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The Impact of Public Funding to Private R&D: Evidence from Spain

El impacto de las ayudas públicas a la I+D privada: Evidencia en España

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Resumen: El artículo analiza el impacto de las subvenciones públicas a la I+D privada en España. Evaluamos del programa de ayudas del Centro para el Desarrollo Tecnológico Industrial (CDTI) desde 2015 hasta 2020. El CDTI es el principal organismo público en España que concede ayudas públicas a las empresas para la realización de proyectos de I+D+i. Combinamos la información de las ayudas públicas del CDTI con el Panel de Innovación Tecnológica (PITEC) que integra la información de la encuesta sobre innovación y actividades de I+D+i de las empresas (Encuesta de Innovación). La muestra es un panel no balanceado que contiene 57.988 observaciones de las cuales 9.116 (16%) corresponden a empresas beneficiarias. Utilizamos un enfoque mixto de diferencias en diferencias con "propensity score matching" (DD-PSM) en su versión de "common support" para controlar algunos de los sesgos que ocurren al analizar los efectos causales. Encontramos que el apoyo público tiene efectos positivos en los recursos de I+D de

las empresas (es decir, la inversión interna en I+D y la creación de empleo) -adicionalidad de insumos- y cooperación -adicionalidad de comportamiento. Sin embargo, el impacto del apoyo público en los productos tecnológicos de las empresas varía considerablemente entre sectores, teniendo un efecto positivo limitado a los sectores de orientación tradicional.
Palabras clave: Evaluación de impacto; ayudas públicas; I+D privada; innovación; evaluación de políticas.
Abstract: The paper analyses the effects of public subsidies to private R&D in Spain. We carried out an evaluation assessment of the program aid of the Centre for the Development for Industrial Technology (CDTI) from 2015 to 2020. CDTI is the main public agency in Spain that grants public support for firms to carry out R&D projects. We combine information on public grants from CDTI with the Technological Innovation Panel (PITEC) that integrates information from the survey on innovation and R&D activities of companies (Innovation Survey). The sample is an unbalanced panel containing 57,988 observations of which 9,116 (16%) correspond to beneficiary companies. We use a mixed approach of Differences-in-Differences with propensity score matching (DD-PSM) in the common support to control for some of the biases that occur when analysing causal effects. We find that public support has positive effects on firms' R&D resources (i.e. internal R&D investment and job creation) - input additionality- and cooperation -behavioural additionality. However, the impact of public support on firms' technological outputs varies importantly across sectors, having a positive effect limited to traditional-oriented sectors.
Keywords: Impact assessment; public subsidies; business R&D; innovation; policy evaluation

1. INTRODUCTION

The need of providing public funds to support private R&D and of analysing its impact lies on several reasons. Governments devote, especially in developed economies, important amounts of public funds to encourage private R&D through different direct and indirect mechanisms, such as, subsidies, public procurement, loans, collaterals, or tax credits on R&D (e.g., EC, 2003). These public policies are partially justified based on market failures and the inability of companies to take ownership of all the benefits of R&D investments (knowledge spillovers), resulting in insufficient investment in relation to what is socially optimal (Arrow, 1962). Similarly, other goals of public innovation policy focus on changing the behaviour of companies towards innovation and increased collaboration. These goals translate into the analysis of different types of short- and long-term impacts or additionalities -input additionality, output additionality, and behavior additionality- (Cunningham et al., 2013). These benefits need to be aimed and achieved, while avoiding the negative consequences of public intervention, namely, market distortion or crowding-out effects that occur when public support for R&D substitute instead of complement for private R&D (David et al., 2000). The reviews on the impact of direct support to R&D and innovation in firms (e.g., OECD, 2006; Cunningham et al., 2013) show heterogeneous results across countries and even within countries.

After the economic crisis and the austerity measures applied, new concerns emerged, such as, the increasing intra-EU divide in R&D intensity and the failure of some EU countries, such as Spain, to catch-up (Veugelers, 2016). As a result, new objectives arose like the need of maintaining business R&D activity (Cunningham et al., 2013). Within a context of technological and economic change the need of designing and deploying more ambitious and sustainable innovation policies have gained strength. These new frames call for innovation policies to move from fixing market failures to creating new markets (e.g. Mazzucato, 2016) or to aim for a transformative change (Schot and Steinmueller, 2018). These changes and new frames make it necessary to reflect on the impact analysis of public support to private R&D and to envisage new evaluation practices and ways to integrate them with previous impact analysis.

With this background, we conducted an impact analysis of the public funding granted to private firms by the main innovation agency of SpainCentre for the Development for Industrial Technology (CDTI) over the period 2015-2020[1]. This paper presents the results of this impact evaluation, it reflects on the similarities and differences with previous evaluation practices and pinpoints the advantages of broadening the scope of impact evaluation practices.

The paper includes five sections. Section two presents the CDTI funding program. Section three describes the materials and methods used in the analyses. Section four presents the results of the descriptive and multivariate analysis. Last section concludes.

2. CDTI FUNDING PROGRAMMES

The Centre for the Development for Industrial Technology (CDTI) is the main public agency promoting private R&D. It is under the umbrella of the Ministry that holds R&D responsibilities. It was founded in 1979 following the experience of other OECD countries, with the support of the World Bank. It supports R&D through different programmes and mechanisms (CDTI, 2020). Regarding funding for R&D projects, CDTI uses two types of funding mechanisms: loans and subsidies.

The objectives of the centre range from: (1) increasing private expenditure on innovation in Spain; (2) promoting the development and business competitiveness by encouraging cooperation with other companies, research centres and other R&D stakeholders; (3) increasing the quality of R&D projects with a commercial approach and market-oriented; and (4) promoting the internationalization and technological cooperation, as well as exports and investments abroad.

The programs managed by the centre function well from a policy-making perspective (Fernández-Zubieta and Zcharewicz, 2016: 46). Its programs set priorities, include selection criteria, report results regularly their activities (e.g., CDTI, 2020); carry out monitoring exercises (e.g., CDTI, 2018); and publish other relevant exercises on the impact of R&D subsidies that tend to show positive input

[1] This work has been done in the framework of an evaluation contract - "Contrato de un servicio para la realización de un estudio de evaluación de impacto del régimen de ayudas a proyectos de I+D del CDTI" (2015-2020)-

additionality (e.g., Barajas et al, 2009; Huergo et al., 2009). The financial crisis of 2008 had an important impact on the Spanish R&D system as R&D investments are not seen as a counter-cycle mechanism (De No et al., 2018; Fernández-Zubieta and Zcharewicz, 2016). As a result, the CDTI has also suffered the consequences of the 2008 crisis. The national funding for the centre decreased by 39.15% between 2011 and 2010 and this funding in 2019 is still below the 2006 level (CDTI, 2020). Although we do not address specifically the consequences of the financial crisis on the analysis as we focus on the impact of one funding programme in the 2015-2020 period, it is important to take into account this institutional constraints.

As it is indicated in the following section, this paper focuses on the analysis of the Individual and Cooperative funding program (PID) that represent approximately 80% of the funding provided by the centre (CDTI, 2018). PID projects could last from 12 to 30 months, they have a minimum fundable budget of about 175,000 Euros. Beneficiaries are companies (PID individual projects) or consortium of companies (PID Cooperation projects). The funding modality is partially reimbursable aid, that could cover up to a 75% or 85% of the approved budget. The financial aid could include a non-reimbursable part from 10 to 33% that could vary depending on the characteristics of the project and beneficiary.

3. MATERIALS AND METHODS

3.1. Data and Samples

Quantitative information comes from the Technological Innovation Panel (PITEC) and from the CDTI in the 2010-2018 period. The technological innovation panel (PITEC) is a panel-type database that the National Institute of Statistics (INE) prepares annually with information from the survey on innovation and R&D activities of companies (Innovation Survey). This database lets us analyse the technological innovation activities of Spanish companies and their evolution. This database is complemented with the information provided by the CDTI that allows us to identify companies granted and to build suitable control groups – matched samples. This database is referred to as "PITEC-CDTI database" (see Diagram 1 and Diagram 2). Despite the yearly character of the Innovation Survey, the 2017 survey was not available in the PITEC database due to budgetary constraints at national level. Compared to other databases (i.e., the Iberian Balance Sheet Analysis System -SABI), the use of the PITEC database allows us to analyse a wide range of R&D&I activities, resources and results of firms across time.

The PITEC data includes variables relating to fifteen fundamental aspects for analysis: general data, type of innovation, product innovation, process innovation, organizational innovation, marketing innovation, non-successful innovation, R&D activities and expenditures, barriers to innovation and its effects, staff for innovation, cooperation, sources of information and access to knowledge for innovation, protection of the innovation results, and innovation objectives. With regard to the data from the CDTI, merged with PITEC, these include variables related to whether, during the analysed period, the company has finished a project granted from the CDTI and in which year the project granted was completed, and sectoral taxonomy (see Technical note in the Annex and Table A 1). Therefore, we neither can distinguish successful from unsuccessful CDTI applicants, nor firms that have been awarded but not completed the project granted by CDTI. Statistical confidentiality reasons made it difficult to include additional variables or categories. The inclusion of any additional variable to be merged with the PITEC database results in an important loss of information provided by the INE.

The PITEC-CDTI database (or full sample) is an unbalanced panel containing 57,988 observations. Of these, 9,116 (16%) correspond to companies that have received funding from the CDTI subsidy programs of Individual and Cooperative Projects (PID) (beneficiary companies) and finish their project granted and 48,882 (84%) correspond to non-beneficiary companies. PID represents approximately 80% of the CDTI's subsidies in the analysed period. The evaluation focuses on the PID program in order to reduce the potential biases of analysing different aid schemes. In addition, statistical confidentiality reasons made it difficult to include an additional variable identifying the different instruments implemented by CDTI from the INE. The inclusion of any additional variable to be merged with the PITEC database results in an important loss of information provided by the INE.

From the full sample, we extract three matched samples that allow us to:

(I) carry out the final evaluation (matched sample of the final evaluation);

(II) to compare results with the mid-term evaluation (matched sample of the mid-term evaluation);

(III) and to forecast some results for 2017 and 2018 (prospective matched sample).

We implemented this three-matched sample approach instead of a one-matched sample approach for two main reasons. Firstly, the information for the prospective matched sample is limited compared to the other two samples. Secondly, the three-matched samples allow us to increase the comparison points over the required period to be evaluated (2015-2020). Diagram 1 and Diagram 2 provide information about these samples. It has to be noted that the technical specification of the evaluation call required us to carry out a mid-term evaluation and a final evaluation.

In order to build the first two matched samples, we consider companies that have finished a CDTI project in 2015 and 2016 and follow their activities from 2012 and 2013 onwards (up to 2016), respectively. This allows us to compare the situation of these companies before and after the treatment – being granted by CDTI (see next section). The prospective matched sample considers firms that have finished a CDTI project in 2017 and 2018, but we follow their activities up to 2016. Therefore, we have information for these latter firms before the treatment, but we are not able to track them until finishing the project (after the treatment). Despite this limitation, the prospective matched sample allows us to provide some results for firms that have finished a CDTI project in 2017 and 2018. However, the comparison points for these firms are different: "before" and "in the middle" of the treatment. The lack of information for 2016 onwards from the PITEC database, forces us to look for this "prospective" strategy.

Diagram 1. Summary of the approach and databases used (source: Own compilation)

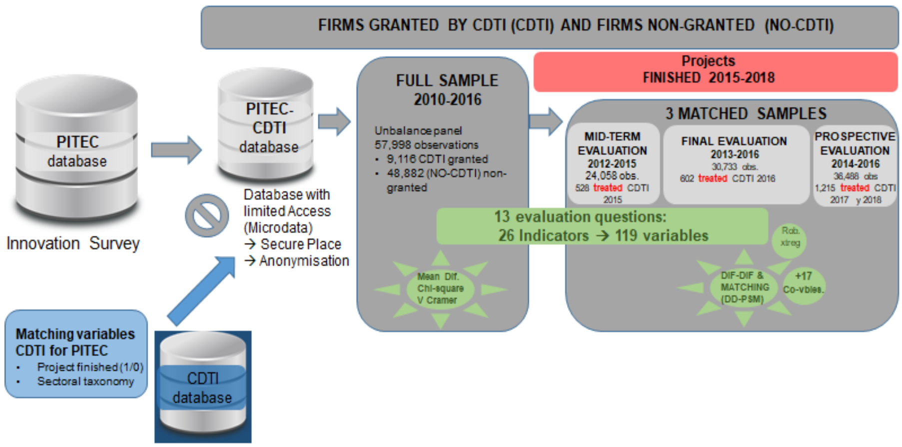
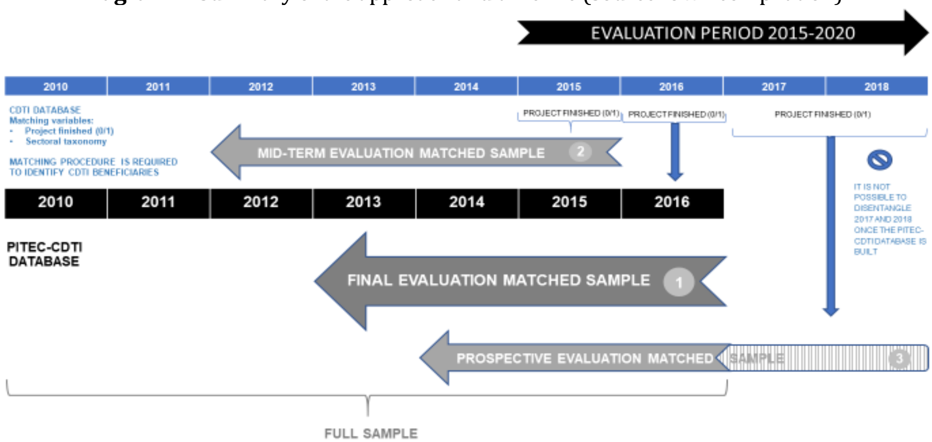


Diagram 2. Summary of the approach and timeline (source: Own compilation)



3.2. Methods and Variables

The quantitative methods include descriptive and multivariate statistics that vary across full and matched samples.

Over the full sample we use a more descriptive approach. We calculate mean differences, percentages and provide graphic representation over time across beneficiary (CDTI) and non-beneficiary firms (NO-CDTI) in order to summarize the behaviour of these two sets of firms.

The methodology applied to build and analyse the matched samples aims to control some of the biases that occur when analysing the results with a more descriptive approach. Firms that received grants from CDTI could, for example, have specific characteristics (i.e. they could be bigger than an average Spanish firm) or could operate in specific markets that could explain the increased performance observed across indicators and over time when analysing the full sample. More specifically, the evaluation faces the problem of econometric evaluation using not-experimental data in which there are no data on the counterfactual situation (what would the company have done if it had not received the subsidy?) and that summarizes the problems of selection bias and endogeneity that could lead to an attribution of effects of public subsidy that are not adjusted. Among the methods to resolve this problem, indicated by the literature (e.g. Heckman et al. 1999, Blundell and Costa Dias, 2000), and in light of the lack of experiments, the alternatives focus on the use of quasi-experimental methods (e.g. cross-sectional matching), use of instrumental variables (IV), selection models ("control function approach") and conditional estimates of Differences-in-Differences (conditional) (DD or DIF-DIF), which require panel data. Although the matching methods do not require assumptions on the form of the functions, they are sensitive to the unobserved effects (Heckman et al., 1999). The use of instrumental variables allows us to deal with the unobserved effects, but it is difficult to find suitable IV. The selection models take into account the observed and unobserved effects, but they need the application of instrumental variables and impose assumptions regarding the form of the equation.

Due to the difficulties in finding a suitable IV, we use a mixed approach of Differences-in-Differences with matching (Villa, 2016) – double difference combined with propensity score matching (DD-PSM) in the common support (see box for more details on the DD-PSM estimation framework)- that allows us to consider parametric, semi-parametric and covariate versions. In this sense, several recent articles use the methodology employed (e.g. Bakucs et al., 2018; Cerulli, 2015; Cummins et al., 2014; Ferraresi et al., 2018; Ibanez and Blackmanb, 2016; Méndez et al., 2016; Olitsky and Cosgrove, 2016). This method allows to establish causal inferences with non-experimental data and deal with the unobserved heterogeneity that does not vary over time. To control the heterogeneity observed, we have considered a series of control variables that enable us to explain the probability of being treated (in this case, completing a project with CDTI funding).

In this sense, the variables considered were: size, turnover, age, to belong to a group, sectoral taxonomy, to be a R&D performer in a continuous way, to perform fundamental research, to carry out technological development, market structure (to be dominated by established companies), two variables that indicate if the company faces liquidity constraints, internal or external, the type of company ownership (foreign), if it is oriented towards a foreign market, or if it is an SME. These covariates are intended to control the various factors that may influence the likelihood of obtaining funding from the CDTI and carrying out R&D activities: including the structure and characteristics of the companies, the market structure, financial constraints, type of ownership, technological opportunities or orientation towards the external market. The covariates were used to estimate the probability of being treated "propensity score" and calculate the weights with a kernel estimate (Heckman et al., 1997, 1998), which, instead of building a control group with a limited number of units similar to those treated, used as a matching the entire control sample according to the "propensity score". The method uses a probit estimation to predict the probability of being treated ("propensity score") and then calculates the "kernel matching". In addition, we restrict the DD-PSM estimation to the common support of the propensity score for treated and control groups in order to increase the internal validity of the DD-PSM estimation (see box on the DD-PSM estimation framework in the Annex).

Therefore, we use a double difference (DD) method refined with a propensity score matching (PSM) (DD-PSM) on the common support. We use PSM with the baseline data to be sure that the comparison, or control, group is similar to the treatment group and, then, we apply double differences to the matched sample (see section 4.2.1 the results of the quality of the balance before and after the matching). Then, the observable heterogeneity in the initial conditions can be dealt with. Following this approach, the criteria indicated in the previous section, we build three matched samples (see Diagram 1 and Diagram 2).

Matched sample of the mid-term evaluation. It includes firms that have finished a project granted by CDTI – our treatment- in 2015 (the starting year of the evaluation period 2015-2020). We follow the activities of these companies ("treated") and their matches ("controls") from 2012 to 2015 in order to be able to compare pre-treatment and post-treatment conditions. The average treatment lasts two years. This matched sample allows us to compare the results of the mid-term evaluation with the final evaluation.

This paper includes the results on thirteen variables.

Matched sample of the final evaluation. Following the same procedure, this sample includes firms that have finished a project granted by CDTI in 2016 (the last year with available information in the PITEC-CDTI panel). We follow the activities of these treated firms and their controls from 2013 and 2016. This matched sample is the core of the final evaluation in which we apply the indicated approach (DD-PSM) and additional tests (e.g., robustness checks).

Over this core evaluation sample, we apply the general approach and the following additional analysis:

We calculate DD-PSM with and without robust standard errors to get results for the 26 indicators requested in the evaluation for which we calculate a total of 119 variables.

We select 12 indicators taking into account the previous results and the strategic character of the indicator and perform additional analysis (For a definition of these indicators see Table A II in the Annex). With these indicators we:

• perform a DD-PSM across sectors -Traditional, Dynamic, Stationary, and Challenges- to assess heterogeneous effects. Construction sector was not considered due to the lack of observations that created anonymity problems with the results (see next table).

• check the consistency of the results when covariates are considered across the treatment period (not only at the baseline year). We use the xtreg stata module. We perform Hausman tests on each 12 indicators-variables and we present the fixed effect or random effects model, accordingly.

Prospective matched sample. It includes firms that have finished a project granted by CDTI in 2017 and 2018. We follow the activities of these companies ("treated") and their matches ("controls") from 2014 to 2016 (last year available in the PITEC-CDTI panel). Therefore, in this sample we compare the conditions before the treatment with the conditions in the middle of the treatment. We consider projects finished in 2017 and 2018 jointly in order not to decrease the number of observations in the merging process of the PITEC-CDTI database due to statistical confidentiality rules (see Diagram 2). Despite this limitation, this approach allows us to forecast some results for projects granted in 2017 and 2018.

Despite the controls applied in the second approach (control samples), several limitations remain. In the first place, the limitations of the original sample (PITEC) that, for example, cannot be considered to be representative for companies with less than 10 employees and which has suffered modifications in its sampling strategy. Secondly, the limitations of the cross-sample (PITEC-CDTI) to safeguard the anonymity, INE limits the use of variables for building the cross-sample (see previous section). For example, we could not use geographical data of firms. Similarly, it prevents the disaggregation of the variables. For example, the sectoral taxonomy was reduced to increase the number of observations (see Technical note in the Annex and Table A 1). In addition, the final cross-sample eliminates observations with the additional aim of safeguarding anonymity. These limitations prevent a more detailed characterization of the beneficiary companies and of those that have completed projects. It was also impossible to take into account the difference between the probability of applying for a subsidy and receiving it, or the difference between the probability of receiving a subsidy and finishing the project granted. However, and despite these limitations, we have used probably the best available database (PITEC-CDTI). CDTI does not rank the unsuccessful applicants, making it impossible to use this information in order to build a natural control group of beneficiary companies. Thirdly, the methodology used, although it controls part of the possible biases, does not allow to control for unobserved heterogeneity that changes over time. As mentioned, this last point is the main drawback of the methodology applied. However, as indicated above, selection models would have required the use of instrumental variables. The lack of information regarding possible instruments (e.g., number of projects won by a firm, Lichtenberg, 1988; Wallsten, 2000) in the database and other limitations of alternative approaches favoured our chosen methodological approach. In any case, the relatively short period of time considered in our DD-PSM approach decreases the possibilities of expecting unobserved dynamic responses of firms (behavioural and choices of targeted firms) to the funding (treatment). In addition, qualitative information did not indicate the presence of conditions (or macroeconomic changes) where treated and control groups would respond differently. Similarly, qualitative information did not indicate the presence of other unobserved characteristics that could be correlated with treatment placement. Therefore, selection biases due to unobserved characteristics that change over time appear not to be very serious in the context of this evaluation.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

As has indicated, the full sample is an unbalanced panel made up by a total of 57,988 observations, of which 9,116 (16%) belong to the CDTI beneficiary companies and 48,882 (84%) to the rest of companies (non-beneficiaries) for the 2010-2016 period.

Beneficiary firms tend to be more innovative than non-beneficiary firms. For example, most beneficiary firms tend to carry out R&D internally, while this is not the case for non-beneficiaries. Figure 1 shows that around 70 and 80 percent of beneficiaries carried out R&D internally in the 2010-2016 period, while around 30 and 40 percent of non-beneficiary firms did so in the same period. This clearly shows that firms' characteristics need to be controlled in order to assess the impact of public support on R&D.

The distribution of observation across sectors is shown in Figure 2. The beneficiary companies are more concentrated in certain sectors, particularly in the dynamic and stationary ones, while the non-beneficiary companies have greater presence in the traditional sector. 40% of the beneficiary companies are concentrated in the dynamic sector compared to 27% of the non-CDTI (3,611 CDTI observations compared to 13,079 non-CDTI). The stationary sector concentrates 25% of the beneficiary companies compared to 17% of the non-CDTI (2,283 CDTI observations compared to 8,48 non-CDTI). On the other hand, the traditional sector represents 36% of the non-beneficiary companies compared to 15% of the CDTI companies (17,788 observations of non-beneficiary companies compared to 1,1361 of the CDTI observations) (Figure 2). Sectoral differences are controlled in the matching samples by including the sectoral taxonomy in the list of covariates (see Technical note in the Annex and Table A 1).

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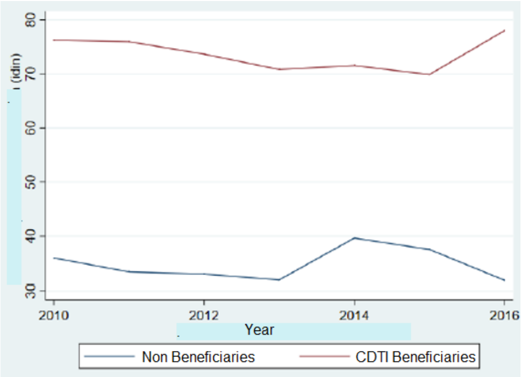

Figure 1. Percentage of beneficiary companies and non-beneficiary companies that by carry out R&D internally 2010-2016 (source: Own compilation)

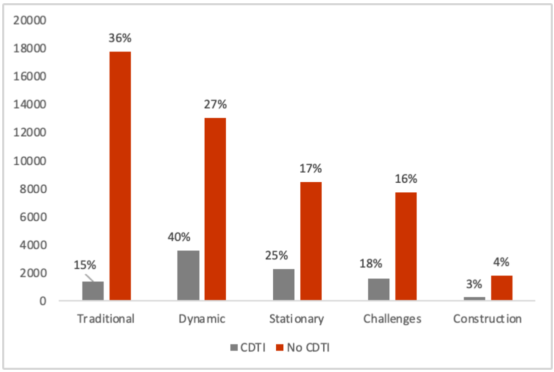

Figure 2. Total number of observations of beneficiary companies and non-beneficiary companies by sectoral taxonomy, expressed in numerical terms (left axis) and relative percentage (tags) (source: Own compilation)

4.2. Multivariate Analysis

Likelihood of Being Treated and Matching Procedure

Before matching, in the full sample there are 57,988 observations of which 16% belong to CDTI beneficiary companies for the 2010-2016 period. Treated group (firms that have finished a project in 2016) consists of a set of observations that are matched with firms that are equivalent but have not received funds from CDTI. This section presents the results of the likelihood of being treated (propensity score) and assesses the quality of the matching procedure of our approach.

Table 1 presents the results of the probability of being treated estimated with a probit model across samples. Regardless of the samples, being a continuous R&D performer increases the likelihood of being treated. Continuous R&D performers appear to have specific experience and skills that might allow them to apply and finish a CDTI project. This result is consistent with previous results, such as, Czarnitzki and Hausinger (2004), Huergo et al. (2016) and Barajas et al. (2017). Firms with foreign capital have lower probability of being treated, similarly to previous evidence (Huergo and Moreno, 2017 and Barajas et al., 2017). However, exports (lexportt_eu) increases the probability of being treated. This result is also consistent with previous findings (e.g., Barajas et al., 2017). It appears that domestic firms are more prone to apply and finish a CDTI project than foreign firms, but the international experience of firms appears to provide the skills or the need to access to a CDTI program. In addition, the probability of being treated for the final evaluation sample increases for firms that present higher turnover, carry out technological developments; and firms that face internal liquidity constraints, but decreases for firms that belong to a group and face external liquidity constraints. These effects are quite similar considering the prospective evaluation sample, but there is a loss of significance for variables, such as belonging to a group. The probability of being treated is significantly higher for the final sample for firms belonging to dynamic or challenge sectors than to firms belonging to the traditional sector. The lower number of observations considered in the estimation used in the mid-term evaluation might explain some inconsistencies across samples.

Table 1. Probability of being treated (propensity score matching) by samples (source: Own compilation)

	MID-TERM EVALUATION SAMPLE			FINAL EVALUATION (2013-2016)			PROSPECTIVE SAMPLE (2017-2018)		
ltamano	0,041		(.060)	-0,014		(.038)	-0,030		(.029)
lcifra	0,076		(.054)	0,127	***	(.035)	0,052	*	(.028)
edad	-0,004	**	(.002)	-0,001		(.001)	0,002	**	(.001)
grupo	-0,053		(.078)	-0,155	***	(.055)	0,005		(.040)
tradicional	-0,172		(.131)				-0,164	***	(.061)
dinamico	0,057		(.087)	0,395	***	(.080)	0,073		(.047)
estacionario	0,161	*	(.093)	0,392		(.079)	0,162	***	(.049)
reto				0,341	***	(.084)			
idcont	0,183	**	(.091)	0,710	***	(.056)	0,475	***	(.041)
infun	0,000		(.003)	-0,002		(.003)	0,001		(.002)
destec	0,001		(.001)	0,001	**	(.001)	0,004	***	(.000)
mdodom	0,151	*	(.078)	-0,033		(.024)	-0,015		(.018)
fcinter	-0,083		(.082)	0,130	***	(.032)	0,093	***	(.025)
fcexter	0,202	**	(.080)	-0,175	***	(.031)	-0,142	***	(.024)
extranjera	-0,413	***	(.102)	-0,313	***	(.068)	-0,443	***	(.055)
lexportt_eu	0,063	**	(.026)	0,063	***	(.019)	0,107	***	(.015)
pyme	-0,113		(.116)	-0,113		(.079)	0,256	***	(.064)
cons	-4,275	***	(.575)	-5,140	***	(0.375)	-4,449	***	(.575)
Log. Likelihood	-901,24			-1832,40			-3.272,38		
Pseudo R2	0,0607			0,1557			0,1315		
Num. Observations	4168			14654			17894		

*** p<0,01; ** p<0,05; * p<0,1. Standard Errors in brackets

We assess the matching quality by testing: the standardized biases (Rosenbaum and Rubin, 1985); the difference of means (t-test) (Rosenbaum and Rubin, 1985); and the Pseudo R2 (Sianesi, 2004) before and after matching the limited sample (Table 2 and Table 3). The different tests indicate that the matching procedure is able to balance the distribution of the covariates quite well in both the control and treated group. The standardized biases of the different covariates (% bias) are quite high before matching, but quite low after the matching procedure, being "estacionario" the variable with the highest percentage biases (-11.1) (Table 2). Accordingly, the difference of means before matching is statistically significant at 0.001 p-level, while any of the covariates shows this significance level after matching. Variance ratios are "of concern" for eight variables before matching –edad, tradicional, idcont, destec, fcinter, fcexter, lexportt_eu; pyme-, but only one after the matching procedure –infun. It could be noted that variance ratios of all sectoral variables are not "of concern" after the matching procedure. Finally, Table 3 shows a close to zero Pseudo-R2 after matching, suggesting that the covariates do not explain the probability of participation well after matching. See Tables in the Annex (Table A III, Table A IV, Table A V and Table A VI for the results of the tests for the mid-term and prospective matched samples, indicating similar balances after matching (i.e. low pseudo-R2), but less optimal (i.e. three variables with "of concern" variance ratio after matching).

In addition, balance and density plots of the propensity scores before and after matching (Figure 3 and Figure 4). The graphs confirm that our approach balances the covariates (see Figure A I and Figure A II in the Annex for the balance boxes and density plots on the mid-term and prospective samples).

Table 2. Balancing test. Mean differences (Final evaluation matched sample) (source: Own compilation)

Variable	Unmatched Matched	Mean				T-Test		
		Treated	Control	% bias	%Reduction bias	t	p>|t|	V(T)/VI)
Final evaluation sample								
ltamano	U	4.84	4.00	52.1		15.59	0.000	0.82
	M	4.84	4.88	-2	96.1	-0.53	0.594	0.98
lcifra	U	17.08	15.64	70.8		21.74	0.000	0.83
	M	17.08	17.19	-5.3	92.5	-1.33	0.184	0.94
edad	U	34.43	29.15	24.4		8.28	0.000	1.25*
	M	34.43	32.91	7	71.2	1.63	0.104	1.21
grupo	U	0.57	0.41	31.7		10.57	0.000	0.97
	M	0.57	0.58	-2	93.6	-0.46	0.645	1.04
tradicional	U	0.11	0.38	-67.6		-18.98	0.000	0.50*
	M	0.11	0.08	7.3	89.3	2.32	0.02	1.08
dinamico	U	0.37	0.28	19.6		6.78	0.000	1.1
	M	0.37	0.33	8.2	58.3	1.82	0.069	0.97
estacionario	U	0.32	0.18	32.6		12.01	0.000	1.18
	M	0.32	0.36	-11.1	65.9	-2.29	0.022	0.89
reto	U	0.21	0.16	11.6		4.03	0.000	1.04
	M	0.21	0.23	-5.2	55	-1.12	0.264	0.95
idcont	U	0.78	0.26	119.5		38.74	0.000	0.80*
	M	0.78	0.82	-9	92.5	-2.18	0.03	0.93
infun	U	1.84	1.01	13		4.38	0.000	0.98
	M	1.84	1.78	1	92.3	0.2	0.839	0.76*
destec	U	49.37	17.68	84.4		30.14	0.000	1.33*
	M	49.37	50.35	-2.6	96.9	-0.54	0.586	0.85
mdodom	U	2.40	2.75	-34.6		-10.9	0.000	0.8
	M	2.40	2.43	-2.7	92.2	-0.65	0.514	0.9
fcinter	U	2.22	2.33	-10.2		-3.13	0.002	0.77*
	M	2.22	2.25	-2.6	74.5	-0.65	0.518	0.96
fcexter	U	2.14	2.45	-27.7		-8.47	0.000	0.74*
	M	2.14	2.16	-1.6	94.3	-0.39	0.699	0.82
extranjera	U	0.14	0.13	1.5		0.5	0.619	0.81
	M	0.14	0.14	-0.7	51.7	-0.16	0.872	1.03
lexportt_eu	U	15.90	14.47	62.7		18.14	0.000	0.77*
	M	15.90	15.99	-4	93.7	-0.9	0.366	0.98
pyme	U	0.68	0.79	-24.7		-8.78	0.000	1.39*
	M	0.68	0.69	-3.9	84.1	-0.85	0.397	1

* ‘f 'of conc’rn', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]

Table 3. Overall measures of covariate balancing (Final evaluation matched sample) (source: Own compilation)

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%concern	%bad
Unmatched	0.163	1305.98	0.00	40.5	31.7	131.3*	0.65	47	0
Matched	0.004	9.47	0.89	4.5	3.9	14.1	0.87	6	0

* if B>25%, R outside [0.5; 2]

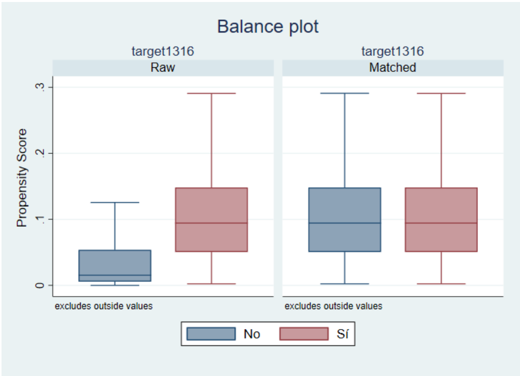

Figure 3. Balance plot before and after matching propensity score (Final eval. matched sample) Note: Outliers were excluded for anonymity reasons (source: Own compilation)

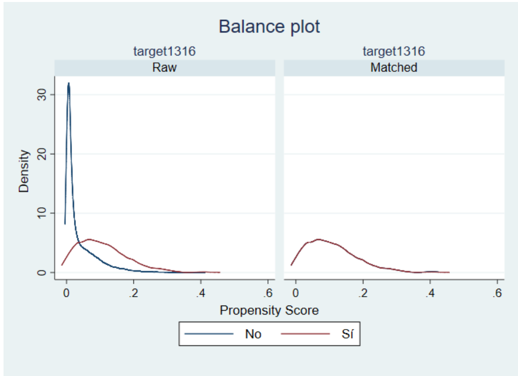

Figure 4. Density plot before and after matching propensity score (Final evaluation matched sample) (source: Own compilation)

Results after matching

Table 4 includes results of the double difference combined with propensity score matching (DD-PSM) analysis for the three matched samples (mid-term, final and prospective evaluation samples) for a selected number of indicators. In addition, Table 4 includes additional results for the final evaluation matched sample, including results of the DD-PSM with robust standard errors and DD-PSM results across the sectoral taxonomy.

The different columns across matched samples indicate:

Baseline. Considers the situation of beneficiary companies (treated) and non-beneficiary companies (control) at the beginning of the period. A positive sign (+) indicates that treated companies outperform their controls in the corresponding indicator. A negative sign (-) indicates the reverse situation. Significant results are indicated in bold. Colours aim to facilitate the reading of the table: green indicates a positive and significant difference (T-C); red indicates a negative and significant relationship, while yellow corresponds to non-significant positive or negative results of the treated versus control difference.

Follow-up. Shows the difference of the treated versus controls companies at the end of the period considered for the different indicators.

Diff-Diff. This shows whether the evolution of the beneficiary companies regarding the non-beneficiaries has been better (+) or the worse (-). Bold font and colours follow the pattern indicated above.

Table 4. Difference in difference results across mid-term, final, and prospective evaluation matched samples for selected indicators (DD-PSM) (source: Own compilation)

			MID-TERM EVALUATION TREATED - CONTROL			FINAL EVALUATION (2013-2016) TREATED - CONTROL						PROSPECTIVE EVALUATION (2017-2018) TREATED - CONTROL		
			BASELINE	FOLLOW-UP	DIFF-DIFF	BASELINE	FOLLOW-UP	DIFF-DIFF	Robust	TAXONOMY	DIFF-DIFF	BASELINE	FOLLOW-UP	DIFF-DIFF
	Indicator I1: Companies that decide to invest in R&D													
3	idin	Internal R&D expenditure	(-)***	(+)***	(+)***	(+)***	(+)***	(+)***	R(***)	Traditional Dynamic Stationary Challenges	(+)*** (+)*** (+)*** (+)***	(+)***	(+)***	(+)***
16	esfgintidtam	Effort in internal R&D expenditure (staff)	(-)**	(-)	(+)	(+)***	(+)***	(+)***	R(**)	Traditional Dynamic Stationary Challenges	(+)*** (+)*** (+)*** (+)***	(+)***	(+)***	(+)*
	Indicator I2: Expenditure on innovation as a percentage of the turnover/staff													
44	esfinntam	Total effort in innovation (staff)	(-)**	(+)	(+)**	(+)***	(+)***	(+)	R	Traditional Dynamic Stationary Challenges	(+) (-) (+)*** (+)**	(+)	(+)	(-)
	Indicator I3: Companies that have created jobs in R&D													
46	creaempid	Has created jobs in R&D with respect to t-1	(-)	(+)*	(+)**	(+)***	(+)***	(+)***	R(***)	Traditional Dynamic Stationary Challenges	(+)*** (+)*** (+)*** (+)***	(+)***	(+)***	(+)***
	Indicator I5: Companies that develop product innovations													
52	innprod	Product innovation from (t-2) to t	(-)	(-)	(-)	(+)***	(+)***	(+)	R	Traditional Dynamic Stationary Challenges	(-) (+)* (-)* (+)	(+)***	(+)***	(+)
	Indicator I6: Companies that develop process innovations													
53	innproc	Process innovation from (t-2) to t	(-)	(+)***	(+)*	(+)***	(+)***	(+)	R	Traditional Dynamic Stationary Challenges	(+)*** (-) (+) (-)	(+)*	(+)***	(+)***
	Indicator I9: Companies that patent													
63	pat	Patent application	(+)***	(+)***	(-)	(+)***R	(+)***R	(+)**		Traditional Dynamic Stationary Challenges	(+)*** (+) (+) (+)	(+)***	(+)***	(-)
	Indicator I10: Number of patents registered													
65	patnum	Number of patent applications	(-)	(+)	(+)	(+)R***	(+)R**	(-)		Traditional Dynamic Stationary Challenges	(+)*** (+)** (-)** (-)	(+)*	(-)	(-)**
	Indicator I19: Companies that cooperate with research centres													
99	coopcentro	Number of partnerships with research centres	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***	R(**)	Traditional Dynamic Stationary Challenges	(+)*** (-) (+)*** (+)***	(+)***	(+)***	(+)***
100	coopcentroNAC	Number of partnerships with national research centres	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***	R(**)	Traditional Dynamic Stationary Challenges	(+)*** (+) (+)*** (+)***	(+)***	(+)***	(+)***

	Indicator I25 diversity in the network of cooperation													
107	divcoopINT	No. of international partnerships Outside of the group	(-)*	(+)***	(+)***	(+)***	(+)***	(+)***	R(*)	Traditional Dynamic Stationary Challenges	(+)*** (+) (+)*** (+)	(+)***	(+)***	(+)***
	Indicator I26: Companies that find alternative sources of funding [to the company:f1 (own funds); the group: f2 (other group companies); and subsidy: f5 (AGE grants) and													
117	otrafina	Has obtained alternative financing	(+)***	(+)***	(+)*	(+)***R	(+)***R	(+)***		Traditional Dynamic Stationary Challenges	(+)*** (+)** (+)*** (-)**	(+)***	(+)***	(+)*
119	divotrafina	Diversity index alternative financing	(+)**	(+)	(-)	(+)	(+)***	(+)***	R(***)	Traditional Dynamic Stationary Challenges	(+)*** (+)** (+)*** (+)***	(+)	(+)***	(+)***

Note:* p<0.1, **p<0.05, *** p<0.01. Significant results are indicated in bold. Green colour indicates a positive and significant difference (T-C); red indicates a negative and significant, while yellow corresponds to non-significant positive or negative results.

In addition, Table 5 and Table 6 provide some outcome variable means and impact measures for the list of selected indicators across matched samples (mid-term, final and prospective evaluation samples. The difference of the results when using the full sample (without controlling some biases) and the matched samples is important. For example, full sample indicated that beneficiary firms tend much more frequently than non-beneficiary firms to carry out R&D activities internally (idin) (73,44% against 33,94%) for the whole period (see Figure 1). This difference of about forty percentual points could be partially explained by the characteristics or behaviour of the beneficiary companies, the market structure in which firms operate, etc. When we consider these covariates (balance the distribution of the covariates across treated and control groups), beneficiary companies tend to carry out R&D activities more often than non-beneficiaries, but to a lesser extent (87% against 77% at the baseline of 2013) (see Table 5). This is generally the behaviour for all the selected indicators at the baseline (2013) and follow-up (2016) of the final evaluation. Table 6 provides impact values of the difference-in-differences, being idin, creaempid, coopcentro, divcoopINT, otrafina the variables with positive, significant and consistent results cross matched samples. For example, the results of R&D expenditures (idin) indicate that firms that have received CDTI funding increased the likelihood of carrying out internal R&D activities by 13 percentual points compared to their controls in the 2013-2016 period. Results on cooperation (Coopcentro) indicate that beneficiary firms increase the number of partnerships with research centres by about 0.26 [Final Evaluation sample], becoming more internationally oriented in their cooperation with research centres. The total value of this variable for 2016 is 1.189 indicating that collaboration remains on mainly at national level (see Table 5). Similarly, results considering the international and outgroup collaboration of firms (divcoopINT) indicate that beneficiary firms increase the number of international partnerships outside the group by about 0.3 [Final Evaluation sample], diversifying international partnerships. However, the total number of international partnerships outside the group is low. Considering other alternative funding sources (otrafina), beneficiary firms increase the probability of using alternative funding sources by 5 percentage points.

Table 5. Outcome variable means, treated (CDTI) and control (NO-CDTI) for selected indicators (source: Own compilation)

			2013		2015		2016		Prospective (2017-2018)	
			Treated (CDTI)	Control (NO CDTI)	Treated (CDTI)	Control (NO CDTI)	Treated (CDTI)	Control (NO CDTI)	Treated (CDTI)	Control (NO CDTI)
	R&D and innovation resources									
	R&D expenditure and R&D effort									
3	idin	Internal R&D expenditure	0.87	0.77	0.908	0.827	0.928	0.694	0.862	0.664
16	esfgintidtam	Effort in internal R&D expenditure (staff)	11,000.00	6,221.92	6,600.00 (&)	7,000.00 (&)	15,000.00	5,734.21	6,949.96	5,384.32
44	esfinntam	Total effort in innovation (staff)	26,000.00	8,827.06	9,307.57	8,975.05	26,000.00	8,521.94	8,613.68	8,224.55
	R&D job creation									
46	creaempid	Has created jobs in R&D with respect to t-1	0.743	0.562	0.344	0.315	0.706	0.384	0.653	0.386
	Innovation results									
	Product and process innovation									
52	innprod	Product innovation from (t-2) to t	0.795	0.656	0.689	0.695	0.765	0.624	0.684	0.594
53	innproc	Process innovation from (t-2) to t	0.705	0.62	0.616	0.575	0.648	0.555	0.566	0.514
	Patenting activity									
63	pat	Patent application	0.243	0.17	0.222	0.174	0.247	0.146	0.204	0.129
65	patnum	Number of patent applications	2.11	1.025	1.406	1.384	2.678	1.867	0.939	1.163
	Other results									
99	coopcentro	Number of partnerships with research centres	0.881	0.625	0.939	0.542	1.189	0.67	0.966	0.641
107	divcoopINT	No. of international partnerships Outside of the group	0,749	0.55	0.832	0.584	1.117	0.676	0.945	0.611
117	otrafina	Has obtained alternative financing	0.266	0.162	0.23	0.143	0.296	0.143	0.211	0.123
119	divotrafina	Diversity index alternative financing	148.56	141.958	149.129	129.174	243.728	128.547	185.468	113.984

(&): estimated values for 2015

Overall, we find getting CDTI funding for R&D has clearly a positive effect on R&D resources (input additionality): R&D expenditures (idin) and job creation (creaempid), with robust and positive results across samples and sectors. We also find positive results on cooperation (behavioral additionality) (coopcentro) and positive indirect results on collaboration (divcoopINT) and the use of alternative funding (otrafina), although the last one is not significant in the robust estimation due probably to the negative effect on the challenge sector. However, the results are less clear for innovation results (output additionality). The heterogeneous effects across sectors appears to partially explain the lack of results on output additionality (see Table 4). The impact on product innovation varies across sectors, being positive and significant for dynamic and negative for stationary sectors (innprod). The positive impact on process innovation (innproc) is limited to the traditional sector. Regarding patenting activity (pat) we find positive results for the final evaluation sample. This result is not confirmed in the robust specification and it is not consistent across samples. We also find a heterogeneous effect across sectors on patent number, being positive for traditional and dynamic sectors, but negative for stationary ones. These positive results of public grants on input additionality and lack of significance on the company's economic performance is consistent with previous literature at national (e.g. Barajas et al., 2017) and international level (e.g. Czarnitzki and Delanote, 2017). These results on the CDTI aid scheme have been quite consistent through the different reviews and evaluation processes across the years which indicates that the CDTI support scheme for R&D projects works. However, it is necessary to study more in detail the heterogeneous effects of the aid across sectors. Similarly, the consistency of the positive and less positive results might indicate that the centre could aim at addressing new measures to consider the so-called third frame for innovation policy (Schot and Steinmueller, 2018), which calls for transformative changes linked to social and environmental challenges. The openness to different types of failures (e.g. reflexivity failure), its experimental character and the use of a deliberative process needed for a transformative change might help to envisage new paths and evaluation objectives.

Table 6. Impact values for selected indicators (source: Own compilation)

			MID-TERM EVALUATION DIFF-DIFF	t-ratio	FINAL EVALUATION (2013-2016) DIFF-DIFF	t-ratio	Time Series	PROSPECTIVE EV. (2017-2018) DIFF-DIFF	t-ratio
R&D and innovation resources									
R&D expenditure and R&D effort									
3idin	Internal R&D expenditure		0.131	11.08	0.132	12.85		0.105	9.11
		Std. Errors	(0.012)***		(0.01)***		YES **	(0.012)***	
					0.125	6.12			
		Robust Std. Errors			(0.020)***				
16esfgintidtam	Effort in internal R&D expenditure (staff)		590.00(&)	0.88	4455.343	5.86		701.89	1.84
		Std. Errors	(660)		(760.940)***		YES ***	(381.939)	
					4455	2.03			
		Robust Std. Errors			(2193.183)**		YES **		
44esfinntam	Total effort in innovation (staff)		2001	2.07	519.447	0.17		-387.692	-0.34
		Std. Errors	(965.322)**		(3109.888)			(1145.164)	
					889.826	0.1			
		Robust Std. Errors			(8885.983)				
R&D job creation									
46creaempid	Has created jobs in R&D with respect to t-1		0.048	2.21	0.141	9.67		0.075	4.84
		Std. Errors	(0.022)**		(0.015)***		YES *	(0.016)***	
					0.138	4.09			
		Robust Std. Errors			(0.034)***		YES *		
Innovation results									
Product and process innovation									
52innprod	Product innovation from (t-2) to t		-0.002	-0.1	0.002	0.16		0.006	0.43
		Std. Errors	(0.020)		(0.012)		YES *	(0.014)	
					0.012	0.45			
		Robust Std. Errors			(0.028)				
53innproc	Process innovation from (t-2) to t		0.042	1.96	0.008	0.57		0.038	2.67
		Std. Errors	(0.022)*		(0.013)		YES *	(0.014)***	
					0.006	0.19			
		Robust Std. Errors			(0.031)				
Patenting activit									
63pat	Patent application		-0.007	-0.39	0.029	2.56		-0.016	-1.47
		Std. Errors	(0.019)		(0.011)**			(0.011)	
					0.031				
		Robust Std. Errors			(0.029)				
65patnum	Number of patent applications		0.066	0.16	-0.274	-0.65		-0.424	-2.03
		Std. Errors	(0.402)		(0.422)		YES *	(0.208)**	
					-0.261	-0.23			
		Robust Std. Errors			(1.131)				
Other results									
99coopcentro	Number of partnerships with research centres		0.271	5.48	0.263	5.7		0.157	3.59
		Std. Errors	(0.049)***		(0.046)***		YES ***	(0.044)***	
					0.24	2.4			
		Robust Std. Errors			(0.100)**		YES ***		
107divcoopINT	No. of international partnerships Outside of the group		0.246	3.38	0.241	3.79		0.193	3.18
		Std. Errors	(0.073)***		(0.064)***		YES ***	(0.061)***	
					0.253	1.79			
		Robust Std. Errors			(0.141)*		YES **		
117otrafina	Has obtained alternative financing		0.035	1.89	0.049	4.23		0.021	1.94
		Std. Errors	(0.018)*		(0.012)***			(0.011)*	
					0.046	1.53			
		Robust Std. Errors			(0.030)				
119divotrafin	Diversity index alternative financing		-22.92	-0.9	108.578	6.94		64.509	4.15
			(25.568)		(15.639)***		YES ***	(15.553)***	
					116.18	2.92			

**** p<0,01; ** p<0,05; * p<0,1.* (&): estimated values for 2015. We have detected an error in the mid-term calculation that was addressed in the final evaluation

5. CONCLUSIONS

We have analysed the impact of public support for private R&D in Spain in a post-austerity context that calls for transformative R&D policy approaches.

We have used information on public support granted by CDTI to private firms for the execution of R&D projects. CDTI is the main innovation agency of the country. In order to deal with selection biases and endogeneity problems we have used a mixed approach of differences in differences combined with propensity score matching (DD-PSM) in the common support. We used three matched samples (mid-term evaluation; final evaluation and prospective evaluation samples) as data was accessed in two different waves (mid-term and final evaluation) and project data was different for the prospective sample (follow up in the middle of the treatment and two-year information combined).

Probability of being treated increases for continuous R&D performers but decreases for firms with foreign capital. These results are consistent with previous research (e.g. Huergo et al., 2016, and Barajas et al., 2017). The exporting activity of a firm increases the probability of being treated. This indicates that domestic firms are more inclined to apply and finish a CDTI project that foreign firms, but the international experience of firms appears to grant the skills or the need to access to a CDTI grant program. In addition and considering the final evaluation sample, the probability of being treated increases for firms that have high turnover, carry out technological development, and face internal liquidity constraints. However, this probability decreases for firms belonging to a group of facing external liquidity constraints. Regarding sectors for the same sample, the probability of being treated is significantly higher for firms belonging to the dynamic or challenge sectors than to firms belonging to the traditional sector.

Regarding the impact of the CDTI public support for firms, we found that public subsidies present additionality on R&D inputs: R&D expenditures and job creation. Beneficiary firms increase the probability of carrying out internal R&D activities by about 13 percentual points compared to their controls and increase the likelihood of having created R&D job by about 4 to 14 percentual points. Similarly, we found behaviour additionality and other positive indirect effects on collaboration patterns and the use of alternative funding. Beneficiary firms increase the number of partnerships with research centres by about 0.15 to 0.26, becoming more internationally oriented. Beneficiary firms increase the number of international partnerships outside the group by about 0.2 to 0.3, diversifying international partnerships. Beneficiary firms increase the probability of obtaining alternative funding by about 2 to 5 percentual points, but this is not confirmed by the robust specification due probably to the negative impact on the challenge sector.

However, the results are less clear when considering output additionality due to the heterogeneous effects across sectors. The impact of the public R&D subsidy on product innovation varies across sectors, being positive and significant for the dynamic sector but negative for the stationary one. The positive impact on process innovation is limited to the traditional sector. The positive effect on patent activity is not consistent across samples and specifications. We find a heterogeneous effect across sectors on patent number, being positive for traditional and dynamic sectors, but negative for the stationary one. These results on the effect of public subsidies on firm R&D are consistent with previous literature as we found clear positive effects on input R&D additionality and collaboration patterns but not very clear results on innovation outputs and the economic performance of firms. This indicates that the CDTI aid scheme somehow works. In addition, we have provided an alternative definition of sectors that could help to better understand the different impacts across sectors. Considering the consistency of the positive and less positive results, we have suggested that the centre could benefit from including some innovative characteristics of the transformative change frame for innovation policy (Schot and Steinmueller, 2018), such as the reflexivity towards failure and the use of deliberative process.

This paper presents some limitations coming from the representativeness of the sample (i.e. it is not representative for companies with less than 10 employees) and the anonymity rules applied by the Spanish Statistical National Institute that limits the use of variables to build the cross-sample. For example, we could not consider the difference between the probability of receiving a subsidy and finishing a project granted. In addition, the methodology used, although it controls part of the possible biases, does not allow to control for unobserved heterogeneity that changes over time. The relatively short period of time considered, and qualitative information did not indicate the presence of unobserved characteristics that could be correlated with the treatment placement. The limitations on data availability have been quite consistent across studies (e.g. Barajas et al., 2017) and will probably remain if confidentiality rules of the Spanish Institute of Statistics are not changed. This change is probably neither feasible nor desirable, as anonymity needs to be preserved in research. In addition, firms will not disclose information that could give advantage to their competitors. For this reason, it was suggested to the centre to rank unsuccessful applicants and to apply and to implement an open data strategy to improve decision-making.

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Appendices

Box A I. DD-PSM SPECIFICATION FRAMEWORK AND ASSUMPTIONS

Differences in Differences (DD): Single Analysis

Following Villa (2016), the DD treatment effects estimated requires a a pair of before-and-after periods; one being the baseline (t=0) and the follow-up (t=1). It requires two groups of units i, being the treatment group (Z_i =1) and the control group (Z_i =0). It requires the absence of intervention in the baseline for either group ($D_{i,t=0}$ =0| Z_i=1, 0), and it requires the intervention to be positive for the treated group in the follow-up (($D_{i,t=1}$ =1| Z_i=1). For any outcome variable, Y_{it}, the DD treatment effect is given by the difference in the outcome variable for the treated and control units before and after the intervention.

Then, the single DD is given by:

$$DD = \{E(Y_{it=1} \mid D_{it=1} = 1, Z_i = 1) - E(Y_{it=1} \mid D_{it=1} = 0, Z_i = 0)\}$$
$$- \{E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 1) - E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 0)\} \quad (1)$$

DD with Covariates

As mentioned, DD can be combined with other nonexperimental evaluation methods. Further control covariates can be included in order to control for observed heterogeneity, confounding factors that could lead to an overestimation of the relationship. Then, observed covariates could be relieved form the effect of the treatment.

The DD analysis with observed covariates (Xi) added is as follows:

$$DD = \{E(Y_{it=1} \mid D_{it=1} = 1, Z_i = 1, X_i) - E(Y_{it=1} \mid D_{it=1} = 0, Z_i = 0, X_i)\}$$
$$- \{E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 1, X_i) - E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 0, X_i)\} \quad (2)$$

DD Covariates (Controls) and Kernel Propensity-Score Weights

Observed covariates can be also used to estimate the propensity score, or the likelihood of being treated, and to calculate kernel weights following Heckman et al. (1997, 1998). This method matches treated and controls according to their propensity score, matching each treated unit to the whole sample of control units instead of on a limited number of nearest neighbours.

The propensity score (pi) is given by:

$$p_i = E(Z_i = 1 \mid X_i)$$

Following Heckman et al. (1997), kernel weights are given by the following expression that considers propensity scores, given the covariates,

$$w_i = \frac{K(\frac{p_i - p_k}{h_n})}{\sum K(\frac{p_i - p_k}{h_n})}$$

K () is the kernel function and h_n bandwidth. The kernel propensity score matching DD treatment effect is given by,

$$DD = \{E(Y_{it=1} \mid D_{it=1} = 1, Z_i = 1) - w_i \times E(Y_{it=1} \mid D_{it=1} = 0, Z_i = 0)\}$$
$$- \{E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 1) - w_i \times E(Y_{it=0} \mid D_{it=0} = 0, Z_i = 0)\} \quad (4)$$

DD Covariates (Controls) and Kernel Propensity-Score Weight Common Support

In addition, we can increase the internal validity of the DD estimation, by restricting the previous setting (4) to the common support of the propensity score for treated and control groups. The common support is the overlapping region of the propensity for treated and control groups defined by,

$$(i : p_i \in [\max\{\min(p_i \mid Z_i = 1), \min(p_i \mid Z_i = 0)\}, \min\{\max(p_i \mid Z_i = 1), \min(p_i \mid Z_i = 0)\}])$$

DD ASSUMPTIONS

The correct interpretation of the DD estimator requires that (Khandker et al., 2010):

1. The correct specification of the model in equation (outcome).
2. The error term is uncorrelated with other variables in the equation.

The last of these assumptions is the most critical for the DD strategy. It is also known as the parallel-trend assumption. It implies that the outcome in the treatment and control group would follow the same time trend in the absence of the treatment. In other words, it implies that unobserved characteristics affecting program participation do not vary over time. We present a visual representation of outcome variables from the 2010-2016 period to check this assumption, indicating similar pre-treatment

Table A I. Sectoral correspondence between reduced taxonomy, CNAE and PITEC sectors

REDUCED TAXONOMY		CNAE 2009	ACTIN (PITEC)
1	TRADITIONAL	• Agricultura, livestock, forestry and fishing (01, 02, 03). • Extractive industries (05, 06, 07, 08, 09). • Manufacture of wood and of products of wood and cork, except furniture; basketmaking and wickerwork (16). • Manufacture of other non-metallic mineral products (23). • Shipbuilding (301). • Electricity, gas, steam and air conditioning supply (35). • Water supply, sewage, waste management and remediation activities (36, 37, 38, 39). • Wholesale and retail trade; repair of motor vehicles and motorcycles (45, 46, 47). • Transportation and storage (49, 50, 51, 52, 53). • Hostelry (55, 56). • Information and communications (58, 59, 60, 63). • Financial and insurance activities (64, 65, 66). • Real estate activities (68). • Administrative and support service activities (77, 78, 79, 80, 81, 82). • Education (85). • Human health and social work activities (86, 87, 88). • Arts, entertainment and recreation activities (90, 91, 92, 93). • Repair of computers and personal and household good (95). • Other personal services (96).	00,01,07,13,20,26,27,29,30,31,34,35,36,39,40,41,42,43
2	DYNAMIC	• Textile industry (13). • Leather and footwear industry (15). • Metallurgy; manufacture of iron, steel and ferro-alloy products (24). • Manufacture of electrical material and equipment (27). • Manufacture of machinery and equipment n.e.c. (28). • Manufacture of air and spacecraft and related machinery (303). • Telecommunications (61). • Computer programming, consultancy and other activities related to IT (62). • Professional, scientific and technical activities (69, 70, 71, 72, 73, 74, 75).	04,06,14,17,18,21,32,33,37,38
3	STATIONARY	• Food industry (10). • Manufacture of beverages (11). • Tobacco industry (12). • Paper industry (17). • Graphic arts and reproduction of recorded media (18). • Manufacture of coke and refined petroleum products (19). • Chemical industry (20). • Manufacture of pharmaceutical products (21). • Manufacture of rubber and plastic products (22).	02,03,08,09,10,11,12
4	CHALLENGES	• Manufacture of garments (14). • Manufacture of fabricated metal products, except machinery and equipment (25). • Manufacture of computer, electronic and optical products. • Manufacture of motor vehicles, trailers and semi-trailers. • Railway equipment (302). • Manufacture of military fighting vehicles (304). • Manufacture of other transport equipment (309). • Manufacture of furniture (31). • Other manufacturing industries (32). • Repair and installation of machinery and equipment (33).	05,15,16,19,22,23,24,25
5	CONSTRUCTION	• Construction industry (41, 42, 43).	28

TECHNICAL NOTE ON THE SECTORAL TAXONOMY

The sectoral taxonomy includes five categories (traditional, dynamic, stationary, challenges, and construction) for those indicators whose results are considered more relevant. This taxonomy based on technological intensity, technological dynamism and technological advantage revealed a taxonomy reduced to five categories by limitations on access to INE data to ensure the anonymity of the companies and which reduces the original taxonomy proposal (Molero and Garcia, 2008; García Sánchez and Molero, 2010, and García Sánchez et al., 2016). The construction sector was not considered in the final result in order to avoid the limitations imposed by the INE on the delivery of the results. INE reviews all the results conducted in the secure place in order to assure anonymity. For example, all categories whose results are based on less than ten observations have to be deleted. This was frequently the case in the construction section and, therefore, it had to be removed.

Traditional: includes farming and mining activities and those included as "sectors in withdrawal" in the Molero-Garcia taxonomy (sectors with little global dynamism and where Spain has technological disadvantages).

Dynamic: made up by the manufacturing sectors with "dynamic specialisation" and which are those where Spain has technological advantages and has significant global dynamism. They are added to the knowledge intensive business services sectors (KIBS).

Stationary: made up by the manufacturing sectors with "stationary specialisation" and which are those where Spain has technological advantages, but has less global technological dynamism.

Challenges: sectors called "missed opportunities", and that are dynamic sectors at a global level, but where the Spanish industry has technological disadvantages.

Construction: made up by the construction industry.

Table A 1 aboveshows the sectoral correspondence of the reduced taxonomy that has been used with both sectors included in PITEC and the CNAE 2009 classification.

Table A V. Balancing test. Mean differences (Prospective evaluation matched sample) (source: Own compilation)

Variable	Unmatched Matched	Mean: Treatment	Mean: Control	Mean: % bias	Mean: %Reduction bias	T-Test: t	T-Test: p>|t|	V(T)/V(C)
Prospective evaluation sample								
ltamano	U	4.42	4.00	27		9.83	0.000	0.62*
	M	4.46	4.39	5	81.6	1.59	0.111	0.75*
lcifra	U	16.52	15.64	44.5		16.54	0.000	0.60*
	M	16.69	16.64	2.6	94.1	0.82	0.41	0.71*
edad	U	33.27	29.15	20.2		8.09	0.000	1.09
	M	34.76	34.51	1.2	93.9	0.31	0.753	0.83
grupo	U	0.52	0.41	21.7		9.07	0.000	1
	M	0.53	0.52	2.1	90.4	0.53	0.595	0.98
tradicional	U	0.12	0.38	-63.4		-22.6	0.000	0.55*
	M	0.10	0.10	0.3	99.6	0.1	0.923	1.01
dinamico	U	0.39	0.28	25		10.81	0.000	1.09
	M	0.36	0.35	1.4	94.6	0.34	0.733	1.02
estacionario	U	0.30	0.18	28.7		13.02	0.000	1.18
	M	0.34	0.35	-3.3	88.6	-0.74	0.458	1.02
reto	U	0.19	0.16	6.3		2.67	0.008	0.99
	M	0.20	0.20	1.7	73.6	0.4	0.689	1.03
idcont	U	0.73	0.26	106.6		44.23	0.000	0.88
	M	0.74	0.69	12.4	88.3	3.13	0.002	0.81
infun	U	1.77	1.01	11.5		4.98	0.000	0.98
	M	1.73	1.59	2.1	81.6	0.52	0.603	0.99
destec	U	52.46	17.68	90.5		41.06	0.000	1.31*
	M	52.21	49.21	7.8	91.4	1.79	0.074	0.85
mdodom	U	2.49	2.75	-26.2		-10.25	0.000	0.79*
	M	2.46	2.42	4.5	82.7	1.24	0.215	0.96
fcinter	U	2.15	2.33	-17.4		-6.65	0.000	0.75*
	M	2.17	2.18	-1.5	91.2	-0.43	0.668	0.88
fcexter	U	2.07	2.45	-34.7		-13.15	0.000	0.70*
	M	2.10	2.16	-5.6	83.8	-1.56	0.118	0.79*
extranjera	U	0.11	0.13	-8.4		-3.33	0.001	0.71*
	M	0.12	0.13	-2.5	69.6	-0.64	0.523	0.96
lexportt_eu	U	15.58	14.47	50.7		17.22	0.000	0.66*
	M	15.58	15.47	5.2	89.8	1.42	0.155	0.81
pyme	U	0.82	0.79	9.5		3.82	0.000	1.04
	M	0.82	0.85	-6.1	35.5	-1.67	0.094	0.99

* if 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]
** if 'bad', i.e. variance ratio <0.5 or >2

Figure A I. Balance plot before and after matching propensity score (Mid-term (left) and prospective (right) evaluation matched sample) Note: Outliers were excluded for anonymity reasons (source: Own compilation)

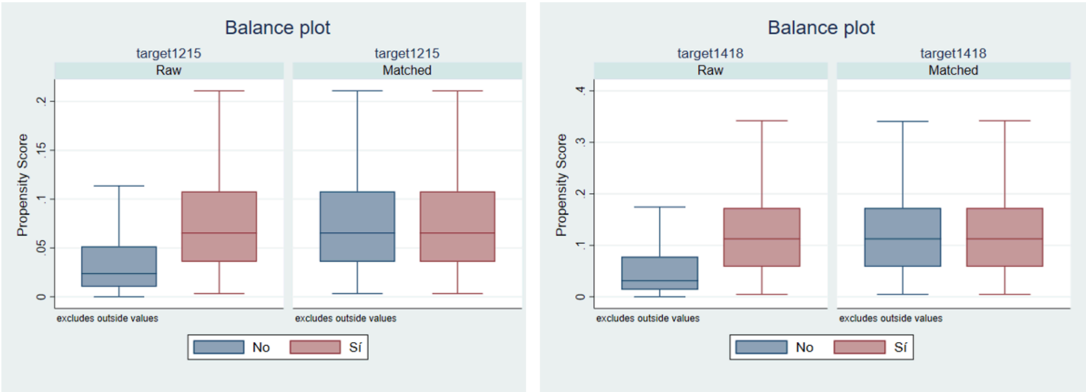

Figure A II. Density plot before and after matching propensity score (Mid-term (left) and prospective (right) evaluation matched sample) (source: Own compilation)