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Matching methods for impact evaluation of public subsidies to business R&D: Measuring heterogeneous effects

by

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Abstract

The objective of this paper is to offer a broad profile of firms with publicly supported R&D projects, which allows us to explain their different degrees of additionality. With this objective, in a first step we use standard Propensity Score Matching techniques to estimate treatment effects at the firm level, and then we explore the determinants of the heterogeneity in these individual effects through the estimation of an equation for their determinants. For our analysis, we use information from a sample of 8,168 Spanish firms for the period 2007-2014. We report three main results. First, firms with multiple program participation show higher additionality. However, individual treatment effects, which are positive for firms with low support intensities, go sharply below the average for firms with very high support intensities. Second, the degree of additionality is positively related to firm characteristics denoting a more innovative nature, while it is negatively associated with features present in firms involved in more market-oriented R&D projects. Third, firm size has a positive relation to the probability of full additionality, but a negative association with the degree of additionality in terms of net R&D intensity. These results can provide public agencies with some tools for adjusting their selection procedures.

Keywords: R&D support; policy evaluation; heterogeneous treatment effects; propensity score matching.

JEL classification: L25; O32

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1. Introduction

A large number of evaluation studies regarding public support to business R&D and innovation focus on the existence of financial or input additionality, that is, the increase in business expenditure on R&D (BERD) caused by the support. With this objective, and having in mind the potential endogeneity of subsidies, most recent studies use Propensity Score Matching (PSM) methods, which allow matching each subsidized firm with a similar non-supported one and computing the average treatment effect on the treated (ATET) as the average difference between the BERD of supported firms and the BERD of the control group of similar non-supported companies (Correa et al., 2013).

However, only a few studies investigate the existence or the determinants of the heterogeneous effects of public support among backed firms. In these cases, the usual methodology consists of estimating the average treatment effect by different subsamples of firms defined in terms of one specific dimension (size, sector, etc.) considered as the source of the heterogeneity in estimated impacts. In addition, sometimes these analyses provide contradictory results about the role of the dimension chosen. To our knowledge, there is no study that takes simultaneously into account a wide set of dimensions of the firms or the support programs so that it allows characterizing the profile of supported firms. In fact, this is one of the main shortcomings of the existing studies pointed out in the review by Zúñiga-Vicente et al. (2014).

Therefore, the main objective and novelty of this paper is to offer a broad profile of publicly supported firms with different degrees of additionality, simultaneously considering variables that reflect structural characteristics of the firms, their innovative behavior and features of the support schemes. An additional objective of our study is to shed some light on the contradictions in previous literature on this subject.

For this purpose, in a first step we use standard PSM techniques to estimate the effect of the public program in terms of the ATET on the gross or net (of subsidies) R&D intensity. In a second step, we focus on the heterogeneity of estimated individual effects among the firms, and we investigate this heterogeneity by estimating an equation of the determinants of individual treatment effects on net R&D intensities.

For our analysis, we use information from the Spanish Panel of Technological Innovation for the period 2007-2014. Our sample consists of 36,497 observations which correspond to 8,168 Spanish firms, 41% of which received subsidies from regional, national and/or European public agencies during the period.

Spanish firms provide a good testing case for our research. Since the beginning of the economic crisis, the evolution of the Spanish innovation system has shown a negative trend, with reductions in the percentages of gross expenditure on R&D (GERD) and the BERD over gross domestic product (GDP).[1] Moreover, Spain has exhibited a drastic reduction in the number (and percentage) of firms that introduced product or process innovations (from 16,443 (37%) in 2002 to 6,852 (24%) in 2016). According to the data from Eurostat, these trends diverge from those of the largest European countries, which in some cases even increased their GERD to overcome the crisis. Therefore, the evaluation of innovation policies for Spanish firms in this context is important.

We report three main results. First, we find that firms that receive support from multiple levels of the public administration show higher levels of impact. However, at the same time, individual treatment effects, which are positive for firms with low support intensities, go sharply below the average for firms with very high support intensities. Second, we show that the degree of additionality is positively related to firm characteristics denoting a more innovative nature, while it is negatively associated with features present in firms with more market-oriented R&D projects and that operate in more competitive environments. Third, effect of firm size on the probability of full additionality is different from its effect on the magnitude of treatment effects on net R&D intensity. These results can provide support agencies with some tools for adjusting their selection procedures.

The outline of the paper is as follows. Section 2 reviews the empirical literature on the heterogeneous effects of public support to business R&D. Section 3 presents the methodology and the database used for our analysis. In this section, we also offer a discussion on the additionality concept used in this paper. In Section 4, we summarize the main results in terms of ATETs and elaborate the profile of backed firms with different individual treatment effects. In the last section, we offer some final remarks and conclusions.

[1] GERD (BERD) as a percentage of GDP decreased from 1.35% in 2009 to 1.2% in 2017 (from 0.55% to 0.52%).

2. Empirical evidence on heterogeneous impacts

The theoretical conceptualization of the term *additionality* can be expressed in a very simple way: *"something that is obtained thanks to public intervention, which would not exist without it and which basically responds to the incentive effect of public policy"* (Georghiou, 1994). In the case of evaluation studies, additionality would imply the existence of an empirically observed effect that is undoubtedly caused by the existence of the support and that is not attributable to other explanatory factors (attributable causality). In economic terms, it implies the Marshallian notion of "ceteris paribus" by isolating the economic effect of the support, assuming that all other (micro and macro) economic parameters remain constant.

The essential methodological problem for the evaluation of public support for innovation is the existence of the so-called selection bias, a problem defined by Heckman (1979). This bias occurs because, in the case of public aid to business R&D or innovation, companies with and without the aid are, by definition, different from each other. A generally accepted solution applied to overcome the selection bias in the case of evaluation studies is the use of matching methods (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008).

Although the use of matching methods for impact evaluation of innovation subsidies is quite common, previous empirical evaluations with these procedures offer heterogeneous results, especially when the studies allow for differentiated impacts by type of firm or support program. According to Zúñiga-Vicente et al. (2014), *"this heterogeneity cannot be explained fully by methodological issues. The theoretical framework of analysis, the population under study and the sources and characteristics of the subsidy programs may determine the existence of additionality or crowding-out effect*".

For instance, regarding the heterogeneity in estimated impacts by firm size, some studies offer evidence of a higher impact of public support in large firms (González and Pazó, 2008; Marino et al., 2015; Crespi et al., 2016), while others reach the opposite conclusion (Herrera and Bravo, 2010; Cerulli and Potì, 2012; Huergo and Moreno, 2017; Starlacchini and Venturini, 2018). González and Pazó (2008) suggest that this contradiction could be explained by the composition of the control group. If non-innovative firms were also included in the control group, larger firms would show a higher effect, while the relation would be the opposite when only firms with R&D activities are considered. Moreover, Czarnitzki and

Hussinger (2004) show that the effect in the sub-sample of small and medium-sized enterprises (SMEs) is lower when the magnitude of R&D expenditure is used as a dependent variable, while it is higher when the dependent variable is the intensity of BERD.

Since the effect of public subsidies might vary among sectors with different technological levels, especially between high-tech and low-tech industries, Cerulli and Potì (2012), Dai and Cheng (2015), Czarnitzki and Delanote (2015) and Afcha and García-Quevedo (2016) estimate the effect of the aid by repeating the PSM procedure by subsamples defined according to the technological level of the sector where the company operates. These studies find, in general, higher impacts in more R&D-intensive sectors. The exception is Cerulli and Potì (2012), whose results show a higher effect for medium-low technology sectors.

Another aspect analyzed by several studies to explain the heterogeneity in the impacts of public aid is the specific type/design of the support program. In this line, Carboni (2011), Marino et al. (2015) and Hottenrott et al. (2017) find that firms that receive public aid from multiple instruments or levels of administration experience greater impacts, while Czarnitzki and Lopes-Bento (2014) estimate a higher effect for firms that receive European funds than for firms awarded national funds. Moreover, in some cases, the existence of crowding-out effects between different instruments of support cannot be rejected (Huergo and Moreno, 2017). Aschhoff (2009) and Czarnitzki and Lopes-Bento (2013) also find that firms that frequently participate in public support programs show a higher level of financial additionality.

Regarding the subsidy intensity (amount of support as a percentage of R&D expenditures), Görg and Strobl (2007) and Marino et al. (2015) obtain a higher level of impact for firms with a high subsidy intensity. Nevertheless, Dai and Cheng (2015) show a non-linear effect; namely, there is a saturation point beyond which a further increase in public subsidies does not yield an increase of a firm's total R&D investment.

In order to control for the overall context of the support program, Czarnitzki and Licht (2006) and Cerulli and Potì (2012) analyze the dissimilar effect for different types of regions within the country. They find a higher level of impact for the firms of poorer and less innovative regions located in eastern Germany and southern Italy. Czarnitzki and Lopes-Bento (2013), Hud and Hussinger (2015) and Hottenrott et al. (2017) evaluate the heterogeneity of the impact for the economic up and down swing (crisis) periods. The first two studies obtain a stronger effect in the crisis period, while the last one does not find any significant difference in the period before versus during the crisis.

As can be observed, most of the studies cited consider only one to three dimensions to explain the heterogeneity of impacts. With the exception of firm size, for most of these dimensions, there is evidence in only a few papers and the results are not always homogeneous. This is maybe because of a lack of standardization in the choice of the dependent variable and the set of independent covariates for the matching process. The exact specification of empirical models is sometimes a discretionary decision, and often depends on data availability (see the discussion in Section 3). These facts and the small number of studies that analyze each dimension make it difficult to detect patterns that explain contradictory results.

From a methodological point of view, the alternative used in most studies to capture heterogeneous effects is the estimation of average treatment effects by different subsamples of firms that are defined in terms of the heterogeneity factor to be considered (large firms vs SMEs, firms with low support intensity vs firms with high intensity, etc.). This procedure prevents us from taking into account the interaction of the selected factor with other dimensions.

Two exceptions are the studies by Czarnitzki and Delanote (2015) and Hottenrott et al. (2017), who focus on the determinants of individual treatment effects (ITEs).[2] Czarnitzki and Delanote (2015) estimate a regression model using the ITEs (in absolute value) as a dependent variable to examine the difference in the intensity of the impact between new technology-based firms (NTBF) and other firms. They simultaneously include a large number of explanatory variables, though they use them only as pure control variables and do not offer a broad characterization of the heterogeneous impact level of the subsidies. Hottenrott et al. (2017) use estimated ITEs to analyze the different effects of public support between the crisis and up-swing period.

In summary, the studies reviewed here find, in general, substantial differences in the impacts of public aid by subsamples of firms, and therefore conclude that the response to the

[2] Chapman et al. (2018) also use a similar methodology, but they analyze the impact of R&D subsidies on external collaborative breadth.

economic stimulus of the subsidy is heterogeneous depending on the firms' characteristics used to define the subsamples. Instead of addressing this issue using subsamples, which implies focusing on a specific dimension of the firm or the support program, our research tries to offer a broad characterization of the profile of firms with different impact levels of public subsidies. To do so, we simultaneously include all the relevant characteristics as explanatory variables of estimated ITEs. With this methodology, we expect to explain at least in part some of the contradictory results found in previous literature.

3. Methodology and data

In order to estimate the effect of public subsidies on business R&D private effort, we carry out an analysis with two different parts. In the first one, we obtain ATETs and test the presence of additionality or crowding out effects. In the second one, we focus on the heterogeneity of estimated individual effects among the firms.

3.1. Treatment effects estimation and types of additionality

The aim of this part of the analysis is the estimation of the effect of public subsidies on the R&D input of supported firms. As we have mentioned before, to obtain the subsidy effect, we use standard PSM techniques. Under certain conditions, this procedure allows us to compute the effect of the public program or treatment in terms of the difference in the outcomes between subsidized or treated firms and a 'comparable' control group of non-subsidized firms.

Consider that each firm can have two states that we represent by $T=1$ if the firm has been subsidized, and by $T=0$ otherwise. The treatment effect on firm i can be written as:

$$\tau_i = Y_{1i} - Y_{0i}, \tag{1}$$

where Y_{1i} denotes the treatment outcome if the firm obtained the subsidy and Y_{0i} if the firm was not subsidized. In order to evaluate the impact of public subsidies on subsidized firms, most studies are interested in the estimation of the Average Treatment Effect on the Treated (*ATET*):

$$ATET = E\left[Y_1 - Y_0 \mid T=1\right] = E\left[Y_1 \mid T=1\right] - E\left[Y_0 \mid T=1\right] \tag{2}$$

The fundamental evaluation problem arises because we can only observe one of the potential treatment outcomes for each individual i (Holland, 1986). If subsidies were assigned randomly, this issue could be addressed by comparing the outcomes of treated and untreated firms. However, the main drawback of the estimation is that the selection of supported firms is not usually random, which could lead to a presence of the selection bias (Heckman, 1979), because supported firms are different from non-subsidized ones. Therefore, we need to estimate the counterfactual, that is, to construct a control sample of firms with characteristics similar to those of the treated group. Given the difficulty of finding firms with the same characteristics, one alternative is the use of the PSM. Through this non-parametric approach, we condensate the information of all characteristics (*X*) in only one, the estimated likelihood of program participation conditioned on *X* (Rosenbaum and Rubin, 1983).

This methodology is based on the Conditional Independence Assumption (CIA), which indicates that, given a set of observable covariates (*X*) which are not affected by the treatment, potential outcomes are independent of the treatment assignment (Rubin, 1977):

$$(Y_{1i}, Y_{0i}) \perp T \mid X \tag{3}$$

If the CIA holds, the estimated treatment effect at the firm level, $\hat{\tau}_i$, can be obtained by substituting the non-observed Y_{0i} for the treatment outcome of a firm with a similar propensity score (matched firm), but without the subsidy, $\hat{Y}_{0i}$:

$$\hat{\tau}_i = Y_{1i} - \hat{Y}_{0i} \tag{4}$$

Consequently, we can compute the *ATET* as the mean of estimated individual treatment effects:

$$A\hat{T}ET = \frac{1}{N}\sum_{i=1}^{N} \hat{\tau}_i \tag{5}$$

In our analysis, we use equation [4] to estimate the treatment effect for each firm using two different measures of R&D input as treatment outcomes: gross and net R&D expenditures. The latter correspond to R&D expenditures funded with own resources, while gross R&D expenditures also include the quantity of public subsidies. In other words, in the case of net expenditures, public aid is excluded for the estimation of the treatment effect. The use of each option implies important differences in terms of the interpretation of the results.

When we use net BERD as a treatment outcome, a positive $\hat{\tau}_i^{net}$ implies that the firm used at least all the support obtained to increase its initially foreseen BERD, adding extra private funds. A negative $\hat{\tau}_i^{net}$ refers to a firm with a partial additionality effect or with a total crowding out effect. In the estimations based on gross BERD, a positive $\hat{\tau}_i^{gross}$ reveals that, at least, a partial additionality effect exists. However, in this case it is not clear whether the increase of the BERD is equal to or less than the amount of the public support.

Using the combination of results about treatment effects, we can define three excluding types of additionality effects (see Table 1): **(1) Full additionality (FADD)** $(\hat{\tau}_i^{net} > 0 \text{ and } \hat{\tau}_i^{gross} > 0)$: The support scheme encourages the firm to increase its initially foreseen BERD level with an amount greater than the public funds obtained; **(2) Partial substitution (PSUB)** $(\hat{\tau}_i^{net} \leq 0 \text{ and } \hat{\tau}_i^{gross} > 0)$: The company increases its R&D expenditures initially envisaged, but with an amount lower than the grants obtained. **(3) Full crowding out or substitution (FSUB)** $(\hat{\tau}_i^{net} \leq 0 \text{ and } \hat{\tau}_i^{gross} \leq 0)$: In this case, the companies replace the initially foreseen investment of private funds with the public funds obtained and keep their R&D spending at (or below) the pre-aid level. In these circumstances, there is no financial additionality at all, a situation known in the literature as full "crowding out" or free riding effect.

Table 1 about here

3.2. Analysis of the heterogeneity of individual treatment effects

Since differences in the characteristics of the firms like their absorptive capacity, path dependency or technological opportunity could lead to different treatment effects on the individual R&D effort, to analyze the determinants of this heterogeneity in a second step, we carry out two different estimations based on estimated treatment effects at the firm level. The first is oriented to study the determinants of the likelihood of showing total additionality, that is, $\Pr(\theta_i = 1 | Z_i)$. Therefore, we estimate a Probit model where the dependent variable takes the value one if the firm has positive estimated treatment effects on both gross and net expenditures, and zero otherwise:

$$\theta_i = \begin{cases} 1 & \text{if } \hat{\tau}_i^{gross} > 0 \text{ and } \hat{\tau}_i^{net} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Secondly, to explore the determinants of the heterogeneity in the magnitude of the effects rather than on the probability of showing additionality, following Hottenrott and Lopes-Bento (2014), Czarnitzki and Delanote (2015) and Chapman et al. (2018), we estimate an equation that considers the estimated individual treatment effect a dependent variable:[3]

$$\hat{\tau}_i^{net} = \beta_0 + \beta_j Z_i + \varepsilon \tag{8}$$

One contribution of our analysis is that, to compute $\hat{\tau}_i$, we consider both absolute and relative measures of R&D expenditures in our estimates. To classify supported firms by type of additionality as defined in Table 1, $\hat{\tau}_i^{net}$ and $\hat{\tau}_i^{gross}$ are obtained by using the absolute amount of net and gross R&D expenditures, respectively. However, to compute ATETs and to study the determinants of individual treatment effects, $\hat{\tau}_i^{net}$ and $\hat{\tau}_i^{gross}$ are expressed in terms of the R&D intensity, that is, the percentage of (net or gross) R&D expenditures over sales.

The advantage of using R&D intensities to analyze the heterogeneity in treatment effects is that they reflect the impacts relative to the firm size. The magnitude of subsidized projects usually depends on the activity sector in which the firm operates and also varies with firm size. When using the level of net R&D expenditures for computing ATETs, the volume of R&D expenditures of large firms dominates ATETs to the detriment of smaller firms. This dominance disappears when R&D expenditures are introduced in percentages over sales. Moreover, the use of the R&D intensity as an outcome indicator can also be interpreted as a sign of behavioral additionality in terms of the firms' innovative culture.

Notice that measuring financial additionality through the effects on R&D intensities implies a more demanding definition of additionality than the traditional concept in the literature

[3] Since the effect of individual treatment comes from an estimate, the effect of the error in the previous estimation should be controlled for. To avoid the influence of outliers, we opt for bootstrapping standard errors in our estimations, like Beck et al. (2016).

(Buisseret et al., 1995). In this sense, a positive effect of public support on R&D intensity is consistent not only with increases in BERD, but also with decreases in sales or with higher growth rates of BERD than those of sales.

3.3.Data and variables

The dataset used in our analysis consists of firm-level panel data from the Spanish Innovation Survey, which uses the so-called 'Panel of Technological Innovation' (PITEC). This survey is conducted by the Spanish National Institute of Statistics (INE) and the Spanish Science and Technology Foundation (FECYT). The database was initiated in the year 2003, but this study is focused on the period 2007-2014 because information about the amount of public subsidies is not available for the whole period. The structure of the data allows us to use lags of the variables to alleviate the endogeneity problem.

Despite the fact that the sample contains information for both innovative and non-innovative firms, we restrict our analysis to the innovative firms; this guarantees better matches since we compare firms with similar structures of R&D expenditures. After cleaning the data of firms with missing information for the relevant variables, our sample consists of 36,497 observations which correspond to 8168 different firms, 41% of which have received "selective" subsidies from regional, national and/or European public agencies, with an average support intensity (amount of subsidies over total BERD) of 8.7%.[4]

Regarding national support, between the years 2007 and 2014, three national plans of R&D&I were implemented, for the periods 2004-2007, 2008-2011 and 2013-2016, respectively. In all the plans, the financing of business R&D projects was subject to an ex-ante evaluation for the selection of the proposals. In the case of technological innovation projects, the Center for the Development of Industrial Technology channeled most of the direct R&D support. As for European aid, during the same period, Spanish firms got financing mainly through the 7th Framework Programme (FP) of the EU (2007-2013). In this FP, the selection of proposals followed criteria of excellence and most awarded projects were complex and science-oriented.

[4] Following Colombo et al. (2011), we consider a subsidy "selective" if it is a public subsidy awarded through a competitive procedure that requires ex-ante evaluation of the firm's R&D project by the public agency.

In addition, to encourage inter-European cooperation, the conditions for being awarded involved the participation of partners from several countries.[5]

For the estimation of the propensity score, we construct a binary variable, which takes the value one if the firm has received public subsidies from at least one of the three different administrative levels –regional, national or European– and zero otherwise.

As we have mentioned, our outcome indicators are based on firms' gross or net R&D expenditures, whether expressed in levels or as percentages of total sales. As expected, the statistics in Table 2 show that the sample averages of gross or net R&D intensities are higher in the case of awarded firms.

Table 2 about here

Following related literature and considering our theoretical framework, we select a broad variety of control variables that could have an influence in the firm's participation status. The set of explanatory variables includes characteristics of ownership structure of the firms, their innovative behavior and their perceptions about the difficulties of carrying out innovative activities.

The *size* of the firms in terms of the number of employees (in logs.) has been included as a control variable since it is considered that larger firms participate more frequently in the subsidies, because the development of innovations may involve fixed set-up costs, and expected revenues generated by the innovations will be a function of the price and size of demand. In this sense, larger firms could more easily overcome the fixed cost barrier and have market power (Blanes and Busom, 2004). In fact, as we can see in Table 2, the average size of supported firms is slightly larger than the size of non-participants in public programs. In the estimates, we also include the square of the size in order to allow for a non-linear relationship.

The logarithm of the firm's *age* (number of years since creation) is included to capture learning effects associated with the time that the firms have been in the market. For instance,

[5] Unfortunately, we cannot control for the effect of other policy instruments like R&D tax credits or soft loans, because we do not have access to information related to the use of these instruments in our database. We share this limitation with most empirical studies about the Spanish Innovation System. Two exceptions are Huergo and Moreno (2017) and Busom et al. (2017).

older firms could have more experience in dealing with public support agencies, although in our sample, supported firms are, on average, younger than non-supported ones.

Exporting companies tend to present a greater capacity to transform research into product innovations (Czarnitzki and Licht, 2006), as international markets are usually more competitive than the local ones; firms with a presence in foreign markets could participate in the programs more frequently if public agencies attempt to improve the competitiveness of their firms. Therefore, to take into account this possibility, we define a binary variable that takes the value one if the firm is an *exporter*. As we can see in Table 2, the percentage of exporters among awarded firms is 66.7, while this percentage is lower (64.7%) in the case of untreated firms.

There can be considerable differences in the incentives to apply for public funding depending on a firm's property structure. Affiliates of foreign-owned companies might be discriminated against in the participation of the subsidies because regional agencies would prefer to support local firms. In the case of multinational enterprises, if European agencies support the parent company, the affiliates might not have incentives to apply for more aid. On the other hand, firms with public property might be more inclined to apply for the funding because of their relationship with the administration and their knowledge of the bureaucratic process. In our sample, the percentage of firms with participation of *public capital* is higher among supported firms, while the percentage of firms with a presence of *foreign capital* is greater among non-supported ones. Also, in the case of awarded firms, we find a higher proportion of firms that belong to a *domestic group*.

Related to innovative behavior, we consider several variables that reflect the capabilities of the firms. First, to reflect previous experience in successful innovation activities, we use the number of *patent applications* (in logs.), since it might have an important role if the agencies adopt a picking-the-winner strategy. Second, to capture the influence of firms' absorption capacity, we include a dummy variable for *technological cooperation* and a measure of *human capital* in terms of the ratio of the number of workers with higher education over the total number of employees. Researchers are considered more productive when they can exchange knowledge (Kamien and Schwartz, 1982). In addition, if the aim of public agencies is to repair market failures associated with the lack of whole appropriability of profits and uncertainty, firms that undertake basic research should be preferred (Nelson, 1959). In order to capture this effect, three binary variables have been included. These variables take the value one if, respectively, the firms have designated funds to *basic research, applied research* or *technological development*.

Finally, we take into account the importance of certain *obstacles to innovation*, since such barriers could be determinants of applying for or being awarded public aid. We are especially interested in analyzing the role of financial factors, as firms with financial restrictions are more prone to using public support to amplify their R&D expenditures. On the one hand, one of the most frequent objectives of public agencies is to support firms that have good ideas but suffer from financial constraints. On the other hand, it might be interesting to analyze whether firms with more financial restrictions show a higher impact level.

Additionally, recent empirical literature finds that not only financial obstacles act as deterrent barriers to engaging in innovation activities or translating these activities into new products or processes. For instance, García-Quevedo et al. (2017) find that a lack of demand for innovation has a negative impact on both the likelihood of engaging in R&D activities and the amount of investment in R&D of Spanish firms. Also, Pellegrino and Savona (2017) obtain that market-related obstacles (concentrated market structure and lack of demand) are important financial constraints in determining innovation failures of UK firms. For this reason, we also consider knowledge and market factors as potential determinants in equation [8].[6]

In our database, the companies declare how important some factors are as elements that hamper their innovation in a three-year period (during the current and last two years). For each of the factors, a firm can answer that the importance of the factor is high, intermediate, low or not relevant. With this information, we construct three dummy variables to reflect the relevance of financial, knowledge and market factors, respectively. Each dummy variable takes the value one when companies reported that the importance of at least one factor in the category was high and 0 otherwise.

Furthermore, time and sectoral dummies have been included in order to capture the influence of differences between companies that belong to different sectors, at the level of both

[6] See a more detailed explanation of the specific financial, knowledge and market-related obstacles considered in our analysis in Appendix A.

technology sources and the appropriation of knowledge. The sectoral dummies have been defined on the basis of an extended, updated version (Bogliacino and Pianta, 2016) of the well-known taxonomy of Keith Pavitt (1984), since this classification takes into account both the activities of the sector and the technology level. Apart from overcoming market failures, public agencies may prefer to finance R&D projects with higher spillover potential (Busom, 2000). If this is the case, we expect public programs will prefer companies that belong to services or high technology sectors, while companies that belong to industrial and non-technological sectors will probably benefit less frequently from public aid.

We use the same set of explanatory variables as the vector of potential determinants (*Z*) in equations [7] and [8]. The main economic rationale for public intervention is that, because of market failures, the level of privately financed R&D activities will be lower than the socially desired level (Arrow, 1962). If the goal of public agencies is to stimulate firms' private effort, they might select those firms with a higher probability of spending more of their own resources on R&D. Therefore, the variables that influence public awarding would be the same as the ones that influence the magnitude of the effect of public support.

4. Results

4.1. Estimation of average and individual treatment effects.

In this section, we summarize the results of the PSM model used to estimate average and individual treatment effects. In Table A.1 of Appendix B, we present the results of the Probit model used to compute the propensity score. The quality of the matching procedure can be considered satisfying. The averages of explanatory variables in the Probit model converge after the matching process, and the analysis shows an almost perfect equality of the distribution of the propensity score between supported and non-supported firms (for details, see Appendix B).

ATETs in Table 3 correspond to the application of the PSM procedure, using gross and net R&D intensities as outcome variables, respectively. We compute these effects through three estimators that address different issues related to the composition of the control group. Firstly, we implement the matching procedure with replacement so that a control firm can be used more than once. In order to avoid bad matches, we impose the common support condition and a maximum distance of 0.0015 between the propensity score of the treated firms and their control ones.[7] In the second matching procedure, to avoid the influence of a firm used several times as control, we use five neighbors to build counterfactual outcomes. Finally, we estimate the counterfactual outcomes using Kernel matching, which uses the weighted averages of observations from all individuals in the control group.

Table 3 about here

Regardless of the method used for the matching procedure, estimated ATETs in Table 3 suggest that supported firms spend on average around 16% more on R&D than firms without public aid do, while the difference in net R&D intensity between supported and non-supported firms is around 5%. As mentioned before, the difference between both levels of ATEs depends basically on the amount of support obtained by the firms. In Figure 1, we show the kernel density estimation of ITEs on gross and net R&D intensities.[8]

Figure 1 about here

4.2. Profile of firms' additionality in Spain

To characterize the profile of firms' additionality in Spain, in this section we use two complementary methodologies. First, we use estimated ITEs on the absolute magnitudes of net and gross R&D expenditures to classify supported firms by type of additionality as defined in Table 1. With this classification, we also perform a descriptive analysis that allows us to get an image of the distribution of supported firms not only by type of additionality but also in terms of the set of firm characteristics that might be associated with the heterogeneity in estimated ITEs. As we can see in Table 4, in our sample, 60.4% of supported firms show full additionality (FADD), while we obtain a full crowding out effect (FSUB) for 31.9% of the firms. The remaining 7.8% of the firms show a partial substitution effect (PSUB).

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[7] Adopting these constraints involves dropping 479 observations (4.5%) from the treated group. However, the Kolmogorov-Smirnov test suggests that there are no significant differences between the distributions of the PS after the exclusion of the observations (see Figure B.1 of Appendix B).
[8] To facilitate image clarity, density functions are represented between percentiles 5 and 95.

Second, as we explained in Section 3, we estimate equations [7] and [8] using Probit and regression models, respectively (see Table 5).[9] The advantage of these estimations is that it allows us to simultaneously take into account the interaction of several potential determinants in the model. In column (1) of Table 5, $\hat{\tau}_i$ corresponds to the impact on BERD, while in columns (2) and (3), it refers to the individual treatment effect on net R&D intensity.

Tables 4 and 5 about here

The first variables that we consider as potential determinants of heterogeneity in estimated ITEs are a set of dummy variables that represent the different levels of governance of public agencies supporting R&D projects of Spanish firms. In the last decade, there has been a broad discussion about the effect of innovation policies that imply a multi-level approach (Czarnitzki and Lopes-Bento, 2013; Marino et al., 2015; Huergo and Moreno, 2017). The implicit question is whether firms that obtain support from more than one administrative level are more prone to following a free rider attitude. In our sample, firms receive subsidies from three administrative levels: regional, national and European. For supported firms, we define seven excluding dummy variables to represent each of the possible combinations of support: only regional, only national, only European, regional and national, regional and European, national and European, and all types.

In Table 5, the excluded dummy corresponds to firms with regional and national support that, therefore, is the reference category for interpreting marginal effects. Those firms that got support from only one administrative level show a lower probability of FADD than firms with regional and national support, a fact confirmed by the descriptive data in Table 4. Within firms supported through a unique level of governance, the magnitude of the effect is higher for the EU-supported firms than for the other two groups. Moreover, the effect of being awarded European aid on ITEs is not statistically different from the effect of being awarded regional and national support, while the highest impacts correspond to firms that simultaneously received EU and regional aid, especially those which benefitted from support from the three administrative levels.

[9]We performed the same estimates for the probability of full or partial additionality $\Pr(\hat{\tau}_i^{gross} > 0)$ and for gross ITEs ($\hat{\tau}_i^{gross}$). See Table C.1 in Appendix C. In terms of the validity of the models, it can be highlighted that estimated Probit models correctly classify around 72% of the observations in the case of full additionality, while the percentage is around 74% in the case of positive gross ITEs. Also, in the case of regression models, the adjustment is better in the case of net ITEs than for gross ITEs.

Notice that these results are obtained after controlling for other variables and, in particular, the intensity of the subsidy.[10] In addition, the effects keep their sign and significance regardless of whether ITEs are expressed in levels or in relative (to sales) terms. Taking those facts into account, the evidence presented here confirms that firms that receive support from multiple levels of the public administration show, in general, higher levels of impact (Czarnitzki and Lopes-Bento, 2014; Marino et al., 2015; Huergo and Moreno, 2017; Hottenrott et al., 2017). Moreover, our results also suggest that firms with support from the EU in general show the biggest effects.[11]

In the case of support intensity (the amount of support as a percentage of total BERD), the results of our models in Table 5 reflect a negative and non-linear relationship with both the probability of FADD and the ITEs on net R&D intensity. To delve deeper into this relation, in Figure 2 we show the ATETs on net R&D intensity by cohorts of the subsidy intensity. In order to build the figure, all supported firms are ranked from the lowest (but positive) to the highest level of support intensity and classified in 20 cohorts of 5% of the firms. In the figure, we can see that ATETs are positive for firms with low support intensities (first eight cohorts) and go sharply below the average for firms with very high support intensities (last five cohorts).

Figure 2 about here

This result is partially consistent with the inverted-U correlation between public subsidies and private R&D that Dai and Cheng (2015) find for Chinese manufacturing firms through the estimation of a dose response function.

Following the literature review in Section 2, the next variable that we consider as a potential determinant of heterogeneity in estimated ITEs is the firm size. In Table 4, we can observe that the higher the size stratum, the smaller the percentage of firms with a full crowding-out effect is. It seems that micro and small firms (with fewer than 50 employees) use public funds

[10] For example, firms that participate in EU programs in general have a larger size, and firms that receive support from the three administrative levels have a higher support intensity.

[11] However, Czarnitzki & Lopes-Bento (2014) do not find differences between the impacts of firms with only national versus only European support.

less frequently in the intended way.[12] In parallel, the profile of firms with full additionality effect is clearly characterized by the largest firms (83.2%).

However, firm size shows a negative relationship with treatment effects when these are measured in terms of R&D intensities. The results in Table 5 confirm the positive relation of firm size with the probability of full additionality (see column (1)), while at the same time suggest a negative impact on both the probability of positive ITEs on net R&D intensity and the magnitude of these latter ITEs. Additionally, the effect appears to be non-linear, although it only turns positive for very large firms (with more than 8,625 employees). This evidence allows us to partially reconcile the contradictions observed in previous literature regarding the effect of firm size.

In relation to the age of firms, both start-ups and old firms often exhibit total additionality (see Table 4). When we include the age (in logs.) as an explanatory variable in the specifications of Table 5, the effect is positive in columns (1) and (2), while it is not statistically significant in column (3).

As for exporting behavior, the descriptive statistics in Table 4 suggest that full additionality is more present among exporters than among non-exporters, regardless of the export intensity of exporters. However, this variable does not seem to have any impact on the probability of full additionality, probably because the exporter character is more frequent among large firms and, therefore, the firm size is indirectly capturing its effect. In fact, the effect of being an exporter changes to being negative when ITEs are measured in terms of R&D intensities (columns (2) and (3) in Table 5).

Another outstanding element in Table 4 is the ownership structure. About half of independent firms show full additionality and around 40% display a total substitution effect. On the contrary, the percentage of firms in foreign or domestic groups with full additionality is above the average percentage in the total sample. These results are qualified once we control for other explanatory variables. Probit models in Table 5 confirm that firms in foreign and domestic groups are more likely to present full additionality than independent firms (the

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[12] In this paragraph, the percentages refer, respectively, to firms with full additionality versus those with a full crowding out effect. Firms that have an above average score in one of these two indicators almost automatically have a below average score for the other. Therefore, in the text of this section, we often only mention one of the two numbers in order to avoid unnecessary reiterations.

reference group). Nevertheless, while firms that belong to foreign groups also show greater effects on net R&D intensity in terms of ITEs, we observe the opposite for companies in domestic groups. On the one hand, foreign-owned firms would have advantages over independent domestic firms –the group of reference– because they might face typical factors that hamper innovation with financial resources and managerial expertise of their enterprise group (Dachs and Ebersberg, 2009). On the other hand, geographical and cultural proximity may allow enterprises in domestic groups to minimize monitoring costs and overcome agency problems, which would lead to lower R&D expenditures.

Looking at the variables that characterize the innovative behavior of firms, we can see that companies that applied for patents have a higher probability of full additionality (column (1) in Table 5). These firms are expected to have a more innovative culture, which results in a positive influence also on the magnitude of ITEs (column (3) in Table 5). Surprisingly, regardless of the specification, firms that cooperate in R&D show a lower probability of full additionality and minor ITEs on net R&D intensity. Firms whose human capital is better educated also seem to have less probability of full additionality, although this variable tends to lose statistical significance in columns (2) and (3) of Table 5, probably because their impact is indirectly captured through the effect of the R&D intensity. In fact, firms with the highest gross R&D intensities in the previous year also show the greatest probability of FADD and the highest ITEs on net R&D intensity.

As for the type of R&D activities, both percentages in Table 4 and estimated coefficients in Table 5 suggest that firms oriented to basic R&D show a higher probability of financial additionality and also greater treatment effects on net R&D intensity. The opposite is observed regarding firms oriented to applied research or technological development.[13] Notice that these latter activities are shorter-term and closer to the market, and therefore less affected by the inherent uncertainty of the technical and commercial success of the resulting innovations. This evidence is in line with Clausen (2009) and Neicu (2019).

Companies that attach great importance to obstacles to innovation, regardless of the type (related to economic, knowledge or market factors), present FADD in a slightly lower proportion than the average (Table 4). However, once we control for other variables, only

[13] The dummies for the type or R&D activities are not excluding.

financial obstacles to innovation have a negative impact on the probability of full additionality. The results in column (3) of Table 5 also suggest that the relationships among explanatory and outcome variables are, again, different when ITEs are estimated on net R&D intensity. In this case, none of the three types of obstacles to innovation appears to affect the magnitude of the ITEs in our sample. This absence of effect might also be associated with the positive correlation between the three indicators of perceived obstacles among supported firms.

In terms of the activity sector, previous empirical evidence just focuses on the differential impact for firms in R&D-intensive sectors compared with firms in other sectors. Our results suggest that the impact of the type of activity carried out by the firm is different depending on whether we choose absolute or relative measures for ITEs. Specifically, as expected, firms in scale-intensive, science-based and high-tech services sectors show a higher probability of positive ITEs on net R&D intensities than firms in low-tech services and construction (the reference-excluded category). However, no significant difference is found relative to companies in traditional sectors (producers of traditional consumer goods and suppliers of basic or traditional intermediate goods) or in sectors of specialized suppliers. Firms in scale-intensive and especially in high-tech services sectors also present greater effects on estimated ITEs.

5.- Conclusions and final remarks

Nowadays, propensity score matching (PSM) is accepted as a standardized procedure for evaluating the impact of public support to private R&D and innovation. Using this methodology, the main research question in most existing studies is whether public R&D spending complements or displaces private R&D spending. In the absence of information about the amount of subsidies awarded, the answer to this question is reinterpreted in terms of rejecting the full crowding-out hypothesis or not.

However, only a few studies shed some light on the existence of differential effects of the subsidies among supported firms and try to relate these differences to specific firm characteristics. Moreover, as we showed in Section 2, these studies focus only on one or a very small number of firm dimensions to explain the heterogeneity in estimated impacts. In these cases, the methodological alternative usually consists of estimating average treatment effects by different subsamples of firms defined in terms of the heterogeneity factor that is considered.

In this context, the main contribution of this paper is the implementation of a broad characterization of the profile of firms with publicly supported R&D projects, which allows us to explain their different degrees of additionality. This depiction is made in terms of a wide set of variables that refer to some structural features of the firms, their innovative behavior, their perceived obstacles to innovation and several aspects of the public program.

With this objective, in a first step we use standard PSM techniques to estimate the effect of public financial aid in terms of the difference in the outcomes between subsidized or treated firms and a 'comparable' control group of non-subsidized firms. This also allows us to test the presence of additionality or crowding out effects in our sample. In a second step, we focus on the heterogeneity of estimated individual effects among the firms. We explore the determinants of this heterogeneity through the estimation of an equation for estimated individual treatment effects as a dependent variable.

One additional contribution of our analysis is that, to compute individual treatment effects, we consider both absolute and relative measures of R&D expenditures in our estimates. To identify firms with full additionality, we use the amounts of (gross and net) R&D expenditures, while to study the determinants of the heterogeneity in the effects, we consider treatment effects on net R&D intensity, which is measured as the percentage of net R&D expenditures over sales. Such a way of measuring the "impact" of public support allows an expression of estimated effects relative to firm size.

The results obtained for a sample of Spanish firms during the period 2007-2014 can be summarized as follows:

First, regarding the features of support programs, the lowest impacts correspond to firms that are awarded aid by only one administrative level. On the contrary, firms that obtain support from regional, national and European levels show the highest impacts. The support intensity shows a non-linear relationship with the impact level. Financial additionality is positive for firms with low support intensity and goes sharply below the average for firms with very high support intensity.

Second, we find a higher level of impact –in terms of the probability of showing full additionality and the magnitude of treatment effects– in firms operating in scale-intensive sectors, oriented to basic R&D and with more applications for patents, higher R&D intensity or a majority presence of foreign capital. Notice that these features often coincide in firms that generate the most radical innovations. In contrast, firms in export markets, which establish technological cooperation agreements and which have positive expenditures on applied research or technological development, show lower additionality levels of public support. These latter dimensions are usually present in firms involved in more market-oriented R&D projects, probably because they are subject to greater competitive pressures. Obviously, these relationships can be conditioned by the complementarity or substitutability among the effects of some of the explanatory variables.

Third, firm size has a different effect on the probability of full additionality than it does on the magnitude of the treatment effect on net R&D intensity. In particular, SMEs appear to have a lower probability of full additionality. However, at the same time, they show higher treatment effects on net R&D intensity. This evidence allows us to partially reconcile the contradictions observed in previous literature regarding the effect of firm size. During the period of analysis, which corresponds to the economic crisis, most SMEs show a negative evolution in their sales. Therefore, even a partial additionality of public support implies a growth in the rate of net R&D expenditures that would result in an increase in R&D intensity.

The profile revealed by our analysis provides support agencies with some suggestions for adjusting their programs or selection procedures for some specific cases. For instance, while foreign firms seem to be discriminated during the selection procedure, participating less frequently in public programs[14], at the same time they show higher additionality effects, so the agencies should reconsider the discrimination. Something similar happens with basic research. Firms with positive expenditures on basic research show a lower participation propensity in public programs than those with expenditures on applied research or technical development. However, our results suggest higher impact levels for such firms.

[14] See Table B.1 of Appendix B.

Regarding the design of support programs, although we have seen that the highest intensities of additionality correspond to the most innovative firms, this does not imply not supporting less innovative companies. On the one hand, we have analyzed the heterogeneity in treatment effects of supported firms that, by definition, are R&D performers. On the other hand, public support can also affect the probability of undertaking R&D activities (extensive margin). In addition, the policy mix may develop additional tools to incentivize R&D and innovation activities in firms with a less innovative culture.

Based on the results of this paper, three future research questions can be mentioned. Firstly, it would be interesting to analyze the underlying reasons for the higher impact of European support. On one side, it could be related to the more-basic type of R&D that is financed through the European Union Framework Programme. On the other, it could be explained by a not "picking-the-winners" selection strategy in national or regional support programs. In the case of Spain, it is often argued that public support for R&D is used as an economic convergence policy for firms in lagging regions (Heijs, 2012). Secondly, the implications of the higher level of impact in the case of firms with foreign capital justify a more detailed analysis of the role of foreign groups in national innovation systems, especially with regard to the measure of unintentional spillovers to other firms. And, thirdly, more research is needed about the effect of financial constraints on the level of additionality of public aid. For this analysis, it would be relevant to have information not only about firm-perceived economic obstacles to innovation but also about effective financial constraints.

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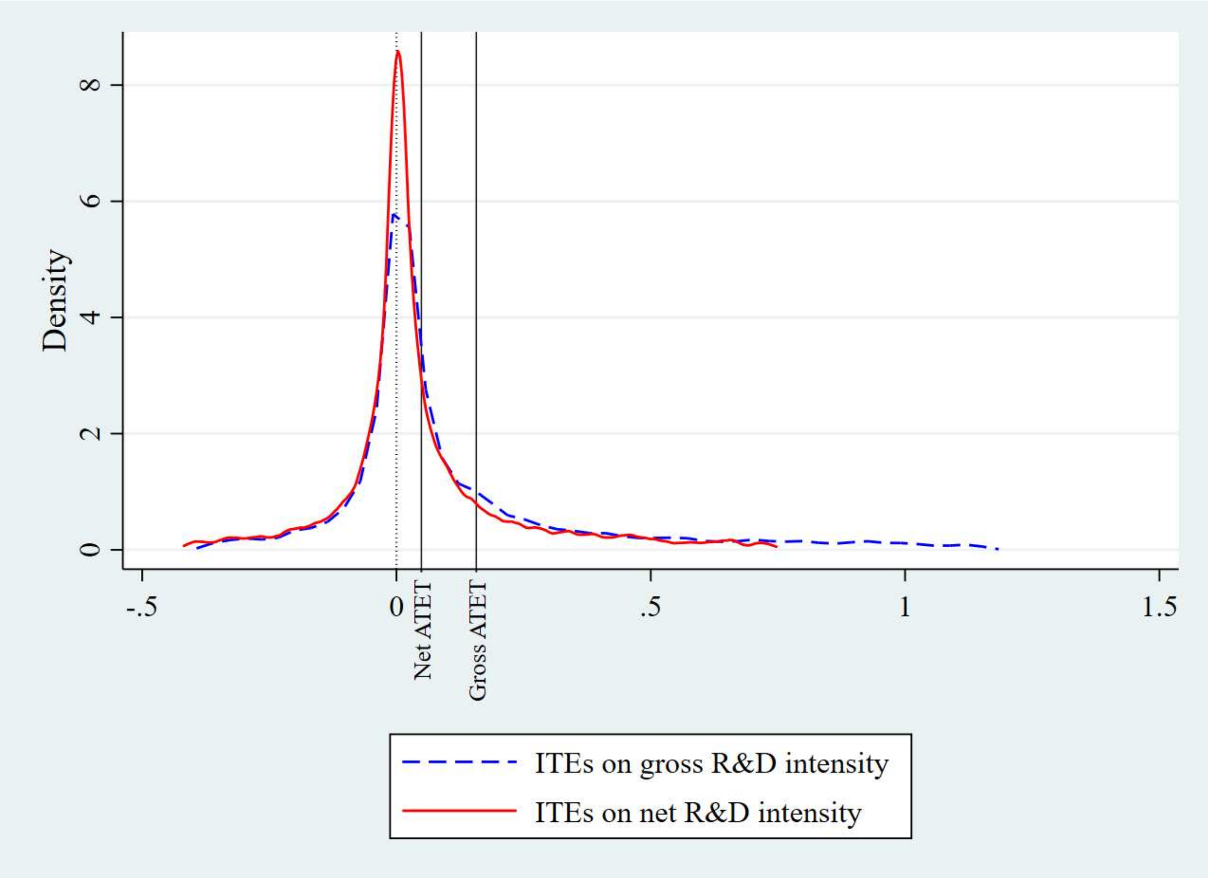
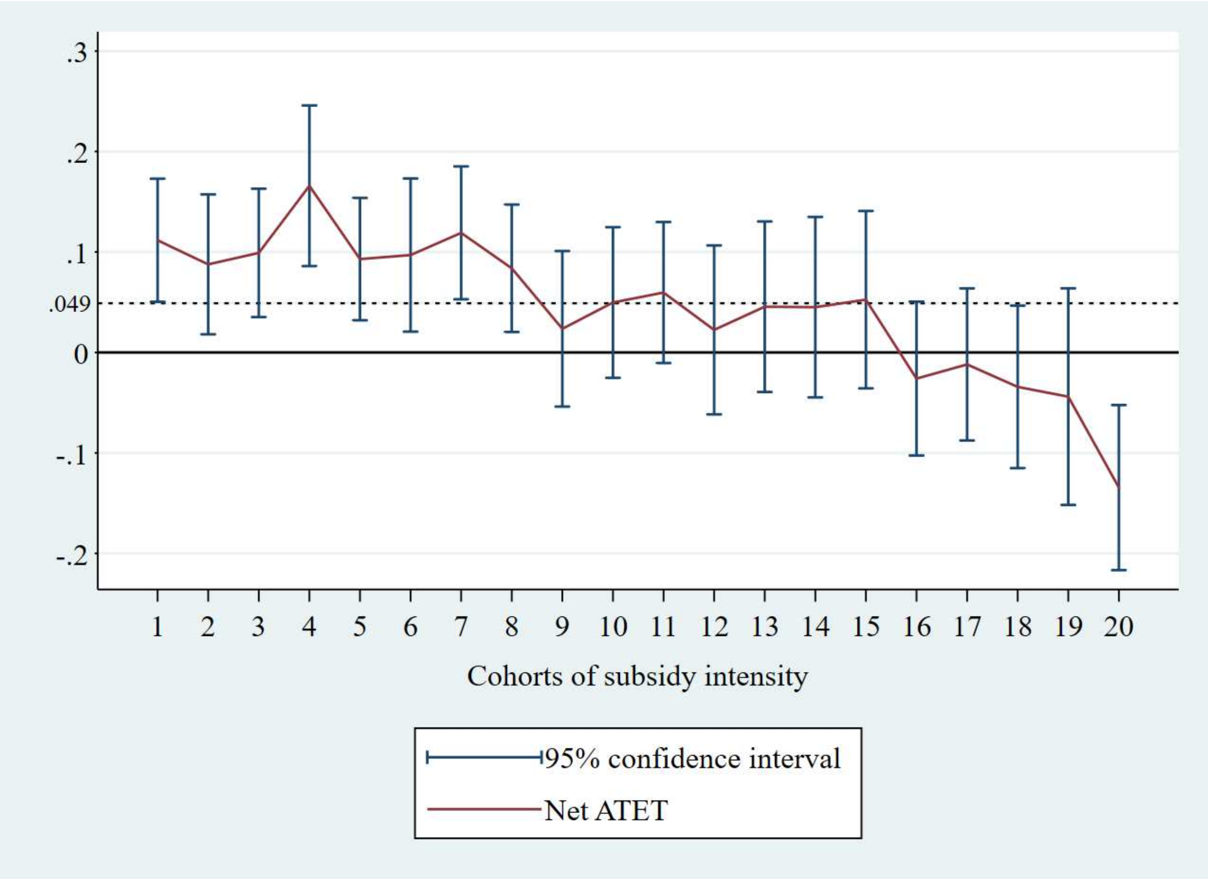
Figure 1.- Densities of estimated individual treatment effects (ITEs) on gross and net R&D intensity



Notes: Kernel density estimations between ITE percentiles 5 and 95. Gross (net) ATET: Average treatment effect on gross (net) R&D intensity.

Figure 2.- ATETs on net R&D intensity by cohort of subsidy intensity



Notes: Supported firms are ranked from the lowest (but positive) to the highest level of support intensity and classified in 20 cohorts of 5% of the firms. Net ATET: ATET on net R&D intensity.

Table 1.- Types of additionality based on the combination of estimated treatment effects on net and gross R&D expenditures

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Treatment effect on net R&D expenditures ($\hat{\tau}_i^{net}$)</td></tr>
<tr><td>$\hat{\tau}_i^{net} > 0$</td><td>$\hat{\tau}_i^{net} \leq 0$</td></tr>
<tr><td rowspan="2">Treatment effect on gross R&D expenditures ($\hat{\tau}_i^{gross}$)</td><td>$\hat{\tau}_i^{gross} > 0$</td><td>Full additionality
(FADD)</td><td>Partial substitution*
(PSUB)</td></tr>
<tr><td>$\hat{\tau}_i^{gross} \leq 0$</td><td>Impossible</td><td>Full crowding-out or substitution
(FSUB)</td></tr>
</table>

* Or partial additionality effect.

Table 2.- Means of main variables by type of public support

	Supported firms		Non-supported firms		Difference of means test[a]
	Mean	S.D.	Mean	S.D.	
Outcome variables					
Gross R&D intensity	0.313	0.768	0.073	0.334	0.241***
Net R&D intensity	0.197	0.502	0.073	0.334	0.125***
Firm characteristics					
Size (in logs.)	4.299	1.643	4.257	1.607	0.042***
Age (in logs.)	3.072	0.66	3.221	0.619	-0.149***
Exporter (Yes/No)	0.667	0.471	0.647	0.478	0.020***
Ownership structure					
- Public capital (Yes/No)	0.034	0.182	0.020	0.142	0.014***
- Foreign capital (Yes/No)	0.084	0.278	0.151	0.358	-0.067***
- Domestic Group (Yes/No)	0.379	0.485	0.315	0.465	0.064***
Patent applications (in logs.)	0.351	0.744	0.145	0.466	0.205***
Technological cooperation (Yes/No)	0.701	0.458	0.348	0.476	0.353***
Human capital (%)	0.418	0.317	0.277	0.268	0.141***
Type of R&D activities:					
- Basic Research (Yes/No)	0.141	0.348	0.079	0.270	0.062***
- Applied Research (Yes/No)	0.685	0.464	0.461	0.498	0.224***
- Technological Development (Yes/No)	0.801	0.399	0.536	0.499	0.265***
Obstacles to innovation:					
- Financial factors (Yes/No)	0.592	0.491	0.514	0.500	0.079***
- Knowledge factors (Yes/No)	0.252	0.434	0.207	0.405	0.045***
- Market factors (Yes/No)	0.375	0.484	0.339	0.473	0.037***
Activity sector:					
- P. trad. consumer goods (Yes/No)	0.140	0.347	0.218	0.413	-0.079***
- P. trad. intermediate goods (Yes/No)	0.069	0.254	0.075	0.263	-0.005*
- Specialized suppliers (Yes/No)	0.095	0.294	0.120	0.324	-0.024***
- Scale-intensive (Yes/No)	0.118	0.322	0.109	0.311	0.009***
- Science-based sectors (Yes/No)	0.074	0.262	0.110	0.312	-0.035***
- High-tech services (Yes/No)	0.228	0.419	0.087	0.283	0.140**
No. observations	10,575		25,922		

Notes: S.D.: Standard deviation. [a]: two-sample difference of means test. ***p-value<0.01, **p-value<0.05, *p-value<0.1.

Table 3.- Average treatment effect on the treated (ATET)

	Effect on gross R&D Intensity		Effect on net R&D Intensity	
	ATET	S.E.	ATET	S.E.
NNM(1) comm cal(0.0015)	0.157***	0.014	0.049***	0.011
NNM(5) comm	0.161***	0.011	0.050***	0.011
Kernel comm	0.160***	0.008	0.049***	0.006

Notes: ***p-value<0.01, ** p-value<0.05, * p-value<0.1. S.E. = Standard errors have been bootstrapped 100 times. NNM (n) = Nearest Neighbor Matching with n firms. Comm = Common support. Cal(0.0015)=the maximum distance allowed between treated and control firm is 0.0015. Kernel=Matching using kernel algorithm.

Table 4.- Distribution of supported firms by type of additionality and other firm characteristics

Variable		Number of firms (1)	Type of additionality (percentage of firms by row) FADD (2)	PSUB (3)	FSUB (4)
Public support (yes/no):	Only regional	3359	53.1	6.3	40.6
	Only national	3046	62.7	6.9	30.4
	Only EU	445	51.9	9.4	38.7
	Regional and national	1625	64.1	8.9	27.0
	Regional and EU	256	58.2	11.3	30.5
	National and EU	467	68.7	10.5	20.8
	All types	892	73.2	11.3	15.5
Subsidy intensity:	<25%	2527	77.7	0.8	21.5
	25% - 50%	2527	65.3	2.6	32.2
	50% - 75%	2514	57.8	6.8	35.5
	>75%	2522	40.7	21.1	38.3
Size (number of employees):	< 20	2317	38.7	10.4	51.0
	21–50	2240	54.3	8.9	36.8
	51-100	1616	63.1	8.8	28.1
	101-200	1309	69.7	6.6	23.7
	201-500	1356	74.0	5.0	20.9
	> 500	1252	83.2	3.9	12.9
Age:	Start-up (<3 years old)	33	63.6	12.1	24.2
	Old firm (>20 years old)	5063	66.7	6.9	26.4
Export intensity:	0%	4729	53.1	9.7	37.3
	> 0% - < 10%	2527	64.5	6.3	29.2
	10% - 50%	2233	69.1	6.2	24.6
	> 50%	592	67.9	4.9	27.2
Ownership structure:	Public capital	347	58.2	10.7	31.1
	Foreign capital	866	77.9	5.1	17.0
	Domestic group	3843	69.0	6.0	25.1
	Independent firm	5034	50.9	9.4	39.6
Patenting (yes/no)		2610	2458	71.9	6.1
Technological cooperation (yes/no)		3081	7099	60.7	7.6
Human capital	Low	3372	63.2	6.9	29.8
	Medium	3361	64.9	6.2	28.9
	High	3357	53.0	10.2	36.8
Gross R&D intensity:	< 1%	1694	58.6	7.4	33.9
	1% - 2.5%	1484	61.5	6.2	32.3
	2.5% - 5%	1475	65.6	6.0	28.4
	>5%	5437	59.2	8.8	32.0
Type of R&D activities:	Basic research	1420	65.1	7.5	27.4
	Applied research	6871	62.0	7.7	30.3
	Technological development	8069	62.0	7.5	30.5
Obstacles to innovation (yes /no):	Financial factors	5993	57.6	8.1	34.4
	Knowledge factors	2540	57.6	7.5	34.9
	Market factors	3797	58.7	7.6	33.7
Sector (yes/no):	P. trad. consumer goods	1427	59.2	6.4	34.3
	P. trad. intermediate goods	714	64.1	5.6	30.3
	Specialized suppliers	980	62.9	6.6	30.5
	Scale-intensive	1214	75.6	4.9	19.5
	Science-based	767	69.2	5.7	25.0
	High-tech services	2180	55.6	9.6	34.9
	Low-tech services/construction	2808	53.8	9.8	36.3
Total sample		10,090	60.4	7.8	31.9

Table 5.- Determinants of individual treatment effects.

	Probability of full additionality (1)		Probability of positive ITE on net R&D intensity (2)		ITEs on net R&D intensity (3)	
	dy/dx	S.E.	*dy/dx*	S.E.	Coef.	S.E.
Public support:						
- Only regional	-0.139***	0.017	-0.076***	0.016	-0.095***	0.024
- Only national	-0.077***	0.017	-0.046***	0.016	-0.074***	0.025
- Only EU	-0.112***	0.029	-0.098***	0.027	-0.045	0.033
- Regional and EU	0.008	0.035	0.041	0.035	0.051*	0.031
- National and EU	0.039	0.029	-0.018	0.027	-0.015	0.047
- All types	0.140***	0.024	0.066***	0.022	0.113***	0.038
Subsidy intensity	0.107***	0.028	-0.056**	0.024	0.082***	0.032
Subsidy intensity squared	-0.042***	0.005	0.006	0.004	-0.028***	0.006
Size (t-1)	0.097***	0.016	-0.120***	0.016	-0.157***	0.019
Size squared (t-1)	-0.001	0.002	0.005***	0.002	0.009***	0.002
Age	0.026**	0.010	0.025***	0.009	-0.008	0.013
Exporter (t-1)	-0.005	0.012	-0.030**	0.012	-0.060***	0.016
Ownership structure:						
- Public capital	-0.059*	0.031	-0.008	0.030	0.070**	0.031
- Foreign capital	0.117***	0.022	0.067***	0.020	0.071***	0.017
- Domestic group	0.050***	0.012	-0.024**	0.012	0.007	0.017
Patent applications (t-1)	0.041***	0.009	-0.006	0.007	0.032***	0.012
Technological cooperation (t-1)	-0.116***	0.012	-0.120***	0.011	-0.055***	0.010
Human capital (t-1)	-0.047**	0.023	-0.036	0.022	0.007	0.027
Gross R&D intensity (t-1):						
- Between 1% and 2.5%	0.058***	0.019	0.100***	0.016	-0.025	0.019
- Between 2.5% and 5%	0.123***	0.020	0.209***	0.017	-0.029	0.018
- More than 5%	0.201***	0.018	0.370***	0.017	0.065***	0.017
Type of R&D activities (t-1):						
- Basic research	0.014	0.016	0.034**	0.016	0.108***	0.024
- Applied research	-0.045***	0.012	-0.064***	0.011	-0.048***	0.015
- Technological development	-0.057***	0.013	-0.103***	0.013	-0.088***	0.016
Obstacles to innovation (t-1):						
- Financial factors	-0.029***	0.011	-0.005	0.010	-0.005	0.014
- Knowledge factors	0.006	0.012	0.001	0.012	0.003	0.014
- Market factors	-0.016	0.011	0.026**	0.011	0.005	0.014
Activity sector:						
- P. trad. consumer goods	0.046**	0.019	0.009	0.018	0.034	0.024
- P. trad. intermediate goods	0.037	0.024	0.009	0.022	-0.002	0.027
- Specialized suppliers	0.041*	0.021	-0.003	0.020	-0.009	0.023
- Scale-intensive	0.113***	0.020	0.040**	0.019	0.057**	0.027
- Science-based	0.083***	0.023	0.066***	0.022	0.002	0.025
- High-tech services	0.002	0.016	0.066***	0.016	0.169***	0.025
Log likelihood	-5,692.75		-5,644.56			
Observed probability	0.60		0.55			
Predicted probability	0.61		0.62			
Correct predictions	70.45		71.57			
Correct predictions: 1/0	75.42/62.79		75.39/65.34			
No. observations	10,090		10,090		10,090	

Notes: S.E: Robust standard errors. ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Marginal effects (*dy/dx*) are calculated at sample means. All estimates include the constant and time dummies. Excluded variables: Independent firm; Low-tech services and construction sectors; Firms with R&D intensity lower than 1%; and Firms with regional and national support.

Appendix A. Definitions of variables

Variable	Definition
Outcome variables:	
Gross R&D intensity	Total R&D expenditures over sales
Net R&D intensity	Net R&D expenditures (total R&D expenditures net of public subsidies) over sales
Firm characteristics:	
Size	Number of employees (in logarithms).
Age	Age of the firm (number of years since creation in logarithms).
Exporter	=1 if the firm exported during the period, 0 otherwise.
Ownership structure:	
- Public capital	=1 if the firm has public capital, 0 otherwise.
- Foreign capital	=1 if the firm has foreign capital (at least 50%), 0 otherwise.
- Domestic group	=1 if the firm belongs to a domestic group, 0 otherwise.
Patent applications	Number of patents requested (in logarithms).
Technological cooperation	=1 if the firm has established technological cooperation during the last three years with other partners, 0 otherwise.
Human capital	Number of workers with higher education over total number of employees (percentage)
Type of R&D expenditure:	
- Basic research	=1 if the firm has positive expenditures on basic research, 0 otherwise.
- Applied research	=1 if the firm has positive expenditures on applied research, 0 otherwise.
- Technological development	=1 if the firm has positive expenditures on technological development, 0 otherwise.
Obstacles to innovation:	
- Financial factors	=1 if the lack of funds in the firm or group, lack of external financing or high innovation costs are considered as factors with high or medium importance in at least one of the questions used, 0 otherwise
- Knowledge factors	=1 if the lack of qualified staff, information on technology and information about markets, and difficulties to in cooperating are considered as factors with high or medium importance in at least one of the questions used, 0 otherwise.
- Market factors	=1 if the dominance of market by established firms, uncertain demand of innovative goods and services or lack of demand of innovations are considered as factors with high or medium importance in at least one of the questions used, 0 otherwise.
Activity sector:	=1 if the firm belongs to the following sector (0 otherwise):
- P. trad. consumer goods	Producers of traditional consumer goods (Pavitt1)
- P. trad. intermediate goods	Producers of traditional intermediate goods (Pavitt2)
- Specialized suppliers	Producers specialized in intermediate goods and equipment (Pavitt3)
- Scale-intensive	Assemblers and sectors with the advantage of scale (Pavitt4)
- Science-based	Science-based sectors
- High-tech services	High technology services sector

Appendix B. Matching procedure

Table B.1: Probability of being supported. Probit model

	dy/dx	S.E
Size (t-1)	0.057***	0.007
Size squared (t-1)	-0.004***	0.001
Age	-0.031***	0.005
Exporter (t-1)	0.029***	0.006
Ownership structure:		
- Public capital	0.065***	0.016
- Foreign capital	-0.140***	0.009
- Domestic group	-0.001	0.006
Patent applications (t-1)	0.051***	0.004
Technological cooperation (t-1)	0.215***	0.005
Human capital (t-1)	0.240***	0.011
Type of R&D activities (t-1):		
- Basic research	-0.006	0.008
- Applied research	0.113***	0.005
- Technological development	0.134***	0.006
Obstacles to innovation (t-1):		
- Financial factors	0.026***	0.005
- Knowledge factors	0.011*	0.006
- Market factors	0.008	0.006
Activity sector:		
- P. trad. consumer goods	-0.041***	0.009
- P. trad. intermediate goods	0.034***	0.011
- Specialized suppliers	0.002	0.010
- Scale-intensive	0.013	0.010
- Science-based	-0.082***	0.010
- High-tech services	0.103***	0.009
Wald test		
Sectorial dummies χ^2 (6)	330.75***	
Time dummies χ^2 (6)	130.53***	
LR Chi^2 (28)	6965	
Log of likelihood	-17531	
Pseudo R^2	0.166	
No. observations	34,569	

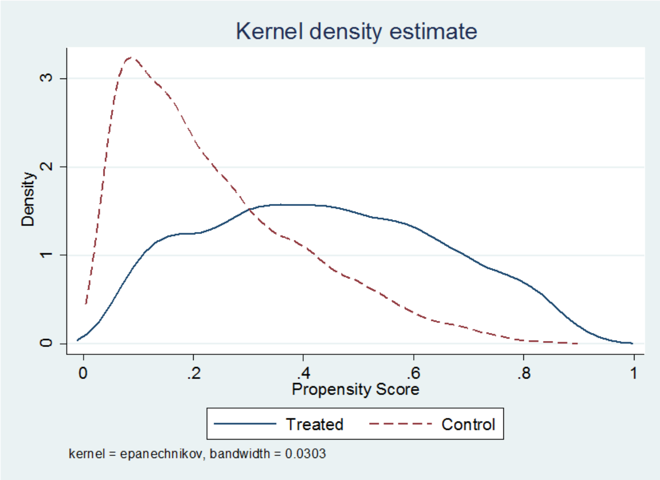
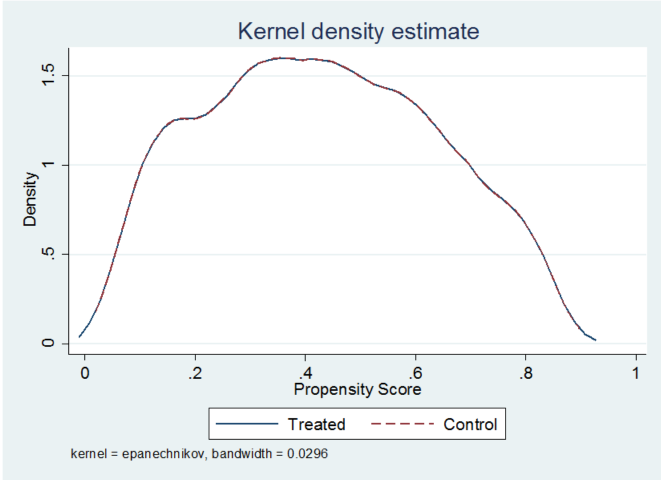
Notes: ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Marginal effects (*dy/dx*) are calculated at the sample means. S.E. = Standard errors. The model includes the constant and time dummies.

Table B.2: Quality of the matching procedure: Comparing the average values for the variables before and after matching

	Before Matching			After Matching		
Variable	Treated	Control	p>|t|	Treated	Control	p>|t|
Size (t-1)	4.301	4.288	0.473	4.302	4.282	0.377
Size squared (t-1)	21.215	20.934	0.116	21.216	20.971	0.270
Age	3.072	3.221	0.000	3.081	3.073	0.378
Exporter (t-1)	0.620	0.611	0.123	0.629	0.635	0.358
Ownership structure:						
- Public capital	0.034	0.020	0.000	0.034	0.038	0.133
- Foreign capital	0.084	0.151	0.000	0.086	0.087	0.764
- Domestic group	0.379	0.315	0.000	0.381	0.384	0.622
Patent applications (t-1)	0.350	0.155	0.000	0.329	0.346	0.101
Technological cooperation (t-1)	0.678	0.350	0.000	0.673	0.665	0.188
Human Capital (t-1)	0.418	0.272	0.000	0.412	0.418	0.174
Type of R&D activities (t-1):						
- Applied research	0.645	0.452	0.000	0.655	0.652	0.723
- Basic research	0.132	0.077	0.000	0.132	0.130	0.677
- Technological development	0.751	0.529	0.000	0.766	0.770	0.463
Obstacles to innovation (t-1):						
- Financial factors	0.569	0.496	0.000	0.574	0.564	0.164
- Knowledge factors	0.258	0.213	0.000	0.260	0.266	0.345
- Market factors	0.367	0.338	0.000	0.369	0.361	0.279
Activity sector:						
- P. trad. consumer goods	0.140	0.218	0.000	0.141	0.147	0.237
- P. trad. intermediate goods	0.069	0.075	0.077	0.071	0.073	0.623
- Specialized suppliers	0.095	0.120	0.000	0.097	0.091	0.111
- Scale-intensive	0.118	0.109	0.010	0.120	0.125	0.345
- Science-based	0.074	0.110	0.000	0.076	0.082	0.124
- High-tech services	0.228	0.087	0.000	0.216	0.218	0.720
Year 2009	0.177	0.163	0.001	0.176	0.172	0.373
Year 2010	0.161	0.150	0.005	0.162	0.157	0.356
Year 2011	0.143	0.139	0.348	0.144	0.143	0.794
Year 2012	0.120	0.134	0.001	0.121	0.126	0.295
Year 2013	0.108	0.124	0.000	0.109	0.109	0.928
Year 2014	0.103	0.113	0.006	0.105	0.107	0.648
Pseudo R^2		0.166			0.001	
LR Chi^2		6965.18			36.42	
p > Chi^2		0.000			0.132	
Mean Bias		16.4			1.3	

Notes: ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Results obtained using the nearest neighbor procedure with only 1 neighbor, common support and caliper (0.0015).

Figure B.1.- Distribution of propensity score

<table>
<tr><th>Before Matching</th><th>After Matching</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>K-S test: 0.399***</td><td>K-S test: 0.211</td></tr>
</table>

Notes: ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Results obtained using the nearest neighbor procedure with only 1 neighbor, common support and caliper (0.0015). K-S: Two-sample Kolmogorov-Smirnov test for equality of distribution functions.

Table C.1.- Complementary estimates

	Probability of positive ITE on gross R&D expenditure (1)		Probability of positive ITE on gross R&D intensity (2)		Treatment effect on gross R&D intensity (3)	
	dy/dx	S.E.	*dy/dx*	S.E.	Coef.	S.E.
Public support:						
- Only regional	-0.127***	0.015	-0.076***	0.016	-0.128***	0.026
- Only national	-0.063***	0.015	-0.046***	0.016	-0.117***	0.025
- Only EU	-0.101***	0.026	-0.098***	0.027	-0.072*	0.039
- Regional and EU	0.012	0.032	0.041	0.035	0.106**	0.046
- National and EU	0.057**	0.027	-0.018	0.027	-0.001	0.049
- All types	0.142***	0.023	0.066***	0.022	0.323***	0.050
Subsidy intensity	-0.093***	0.026	-0.056**	0.024	-0.090**	0.037
Subsidy intensity squared	0.007*	0.004	0.006	0.004	0.014**	0.007
Size (t-1)	0.096***	0.014	-0.120***	0.016	-0.236***	0.031
Size squared (t-1)	-0.002	0.001	0.005***	0.002	0.014***	0.003
Age	0.027***	0.009	0.025***	0.009	-0.004	0.015
Exporter (t-1)	-0.005	0.011	-0.030**	0.012	-0.086***	0.018
Ownership structure:						
- Public capital	-0.052*	0.028	-0.008	0.030	0.171***	0.056
- Foreign capital	0.106***	0.021	0.067***	0.020	0.090***	0.022
- Domestic group	0.044***	0.011	-0.024**	0.012	0.004	0.021
Patent applications (t-1)	0.033***	0.009	-0.006	0.007	0.051***	0.014
Technological cooperation (t-1)	-0.110***	0.011	-0.120***	0.011	-0.053***	0.015
Human capital (t-1)	-0.030	0.021	-0.036	0.022	0.101***	0.037
R&D intensity (t-1):						
- Between 1% and 2.5%	0.057***	0.017	0.100***	0.016	-0.029	0.018
- Between 2.5% and 5%	0.100***	0.018	0.209***	0.017	-0.036*	0.019
- More than 5%	0.183***	0.017	0.370***	0.017	0.095***	0.019
Type of R&D activities (t-1):						
- Basic research	-0.011	0.015	0.034**	0.016	0.178***	0.031
- Applied research	-0.035***	0.011	-0.064***	0.011	-0.053***	0.020
- Technological development	-0.053***	0.012	-0.103***	0.013	-0.112***	0.023
Obstacles to innovation (t-1):						
- Financial factors	-0.031***	0.010	-0.005	0.010	-0.007	0.018
- Knowledge factors	0.003	0.011	0.001	0.012	0.015	0.022
- Market factors	-0.022**	0.010	0.026**	0.011	0.001	0.017
Activity sector:						
- P. trad. consumer goods	0.024	0.017	0.009	0.018	0.053**	0.022
- P. trad. intermediate goods	0.020	0.022	0.009	0.022	0.025	0.027
- Specialized suppliers	0.038*	0.019	-0.003	0.020	-0.001	0.023
- Scale-intensive	0.096***	0.019	0.040**	0.019	0.075**	0.030
- Science-based	0.075***	0.021	0.066***	0.022	0.012	0.025
- High-tech services	-0.003	0.014	0.066***	0.016	0.290***	0.035
Log likelihood	-5569.17		-5,212.86			
Observed probability	0.68		0.66			
Predicted probability	0.69		0.65			
Correct predictions	69.71		73.81			
Correct predictions: 1/0	75.42/62.79		81.14/60.35			
No. observations	10,090		10,090		10,090	

Notes: S.E: Robust standard errors. ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Marginal effects (*dy/dx*) are calculated at sample means. All estimates include the constant and time dummies. Excluded variables: Independent firm; Low-tech services and construction sectors; Firms with R&D intensity lower than 1%; and Firms with regional and national support.