Public RD support in Italy. Evidence from a new firm-level patent data set

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Public R&D support in Italy. Evidence from a new firm-level patent data set[1]

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This paper evaluates the impact of R&D public support on the innovation activities of a sample of Italian SMEs. Unlike most of the literature, the analysis focuses more deeply on the innovation output than on the innovation input. The innovation output is measured through patent data. By using a new data set obtained by combining information from EPO records and the Capitalia data set on Italian corporations, we find that publicly supported firms have similar patenting activity to other R&D performers, regardless of the type of policy tool used to foster innovation. However, as far as patenting is concerned, supported SMEs face higher R&D spending than others.

Keywords: Patents; R&D policy support; SMEs.
JEL classification: O31; O38; L1; C21.

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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 advantage of the innovative efforts made by others. The final outcome is a level of private R&D that is lower than is desirable at the 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 conducted by firms. All this is particularly true for Italy, where the capital market is not highly developed and the low propensity to innovate is also due to specific characteristics of its industrial sector, such as the large proportion of small firms and the specialization in low-tech sectors.

These considerations help us to understand state intervention in favour of innovation. Any policy aims to compensate for the difference between social and private returns on R&D efforts and ensure financial facilities for innovators, particularly in the first stage of the innovation process. While the initial objective of an R&D policy is to increase the amount of innovation, the aim is to strengthen the position of each country among the leading knowledge- and competence-based countries. This is basically the mission of many R&D programmes, for example Europe 2020, which is part of the EU's growth strategy to promote a more competitive economy in the coming years. With regard to the theme of this paper, it is of value to point out that, among many other objectives, Europe 2020 fixes the proportion of the EU's GDP to be invested in R&D up to 2020 at 3 per cent. According to the EU Commission, this is a prerequisite for achieving smart growth, which is based on more effective investments in education, research and innovation.[2]

[2] As mentioned before, the level of actual R&D efforts is lower than the optimum and very far from 3 per cent. For instance, in Italy R&D investments have fluctuated around 1.1–1.3 per cent of the GDP in the last years, while the average of the EU-27 has been around 2 per cent (the intensity was more than

However, whether, and to what extent, the objectives of R&D programmes have been achieved is an issue to be addressed through empirical studies. On one hand, most papers assess whether R&D incentives have additional effects on firms' *innovation input*, for example on investment in R&D, tangible assets or employment (see, for example, the recent surveys by Zúñiga-Vicente et al. 2014 and Becker 2015; for earlier reviews see David et al. 2000 and Klette et al. 2000). On the other hand, 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, Bronzini and Piselli 2016), thereby leaving room for further research.

Since the ultimate goal of most programmes supporting R&D activity is to increase innovation, this paper contributes to this stream of research by evaluating the effect of R&D public support on firm innovation activity. The latter is measured by patent applications. More specifically, the study evaluates the effect of publicly funded R&D on the probability of applying for a patent (and on the number of patent applications of recipient firms) among a representative sample of Italian manufacturing SMEs. Our main source of qualitative information includes a number of details on firm characteristics (the structure, ownership, workforce and degree of internationalization), thereby allowing us to identify not only the amount of individual R&D expenditure but also the way in which firms finance the investment. Crucial information traces whether firms have received public support for R&D and the type of policy instrument utilized (subsidies or tax incentives).[3] This renders this data set particularly useful for the scope of the study, as it allows us to compare the impact of private and public R&D funds on the R&D effort itself as well as on the outcome of the innovation process.

The paper's contributions are fourfold. First of all, the evidence confirms the clear additional effect of R&D incentives on the amount of R&D carried out by

3 per cent in some Nordic countries (Finland, Sweden and Denmark) and more than 2 per cent in Austria, France, Germany and Slovenia). However, compared with the early 2000s, Italy has increased its R&D investments by about 20–25 basis points from just over 1 per cent of the GDP in 2000.

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

financed firms. This is in line with a large stream of pre-existing research. Secondly, we shed some light on the effects of R&D incentives on firm innovation output, which is an issue that is scantily investigated by the evaluation literature. Interestingly, the empirical setting that we refer to also allows an exploration of the link between innovation input and innovation output for any policy tool. This is another issue that is hardly addressed in the literature. In particular, we verify whether government-funded R&D is less or more efficient than privately funded R&D in generating patents (see e.g. Czarnitzki et al. 2006). Thirdly, we work with a large sample of firms, highly representative of the Italian business sector, with the aim of reconciling the previous results of experimental studies linked to a small, context-specific sample of firms. Finally, thanks to the sample size, we are able to compare the innovation activity of subsidized firms with respect to those in which the R&D activity is backed by private resources only, even while taking into account geographical, sectorial and technological differences.

The results show that the effect of publicly supported R&D on innovation output is very similar to that exerted by privately funded R&D. Importantly, this evidence turns out to be robust to several model specifications and sample compositions. However, after combining the results on patent application and R&D expenditure, we find that the efficiency of R&D efforts in generating innovation is significantly lower for publicly funded expenditure.

The rest of the paper is organized as follows. The next section points out the theoretical background and the empirical literature. Section 3 provides some arguments for the use of patents as a measure of innovation, while Section 4 describes the data set. Section 5 presents some simple evidence regarding innovation input. In Section 6 we introduce the empirical strategy and set out the main results concerning the innovation output. Concluding remarks make up the final section.

2. The effect of R&D subsidies: empirical evidence

The evidence on the impact of incentives for R&D or innovation measures is large and heterogeneous, depending on several features of each paper (the kind of incentives, objective variable, samples and methodologies). The most diffuse policy instruments to support private firm innovation are subsidies and fiscal incentives. Both are expected to increase the R&D activity by reducing the cost of the investment. However, firms using subsidies receive the grants after a competitive procedure and an evaluation of the projects. In the case of tax incentives, instead, the reduction of firms' tax burden is automatic – typically depending on the amount of R&D expenditure realized – and without a system of evaluation. In this respect tax incentives are more neutral than subsidies (OECD 2016).

The related literature on the impact of incentives on private R&D investment (on the innovation input side) is huge and summarized in several surveys.[4] Even though results supporting the additionality hypothesis tend to prevail, there is no conclusive evidence that R&D policies positively affect R&D efforts. However, in a more recent study, Zúñiga-Vicente et al. (2014) indicate that public subsidies are expected to exert either additionality or substitution effects on private R&D investment under different conditions. In particular, some papers point out that public support exerts positive impacts on R&D activity, especially when the evaluation study regards small and financially constrained firms (Becker 2015). An explanation for this is that innovative activity is risky and hence small or young firms have to resort to internal funds to finance it more than large firms. In this case the purpose of the public incentive is to provide firms with sufficient funds to implement innovation (Hall and Lerner 2009).

Compared with the large body of evidence on the effects on innovation inputs, the papers based on output innovation are very few. Some examine the effects of fiscal

[4] 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) and de Blasio et al. (2015).

incentives, such as tax credits. Czarnitzki et al. (2011) find a positive effect of R&D tax credits, while, according to Cappelen et al. (2012), the tax incentives introduced in 2002 in Norway had no impact on the patenting activity and on the introduction of new products to the market. In a recent study, Bronzini and Piselli (2016) evaluate the impact of an R&D subsidy programme implemented in a region of northern Italy. They use a regression discontinuity design and find that subsidies increased the number of patent applications of subsidized firms compared with unsubsidized ones. They also show that the programme was successful in increasing the probability of applying for a patent, but only for smaller firms.

Moreover, only a few papers compare the effects of different incentives within the same framework and data set. Bérubé and Mohnen (2009) use matching methods and show that Canadian firms benefiting from tax credits and grants are more innovative than firms that take advantage of R&D tax credits alone. Moretti and Wilson (2014) focus on two types of state-specific incentives for innovation: the R&D tax credits for any form of R&D investment and the biotech-specific subsidies. The authors evaluate the effect on several innovative outcomes, including patents, and find that both public programmes have a limited effect on spurring patenting activity.

As stated in the introduction, the inadequate attention to innovation output is not motivated, as any R&D public support ultimately aims to increase knowledge and innovation. The motivation to disregard output comes from the line of research according to which it is a function 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 exert a positive impact on any innovative input. In other words, the effectiveness of R&D policies on inputs becomes a sufficient condition to argue that an increase in innovative output is caused by public support. However, there are several other mechanisms through which public incentives might increase the level of innovation output without raising the innovation inputs. On the one hand, this may occur if the policy affects the choice of innovative projects to start keeping R&D spending constant. The public funding might induce the recipient firms: (i) to choose riskier but more challenging and innovative projects; (ii) to increase the likelihood of obtaining the incentive; and (iii) to implement projects that would have been difficult to finance privately from the market. Another justification is that the public policy might shift firms' innovative activity among different components of R&D investments. For example, if supported firms increase their R&D expenditure 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 a given level of overall spending, because innovation is more dependent on research expenditure than on development expenditure (Griliches 1986; Czarnitzki et al. 2009).[5]

3. Patents as a proxy for innovation

Measuring innovation output on the basis of firm patent applications has pros and cons and deserves a brief discussion.

On 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 their innovation, such as maintaining secrecy or exploiting lead time advantages (Anand and Khanna 2000; Cohen et al. 2000). In many cases firms prefer not to apply for a patent because they do not want to disclose their inventions. Moreover, only inventions for which a patent has an economic value above a certain minimal threshold are patented (Griliches 1990; for further discussion see OECD 2009).

On the other hand, patents are probably the most definite measure of innovation. Indeed, compared with other innovation measures, usually gauged through surveys, patents are less exposed to personal views. They also reflect the quality of an

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[5] These arguments are related to the so-called behavioural additionality of the public support of business R&D (see, e.g., OECD 2006), that is, the changes in the way in which firms conduct their R&D activities induced by the policy. Such additionality occurs if the policy affects firms' management of R&D activity.

innovation, as any innovation, in order to be patented, is examined by experts who evaluate 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 subjective judgements.[6] Finally, patent applications are seen as a good measure of innovation, because they are in close temporal proximity to innovation input (Czarnitzki and Licht 2006).[7]

4. Data and variables

The construction of the data set is a delicate phase of this paper, because patent applications are generally outside the scope of firm databases. While these cover balance sheet information and demographic data (i.e., year of incorporation, legal status, location, sectoral membership), patents are made available in specialized data sources. A question concerns the fact that the primary unit of analysis is the patent application, implying that there is no unique identifier for applicants. This causes problems in taking applicants as the unit of reference when one needs to integrate patent data with firm data. To address this issue, this paper refers to three data sets: UniCredit-Capitalia, PATSTAT and CERVED.

For firm characteristics the main source of information is the 9th UniCredit–Capitalia survey. This data set is fairly representative of the whole population of Italian manufacturing firms with more than 10 employees. The survey design followed by Capitalia includes all firms with a minimum of 500 employees and a sample of firms with between 11 and 500 employees selected according to 3 stratifications: 4

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

[7] Other innovation output indicators, for example the share of sales with innovative products and cost reductions due to new processes, are not employed here, because it usually takes some time for the impact of innovation to materialize in such outcomes. We refer to Bronzini and Piselli (2016) and the references therein for a broader discussion of this point.

geographical areas (north-east, north-west, centre and south), 5 firm sizes (11–20, 21–50, 51–250, 251–500 and more than 500 employees) and the Pavitt classification (traditional manufacturing sectors, high economies of scale, specialized manufacturing sectors and high-tech sectors).[8] The survey refers to 2001–2003[9] and includes information on firm characteristics (the structure, ownership, workforce and degree of internationalization). Especially relevant to the objective of the paper is the possibility of knowing the firm's R&D expenditures and the way in which investments are financed: in particular whether a firm relies on public support to finance R&D activities.[10] This makes this data set particularly useful when performing micro-econometric studies on innovation in Italy (see, among many others, Aiello and Cardamone 2008; Hall et al. 2009).

The data from Capitalia are complemented with two other sources of information: the PATSTAT database and the CERVED database. The European Patents Office (EPO) releases the EPO Worldwide Patent Statistical Database (PATSTAT), which is a detailed source about the patent applications presented by firms to the EPO. The available information includes the applicants' names and addresses and the priority date of the application. Moreover, the data include all the EPO applications filed by Italian firms from 1977 to 2009. The CERVED database contains company information and balance sheet data for Italian limited liability companies, 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.

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[8] As is standard in the literature, in the following we refer to Pavitt sector 1 to indicate 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.

[9] The time span might appear not to be very recent. Still, it might be not a limitation if more recent data would include the ongoing largest economic and financial crisis since 1945, with the inevitable impacts on firms' innovation activity (OECD 2016). Our results would be far less general.

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

As mentioned above, the difficulty of matching PATSTAT applications to the other source of data is due to the lack of a firm identifier. To solve this problem, we match the 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 the firm level with other firm databases. In particular, Lotti and Marin (2013) apply an accurate matching procedure to the PATSTAT and AIDA[11] data sets, covering 68 per cent of EPO applications by Italian firms in the period 1977–2009. However, using the 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 harmonize names and addresses in several manners: character cleaning; punctuation cleaning; spelling variation standardization; the elimination of double spaces; and the transformation of lower cases into upper cases. Then, we attribute VAT codes from CERVED to PATSTAT firms on the basis of exact and fuzzy matching of the company name and location using a computer routine.[12] Finally, we perform an extensive visual check of approximate matches using the Google Patent database to disentangle ambiguities and minimize errors. On the whole we are able to match more than 90 per cent of the EPO applications completed by Italian firms in the period 1977–2009.

The last merge between Capitalia and PATSTAT firms is performed using VAT codes as a firm identifier. The matching and cleaning procedures yield a final data set of 3,788 manufacturing SMEs.[13] Table 1 provides a description and the source of the variables used in estimating the empirical models, while the summary statistics are

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[11] 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 (with a turnover of 1.5 million euros or higher) and a small portion of the others.

[12] In particular, we use the Stata program RECLINK (Blasnik 2007).

[13] Of the firms in the Capitalia survey, 96 per cent are limited liability companies. To include the other firms as well (sole proprietorship, partnership and cooperative enterprises), we consider them throughout the matching phase.

displayed in Table 2. It can be noted that micro and small firms (up to 50 employees) represent 58 per cent of the sample. Furthermore, two-thirds of the firms are located in northern Italy (35 per cent in the north-west and 30 per cent in the north-east). Traditional manufacturing firms represent 54 per cent of the sample, whilst the high-tech sectors constitute only about 4 per cent.

Table 3 highlights that there are 1,634 R&D performers,[14] that is, about 43 per cent of the entire sample, although this share varies by area, size and sector. About one-third of these firms received public financial support[15] compared with two-thirds that used only private funds. Importantly, the composition of each group of firms by area, size and sector is fairly similar to that observed for the entire sample. The last two columns of Table 3 point out that the innovators belong mainly to certain clusters (firms with more than 50 employees, specialized manufacturing sectors and high-tech sectors).

5. Some evidence on innovation input

Our aim is to investigate how firms' R&D activity changes after the public support is received. Before analysing in depth the effect on the innovation output, we want to show some evidence regarding innovation input. In particular, a huge literature has investigated whether public R&D spending is a complement or a substitute for private R&D investment. Even though the early findings are mixed (David et al. 2000), the more recent contributions affirm that public R&D spending is (at least in part) complementary and thus 'additional' to private R&D, at least in the case of SMEs (Becker 2015). To check whether that conclusion extends to our data, here we restrict the sample to R&D performers and exploit the information about R&D expenditure. For this analysis our reference variable is a dummy assuming the value one if the firm received public incentives (grants, tax breaks and subsidized credit) for R&D in the

[14] We also have data on the amount of R&D expenditure only for 1,422 firms.

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

period 2001–2003 (RD_policy). We also add other control variables that are possibly related to innovation activity: age, trade performance (exports), group membership, size, geographical location and sector. They are detailed in Table 1.

Table 4 reports the results. Column 1 shows that firms receiving public support for innovation register a significantly higher level of R&D expenditure. The results do not vary if we consider R&D intensity, expressed as the ratio between R&D expenditure and sales (Column 2). Since the average R&D intensity over the sample of R&D-performing firms is 0.017, the estimated coefficient (0.013) indicates a very substantial increase in R&D expenditure. All in all, the results in our sample confirm that public support for R&D affects the quantity of innovation input.

6. Public support and patenting performance

6.1 Strategy

Using a representative sample of Italian SMEs, we have proven that publicly supported firms have a higher level of expenditure than the other R&D performers. This is in line with previous evidence suggesting that public R&D subsidies succeed in stimulating the innovation input of SMEs (Becker 2015). However, as already noted by Czarnitzki and Licht (2006), it is unclear whether the additional spending induced by public policy also improves innovation outcome. Accordingly, we want to assess the role of R&D policy support in innovation output, measured by the probability of applying for a patent. To this end, we estimate a probit model, the dependent variable of which is a dummy variable equal to 1 if the firm submitted at least one patent application to the EPO during the post-policy period and zero otherwise. Since the policy occurs over the 3-year period 2001–2003, the post-policy 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 the value one for firms with at least one patent application.[16] It is worth mentioning that this variable is meant to capture the impact on the extensive margin of firm patenting, that is, on the new applying firms.

The regressors of interest are: 1) a binary variable assuming the value one if the firm received public incentives (grants, tax breaks and subsidized credit) for R&D in the period 2001–2003 (RD_policy); and 2) a binary variable that is unity if the firm had a positive R&D expenditure, but did not receive any public support to R&D in the period 2001–2003 (RD_priv). We also add the following controlling variables: age, export performance, group membership, size, geographical location and sector. Additionally, there is an important issue in the literature on firm-level innovation: firms that 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. 2012).[17] To take into account the persistence in innovation activity, our baseline cross-sectional model is expressed as:

$$PPAT_{2004-2009} = \beta_1 RD_{2001-2003} + \beta_2 PPAT_{1995-2000} + CONTROLS + \varepsilon \qquad (1)$$

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

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

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

6.2 Main results

Table 5 reports the baseline results. Panel A displays the probit estimations, whereas panel B reports the marginal effects. Each column of data refers to different estimated models depending on how R&D efforts and past patenting are treated. All the models include the same set of controlling variables.

As a preliminary check, Column 1 shows that the patent activity in the post-policy period is significantly influenced by the R&D activity carried out in 2001–2003 and by patenting in the pre-policy period. It is worth noticing that the latter evidence is robust to the 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 the 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 of applying for a patent in the post-policy 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). Regarding marginal effects, we find that R&D activity increases the probability of patenting by about 4 per cent. This is not a negligible effect, given that 8 per cent of firms have at least one patent application in the period 2004–2009 (Table 3).

It is also 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 of patenting tends to increase with exports, thereby suggesting that the competitive pressure in global markets acts as a stimulus for innovative outcomes (Romer 1990; Grossman and Helpman 1991; Young 1991; Aghion and Howitt 1998) and/or that firms learn from trade through exposure to superior 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 firm size in patenting (the base group is that of the micro firms). Small-sized firms perform better than micro firms but less well than medium enterprises, indicating that the economies of scale are at work.

Thirdly, firms' 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 that investigate the link between location and technology in Italy (Aiello and Pupo 2014; Aiello and Ricotta 2016).

Finally, Table 5 indicates that sector membership matters: other things being fixed, the probability of patenting is significantly higher for firms belonging to specialized and science-based sectors compared with the 'scale-intensive' ones (Freel 2003). Importantly, the impacts of the 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.

6.3 Heterogeneous effects

To check for possible heterogeneous effects, we proceed by considering several sub-groups of firms. Table 6 reports the results by firm size, geographical area and Pavitt classification. One can observe that only when considering small firms, the differential effect of publicly funded R&D on patent applications is somewhat larger than that of privately funded one:[18] 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 2014; Bronzini and Piselli 2016).

Again, we find that the effect of public funds on patenting is higher than that exerted by private R&D for the firms operating in southern regions of the country and, finally, for those belonging to traditional sectors and with high economies of scale.

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[18] 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.

6.4 Robustness checks

This section refers to the results obtained from some robustness checks that are carried out to test the validity of the empirical design and the sensitivity of the main results. Provided that experience matters in innovation, the first check that we perform is aimed at verifying whether the effectiveness of incentives depends on the patenting history. To this end, we break up the sample into firms that applied for at least one patent in the pre-policy period of 1995–2000 (PPAT_before=1) and firms that did not apply at all (PPAT_before=0). From Table 7 two key results emerge. On the one hand, the impact of publicly funded R&D remains positive and comparable to the effect of private R&D. This reinforces the previous evidence (Table 6), as it is found that the effect of the R&D policy is robust to patent experience and sample type. On the other hand, we find that experience matters considerably, as the effect of R&D activities carried out in 2001–2003 is much larger for firms that had already submitted a patent application in the past. 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 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 with 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 for financing start-up, young or unprofitable firms that might not have enough tax liabilities to take credit advantages (Busom et al. 2014). Grants might also be preferable for 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 smaller allocative distortions than subsidies, because they are more neutral in terms of projects being backed but, on the other hand, represent an instrument that is less suitable for influencing the kind of R&D activity realized by the target firms. While there are only a few studies dealing with these issues (Colombo et al. 2011; Romero-Jordan et al. 2014), our data set allows us to distinguish between tax credit and subsidies, which, in Table 8, replace the RD_policy variable. What clearly emerges from the analysis is that the role of public support is independent of how the incentives are provided: indeed, the marginal effect of tax credit (0.040) is similar to that of subsidies (0.038) and both are statistically equal to that of private R&D.

So far the focus has been on the effect of the R&D activity on the probability of patenting, thus considering the impact of policies on the extensive margin of firm patenting (how the number of firms that apply for a patent is affected by the R&D activity). Now we assess the effect of the policy on the extensive margin, looking at the effect on the number of patent applications submitted by the firms to the EPO. Notice that, focusing on the number of patents in the whole sample, the impact of the R&D is evaluated on both the extensive and the intensive margin of firm patenting, that is, on the number of patents of firms that have already started patenting activity and on the new patenting firms. To pick up the intensive margin only, we re-run the same regressions only on the sub-sample of firms with former patenting activity (PPAT_before=1). Here, despite patenting activity being relatively infrequent, we take advantage of the large size of our sample, which still includes a reasonable number of patenting firms.[19] Since it is a discrete count variable, we estimate parametric estimators that are suitable for count data, thereby following much of the 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 smaller than that of private R&D, even if this result is not robust across the models (Table 9). The final interesting result comes from the joint reading of the results concerning patent applications and R&D expenditure. Table 10 replicates the results of Table 4, except for replacing the dependent variable with an index meant to

[19] Often the subsample of patenting firms turns out to be too small (e.g. Bronzini and Piselli 2016).

gauge the R&D efficiency in generating patents. The index is the ratio between the number of patents in the period 2004–2009 and the R&D expenditure in the period 2001–2003 (NPAT_TO_RD). Taking into account the sample of R&D performers, the results displayed in Table 10 show that the related estimated coefficient is negative (-0.007), thereby indicating that the level of efficiency of the innovative efforts made in generating patents is lower for publicly funded expenditure. This is a meaningful correlation, because we have already proved that R&D public support has a positive impact on the input innovation of R&D performers (Table 4).

7. Conclusions

This paper evaluates the impact of R&D public support on the innovation activities of Italian SMEs. Differently from much of the prevailing literature, it aims to assess the effect of incentives on the output rather than on the input of the innovation process. Firm innovation output is measured by patent data.

By applying a probit model specification to an original data set, the study reveals that the probability of applying for a patent is positively affected by the public and private sources used to finance R&D activities. Furthermore, the impact exerted by private and public capital is the same in magnitude. Similarly, if the focus is on the number of patents, then there is no difference between the impacts exerted by private or public finance. It is worth noticing that these results are robust to a number of sensitivity exercises and, to some extent, they are expected, as producing innovation always requires finance, regardless of the source. Notwithstanding, since we also show that supported firms register a significantly higher level of R&D expenditure, a by-product of the analysis is that, after combining the results on patent application and R&D expenditure, we provide some insights according to which the level of efficiency of R&D efforts in generating innovation is significantly lower for publicly than for privately funded expenditure.

Nevertheless, some results of the paper indicate that there is scope for sustaining the flow of public funds to innovation. In particular, the impact of public funds on patenting is greater than that exerted by private R&D for the smaller firms, the firms operating in southern regions of the country and, finally, those belonging to traditional sectors and with high economies of scale. It is clear that these findings support the arguments in favour of R&D policies when the users face financial constraints. While this is generally the case for small firms, the country-specific dualism of the Italian economy renders southern businesses more financially constrained than their counterparts operating in the north of Italy. In such a case, public funds replace the capital market and make the financing of innovative efforts easier.

While policy considerations are beyond the scope of this study, an observation follows from the results. The paper suggests that R&D policy support could be more advantageous in terms of patenting, especially for small firms and those in the south. Limiting the discussion to the R&D policy support–patents nexus, it seems not only that the *policy making* might be better oriented towards increasing firms' R&D investments but that much more effort ought to be made to select the more promising R&D projects. This would allow firms to translate their R&D efforts into actual economic benefits by exploiting the advantages of patenting. A conclusion that can be drawn is that even regional R&D policies must be oriented towards fostering patenting. Indeed, while large firms refer to large-scale projects with a high probability of yielding innovation that can be patented, small firms are usually eligible and apply for R&D programmes that are launched locally within the development plans funded by the EU regional policy. Broadly speaking, in Italy the past regional policies to promote R&D have consisted of a number of small projects with dispersed efforts and resources that then failed in patenting. Now, in the vein of the Europe 2020 strategy aimed at concentrating the efforts in a few technological areas, the local policies should help the identification of the regional innovative capacity, thereby allowing firms to patent and compete even at the global frontier. Along this line of reasoning, a valuable extension of this paper could attempt to assess whether and to what extent patenting is affected by the size and by the type of the R&D public projects that will be funded in the near future.

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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_expenditure	Log of R&D expenditure 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_expenditure	1,422	11.16	1.63	0.00	17.99
RD_intensity	1,402	0.02	0.03	0.00	0.63
NPAT_TO_RD	1,422	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	Fraction of firms that: invested in R&D in the period 2001-2003	received public financial support to R&D in the period 2001-2003	applied for at least one patent in the period 1995-2000 (pre-policy)	applied for at least one patent in the period 2004-2009 (post-policy)
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. Evidence on innovation input

Dependent Variable:	RD_expenditure	RD_intensity
RD_policy	.750***	.013***
	(.080)	(.002)
Age	.001	-.000
	(.002)	(.000)
Export	.340***	.002
	(.087)	(.002)
Group	.371***	.003
	(.087)	(.002)
D_{NEast}	-.004	.000
	(.090)	(.002)
D_{Center}	.092	.003
	(.119)	(.003)
D_{South}	-.377***	.000
	(.135)	(.003)
D_{Small}	.628***	-.003
	(.115)	(.002)
D_{Medium}	1.417***	-.004*
	(.115)	(.002)
D_{Pav2}	-.089	.002
	(.128)	(.004)
D_{Pav3}	.297***	.005***
	(.086)	(.002)
D_{Pav4}	.844***	.029***
	(.185)	(.007)
Observations	1,422	1,402
Adj R2	.258	.081

Notes: OLS estimates. The sample includes only R&D performing firms. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 5. 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)

Notes: Probit estimates. The dependent variable is PPAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 5. (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

Notes: Probit estimates. The dependent variable is PPAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 6. 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

Notes: Probit estimates. The dependent variable is PPAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 7. 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

Notes: Probit estimates. The dependent variable is PPAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 8. 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

Notes: Probit estimates. The dependent variable is PAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 9. Results by number of patent applications

Model	Full sample				PPAT_before = 1	
	POISSON	POISSON	NEGBIN	NEGBIN	POISSON	NEGBIN
			Panel A: Coefficients			
RD_policy	.786***	.632**	.802***	.761***	.563	.702
	(.262)	(.261)	(.236)	(.233)	(.540)	(.432)
RD_priv	1.037***	.962***	1.017***	.972***	.832	.919**
	(.259)	(.239)	(.206)	(.203)	(.528)	(.416)
PPAT_before	1.967***	1.649***	2.036***	1.584***		
	(.193)	(.176)	(.170)	(.209)		
NPAT_before		.077***		.123***	.385**	.385**
		(.019)		(.037)	(.168)	(.168)
Age	.001	.001	-.005	-.005	.009	.011*
	(.004)	(.004)	(.004)	(.004)	(.006)	(.006)
Export	.370	.501**	.552***	.608***	.713**	1.052***
	(.298)	(.197)	(.210)	(.211)	(.307)	(.350)
Group	.152	.026	.122	.084	-.151	-.182
	(.145)	(.143)	(.174)	(.175)	(.194)	(.212)
			Panel B: Marginal effects			
RD_policy	.205***	.165**	.231***	.247***	1.336	1.798*
	(.069)	(.067)	(.070)	(.090)	(1.330)	(1.072)
RD_priv	.271***	.251***	.293***	.316***	1.975	2.354**
	(.073)	(.064)	(.068)	(.093)	(1.387)	(1.058)
H0: RD_policy=RD_priv (p-value)	.129	.033	.280	.289	.174	.299
Classadd FE	YES	YES	YES	YES	YES	YES
Area FE	YES	YES	YES	YES	YES	YES
Pavitt FE	YES	YES	YES	YES	YES	YES
Observations	3,788	3,788	3,788	3,788	251	251
Adj R2	.407	.427	.165	.168	.240	.079

Notes: The dependent variable is NPAT_after. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 10. The efficiency of R&D expenditure

Dependent Variable:	NPAT_TO_RD
RD_policy	-.007**
	(.003)
Age	-.000**
	(.000)
Export	.005**
	(.002)
Group	-.004
	(.003)
D_{NEast}	-.001
	(.002)
D_{Center}	.008
	(.007)
D_{South}	-.002
	(.004)
D_{Small}	.007**
	(.003)
D_{Medium}	.007**
	(.003)
D_{Pav2}	-.002
	(.003)
D_{Pav3}	.005*
	(.003)
D_{Pav4}	.004
	(.006)
Observations	1,422
Adj R2	0.040.

Notes: OLS estimates. The sample includes only R&D performing firms. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.