in education, research and innovation. As mentioned before, the level of actual R&D efforts is lower than the optimum and very far from 3%. For instance, in Italy, R&D investments floats around 1.1%-1.3% of GDP in the last years, while the average of the EU-27 was around 2% (the intensity was more than 3% in some Nordic countries (Finland, Sweden, Denmark) and more than 2% in Austria, France, Germany and Slovenia. However, compared to the early 2000s, Italy has increased its innovative efforts by about 20-25 basis points from, R&D investments of just over 1% of GDP in 2000.

However if, and to what extent, the objectives of R&D programs have been achieved is an issue to be addressed through empirical studies. In this respect, it is noteworthy to highlight that most of the papers assess whether R&D incentives have additional effects on firms' *innovation input*, e.g. on investment in R&D, tangible assets or employment.[1] By contrast, studies of the impact of subsidies on firms' *innovation output* are relatively scant (see e.g.: Branstetter and Sakakibara 2002, Bérubé and Mohnen 2009, Moretti and Wilson 2014). However, assessing the effects of the public incentives on innovation outputs is crucial for a couple of reasons at least. The first reason is that innovation is the ultimate goal of most programs that support R&D activity. If the policy increases firms' innovative capabilities eventually it will raise firm competitiveness. Second, because the public program might affect innovation output even keeping R&D spending or other innovation inputs constant, for example since it induces firms to carry out more radical projects, start R&D collaborations or improve the R&D management (OECD 2006). As a result, evaluating the effects only on innovation inputs provides a partial assessment of the impact of the incentives.

This paper adds to this stream of research. We evaluate the effect of public support to private R&D on firms' innovation activity, measured by patent applications. More specifically, we study the effect of publicly funded R&D on the probability to apply for a patent (and on the number of patent applications of recipient firms), over a sample of Italian manufacturing SMEs. We contribute to the existing literature in several respects. Firstly, we shed more light on the effects of R&D incentives on innovation output of the firms. This issue is scantly investigated by the evaluation literature that mostly assesses the effects on innovation inputs. Second, we provide evidence on the effect of incentives not only on a small, context-specific sample of firms, but on a large one, highly representative of Italian business sector.

Results show that firm patents are driven by R&D policy. However, the impact of R&D public finance is very similar to that exerted by privately funded R&D. These results are robust to several model specification and sample composition.

[1] See for example the recent surveys by Köhler et al. (2012), Zúñiga-Vicente et al. (2014), Becker (2015). On the econometrics methods see: Cerulli (2010); for earlier reviews: David et al. (2000), and Klette et al. (2000).

The rest of the paper is organized as follows. In the next section we discuss the theoretical background and the empirical literature. Section 3 presents a discussion on the use of patents as a measure of innovation, while in Section 4 we describe the dataset. In Section 5, we introduce the empirical strategy and set out the main results with our full sample of manufacturing SMEs. Section 6 presents the effects we obtain by applying propensity score matching. Concluding remarks make up the final section.

2. R&D subsidies and innovation output: theoretical and empirical framework

The use of R&D incentives to private firms is justified by a pair of market failures. A traditional argument is the existence of technological spillovers in R&D activity that are not taken into account when firms plan their R&D effort (Arrow 1962). Because of positive spillovers, private investments fall short of the socially optimal level and thus public support aims at increasing their level towards this optimal level. Another justification is based on the capital market imperfections that hamper firms' ability to access the financing market. Such market failure is due to informational asymmetries which are amplified in the case of R&D financing because the innovative activity is risky and difficult to evaluate. For these reasons, especially small or younger firms might face financing constraints that might obstacle their R&D activities (Hall and Lerner 2009), unless they can resort to internal funds. The purpose of public incentive is thus to provide firms with sufficient funds to implement innovation.

The most diffused public supports to private firms' innovation take the form of subsidies or fiscal incentives. Both increase R&D activity by reducing the cost of the investment. However, when using subsidies, firms receive the grants after a competitive procedure and evaluation of the projects. In the case of tax incentives, instead, the reduction of firms' tax burden is automatic, typically according to the amount of the R&D expenditure realized, without a system of evaluation. In this respect tax incentives are more neutral in terms of the project being supported than subsidies.

The international diffusion of R&D public support has spurred a huge body of empirical evaluating papers.[2] The dimension of this literature is witnessed by several surveys which focus on the impact of incentives on private R&D investment. Results are rather mixed. On one hand, Zúñiga-Vicente et al. (2014) conclude that the effects are very heterogeneous across programs and studies. On the other hand, Becker (2015) remarks that the impact of the tax credit is positive in several cases, especially for small firms that are likely to be more exposed to financial constraints.

Compared to the large body of evidence on the effects on innovation inputs, the papers based on output innovation are very few. Some papers examine the effects of fiscal incentives such as tax credits. Czarnitzki et al. (2011) found a positive effect of R&D tax credits in Canada over the period 1997-99 on the number of new products, and on the sales shares of new and improved products, of the manufacturing recipient firms. According to Cappelen et al. (2012) the tax incentives introduced in 2002 in Norway had no impact on patenting activity and on the introduction of new products for the market by beneficiary enterprises. Branstetter and Sakakibara (2002), using a matching approach, pointed out that public-sponsored research consortia that benefited from some government subsidization increased the patenting activity of Japanese firms, which are part of a consortium. More recently, Bérubé and Mohnen (2009) with matching methods as well, examine Canadian firms benefiting from R&D tax credits and R&D grants, finding that such firms are more innovative, in terms of new products, than firms that take advantage of R&D tax credits alone. Moretti and Wilson (2014) evaluate the effect of state-based incentives to biotechnology firms in US, namely R&D tax credit and specific subsidies to biotech enterprises on several outcome variables including patents. By exploiting the time and cross-country variability of public funds, they found that the public programs had limited effect on

[2] This evaluation literature includes among others: Lerner (1999), Busom (2000), Wallsten (2000), Lach (2002), Almus and Czarnitzki (2003), Gonzalez et al. (2005), Görg and Strobl (2007), Hussinger (2008), Clausen (2009), Link and Scott (2013), Takalo et al. (2013), Bronzini and Iachini (2014), Einiö (2014), Moretti and Wilson (2014), de Blasio et al. (2015).

spurring state patenting. Finally, Bronzini and Piselli (2016) evaluate the impact of an R&D subsidy program implemented in a region of northern Italy. They use a regression discontinuity design and find that subsidies increase the number of patent applications of subsidized firms compared to the unsubsidized ones. They also show that the program was also successful in increasing the probability of applying for a patent, but only in the case of smaller firms.

This inadequate attention appears puzzling because the increase of innovation output is the ultimate aim of any R&D public support. However, it could be justified by the approach privileged by the evaluators, mainly based on the knowledge production function framework, where the innovative output is considered a function of a set of innovative input, such as R&D investments, the number of researchers or human capital (Griliches 1990). Following this approach, public incentives are supposed to be effective if they positively impact on any innovative input. In other words, R&D policies effectiveness on inputs becomes a sufficient condition to argue that an increase of innovative output is caused by public support.

However, there are several mechanisms through which public incentives might increase the level of innovation output without raising innovation inputs. On the one hand, this may occur if the policy affects the choice of the innovative projects to start keeping R&D spending constant. The public funding might induce recipient firms to choice riskier but also more challenging and innovative projects, to increase the likely to obtain the incentive, or because the public funds allow the firms to implement projects that would have been difficult to privately finance from the market. Another justification is that the public policy might shift the firm innovative activity among different components of R&D investments. For example, if supported firms increase the expenditure in research activity to the detriment of development activity (i.e. the activity necessary to convert the output of research into a plan or project for the realization of new products or processes), public policy might have a stronger effect on innovation output, for given level of overall spending, because innovation is more dependent on research expenditures than on development expenditures (Griliches 1986, Czarnitzki et al. 2009)[3].

3. Patents as a proxy for innovation

Measuring innovation output on the basis of firms' patent applications has pros and cons and deserves a brief discussion. On the one hand, it is well known that not all innovations are patented or patentable. There are several other informal mechanisms that firms can use to appropriate returns from their invention or to protect innovation, as keep the secrecy or exploit the lead time advantages. The choice to patent depends on a number of factors. For example, firms might wish to patent innovation to improve their goodwill reputation or to increase their bargaining power in the cross-licensing market to extract revenues by patented inventions (Cohen et al. 2000; Anand and Khanna 2000). In many cases, firms prefer not to apply for a patent because they do not want to disclose their inventions. Moreover, only inventions whose patent has an economic value above a certain minimal threshold are patented (Griliches 1990, and for further discussion see OECD 2009)

Furthermore, the propensity to patent might vary, ceteris paribus, from country to country, over time or across sectors. Cohen et al. (2002), for example, explain the difference in patent propensity between Japanese and US businesses by the fact that US firms perceive patents as a less effective means of protecting property rights than do Japanese firms. In addition, the degree of patent enforceability and the criteria that an innovation must satisfy to be patented (novelty, non-obviousness) can also vary across countries and over time, and these differences might affect the propensity to patent (Nagaoka et al. 2010).

[3] These arguments are related to the so-called behavioral additionality of the public support of business R&D (see, e.g.: OECD 2006), i.e. changes on how firms conduct their R&D activities induced by the policy. Such additionality occurs if the policy affects firm management of R&D activity.

On the other hand, patents are probably the most definite measure of innovation. Compared with other proxies, usually measured through surveys, such as the number of new products or processes introduced by the firms, they are less exposed to personal or subjective considerations. Moreover, patents also reflect the quality of an innovation. To be patented an invention is examined by experts who judge its novelty and utility. By contrast, reliable information on the quality of an innovation can rarely be gathered from other sources, especially if they are based on personal judgment.[4]

Griliches (1990) suggests interpreting patenting activity as an indicator of the increase of economically valuable knowledge and hence a good way to measure inventive activity, even if only a (random) fraction of inventions is patented. OECD (2009) and Nagaoka et al. (2010), among others, argue that using patents as a proxy for the invention is possible, but warn that researchers should be aware of the pros and cons. As regards enterprises, Hagedoorn and Cloodt (2003) conclude that patents are a good indicator to capture innovative performance at firm level. All in all, we believe that patenting activity is a suitable measure of innovation output that can be used in a satisfactory way in our empirical exercise. In addition, this is also a rather standard choice in the econometric literature on innovation.[5]

Because the costs of patenting are among reimbursable outlays under the public program, an objection that could be raised in our case is that the incentives might boost the propensity to patent previous inventions rather than enable firms to engage in innovation-spurring R&D activity which they would otherwise have not carried

[4] In a leading international survey on firms' innovation (the Community Innovation Survey), products and processes are considered new and firms innovative if the firm produced goods and services or adopted processes that are new for the firm but not necessarily for the market. Instead, by using patents we are able to capture innovations for the market.

[5] For instance, Crepon et al. (1998) and Criscuolo et al. (2010) use patents as an indicator of innovation output to estimate a knowledge production function; Aghion et al. (2009) to assess the effect of firm entry on innovation performance of incumbent firms; Branstetter and Sakakibara (2002) to evaluate the role of Japanese government-sponsored research consortia in increasing research productivity of participating firms; and Moretti and Wilson (2013) to evaluate the effect of place-based policies on innovation output.

out. However, we think our exercise might capture this effect only marginally, since the costs of filing patent applications with the EPO are low compared with the admissible costs of the proposals (Bronzini and Piselli 2016).

4. Data and variables

Preliminary to the empirical analysis is the construction of a dataset containing data on patents and firm characteristics. Data on patent applications are generally outside the scope of databases on firms, which cover balance-sheet information and demographic data (i.e., the year of incorporation, the legal status, the location and the sector of activity). Patents are made available in specialized databases, which have no unique identifier for applicants, because their primary unit of analysis is the patent application. This causes problems in taking applicants as unit of reference, when one needs to integrate patent data with firm data. This paper refers to three datasets, that is UniCredit-Capitalia (CAPITALIA), PATSTAT and CERVED.

As far as firm characterizes are concerned, the main source of information is the 9th UniCredit-Capitalia (Capitalia) survey of Italian manufacturing firms. The survey design followed by Capitalia includes all firms with a minimum of 500 employees and a sample of firms with between 11 to 500 employees selected according to three stratifications: 4 geographical area (North-East, North-West, Centre, South), 5 firm size (11–20, 21–50, 51–250, 251–500, more than 500 employees) and the Pavitt classification (traditional manufacturing sectors, high economies of scale, specialized manufacturing sectors and high-tech sectors). [6] The survey questionnaire refers to 2001-2003 and includes a number of information on firm characteristics (structure, ownership, work force, as well as the degree of internationalization). Especially relevant to our aim is the possibility to know firms' R&D expenditures and how they

[6] As is standard in the literature, in what follows we refer to Pavitt sector 1 to mean the traditional manufacturing sectors, to Pavitt 2 for the sectors with high economies of scale, to Pavitt 3 for the specialized manufacturing sectors, and to Pavitt 4 for the high-tech sectors

financed their investments (in particular, if they received incentives to R&D).[7] This makes this data set particularly useful when performing micro-econometric studies on innovation in Italy (see, among others, Aiello and Cardamone 2008; Hall et. al. 2009).

Data from Capitalia are complemented with two other sources of information: the PATSTAT database and the CERVED database. The EPO Worldwide Patent Statistical Database (PATSTAT) contains information about patent applications presented by firms to EPO. The available information includes the applicants' name, their addresses and the priority date of the application. In particular, the data include all EPO applications filed by Italian firms from 1977 through 2009. The CERVED database contains company information and balance sheet data for Italian limited liability companies (Spa & Srl), available since 1996. Information is drawn from official data recorded at the Italian Registry of Companies and from financial statements filed at the Italian Chambers of Commerce.

As anticipated above, the difficulty of matching PATSTAT applications to the other source of data is due to the lack of a firm identifier. In order to solve this problem, we match names recorded in PATSTAT to the names of the Italian firms in CERVED. Here, it is also important to note that many attempts have been made to integrate patent data at firm level with other firm databases. In particular, Lotti and Marin (2013) apply an accurate matching procedure to PATSTAT and AIDA[8] datasets, covering 68 percent of EPO applications by Italian firms in the period 1977-2009. However, using CERVED database allows us to extend the search to the universe of Italian limited liability companies.

The details of our matching procedure are as follows. First, as discussed by Thoma et al. (2010), we harmonized names and addresses in several manners:

[7] In particular, the CAPITALIA survey takes into consideration three type of public incentives: grants, tax breaks and subsidized credit.

[8] AIDA is a commercial database on Italian firms, maintained by Bureau van Dijk. Lotti and Marin (2013) use the AIDA top version, which covers only larger firms (turnover of 1.5 million euros or higher) and a small portion of the others.

character cleaning; punctuation cleaning; spelling variation standardization; elimination of double spaces; the transformation of lower cases into upper cases. Then, we attributed VAT codes from CERVED to PATSTAT firms on the basis of exact and fuzzy matching of the company name and location, by using a computer routine[9]. Finally, we performed an extensive visual check of approximate matches, by using the Google Patent database in order to disentangle ambiguities and minimize errors. On the whole, we were able to match more than 90 percent of the EPO applications filled by Italian firms in the period 1977-2009. The last merge between CAPITALIA and PATSTAT firms was obtained using VAT codes as firms' identifiers. Matching and cleaning procedures yield a final dataset of 3,788 manufacturing SMEs.[10]

Table 1 reports a description and the source of the variables used in estimating the probit model, while the summary statistics are displayed in Table 2. It can be noted that small firms (up to 50 employees) represent 58% of the sample. Furthermore, 2/3 of firms are located in Northern Italy (35% in the North West and 30% in the North East). Traditional manufacturing firms represent 54% of the sample, whilst the high-tech sectors are represented by 144 firms.

Table 3 highlights that there are 1,634 R&D performing firms,[11] that is about 43% of the entire sample, even if this share varies by area, size and sector. Among them, about 1/3 of firms received public financial support,[12] compared to 2/3 that used only private funds. Importantly, the composition of each group of firms by area, size and sector is pretty similar to that observed for the entire sample. The last two columns of Table 3 point out that the innovators belong more in some clusters (firms

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[9] In particular, we used the Stata program RECLINK (Blasnik, 2007).

[10] The 96 percent of firms in the CAPITALIA survey are limited liability companies. In order to include also the other firms (sole proprietorship, partnership and cooperative enterprises), we considered them throughout the matching phase.

[11] Only for 1,402 firms we have also data on the amount of R&D expenditure.

[12] Among the beneficiary firms, the ratio of publicly funded to total R&D expenditure is substantial and equals about 40 percent on average.

with more than 50 employees, specialized manufacturing sectors and high-tech sectors) than in others (i.e., firms up to 20 workers, traditional manufacturing sectors, firms located in the South).

5. Empirical setting and results

5.1 Strategy

From an empirical perspective, this paper aims at assessing the role of R&D policy support on the probability to apply for a patent of Italian firms. To this end, we estimate a probit model, whose dependent variable is a dummy variable equal to 1 if the firm submitted at least one patent application to the European Patent Office (EPO) during the post-treatment period and zero otherwise. The treatment occurs over the 3-years period 2001-2003, and therefore, the post-treatment period is 2004-2009. We sum the applications by firm over the years 2004-2009 (NPAT_after) and then we build the dummy variable PPAT_after assuming value one for firms with at least one patent application.[13] Notice that with this variable we evaluate the impact on the extensive margin of firm patenting, i.e. on the new applying firms.

The regressors of interest are: 1) a binary variable assuming value one if the firm received public incentives (grants, tax breaks and subsidized credit) to R&D in the period 2001-2003 (RD_policy); 2) a binary variable which is unity if the firm had a positive R&D expenditure without receiving public incentives in the period 2001-2003 (RD_priv).

However, there is an important issue in the literature on firm-level innovation, that is firms which innovate once have a higher probability of innovating again in the future (Geroski et al. 1997, Malerba and Orsenigo 1999, Cefis 2003, Antonelli et al.,

[13] Patents are attributed to firms using the priority year of application as the reference date. We use patent applications instead of patent granted because the patent granting procedure lasts some time, and would have been completed only for few applications over our post-program time window.

2012).[14] In order to take into account the persistence in innovation activity our baseline cross-sectional model is expressed as:

$$PPAT_{2004-2009} = \beta_1 \mathrm{RD}_{2001-2003} + \beta_2 \mathrm{PPAT}_{1995-2000} + \mathrm{controls} + \varepsilon \qquad (1)$$

In particular, a lagged innovation variable is the specification used in many studies to account for this phenomenon (Clausen et al. 2011). Hence, we include a variable gauging what happened over the pre-treatment period, which, in our case, covers the 6-years period 1995-2000. In this case, NPAT_before and PPAT_before are again, respectively, the number of patent applications and a dummy variable assuming value one for firms with at least one patent application.

Finally, we add other control variables related to age, trade performance (exports), group membership, size, geographical location and sector membership of each firm. They are detailed in Table 1.

5.2 Main results

Table 4 reports the baseline results. Each column of data refers to different estimated models depending on how R&D efforts and past patenting are treated. All models included the same set of controlling variables. Before presenting the estimations of R&D policy support, it is worth noticing how patents are related to the control factors included in the model. The first evidence regards the impact exerted by exporting activity: we find that the probability to patent tends to increase with exports, thereby suggesting as in some well-known papers in the strand of endogenous growth theory that the competitive pressure in global markets acts as a stimulus for innovative outcomes (Romer 1990; Grossman and Helpman 1991; Young 1991; Hobday 1995; Aghion and Howitt 1998) and that firms learn from trade through exposure to superior

[14] The theoretical literature presents many explanations for this state-dependent behavior such as (Peters 2009): i) success breeds success (Mansfield 1968); (ii) dynamic increasing returns (Nelson and Winter 1982, Malerba and Orsenigo 1999); (iii) sunk costs in R&D investments (Sutton 1991).

foreign technology and knowledge, the so-called ‘learning-by-exporting’ effect (De Loecker 2013).

Secondly, the positive coefficients associated with the D_{Small} and D_{Medium} dummies highlight the role of size in patenting (the base group comprises the micro firms). Small-sized firms perform better than micro firms, but less well than medium enterprises, indicating that some type of economies of scale are at work. Thirdly, firm propensity to patent is influenced by the territorial specificities of the regions where they operate. As the D_{South} dummy is negative and highly significant, we prove that the dualistic nature of the Italian economy holds even in patenting. This is consistent with the results of previous works which investigate the link between location and technology in Italy (Aiello and Pupo 2014). Finally, Table 4 indicates that sector membership matters: other thing being fixed, the probability to patent is significantly higher for firms belonging to specialized and science-based sectors compared to the traditional and large economies of scales. Importantly, the impact of control variables are robust to the model specification, as their magnitude, sign and significance do not vary when moving from model 1 to model 4.

Turning back to the objective of the paper, panel A of Table 4 displays probit estimations, whereas panel B reports the marginal effects. As a preliminary check, Column 1 shows that patent activity in the post-treatment period is significantly influenced by R&D activity carried out in 2001-2003 (treatment period) and by patenting in the pre-treatment period. It is worth noticing that the latter evidence is robust to model specification, as the coefficient of PPAT_before is highly significant in every regression, in line with the evidence of persistence in firm innovation activity.

Column 2 is our reference specification since it distinguishes between publicly funded R&D (RD_policy) and private R&D activity (RD_priv). The result is that both types of R&D efforts have a similar impact on the probability to apply for a patent in the post-treatment period. Additionally, this evidence does not change even when considering a longer patenting history (Column 3), or adding the number of past patent applications (Column 4). Coming to marginal effects, we obtain that R&D activity increases the probability of patenting by about 4 percent. This is not a negligible effect, given that the percentage of firms with at least a patent application in the period 2004-2009 is 8 percent (Table 3).

As said before size, location and sector membership matter in patent activity. Therefore, in order to verify whether our results are robust to sampling, we proceed by considering several sub-groups of firms thanks to the large size of our dataset. Table 5 reports the results by firm size, geographical area and Pavitt classification. As we can observe, the effect of publicly funded R&D on patent applications is always positive and significant whatever the firms size, although it is less relevant for medium firms.[15] This is in line with some previous empirical evidence, showing that incentives have been more effective when they were disbursed to smaller firms (Lach 2002; Gonzalez et al. 2005; Bronzini and Iachini 2011; Bronzini and Piselli 2016). Again, we find that R&D incentives are less significant for the firms located in the South. Furthermore, we obtain that R&D incentives are more effective for specialized manufacturing sectors and high-tech sectors. Finally, we find no significant difference between publicly funded and private R&D activity.

5.3 Robustness checks

This section refers to the results obtained from some robustness checks which have been carried out to test the validity of the empirical design and the sensitivity of main results. Provided that experience matters in innovation, the first check we perform is aimed at verifying if the effectiveness of incentives depends on the patenting history. To this end refer to the firms that applied (PPAT_before=1) or did not apply (PPAT_before=0) for a patent at least once in the pre-treatment period 1995-2000.

[15] Estimates (not reported) suggest that the effect of RD_policy is even less relevant and barely significant for firms with more than 250 workers, which are excluded from our sample.

From Table 5 two key results emerge. On one hand, the impact of publicly funded R&D is always positive and comparable to the effect of private R&D: when using homogenous group, that is to say firms with no patent (column 1 of Table 6) or with at least one patent (column 2 of Table 6) before 2001-2003, the estimations are very similar. This reinforces previous evidence (Table 5), as it is found that the effect of R&D policy is robust to patent experience and sample-type. On the other hand, we find that experience matters a lot, as the size effect of R&D activities carried out in 2001-2003 is high for firms which had already applied in the pre-treatment period. This seems to suggest that cumulative effects are at work: provided that R&D effort is essential for innovation output (whatever the financing), its effect is amplified by the experience in patenting.

As a further analysis, we distinguish the type of R&D policy tool. In the innovation policy literature, an open issue is how the nature of the incentives might influence their effects. Compared to subsidies that are usually granted after selective procedures, automatic incentives like tax credits or other forms of fiscal incentives present some advantages like simple implementation and low administrative costs. On the other hand, the reduction of the tax burden (usually proportional to the volume of firm R&D activity) depends on, and can be bounded by, the actual amount of tax liabilities of the firms. In this respect, the instrument is less suitable to finance start-up, young or unprofitable firms that might not have enough tax liabilities to take credit advantages. Grants might also be preferable to firms that have worse access to capital markets, because unlike tax incentives firms do not have to finance their projects in advance. Finally, fiscal incentives tend to induce lower allocative distortions than subsidies, because they are more neutral in terms of project being backed but, on the other hand, they represent an instrument less suitable to influence the kind of R&D activity realized by the target firms. While there are only a few studies dealing with this issues (Colombo et al. 2011, Romero-Jordan et al. 2014), our dataset allows us to distinguish between tax credit and subsidy, which, in Table 7, replace the RD_policy variable. In our case, what clearly emerges is that the role of public support is independent on how the incentives are provided: indeed, the marginal effect (0.040) of tax credit is similar to the one (0.038) of subsidy and both are statistically equal to private R&D.

Finally, the number of patent applications is used as outcome measure. Since it is a discrete count variable, we estimate parametric estimators suitable for count data, following in this much of empirical literature on innovation (Hausman et al., 1984; Cincera, 1997). The estimators are the Poisson and negative binomial models. We generally find that the effect of publicly funded R&D is lower than that of private R&D, even if this result is not robust across models (Table 8).

6. Testing policy effectiveness and outcomes

The main evidence of previous sections is that publicly and privately funded R&D has a comparable effect on patenting activity. This result is robust to different model specification and sample of firms. However, it may be may be biased by the existence of confounding factors, as the analysis is based on the use of a non-randomized observational survey. As suggested by Rosenbaum and Rubin (1983), this issue can be addressed by performing a propensity score (PS) matching which corrects the estimation of treatment effects by comparing treated and control firms that are as similar as possible. Accordingly, this solution has been widely used in the literature of industrial policy evaluation (see, for instance, Oh et al. 2009, Foreman-Peck 2013). Bearing in mind this, in what follows we restrict the sample to R&D performers in 2001-2003 and define the treatment status as the presence of a public support. Then, we match the treated sample to a comparable sample of controls, by linking each firm only to its nearest neighbor in terms of propensity scores. [16] The variables used to perform the PS matching are those used in the previous section: past patenting activity, age, trade performance (exports), group membership, size, geographical

[16] In particular, we focus on matching with replacement, allowing each unit to be used as a match more than once. As discussed in Abadie and Imbens (2006, 2011), this produces results of higher quality by increasing the set of possible matches.

location and sector membership of each firm.[17] The aim is to investigate potential effects on the patenting activity after the public support is received.

Results are presented in Table 9.[18] We find again that publicly and privately funded R&D have a comparable impact on patenting activity (Column 1). This holds true even when considering the number of patents registered in 2004-2009 as an outcome (Column 2).

With this exercise, we are able also to exploit the information about R&D intensity, expressed as the ratio between R&D expenditure and sales (RD_intensity). In particular, our results indicate that firms receiving public support for innovation register a significantly higher level of R&D intensity than private funded firms (Column 3). This explains why the efficiency of R&D expenditure in generating patents, measured by the ratio between patents applications in the period 2004-2009 and R&D expenditure in the period 2001-2003 (NPAT_TO_RD), is significantly lower for publicly funded R&D (Column 4). Accordingly, different R&D expenditure funded by different channels in the treatment period generates asimilar number of patent applications in the post-treatment period.

7. Conclusions

This paper evaluates the impact of public support to private R&D on the innovation activities of recipient firms. Unlike most of the literature, we look at the effect of incentives on innovation output rather than on innovation input, measuring firm innovation by patenting activity.

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[17] Note that this method allows us to deal with the selection bias only due to observables factors. However, the inclusion of the firm's past patenting activity in the PS matching makes us confident that we are taking into account a number of sources of the innovative capacity of firm.

[18] In order to check the results, we used also a nearest-neighbor procedure using exact matching for size, geographical location and sector membership and Mahalanobis distance for the other control variables. However, results (available upon request) are similar to those shown in Table 9.

Using a unique set of data on a sample of Italian manufacturing firms, we find that publicly and privately funded R&D have a similar positive effect on patenting activity. Our results are robust to a number of sensitivity exercises and are also confirmed by a propensity score matching estimation on the R&D performing firms. However, combining data on patent application and R&D expenditure we show that the efficiency of R&D efforts in generating innovation is significantly lower for publicly funded expenditure.

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Table 1. Description of the variables

Variable	Description	Source
NPAT_all	Number of patents applications to the European patent office in the period 1977-2009	PATSTAT
NPAT_after	Number of patents applications to the European patent office in the period 2004-2009	PATSTAT
NPAT_before	Number of patents applications to the European patent office in the period 1995-2000	PATSTAT
NPAT_before_long	Number of patents applications to the European patent office in the period 1977-2000	PATSTAT
PPAT_after	Dummy = 1 if the firm applied at least once in the period 2004-2009	PATSTAT
PPAT_before	Dummy = 1 if the firm applied at least once in the period 1995-2000	PATSTAT
PPAT_before_long	Dummy = 1 if the firm applied at least once in the period 1977-2000	PATSTAT
RD_all	Dummy = 1 if the firm had a positive R&D expenditure in the period 2001-2003	CAPITALIA
RD_policy	Dummy = 1 if the firm received public incentives (grants, tax breaks and subsidized credit) to R&D in the period 2001-2003	CAPITALIA
RD_taxcredit	Dummy = 1 if the firm received tax breaks for R&D in the period 2001-2003	CAPITALIA
RD_subsidy	Dummy = 1 if the firm received grants or subsidized credit for R&D in the period 2001-2003	CAPITALIA
RD_priv	Dummy = 1 if the firm had a positive R&D expenditure (without public incentives) in the period 2001-2003	CAPITALIA
RD_intensity	R&D expenditure to revenue ratio in the period 2001-2003	CAPITALIA
NPAT_TO_RD	Ratio between patents applications in the period 2004-2009 and R&D expenditure (1000s euro) in the period 2001-2003	PATSTAT/ CAPITALIA
Age	Age of firm	CERVED
Export	Dummy = 1 if the firm exports at least 10 percent of its product	CAPITALIA
Group	Dummy = 1 if the firm belongs to a group	CAPITALIA

Table 1. (continue)

Variable	Description	Source
D_{NWest}	Dummy =1 if the legal office is located in the North-West	CAPITALIA
D_{NEast}	Dummy =1 if the legal office is located in the North-East	CAPITALIA
D_{Center}	Dummy =1 if the legal office is located in the Center	CAPITALIA
D_{South}	Dummy =1 if the legal office is located in the South	CAPITALIA
D_{Micro}	Dummy = 1 if the number of workers is between 11 and 20	CAPITALIA
D_{Small}	Dummy = 1 if the number of workers is between 21 and 50	CAPITALIA
D_{Medium}	Dummy = 1 if the number of workers is between 51 and 250	CAPITALIA
D_{Pav1}	Dummy = 1 if the firm operates in a traditional manufacturing sector	CAPITALIA
D_{Pav2}	Dummy = 1 if the firm operates in a sector characterized by high economies of scale	CAPITALIA
D_{Pav3}	Dummy = 1 if the firm operates in a specialized manufacturing sector	CAPITALIA
D_{Pav4}	Dummy = 1 if the firm operates in a high-tech sectors	CAPITALIA

Table 2. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
NPAT_all	3,788	0.77	3.90	0	108
NPAT_after	3,788	0.26	1.37	0	37
NPAT_before	3,788	0.18	1.17	0	40
NPAT_before_long	3,788	0.37	2.51	0	106
PPAT_after	3,788	0.08	0.27	0	1
PPAT_before	3,788	0.07	0.25	0	1
PPAT_before_long	3,788	0.10	0.30	0	1
RD_all	3,788	0.43	0.50	0	1
RD_policy	3,788	0.13	0.33	0	1
RD_taxcredit	3,788	0.04	0.20	0	1
RD_subsidy	3,788	0.09	0.29	0	1
RD_priv	3,788	0.31	0.46	0	1
RD_intensity	3,556	0.01	0.02	0.00	0.63
NPAT_TO_RD	1,402	0.01	0.06	0.00	1.64
Age	3,788	26.14	18.12	0	190
Export	3,788	0.54	0.50	0	1
Group	3,788	0.26	0.44	0	1
D_{NWest}	3,788	0.35	0.48	0	1
D_{NEast}	3,788	0.30	0.46	0	1
D_{Center}	3,788	0.18	0.38	0	1
D_{South}	3,788	0.17	0.38	0	1
D_{Micro}	3,788	0.25	0.43	0	1
D_{Small}	3,788	0.33	0.47	0	1
D_{Medium}	3,788	0.42	0.49	0	1
D_{Pav1}	3,788	0.54	0.50	0	1
D_{Pav2}	3,788	0.16	0.37	0	1
D_{Pav3}	3,788	0.26	0.44	0	1
D_{Pav4}	3,788	0.04	0.19	0	1

Table 3. Descriptive statistics of the relevant variables for the analysis

	Number of firms	% of firms that invested in R&D in the period 2001-2003	% of firms that received public financial support to R&D in the period 2001-2003	% of firms with at least a patent application in the period 1995-2000 (pre-treatment)	% of firms with at least a patent application in the period 2004-2009 (post-treatment)
Total	3,788	0.43	0.13	0.07	0.08
North-West	1,309	0.48	0.15	0.08	0.10
North-East	1,141	0.47	0.13	0.09	0.09
Center	683	0.42	0.13	0.05	0.08
South	655	0.28	0.06	0.01	0.02
Micro	946	0.28	0.06	0.01	0.02
Small	1,262	0.41	0.10	0.04	0.05
Medium	1,580	0.54	0.18	0.12	0.14
Pavitt 1	2,042	0.36	0.09	0.03	0.04
Pavitt 2	610	0.36	0.10	0.04	0.04
Pavitt 3	992	0.59	0.20	0.14	0.18
Pavitt 4	144	0.68	0.22	0.13	0.24

Table 4. Baseline econometric results

	(1)	(2)	(3)	(4)
		Panel A: Coefficients		
RD_all	.402***			
	(.079)			
RD_policy		.429***	.462***	.412***
		(.104)	(.104)	(.104)
RD_priv		.390***	.383***	.388***
		(.083)	(.083)	(.082)
PPAT_before	1.285***	1.283***		1.153***
	(.093)	(.093)		(.136)
PPAT_before_long			1.190***	
			(.082)	
NPAT_before				.050
				(.042)
Age	-.003	-.003	-.004*	-.003
	(.002)	(.002)	(.002)	(.002)
Export	.199**	.198**	.203**	.198**
	(.085)	(.085)	(.085)	(.085)
Group	-.033	-.032	-.059	-.045
	(.079)	(.079)	(.078)	(.079)
D_{NEast}	-.092	-.091	-.080	-.097
	(.085)	(.085)	(.086)	(.085)
D_{Center}	.104	.105	.116	.102
	(.102)	(.102)	(.104)	(.102)
D_{South}	-.377***	-.376***	-.319**	-.387***
	(.137)	(.138)	(.138)	(.139)
D_{Small}	.315**	.315**	.280**	.318**
	(.131)	(.131)	(.131)	(.131)
D_{Medium}	.711***	.709***	.644***	.711***
	(.127)	(.128)	(.128)	(.127)
D_{Pav2}	.046	.045	.060	.050
	(.119)	(.119)	(.120)	(.119)
D_{Pav3}	.541***	.540***	.501***	.542***
	(.083)	(.083)	(.084)	(.083)
D_{Pav4}	.904***	.902***	.837***	.903***
	(.145)	(.145)	(.143)	(.145)

Table 4. (continue)

		Panel B: Marginal effects		
RD_all	.043***			
	(.008)			
RD_policy		.046***	.049***	.044***
		(.011)	(.011)	(.011)
RD_priv		.042***	.041***	.041***
		(.009)	(.009)	(.009)
H0: RD_policy=RD_priv				
(p-value)		.677	.395	.793
Observations	3,788	3,788	3,788	3788
Adj R2	.298	.298	.306	.300

Probit estimates. The dependent variabile is PPAT_after.

Table 5. Results by firms' size, area and sector

Sub-Sample	Micro and small	Medium	North-Centre	South	Pavitt 1-2	Pavitt 3-4
			Panel A: Coefficients			
RD_policy	.607***	.359***	.416***	.813*	.551***	.365**
	(.166)	(.130)	(.108)	(.431)	(.145)	(.147)
RD_priv	.330***	.452***	.410***	.262	.412***	.388***
	(.127)	(.113)	(.088)	(.283)	(.111)	(.125)
PPAT_before	1.454***	1.252***	1.247***	2.228***	1.070***	1.401***
	(.185)	(.110)	(.094)	(.505)	(.155)	(.121)
Age	.003	-.006**	-.003	-.021*	-.004	-.002
	(.004)	(.002)	(.002)	(.012)	(.003)	(.003)
Export	.109	.335***	.220**	-.046	.237**	.117
	(.119)	(.125)	(.090)	(.265)	(.107)	(.133)
Group	.063	-.069	-.017	-.662	-.056	-.003
	(.147)	(.094)	(.081)	(.499)	(.115)	(.109)
			Panel B: Marginal effects			
RD_policy	.040***	.058***	.050***	.048*	.038***	.070**
	(.011)	(.021)	(.013)	(.026)	(.010)	(.028)
RD_priv	.022***	.073***	.049***	.016	.029***	.075***
	(.008)	(.018)	(.011)	(.017)	(.008)	(.024)
H0: RD_policy=RD_priv (p-value)	.092	.410	.952	.199	.326	.853
Classadd FE	NO	NO	YES	YES	YES	YES
Area FE	YES	YES	NO	NO	YES	YES
Pavitt FE	YES	YES	YES	YES	NO	NO
Observations	2,208	1,580	3,133	655	2,652	1,136
Adj R2	.198	.288	.289	.270	.179	.265

Probit estimates. The dependent variabile is PPAT_after.

Table 6. Results by patenting history

Sub-Sample	PPAT_before = 0	PPAT_before =1
	Panel A: Coefficients	
RD_policy	.348***	1.132***
	(.117)	(.270)
RD_priv	.309***	1.165***
	(.087)	(.256)
Age	-.005**	.005
	(.002)	(.005)
Export	.198**	.350
	(.087)	(.341)
Group	-.024	-.139
	(.088)	(.192)
	Panel B: Marginal effects	
RD_policy	.031***	.363***
	(.011)	(.081)
RD_priv	.028***	.374***
	(.008)	(.075)
H0: RD_policy=RD_priv (p-value)	.728	.865
Classadd FE	YES	YES
Area FE	YES	YES
Pavitt FE	YES	YES
Observations	3,537	251
Adj R2	.134	.175

Probit estimates. The dependent variabile is PPAT_after.

Table 7. Results by type of incentive

	(1)
	Panel A: Coefficients
RD_taxcredit	.369***
	(.141)
RD_subsidy	.355***
	(.110)
RD_priv	.372***
	(.081)
PPAT_before	1.286***
	(.093)
Age	-.003
	(.002)
Export	.202**
	(.085)
Group	-.035
	(.079)
	Panel B: Marginal effects
RD_taxcredit	.040***
	(.015)
RD_subsidy	.038***
	(.012)
RD_priv	.040***
	(.009)
H0: RD_taxcredit=RD_subsidy=RD_priv (p-value)	.987
Classadd FE	YES
Area FE	YES
Pavitt FE	YES
Observations	3,788
Adj R2	.297

Probit estimates. The dependent variabile is PPAT_after.

Table 8. Results by number of patent applications

Model	POISSON	POISSON	NEGBIN	NEGBIN
		Panel A: Coefficients		
RD_policy	.786***	.632**	.802***	.761***
	(.262)	(.261)	(.236)	(.233)
RD_priv	1.037***	.962***	1.017***	.972***
	(.259)	(.239)	(.206)	(.203)
PPAT_before	1.967***	1.649***	2.036***	1.584***
	(.193)	(.176)	(.170)	(.209)
NPAT_before		.077***		.123***
		(.019)		(.037)
Age	.001	.001	-.005	-.005
	(.004)	(.004)	(.004)	(.004)
Export	.370	.501**	.552***	.608***
	(.298)	(.197)	(.210)	(.211)
Group	.152	.026	.122	.084
	(.145)	(.143)	(.174)	(.175)
		Panel B: Marginal effects		
RD_policy	.205***	.165**	.231***	.247***
	(.069)	(.067)	(.070)	(.090)
RD_priv	.271***	.251***	.293***	.316***
	(.073)	(.064)	(.068)	(.093)
H0: RD_policy=RD_priv				
(p-value)	.129	.033	.280	.289
Classadd FE	YES	YES	YES	YES
Area FE	YES	YES	YES	YES
Pavitt FE	YES	YES	YES	YES
Observations	3,788	3,788	3,788	3,788
Adj R2	.407	.427	.165	.168

Poisson and negative binomial estimates. The dependent variable is NPAT_after

Table 9. Estimation of average treatment effects

Outcome variable	PPAT_after	NPAT_after	RD_intensity	NPAT_TO_RD
ATE	.022 (.023)	-.070 (.091)	.014*** (.003)	-.009*** (.003)
ATT	.014 (.029)	-.141 (.178)	.013*** (.003)	-.014*** (.006)
Observations	1,634	1,634	1,402	1,402

Propensity score matching estimates. The sample is composed by R&D performing firms. The treatment variable is RD_policy.