The impact of public support on firm propensity to engage in R&D: Spanish experience

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Abstract

Our objective is to estimate the effect of public low-interest loans for R&D projects on the probability of performing R&D by Spanish firms. The estimations provide evidence of the effectiveness of public low-interest loans, being the stimulus effect larger for SMEs than for large firms and also higher for manufacturing than for services. Supported firms are approximately 25 percentage points more likely to self-finance their R&D investments than non-supported firms. The effect is quite relevant if we consider that the probability of self-financing R&D activities is 53.2 percentage points higher when the firm has invested in R&D activities in the previous year. This result suggests that firms can be induced persistently to perform R&D activities by means of loans.

***JEL Classification*:** H81, L20, O38.

Key words: Public support, R&D projects, impact analysis, R&D extensive margin.

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1. INTRODUCTION

It is commonly accepted that innovation companies are subject to financial constraints associated with the presence of information asymmetry and moral hazard problems, which provoke a higher cost of financing research and development (R&D) activities with respect to ordinary investment and a lower level of funding by private external financers, who are reluctant to lend when the investment is concentrated essentially on intangible assets (Himmelberg and Petersen, 1994; Hall, 2002; Hall and Lerner, 2010). Also because knowledge is characterized by increasing returns to scale and because of the uncertainty and the incomplete appropriability of R&D returns due to knowledge spillovers, private investment in R&D is expected to be below the optimum social level (Arrow, 1962).

In this context, it is not surprising that the main justification for public intervention is the correction of these market failures (Czarnitzki and Lopes-Bento, 2013), although public agencies may also have other goals when supporting business R&D. Among these objectives, we can emphasize the promotion of national champions, the technological upgrading of firms that are of particular importance in declining or traditional industries, or the funding of R&D projects that would not be otherwise carried out (Blanes and Busom, 2004; Clausen, 2007).

Obviously, public intervention can result in a negative effect on aggregate business R&D if awarded firms reduce their own R&D investment, displacing or crowding out private investment. With this in mind, many empirical articles which try to measure the impact of public aid on private R&D have been published, with several countries studied and many methodologies applied (see Zúñiga-Vicente et al., 2014, and Becker, 2014, for a review). And, from a policy point of view, many of these papers conclude that R&D subsidies generate larger additionality at the extensive margin (share of R&D performers) than at the intensive margin (R&D intensity of actual performers).

This article tries to go more deeply into the knowledge of the actual relationship between public and private R&D expenditures. More in detail, our aim is to analyze the effect of being awarded aid by the Center for the Development of Industrial Technology (CDTI) on the firm’s decision to self-finance R&D. The CDTI is the main public agency providing funding for firms’ R&D projects in Spain. Among the typology of funding programs managed by the CDTI between 2003 and 2005, we focus on the following: Technological Development Projects, Technological Innovation Projects and Joint Industrial Research Projects. By means of these, the CDTI funded firms to conduct R&D projects with low-interest loans (that is, with an interest rate lower than normal rates for the current market) that could reach 60% of the total budget.

Although there are many references which deal with the impact of subsidies on R&D projects, few of them focus on programs based on low-interest loans. Despite the fact that low-interest credits include a hidden subsidy (equivalent to the saving in financial costs), their effects on the firm's decisions are not expected to be the same for at least three reasons: i) low-interest loans are fully compatible with tax benefits; ii) the percentage of the financed budget is usually higher, simultaneously increasing the firm's chances to get private financing; iii) as the firm must pay back the loan, it imposes self-discipline on it, something not present with other types of aid. In that sense, low-interest loans should be expected to generate higher additionality than the equivalent subsidy or limit the crowding out effect.

Notice that the factors that determine participation in the public system of low-interest loans may be the same as those which affect the firm's R&D decision. This fact could have biased the estimates of the impact upward if the CDTI had selected firms with a higher likelihood of self-financing R&D projects. Among the existing methodologies which deal with this bias, in this paper a two-stage procedure is presented. Firstly, we estimate the determinants of participation in CDTI programs (selection equation), trying to assess the characteristics of projects awarded the aid. Then, in a second stage, we estimate the factors affecting the firm's decision to allocate its own resources to R&D activities (impact equation). When dealing with this second equation, the predicted value for the probability of participation obtained from the first one is used as an explanatory variable.

Additionally, the R&D expenditure decision may well show some persistence that should be considered. The presence of sunk costs or learning-by-doing associated with these activities could make, among other reasons, that firms with R&D expenditures one year were more likely to continue investing the next period.

The main contribution of this study to the literature on impact assessment of public support for R&D is that our analysis takes into consideration both the selection problem and potential persistence in the decision to undertake R&D activities. Only a few papers have analyzed the effect of public aid in the presence of persistence in the R&D decision[1], but to our knowledge none of them focus on the impact of low-interest loans. We use the method proposed by Wooldridge (2005) to control for this possibility of persistence. Our results confirm

[1] See, for example, the papers by Arqué-Castells and Mohnen (2012) and Arqué-Castells (2013).

the existence of a positive impact of CDTI low-interest loans on self-financed R&D, even once persistence effects are considered, showing the effectiveness of CDTI programs.

The rest of the paper is divided into four parts. After this introduction, in Section 2 we review empirical evidence. In section 3, we describe the empirical methodology along with the main variables included in the database, trying to obtain a guide of supported firm-related variables that will be used later on as explanatory factors in the econometric analysis. Section 4 shows the estimates of both the selection and the impact equations, stressing the differences in these decisions between small and medium-sized firms (SMEs) and large firms and between manufacturing and services firms. Finally, we present key conclusions in Section 5.

2. PUBLIC SUPPORT AND THE DECISION TO INVEST IN R&D

From a theoretical point of view, the main channel through which public funding can impact business R&D investment is the reduction of the cost of R&D (Bloom, Griffith and Van Reenen, 2002). This is especially obvious in the case of firms deciding to start R&D projects in the presence of financial constraints.[2] Given the higher level of uncertainty surrounding innovative projects and the public good character of knowledge, innovative firms usually face a higher cost of external financing, and can even be credit rationed. Therefore, they mainly rely on their own resources to finance R&D projects. In this context, the decision to engage in R&D is quite sensitive to the availability of internal liquidity, and access to external sources of financing could induce firms to undertake R&D projects that would not otherwise be started (Czarnitzki et al., 2011).

Consistent with this interpretation, González, Jaumandreu and Pazó (2005) model the relationship between R&D subsidy effectiveness and the existence of barriers to R&D in terms of set-up costs. In their model, the decision of whether or not to spend on R&D arises from the comparison of optimal non-zero effort with the effort needed to reach some profitability (threshold effort). Below this threshold, R&D costs cannot be completely recovered and firms will decide not to undertake innovative activities, but this decision can be modified if expected subsidies reduce the cost of R&D.

[2] As Mancusi and Vezzulli (2014) point out for a large representative sample of manufacturing SMEs, credit rationing has a negative impact on both the probability of setting up R&D activities and the level of R&D expenditure (conditioned on the R&D decision), and the global estimated reduction in R&D expenditure is mostly associated with the first impact.

Also considering the existence of fixed R&D costs and a cost of external finance, Takalo, Tanayama and Toivanen (2013a) develop a structural model of strategic interaction among subsidy applicants and public and private sector R&D financiers to analyze the effects of R&D subsidies. From this model, they conclude that higher costs of external finance provide a reason to increase R&D subsidies at the extensive margin, where firms decide whether or not to invest in R&D.

From an empirical point of view, the evidence about the impact of public aid on private R&D is mostly related to subsidy programs for R&D projects. Some interesting examples are the papers by Walsten (2000) analyzing US firms, Lach (2002) for Israeli companies, Busom (2000) and Gonzalez, Jaumandreu and Pazó (2005) for Spain, Almus and Czarnitzki (2003) and Czarnitzki and Licht (2005) for innovative German firms, Duguet (2004) about French firms' spending on R&D, Clausen (2007) for Norway, and Takalo, Tanayama and Toivanen (2013b) applied to Finnish firms. Not surprisingly, the variety of approaches presented in these papers leads to a lack of consensus regarding the complementarity or substitutability between public and private R&D expenditures[3] (García-Quevedo, 2004; Zúñiga-Vicente et al., 2014), although most recent analyses suggest that public R&D subsidies succeed in stimulating private R&D (Becker, 2014).

In general, this evidence is consistent with the idea that public R&D subsidies constitute a public policy instrument to compensate the negative effect of financial constraints on private R&D activities. In this line, Zúñiga-Vicente et al. (2014) indicate that public subsidies can be especially relevant for small and young firms, for which liquidity constraints can be more severe. Becker (2014, p. 9) also establishes that "the additionality effect has been shown to be particularly prevalent for small firms, which are more likely to experience external financial constraints. Moreover, these firms are more likely to start investing in R&D if they receive a subsidy."

With regard to the methodological framework, most of the studies wonder about the behavior of firms in terms of R&D expenditure in the absence of aid. As mentioned before, when answering this question, the key problem is the so-called "selection problem", which arises from the fact that each firm can only be observed either receiving the aid or not. Therefore, the additional effect cannot be measured directly. If public support were randomly grant-

[3] Among the reasons behind the multiplicity of results, we can highlight the absence of a generally accepted model that can be used when proposing econometrically testable hypotheses (David, Hall and Toole, 2000), and the fact that public programs differ in their objectives, funding schemes and methodology, so it seems reasonable that their evaluation also provides different results (Borrás and Edquist, 2013).

ed, it would be possible to estimate its effect just by the difference between the average result for supported firms and the rest. Notwithstanding, public agencies usually have their own criteria for selecting firms, supporting, for example, i) firms or projects with a higher probability of success (picking-the-winners strategy); ii) particular sectors that generate more spillovers; or iii) certain groups of firms facing higher financial constraints (in general SME). As a result, we need an approximation for the counterfactual when quantifying the impact of public aid; that is, we need to take into account that participation in the aid system probably depends on the same characteristics of the firm that determine its R&D behavior. The selection of a control group is quite difficult and could lead to a bias when estimating the impact.

Another problem, closely related to the previous one, is the endogeneity of public funding. Many times, access to public or private financing depends on a similar set of variables (again, this may be a result of an "appropriate" selection by the public agency). Actually, firms awarded aid with higher public funds are those which invest more in R&D, meaning that the estimated impact of the public financing has embedded the effect of other variables influencing R&D expenditure besides the direct increase derived from the subsidy. Additionally, R&D spillovers may imply changes in the behavior of non-participants in the aid system as a result of the conduct of awarded firms.

As Becker (2014) points out in her recent review, the availability of new econometric techniques that control for selection bias is likely one reason for the shift away from earlier findings that public subsidies often crowd out private R&D to finding that subsidies typically stimulate private R&D. In particular, more recent papers have employed matching estimators as a methodological alternative (see Arvanitis, 2013). This procedure is based on comparing results between two groups, one of them made up of "treated" individuals (in our case, firms participating in the public program) and the other consisting of a "comparable" control group. Under some assumptions[4], we can attribute the difference between the results of both groups to the "treatment" (the public program). The advantage of this method is that it is not necessary to specify a functional form for the relationship between subsidies and R&D expenditures, while its main difficulty is the construction of the control group. Almus and Czarnitzki (2003) and Czarnitzki and Licht (2005), with innovative German firms, Duguet (2004), for French firms with R&D expenditures, Aerts and Schmidt (2008), for Flanders and Germany,

[4] The distribution of subsidies must be random, conditioned on some characteristics. For each set of firms awarded aid (or not) with some characteristics, there should be a "similar" control group as well.

Bérubé and Mohnen (2009), applied to Canadian firms, and Carboni (2011), using Italian manufacturing data, are examples of this approach.

The empirical evidence about the impact of public support programs for R&D in Spain is in line with international literature, using a variety of approaches. Noteworthy are the studies by Busom (2000), González, Jaumandreu and Pazó (2004), González and Pazó (2008), Arqué-Castells and Mohnen (2012) and Arqué-Castells (2013). Busom (2000) takes advantage of a database containing both firms awarded aid by CDTI grants in 1988 and innovative firms not granted aid. Apart from general technological and economic information, she uses information about the strategic attitude and the behavior of each firm in the product's market. However, the magnitude of subsidies is unknown, so only total substitution can be tested. Decisions analyzed are both participation and innovative effort. The results suggest that small firms have a higher probability of participation and public aid increases private innovative effort. Notwithstanding, a total crowding-out effect could not be rejected for 30% of the firms.

In the same way, González, Jaumandreu and Pazó (2004) use data from manufacturing firms from the ESEE (Encuesta Sobre Estrategias Empresariales) between 1990 and 1999. In the context of a model with product differentiation, they assume that each competitor is able to increase the demand for its products by elevating their quality through R&D investments. Demand characteristics, technological opportunities and starting costs for R&D activities interact to determine innovation results and the minimum profit margin. Under this threshold, costs cannot be recovered through an increase of sales, meaning the firm will not conduct R&D; anyway, the decision may be changed if the expected subsidy reduces R&D costs. A Tobit model is implemented to analyze the determinants that lead the firm to develop technological activities and, once decided, to fix their intensity. As the ESEE provides information about the amount of the subsidy, the ex-ante expected subsidy can be estimated by taking into account selection and endogeneity problems and these estimations can be used as an explanatory variable of the investment effort. The main conclusions are the following: a) by subsidizing 10% of R&D expenditures, half of large firms without R&D activities would start them; b) if we want to achieve this change for 30% of small firms without R&D expenditures, subsidies should jump to 40%; c) 3% of large firms already doing R&D will stop these activities if subsidies are withdrawn; and d) in the case that subsidies disappear, 14% of small firms performing R&D will stop them. Therefore, subsidies appear to be potentially effective in leading firms to conduct R&D activities. Also, they conclude that most of the firms awarded aid would have had R&D expenditures even without public aid. This can be seen as a signal of a "suitable selection" by risk-adverse public agencies.

Using matching procedures, González and Pazó (2008) also use the ESEE dataset for the period 1990-1999. The main results include an absence of a crowding-out effect, either partial or total, strengthening the international evidence obtained with the same methodology. On average, subsidized firms' effort is 0.35 percentage points higher; this is quite significant, as the average effort is 2.1% in the absence of a subsidy. Moreover, public financing is more effective for small firms operating in low-technology sectors.

Finally, also for Spain, we can highlight the papers by Arqué-Castells and Mohnen (2012) and Arqué-Castells (2013), whose aim is to analyze the impact of subsidies in the presence of persistence in innovative activities. Recent papers suggest that being an innovator in one period has a positive causal effect on the probability of innovating in the next period (Peters, 2009; Raymond et al., 2010). The implication of this fact is that subsidies could be particularly effective in fostering private R&D, as a change in the R&D status of the firm would also increase the probability of being an R&D performer in the future. In order to test this hypothesis, Arqué-Castells and Mohnen (2012) focus on R&D extensive margin and model R&D decisions in a dynamic context with sunk entry costs and public aid. By estimating a dynamic panel data type-2 tobit model for an unbalanced panel of Spanish manufacturing firms observed over the period 1998-2009, they find that 25% of these firms need "extensive" subsidies to start but not to continue doing R&D. In the same line, Arqué-Castells (2013) tests for the existence of subsidies' permanent inducement effects using also panel data from the ESEE. His simulations carried out with the estimated parameters show that subsidies can generate permanent inducement effects for 9% of Spanish manufacturing firms, being the subsidy shares that are needed to generate these effects larger among small firms than among large companies. Our analysis in the next sections closely follows this last paper but with the focus on the impact of low-interest loans instead of subsidies.

3. EMPIRICAL MODEL AND DATASETS

Most of the studies described in the previous section analyze the impact of public aid**,** taking into account both endogeneity and selection problems. David, Hall and Toole (2000), Klette, Moen and Griliches (2000) and, more recently, Aerts, Czarnitzki and Fier (2007) review the main empirical papers about the impact of public subsidies on firms' R&D expenditures, paying special attention to the different methodologies applied to avoid these estimation problems.[5] Among the most usual alternatives, we find Heckman's (1979) selection model, which we will follow in this paper. This methodology is applied in two steps. Firstly, a selection equation for the participation status is estimated. In our case, in this estimate we also take into account the problem of the existence of unobservable idiosyncratic firm characteristics correlated to their participation (selection problem in presence of unobservables)[6]. As in the case of subsidies, low-interest loans do not have a horizontal character. In fact, they are granted to those projects that are better from the agency's point of view in terms of scientific, technologic and social welfare criteria.

Formally, the model consists of two equations. The first is devoted to the participation of firm i $(i=1,...,N)$ in the CDTI loan system during year t $(t=1,...,T)$ and is given by:

$$y_{it}=\begin{cases}1 \quad if \quad y_{it}^{*}=x_{1it}\beta_1+u_{it}>0 \qquad u_i\approx iid\ N(0,\sigma_u^2)\\ 0 \quad otherwise\end{cases} \tag{1}$$

where y_{it}^{*} is a latent dependent variable, x_{1it} represents the set of explanatory variables, β_1 is the vector of coefficients and u_{it} is the error term. Firm i will be a participant if y_{it}^{*} is positive[7].

In order to measure the stimulus effect of the loan system, the second equation deals with the firm's decision to perform R&D with its own resources. Again, this is formalized using a binary model:

$$z_{it}=\begin{cases}1 \quad if \quad z_{it}^{*}=\alpha\,\hat{y}_{it}^{*}+x_{2it}\beta_2+e_{it}>0 \qquad e_i\approx iid\ N(0,\sigma_e^2)\\ 0 \quad otherwise\end{cases} \tag{2}$$

where z_{it}^{*} is a latent variable, $\hat{y}_{it}^{*}$ represents the participation in the low-interest loan system, α is the parameter reflecting the impact of public aid, x_{2it} represents other control variables (allegedly exogenous or predetermined), and e_{it} is the error term. Firm i devotes its own resources to R&D if z_{it}^{*} is positive. This latent variable can be understood as the expected net profit of the R&D project.

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[5] See also Bertoni, Colombo and Grilli (2011) or Cerulli and Potì (2012).

[6] Not controlling for unobservables leads to inconsistent estimates. Other methodologies, like matching procedures, assume that all the relevant unobservable variables are accurately represented by observable variables (Heckman, Urzua and Vytlacil, 2006).

[7] Ideally, we would like to separately estimate the determinants of the two decisions involved in the probability of participation: the firm's decision to apply for the credit and the agency's decision to award it. This would permit the identification of the effects that explanatory variables have on each decision (Blanes and Busom, 2004). This can only be done if rejected proposals are also identified in the database. However, in our case, it is

Notice that in this second step, the participation variable implemented is not the one observed, y_{it}, but the one predicted in the first stage, $\hat{y}_{it}^{*}$. In fact, we are dealing with a selection (and endogeneity) problem as we can assume the latent variable of the first equation to be both an indicator of the R&D project's quality valued by the agency and its fulfillment of the aid program's criteria.

Additionally, the impact equation is also estimated using the observed participation as an explanatory variable. Thus, comparing the results obtained with both estimates (using the predicted or real participation), we will be able to measure the selection bias on this kind of analysis. Given that dependent variables are binary and data have a panel structure, we will apply the maximum likelihood method to a random effects Probit model to obtain the estimates.

Another problem when trying to explain the R&D expenditure decision is that R&D activities are usually persistent (Geroski, Van Reenen and Walters, 1997). That is, investing in R&D in one period increases the probability of investing during the following year. If this persistence is not taken into account, it could imply a bias in the estimates of the impact of public aid. As it was introduced before, in the presence of this pattern, R&D subsidies could be especially effective. If a subsidy induces the firm to change its initial R&D status, this will mean a stimulus to continue performing R&D activities in the future (Arqué-Castells and Mohnen, 2012).

The persistence of R&D activities can be due to various reasons. It could emerge because of sunk costs associated with these activities (Mañez-Castillejo et al., 2009), or maybe as a consequence of a learning-by-doing process with them. In this case, we would say there is "true" state dependence, as investing in one period will "cause" a higher probability of investing the next. Persistence could arise because of heterogeneity, observable or unobservable, between firms as well. Firms may have some characteristics (size, activity, technological opportunities, attitude towards risk) that make them keener on having R&D expenditures. If those characteristics are persistent over time, the induced decision about R&D investment will also be persistent. We can introduce firms' characteristics in the model as control variables, but if some of them are unobservable (like attitude towards risk or business capacity), their omission could bias the results. In this case, we would say there is "spurious" state dependence.

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not possible to match CDTI and INE databases for rejected proposals, so we can only estimate the net effect of explanatory variables on the probability of participation.

Taking into account the existence of persistence, we follow Wooldridge's (2005) methodology, estimating a random effects dynamic Probit model[8]. Then, equation (2) would be:

$$z_{it} = \begin{cases} 1 & \text{if} \quad z_{it}^{*} = \gamma\, z_{it-1} + \alpha\, \hat{y}_{it}^{*} + x_{2it}\beta_2 + \mu_i + e_{it} > 0 \\ 0 & otherwise \end{cases} \tag{2'}$$

where the R&D expenditure decision depends on the decision made last year z_{it-1}, on some observable variables included on the vector x_{2it} and on some firm's specific unobservable characteristics that are assumed to be constant over time and are represented by μ_i. Following Wooldridge, we specify the distribution of μ_i, assuming unobservable heterogeneity depends on the initial condition z_{i0} and some strictly exogenous variables in this way:

$$\begin{aligned} &\mu_i = \delta_0 + \delta_1 z_{i0} + \delta_2 \overline{y}_i^{*} + \overline{x}_{2i}\delta_3 + \xi_i \\ &\xi_i \approx iid\ N(0, \sigma_{\xi}^{2}) \text{ and uncorrelated with } \overline{y}_i^{*} \text{ and } \overline{x}_{2i} \end{aligned} \tag{3}$$

where $\overline{y}_i^{*}$ and $\overline{x}_{2i}$ represent averages of $\hat{y}_{it}^{*}$ and x_{2it}, respectively. The resulting equation substituting (3) in (2') will be estimated as a random effects Probit model where z_{it-1}, $\hat{y}_{it}^{*}$, x_{2it}, z_{i0}, $\overline{y}_i^{*}$ and $\overline{x}_{2i}$ are the explanatory variables. Obtaining a statistically positive estimate for γ would confirm the hypothesis of persistence due to true state dependence. Additionally, once the persistence effect has been discounted, parameter α would gather the impact of public aid.

Below, we describe the sample of firms used for econometric analysis along with the explanatory variables employed as regressors. The selection of those factors is guided by both the empirical evidence available for other public support programs and the descriptive analysis of the database.

3.1. Databases

Three data sources for the years 2002 to 2005 are used in this work: the CDTI database, the EIT (Encuesta de Innovación Tecnológica) database, compiled by the INE (Instituto Nacional de Estadística), which is the Spanish version of the Community Innovation Survey, and the PITEC (Panel de Innovación Tecnológica) database, also collected by the INE on the basis of

[8] This methodology has been already implemented when dealing with innovative firms. See Peters (2009).

the annual responses to the Spanish Innovation survey under FECYT and Cotec sponsorship. The CDTI collects information related to Spanish firms' participation in its financing programs. Specifically, during the period analyzed, the CDTI managed five types of low-interest loans: Technological Development Projects (TDP), Technological Innovation Projects (TIP) and Joint Industrial Research Projects (JIRP), Neotec projects and Technological Promotion Projects. In Table 1 the number of projects on each typology is shown yearly.

Table 1: Number of financed projects by typology

	2002	2003	2004	2005	Total
Technological Development (TDP)	189	240	271	273	973
Technological Innovation (TIP)	12	9	52	69	142
Joint Industrial Research (JIRP)	37	33	61	51	182
Neotec	16	18	21	26	81
Technological Promotion	21	14	15	19	69
Total	275	314	420	438	1,447

Source: CDTI database and own elaboration.

This information has been completed with records from the Spanish Innovation Survey from 2002 to 2005. Moreover, INE provided a control sample of firms not receiving aid. These data from the INE were anonymized for some variables, so firms from the control sample cannot be identified. This process introduces two main modifications: a) replacement of individual original values for six quantitative variables (Sales, Exports, Gross investment in material goods, Number of employees, Total expenditure in innovation and Total employees on R&D) with data obtained by a hiding process;[9] b) for the remaining quantitative variables, absolute values are replaced by percentages referring to aggregate values.

Finally, some available information in the PITEC database has been used to construct sectorial indicators of firms' valuation for some elements that could be hindering R&D activities. Due to the anonymization process, we are forced to use PITEC's information just to construct sectorial indicators assigned to each firm through its activity code.

[9] The hiding process implies replacing the firm-level observations with arithmetic means, which are calculated in the following way for each of the variables. Firstly, the variable provided is the arithmetic mean of the values of the 5 firms with the highest values in the variable in question according to the firm's activity (at two digits). If any activity has less than 3 firms, regardless of the firm's activity, the rest of the firm records are ranked in decreasing order according to the variable to be simulated, and the variable provided is the arithmetic mean of the 3 or 4 consecutive values. The expected biases due to this anonymization are small, as shown by López (2011) through the comparison of regressions that alternatively use original and harmonized data from the Spanish Innovation Survey.

After merging the databases, the sample includes 5,689 observations, 2,429 firms and 499 awarded projects, representing 8.7% of the whole sample. For reasons of homogeneity, for ulterior analysis only TDP, TIP and JIRP typologies are selected.

3.2. The Variables

The selection of variables is based on the literature and is usually determined by the availability of information in databases. The empirical literature about the impact of participation in public aid programs on R&D highlights some firms' characteristics that could affect the application and/or the agencies' selection of projects (Blanes and Busom, 2004; González, Jaumandreu and Pazó, 2005; Heijs, 2005; Czarnitzki and Licht, 2005; Clausen, 2007; Huergo and Trenado, 2010; Takalo, Tanayama and Toivanen, 2013b).

First, it is common to use indicators to denote the firm's technological profile, as application would be more probable when the propensity to perform R&D projects is higher. Given the information available in our database, we use internal R&D investment per employee and an indicator reflecting whether the firm has technological cooperative agreements[10]; the latter could be a complementary strategy to internal R&D expenditures (Cassiman and Veugelers, 2002). Additionally, the patents application has been considered as a measurement of technological output that indirectly shows the firm's innovative intensity. In addition, if the objective of the public agency was to support "national champions", then it would be prone to finance those R&D projects with a higher probability of commercial or technological success, and having applied for patents could be signaling just this. As can be seen in Table 2, the sample mean of all these indicators is higher for participants than for non-participants.

Variables reflecting a firm's financial situation are also commonly considered, particularly when financial constraints are present. As we mentioned in previous sections, R&D activities imply high commercial and technical risks. There is no certainty about the achievement of technological objectives and, even if projects finish successfully, these results may not be profitable due to the lack of demand and/or competitors' reaction in terms of new inventions. Consequently, financially healthy firms would be in better conditions to undertake larger investments in R&D. In this sense, financial aid received by awarded firms may imply

[10] In the estimations, lagged values of both variables are included to avoid simultaneity.

a significant incentive for financially constrained firms, increasing their probability of performing technological activities and, therefore, of asking for these credits.

Table 2: Descriptive statistics

	Non-participants		Participants	
Internal R&D expenditures per employee (logs.) (t-1)	3.6	(4.0)	6.7	(3.3)
Technological cooperation (%)	38.4	(48.7)	67.5	(46.9)
Patent application (%)	21.9	(41.4)	43.3	(49.6)
Innovation difficulties: Financial	1.43	(0.28)	1.61	(0.17)
Innovation difficulties: Knowledge	1.07	(0.18)	1.18	(0.13)
Innovation difficulties: Market	1.10	(0.12)	1.16	(0.08)
Size (number of employees)	416.6	(1,175.6)	293.76	(801.3)
Start-up (%)	3.2	(17.7)	4.0	(19.6)
Exports (logs.) (t-1)	7.1	(7.5)	11.9	(6.8)
Experience with CDTI funding (%)	17.1	(37.6)	73.7	(44.1)
Experience with other agencies' funding (%)	26.9	(44.3)	48.3	(50.0)
Foreign capital (%)	17.3	(37.9)	16.0	(36.7)
Group membership (%)	41.8	(49.3)	50.3	(50.1)
R&D performer with own resources (%)	44.0	(49.7)	83.6	(37.1)

Source: CDTI, EIT and PITEC databases, and own elaboration.
Note: Sample averages (Standard deviations). (%) indicates the percentage of observations. The indicators of innovation difficulties take values from 1 to 4.

Furthermore, financial difficulties could be important for agencies awarding aid. Obviously, R&D-related market failures are a fundamental rationale for public intervention. In particular, this support is justified by (i) the incomplete appropriability of R&D outputs due to both knowledge spillovers and the existing gap between private and public return and (ii) the cost of capital when the investor and the innovation financer are not the same. Hall (2002) shows that these market failures are stronger for financially constrained small firms and technology-intensive start-ups. If this is true, we would expect a negative effect of liquidity, size and age on the probability of being awarded aid. As a consequence, the expected effect of financial constraints on application is ambiguous.

Although we do not have information about firms' financial conditions in our database, we have constructed a sectorial indicator by means of PITEC information based on the relative importance assigned by firms during the year to the lack of funds in the firm or group, the lack of external financing or the existence of high innovation costs as factors hampering innovation. For each factor, we assign a number that varies from one (not relevant) to four (high importance). The sectorial indicator is computed as the simple average of firms' values on each 2-digit NACE sector during the year. As can be seen in Table 2, financial difficulties are slightly higher for participants.

Additionally, two other indicators of innovation difficulties have been constructed with the same methodology. The first is related to the troubles in obtaining appropriate equipment and knowledge to carry out the project (indicator of knowledge difficulties). The second reflects the problems of profiting from innovation results when the market is dominated by established firms or due to uncertainty with respect to the demand of goods and services (indicator of market difficulties). Again, both indicators are higher among participants, although the differences are small.

Regarding the sectorial dimension, another possible objective of agencies could be the technological updating of firms in traditional or declining sectors (Blanes and Busom, 2004), whereby the agencies try to increase their probability of survival and avoid employment losses. Firms in traditional sectors tend to be bigger and older, and in Spain are mainly located in the manufacturing sector. In this case, we would expect firms operating in these sectors to have more chances of being awarded aid.

Overall, a firm's size is a characteristic present in most of the papers which deal with the impact of public funding, although its effect on participation is not clear: large firms usually have more resources with which to undertake R&D projects and apply for the aid, but SMEs are usually more affected by innovation-related market failures, so their benefits from public aid could be higher. Statistics in Table 2 show that awarded firms are smaller although both participants and non-participants are, on average, large firms; this is consistent with the hypothesis that size reduces the probability of being awarded aid.

The expected effect of a firm's age is also ambiguous. Older (more experienced) firms are more likely to know and to use public aid. Moreover, they usually have better financial alternatives as external investors can rely more on their track record than in the case of start-ups (Czarnitzki and Licht, 2005). However, young firms tend to be more financially constrained and, as a consequence, they could apply for and receive public aid more frequently. The information in our databases allows us to know whether the firm was born during the last three years. If this is the case, we consider the firm to be a start-up. Table 2 shows that the percentage of start-ups is slightly higher among participants, never going beyond 4%.

Another aspect that should be considered is the firm's competitive position in the reference market, which could be captured by its market share, the evolution of sales or the exporting activity. The key question here is what to expect. Will firms with more market power participate more in public programs? Regarding international competition, the expected answer for exporters will be affirmative, for at least two reasons. Their position in international markets could be a signal of their ability to transform innovations into successful products (Czarnitzki and Licht, 2005). Also, they could be facing lower application costs as they are more experienced in dealing with bureaucracy when compared with non-exporters (Takalo, Tanayama and Toivanen, 2013b). In our sample, the presence of firms with foreign activity is clearly higher among participants (see Table 2).

The learning effect is also considered in many studies through indicators of previous participation in the same or similar programs. The application for different public aid implies both high administrative burdens and operative tasks that experienced firms could have incorporated into their routines (contracting experts, systematic monitoring, etc.). Generally, it is assumed that previous experience reduces application costs. When assessing the impact of R&D subsidies in Finland, Takalo, Tanayama and Toivanen (2013b) find that the number of past applications has a non-linear effect on application costs, first increasing and then decreasing them, which could suggest that a "learning-by-doing" process is taking place.

Trying to take previous experience with the R&D aid system into account, two measures are used in this paper. Both are dummy variables taking the value one when, during the last year, the firm gets: 1) a CDTI loan; 2) financial aid from other organizations. As can be noticed in Table 2, the proportion of firms in the sample with previous "experience with CDTI" is larger for participants (73.7) than for non-participants (17.1). Moreover, firms financed by other institutions are again more frequent among participants, although the differences are not very large.

Finally, additional control variables are introduced. Time dummy variables are included, allowing for business cycle effects or changes in the CDTI budget. As an indicator of the ease of access to external capital markets, possibly meaning better knowledge of the public aid system, a dummy variable representing the presence of foreign capital among shareholders is incorporated. For the same reason, an indicator of business group membership for each firm is considered.

Note that some of these variables might be correlated between each other. In this regard, the numbers of Table 3 reveal that pairwise correlations are reasonably low. The only exceptions are the correlations among the different types of innovation difficulties, which is not surprising given that these indicators have sectoral dimension instead of firm dimension. This will be taken into account for the interpretation of the results presented in the following section. The rest of the correlations are all below 0.5.

Table 3: Pairwise correlation matrix

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
[1]	Internal R&D expenditures per employee (logs) (t-1)	1.000														
[2]	Technological cooperation (t-1)	0.434	1.000													
[3]	Patent application	0.335	0.243	1.000												
[4]	Innovation difficulties: Financial	0.371	0.226	0.243	1.000											
[5]	Innovation difficulties: Knowledge	0.324	0.203	0.260	0.863	1.000										
[6]	Innovation difficulties: Market	0.281	0.151	0.208	0.777	0.722	1.000									
[7]	High and medium-tech manufacturing	0.302	0.196	0.247	0.405	0.379	0.326	1.000								
[8]	High-tech services	0.123	0.031	0.016	0.279	0.047	0.222	-0.104	1.000							
[9]	Size (number of employees in log)	-0.289	-0.069	-0.065	-0.107	-0.105	-0.082	0.024	-0.051	1.000						
[10]	Start-up	0.131	0.059	0.045	0.039	0.005	0.033	-0.007	0.099	-0.180	1.000					
[11]	Export (logs) (t-1)	0.268	0.194	0.262	0.313	0.399	0.245	0.328	-0.108	0.115	-0.084	1.000				
[12]	Experience with CDTI funding	0.389	0.295	0.229	0.312	0.277	0.223	0.279	0.089	-0.008	0.057	0.254	1.000			
[13]	Experience with other agencies' funding	0.303	0.221	0.115	0.032	-0.015	0.006	0.034	0.073	-0.336	0.109	0.006	0.255	1.000		
[14]	Foreign capital	-0.073	-0.015	0.004	-0.040	-0.021	0.006	0.132	-0.024	0.307	-0.040	0.180	-0.039	-0.122	1.000	
[15]	Group membership	-0.051	0.072	0.031	-0.058	-0.051	-0.078	0.078	-0.009	0.434	-0.015	0.149	0.058	-0.116	0.446	1.000

Regarding the R&D investment decision, theoretical works (Arvanitis and Hollenstein, 1994, Klepper, 1996) suggest including variables related basically to technological environment, market conditions, financial constraints, appropriability of technological returns and size (reflecting R&D economies of scale) as determinants. In our case, the dependent variable is a dummy that indicates whether the firm has self-financed internal R&D during the year[11].

As in the participation equation, with the usual control variables (size dummies, belonging to high-tech sectors, year, the firm's ownership, group membership and foreign capital), an indicator of newly born firms (start-ups) is included, trying to capture differences in the investment behavior for them. Empirical evidence suggests that start-ups are usually among the most innovative firms; their survival probability as well as their growth rate depend strongly on their innovative behavior (Audretsch, 1995, Huergo and Jaumandreu, 2004). Representing environment features, a variable reflecting exporting firms is added, as firms operating in competitive international markets have more incentives to innovate and therefore to invest in R&D.

Given the aim of this paper, special attention is devoted to a firm's participation in the CDTI low-interest loan system. This aid, as a tool that reduces a firm's financial constraints, could increase the chances of performing R&D. As can be seen in Table 2, the proportion of participants self-financing R&D almost doubles that of non-participants.

4. RESULTS

In this section, we present the results of the estimation of our model. Given the binary character of the dependent variable, and taking into account the panel structure of the data, the probability of participation (equation (1)) is estimated as a random effects Probit model.

The results are summarized in Table 4, showing marginal effects. In the first column, the coefficients correspond to the whole sample. In the second and third columns, estimates for two sub-samples are presented, SMEs (with a number of employees between 10 and 200) and large firms (more than 200 employees), while in the last two columns, we distinguish between manufacturing and services firms.

[11] We leave the analysis of the impact on R&D intensity for future research. The type of public aid here is not a direct subsidy but a loan that must be paid back, so we should consider the principal of the credit part of the company's own R&D resources. To study the effect on the intensity of R&D investment, we would first need to calculate the equivalent subsidy corresponding to the low-interest loan awarded. Unfortunately, this information is missing from our databases.

Table 4: Probability of participation in the CDTI low-interest loans system

		All firms		SMEs		Large Firms		Manufacturing firms		Services firms	
		dy/dx	S. E.	*dy/dx*	S. E.	*dy/dx*	S. E.	*dy/dx*	S. E.	*dy/dx*	S. E.
Internal R&D expenditures per employee (t-1)		0.002 ***	0.010	0.001	0.001	0.003 ***	0.001	0.004 **	0,002	0.001 *	0.0004
Technological cooperation (t-1)		0.011 **	0.065	0.019 *	0.010	0.004	0.006	0.020 *	0,012	0.001	0.003
Patent application		0.005	0.064	0.006	0.010	0.004	0.006	0.009	0,012	0.0002	0.003
Innovation difficulties	Financial	0.056 **	0.322	0.122 **	0.053	0.015	0.021	0.150 **	0.076	0.017	0.014
	Knowledge	0.047	0.373	-0.061	0.059	0.081 ***	0.029	0.010	0.080	-0.001	0.030
	Market	-0.068 *	0.484	-0.011	0.080	-0.057	0.035	-0.182	0.111	-0.038	0.026
Activity sector	High and medium-tech manufacturing	0.018 ***	0.074	0.044 ***	0.015	-0.004	0.005	0.030 **	0.015		
	High-tech services	-0.005	0.176	-0.022	0.020	0.023	0.029			-0.0003	0.004
Size (number of employees in log)		0.038 ***	0.115	0.171 ***	0.059	-0.014	0.031	0.061 ***	0.023	0.011 **	0.004
Size squared		-0.003 ***	0.012	-0.018 **	0.007	0.001	0.002	-0.005 **	0.002	-0.001 **	0.0004
Start-up		0.010	0.157	0.023	0.028			0.003	0.034	0.008	0.009
Exports (logs) (t-1)		0.001 ***	0.005	0.002 **	0.001	0.001	0.000	0.002 **	0.001	-0.0001	0.0002
Experience with CDTI funding		0.128 ***	0.065	0.123 ***	0.016	0.135 ***	0.024	0.175 ***	0.016	0.089 ***	0.028
Experience with other agencies' funding		0.020 ***	0.065	0.033 ***	0.011	0.004	0.006	0.035 ***	0.013	0.010 *	0.005
Year 2004		0.018 ***	0.077	0.017	0.013	0.019 ***	0.008	0.039 **	0.016	0.001	0.003
Year 2005		0.024 ***	0.071	0.021 *	0.011	0.026 ***	0.008	0.064 ***	0.015	-0.001	0.003
Foreign capital		-0.010	0.088	-0.017	0.014	-0.002	0.005	-0.027 **	0.014	-0.002	0.003
Group membership		0.003	0.069	0.017	0.011	-0.002	0.005	0.002	0.013	-0.0002	0.003
Sigma_u		0.195	0.016	0.192	0.020	0.198	0.027	0.183	0.018	0.226	0.089
Rho		0.037	0.006	0.036	0.007	0.038	0.010	0.032	0.006	0.048	0.036
Log. Likelihood		-1,245.76		-767.01		-413.85		-1,018.92		-174.41	
Number of observations (firms)		5,689 (2,429)		2,739 (1,337)		2,511 (976)		3,017 (1,273)		2,253 (1,002)	

S. E.: Estimated standard error. Coefficients significant at : 1%***, 5%**, 10%*. All regressions include the constant. Dummy variable for year 2003 is excluded. Marginal effects (*dy/dx*) are computed at the sample means. For dummy variables, the marginal effect corresponds to the change from 0 to 1. Rho stands for the proportion of the total variance contributed by the panel-level variance component.

The first fact that can be highlighted from Table 4 is the positive effect of having a higher technological profile on the probability of participation. Both R&D expenditure and technological cooperation agreements during the last year have a statistically positive impact for the whole sample. When we distinguish by size, the effect of internal R&D expenditure is only positive for large firms, suggesting their better position to lead R&D projects that require huge investments. On the contrary, technological cooperation affects SMEs' propensity to participate, but has no impact in the case of large firms. This is coherent with the idea that, through these agreements, SMEs find additional resources (financial, informational and human) that make them capable of undertaking projects that were maybe impossible on their own. Specifically, having conducted those agreements in the last year increases their probability of being awarded aid by around 2 percentage points.

Regarding financial constraints, our sectorial indicator refers to the lack of internal or external funds and also to the presence of large innovation costs. The important positive impact of this indicator on the probability of participation could be explained by two factors: 1) firms with financial problems could try to solve them by applying for public aid; 2) the CDTI plays an important role in financing firms that belong to those sectors affected by market failures that prevent the volume invested in R&D to reach the social optimum, and these sectors are usually the more financially constrained ones. As is shown by the results, the effect is particularly strong for SMEs and manufacturers.

On the contrary, sectorial market problems affect all firms negatively. This suggests that, generally, firms have a lower probability of being awarded aid if they operate in sectors where either information about markets is lacking or established firms have a dominant position or the demand for innovative goods/services is uncertain. This is probably due to the lower incentive to conduct R&D projects in these sectors, which makes it less useful for firms to apply for public aid. However, this result must be interpreted with caution, given the high correlation among sectoral indicators of innovation difficulties shown in Table 3.

Another interesting result in Table 4 is the existence of a non-linear effect of size: as firms are larger, they have a higher probability of being awarded aid, but the increase in size affects the probability of obtaining CDTI financing marginally less. This effect confirms the existence of entry barriers when applying for public R&D support. Applying for CDTI loans has some costs in terms of time and searching for information, so larger firms will have a higher probability of participation, although as a certain amount of resources is obtained, the size effect is smaller. As a consequence, when splitting the sample into small and large firms, the effect is only statistically significant for SMEs. On the contrary, this result is maintained for both the services and manufacturing sub-samples.

The start-up indicator seems to have no effect in any analyzed sample or sub-sample. As previously mentioned, the expected effect of this variable is ambiguous: although more experienced firms are more keen to be aware of these aid programs, younger firms are usually more financially constrained, having more incentives to apply then. In this sense, notice that our sample does not include firms supported by the NEOTEC program, which is specifically designed to provide financial resources to technological start-ups.

A firm's competitive position in international markets is also an outstanding determinant of participation in the CDTI low-interest loan system. More in detail, exports increase the probability of being awarded aid, especially for manufacturing and SME. On the contrary, for services and large firms, their effect is not statistically significant. In this sense, for large firms, being an exporter is not a distinguishing feature, while for SMEs it is clearly influenced by a firm's characteristics. In the case of services, non-exporting firms dominate the sample clearly, representing 75% of the observations.

The effect of previous experience, either with the CDTI or other institutions, is evident in all estimates. As expected, being financed by the CDTI in the recent past increases the probability of being awarded aid again substantially. Actually, this effect is 12.8 percentage points for the whole sample and takes its maximum value (17.5 points) for manufacturers. Previous experience with other institutions also affects the chances of receiving CDTI funds positively, although the magnitude of the impact is lower (2 percentage points). Obviously, expected cuts in application costs due to the learning effect are higher when the aid system is the same.

Finally, regarding control variables, time dummies reflect the increase in the probability of being awarded aid as of 2004, which is due to the spectacular increase in the CDTI budget since this year. It seems that the availability of new funds has favored relatively more manufacturing than services firms. In fact, high-tech manufacturing firms increase their probability of participation 1.8 percentage points (4.4 for SME), strengthening this idea. Analyzing a firm's capital break-down, the presence of foreign capital has a negative effect for manufacturing, while it has no impact when splitting the sample by size. Group membership does not have a significant effect on any of the estimates.

4.1. The decision to perform R&D activities

Once the first stage is completed, we analyze the determinants of the decision to self-finance R&D. Again, a random effects Probit model is used in order to estimate equation (2). Tables 5, 6 and 7 show estimates for the whole sample, distinguishing, as before, by size and sector. In each table, the first column shows the results when observed participation is used as the key explanatory variable. These estimates are included for reasons of comparison, as in this case we are not taking into account endogeneity or selection problems, and therefore the estimated impact for participation in the public system of low-interest loans will probably be biased. The results in the second column are obtained following Heckman's (1979) approach, and gathers the alternative estimates when the predicted probability of participation from the first stage is considered instead of the observed participation status. Comparing the estimates in these columns, selection and simultaneity biases can be assessed. Finally, column (3) shows the results when estimating equation (2') following Wooldridge (2005), enabling us to take into account the persistence in the decision to invest in R&D.

When comparing the first two columns of Table 5, two main conclusions can be outlined: first, being awarded CDTI aid clearly increases the probability of conducting R&D activities with one's own resources, using either the observed or the predicted participation variable; second, the estimation under specification (1) has a positive bias that is corrected when applying the two-stage procedure. That is, if the selection bias is not taken into account, the impact of participation is underestimated.

Another interesting feature relates to presence in international markets. In the second column of Table 5, it is shown that firms involved in exporting activities during the last year are 22.8 percentage points more likely to self-finance internal R&D activities, stressing the complementarity between internationalization and R&D investment strategies. At the same time, although being a start-up seems to have a positive impact in column (1), it loses its significance when taking into account the selection problem.

When dealing with the estimates for sub-samples according to size (Table 6), the selection bias is again positive for both SMEs and large firms, although it is higher for the former group. Previous participation in the CDTI system increases the probability of self-financing internal R&D activities 74.6 percentage points for SMEs and 61.5 for large firms, against the 78.9 percentage points obtained for the whole sample[12]. Actually, in terms of observed participation, the estimated effect is higher for large firms, while the impact appears to be stronger for SMEs when correcting for the selection bias. This result is consistent with previous evidence that indicates that public funding should be especially important for small firms, which are expected to face more liquidity constraints (Zúñiga-Vicente et al., 2014; Becker, 2014).

Table 5: Probability of performing R&D

		(1)		(2)		(3)	
		dy/dx	S. E.	*dy/dx*	S. E.	*dy/dx*	S. E.
Observed participation		**0.431** ***	0.147				
Predicted participation				**0.789** ***	0.105	**0.249** ***	0.063
R&D performer (t-1)						**0.532** ***	0.075
Year 2004		-0.145 ***	0.075	-0.258 ***	0.078	-0.073 ***	0.063
Year 2005		-0.223 ***	0.074	-0.398 ***	0.082	-0.104 ***	0.066
Size	10-49 employees	-0.204 ***	0.186	-0.492 ***	0.181	-0.220 ***	0.106
	50-99 employees	-0.156 *	0.234	-0.422 ***	0.233	-0.235 ***	0.138
	100-199 employees	-0.224 ***	0.251	-0.410 ***	0.251	-0.236 ***	0.150
	200-499 employees	-0.383 ***	0.215	-0.604 ***	0.209	-0.208 ***	0.122
	> 500 employees	-0.373 ***	0.242	-0.472 ***	0.231	-0.200 ***	0.133
Activity sector	High and medium-tech manufacturing	0.652 ***	0.165	0.097 *	0.151	0.065 **	0.074
	High-tech services	0.614 ***	0.288	0.348 ***	0.254	0.146 ***	0.126
Exporter (t-1)		0.573 ***	0.141	0.228 ***	0.123	0.076 ***	0.060
Start-up		0.374 ***	0.315	0.112	0.281	-0.004	0.134
Foreign capital		-0.268 ***	0.187	-0.004	0.169	-0.026	0.083
Group membership		0.197 ***	0.125	0.077 *	0.114	0.041 *	0.062
R&D performer in 2002						0.218 ***	0.090
Sigma_u		2.230	0.085	1.820	0.077	0.430	0.093
Rho		0.833	0.011	0.768	0.015	0.156	0.057
Log. Likelihood		-2,535.53		-2,276.70		-1,952.54	
Number of observations (firms)		5,689 (2,429)		5,689 (2,429)		5,689 (2,429)	

S. E.: Estimated standard error. Coefficients significant at : 1%***, 5%**, 10%*. All regressions include the constant. Dummy variable for year 2003 is excluded. Marginal effects (*dy/dx*) are computed at the sample means. For dummy variables, the marginal effect corresponds to the change from 0 to 1. Rho stands for the proportion of the total variance contributed by the panel-level variance component.

[12] The whole sample also includes micro-firms with fewer than 10 employees and firms in agricultural, construction and public services.

Table 6: Probability of performing R&D by size

		SMEs						Large firms					
		(1)		(2)		(3)		(4)		(5)		(6)	
		dy/dx	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.
Observed participation		**0.341** ***	0.047					**0.514** ***	0.112				
Predicted participation				**0.746** ***	0.063	**0.268** ***	0.032			**0.615** ***	0.065	**0.217** ***	0.032
R&D performer (t-1)						**0.519** ***	0.027					**0.483** ***	0.063
Year 2004		-0.202 ***	0.041	-0.270 ***	0.040	-0.057 *	0.034	0.005	0.028	-0.189 ***	0.029	-0.047	0.034
Year 2005		-0.232 ***	0.040	-0.350 ***	0.039	-0.046	0.034	-0.032	0.026	-0.286 ***	0.035	-0.122 ***	0.034
Size	50-99 employees	0.076	0.068	-0.254 ***	0.065	-0.067	0.042						
	100-199 employees	0.022	0.082	-0.280 ***	0.073	-0.070	0.047						
	> 500 employees							-0.003	0.044	-0.006	0.042	-0.035	-0.003
Activity sector	High / medium-tech manufacturing	0.500 ***	0.048	0.044 *	0.084	0.020 *	0.043	0.829 ***	0.055	0.396 ***	0.089	0.168 ***	0.829
	Hi-tech services	0.504 ***	0.033	0.430 ***	0.062	0.218 ***	0.060	0.497 **	0.227	-0.045	0.091	0.026	0.497
Exporter (t-1)		0.550 ***	0.053	0.318 ***	0.062	0.109 ***	0.034	0.486 ***	0.056	0.072	0.049	0.043	0.034
Start-up		0.272 *	0.120	0.146 **	0.148	0.010	0.079	-0.129	0.042	-0.132	0.057	-0.106	0.097
Foreign capital		-0.153	0.119	0.074 *	0.116	0.016	0.061	-0.222 ***	0.044	-0.091 **	0.045	-0.071 **	0.034
Group membership		0.174 ***	0.062	-0.010	0.064	-0.010	0.036	0.145 ***	0.040	0.108 ***	0.039	0.073 **	0.032
R&D performer in 2002						0.186 ***	0.038					0.317 ***	0.079
Sigma_u		2.118	0.125	1.921	0.127	0.582	0.066	2.511	0.123	1.731	0.104	0.361	0.211
Rho		0.818	0.018	0.787	0.022	0.253	0.043	0.863	0.012	0.750	0.023	0.115	0.119
Log. Likelihood		-1,362.06		-1,282.55		-1,141.56		-899.51		-709.32		-560.16	
Number of observations (firms)		2,739 (1.337)		2,739 (1.337)		2,739 (1.337)		2,511 (976)		2,511 (976)		2,511 (976)	

S. E.: Estimated standard error. Coefficients significant at : 1%***, 5%**, 10%*. All regressions include the constant. Dummy variable for year 2003 is excluded. Marginal effects (*dy/dx*) are computed at the sample means. For dummy variables, the marginal effect corresponds to the change from 0 to 1. Rho stands for the proportion of the total variance contributed by the panel-level variance component.

The selection bias is also positive for manufacturing firms (Table 7). Not correcting for the bias leads to underestimating the stimulus induced by low-interest CDTI loans. The two-stage estimate shows that manufacturing firms increase their probability of investing in R&D 75 percentage points if they have obtained CDTI aid (a number much larger than 19.5, the one obtained using the observed participation). Nonetheless, for services, the bias has the opposite sign; when selection is taken into account, the effect falls to 16.9 percentage points, being overestimated when the bias is ignored. The higher effect obtained with the real participation for services is inverted when taking care of the selection bias.

Column (3) in Tables 5, 6 and 7 analyzes the determinants of the probability of performing R&D, allowing for the existence of persistence in this decision. To do so, the lagged value of the investment decision in the previous year is included. As can be noticed, the coefficient for this variable is always positive, confirming the existence of true state dependence. In particular, firms investing one year are around 50 percentage points more likely to invest in the next period also. Besides, the impact of CDTI aid is still significant, although its size is lower in all cases. For the whole sample, firms getting loans are 24.9 percentage points more likely to invest their own resources in R&D. When distinguishing by size, a greater impact is shown for SMEs (26.8) than for large firms (21.7). By activity, while the impact is still large for manufacturing, for services the effect is reduced to 9.6 percentage points. Although contemporaneous impacts of public loans reduce their strength, their effect is still important as they can induce firms to conduct R&D activities continuously.

Table 7: Probability of performing R&D by activity

		Manufacturing firms						Services					
		(1)		(2)		(3)		(4)		(5)		(6)	
		dy/dx	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.	*dy/dx*	S.E.
Observed participation		**0.195** ***	0.028					**0.409** ***	0.167				
Predicted participation				**0.750** ***	0.060	**0.295** ***	0.033			**0.169** ***	0.029	**0.096** ***	0.017
R&D performer (t-1)						**0.492** ***	0.033					**0.478** ***	0.034
Year 2004		-0.075 **	0.031	-0.230 ***	0.037	-0.059 *	0.032	-0.051 ***	0.013	-0.059 ***	0.014	-0.046 *	0.023
Year 2005		-0.121 ***	0.031	-0.414 ***	0.040	-0.118 ***	0.034	-0.094 ***	0.020	-0.088 ***	0.019	-0.047 *	0.023
Size	10-49 employees	-0.160 *	0.099	-0.496 ***	0.096	-0.207 ***	0.064	-0.048 **	0.020	-0.129 ***	0.026	-0.097 ***	0.027
	50-99 employees	-0.122	0.121	-0.686 ***	0.079	-0.243 ***	0.076	-0.019	0.030	-0.064 ***	0.014	-0.071	0.038
	100-199 employees	0.093	0.086	-0.535 ***	0.121	-0.147 *	0.086	-0.065 ***	0.015	-0.082 ***	0.016	-0.153 ***	0.015
	200-499 employees	-0.060	0.109	-0.553 ***	0.108	-0.103	0.072	-0.166 ***	0.030	-0.261 ***	0.036	-0.153 ***	0.027
	> 500 employees	-0.088	0.137	-0.626 ***	0.103	-0.163 *	0.088	-0.108 ***	0.023	-0.165 ***	0.028	-0.118 ***	0.028
Activity sector	High / medium-tech manufacturing	0.361 ***	0.041	0.120 **	0.050	0.065 **	0.031						
	Hi-tech services							0.623 ***	0.094	0.211 ***	0.080	0.106 ***	0.040
Exporter (t-1)		0.473 ***	0.080	0.229 ***	0.079	0.087 **	0.040	0.169 ***	0.039	0.142 ***	0.033	0.050 **	0.021
Start-up		0.142	0.074	-0.015	0.148	-0.029	0.083	0.325 ***	0.140	0.091	0.080	0.039	0.047
Foreign capital		-0.196 **	0.088	0.070	0.067	0.007	0.043	-0.073 ***	0.017	-0.052 **	0.017	-0.054 *	0.027
Group membership		0.097 *	0.049	0.007	0.052	0.005	0.034	0.062 ***	0.026	0.058 ***	0.024	0.049 **	0.024
R&D performer in 2002						0.265 ***	0.040					0.132 ***	0.029
Sigma_u		2.256	0.100	1.941	0.121	0.584	0.067	1.898	0.126	1.633	0.111	0.215	0.065
Rho		0.836	0.014	0.789	0.021	0.254	0.044	0.783	0.022	0.727	0.027	0.044	0.025
Log. Likelihood		-1,432.85		-1,311.45		-1,158.94		-838.38		-779.44		-631.36	
Number of observations (firms)		3,017 (1,273)		3,017 (1,273)		3,017 (1,273)		2,253 (1,002)		2,253 (1,002)		2,253 (1,002)	

S. E.: Estimated standard error. Coefficients significant at : 1%***, 5%**, 10%*. All regressions include the constant. Dummy variable for year 2003 is excluded. Marginal effects (*dy/dx*) are computed at the sample means. For dummy variables, the marginal effect corresponds to the change from 0 to 1. Rho stands for the proportion of the total variance contributed by the panel-level variance component.

5. CONCLUSIONS

The aim of this paper is to determine the effect of firms' participation in CDTI loans on their decision to invest in R&D. The analysis considers that participation probably depends on the same firm characteristics that determine their investment behavior. To do this, two equations are estimated for a panel of Spanish firms that are observed during the period 2002-2005. The first describes firms' participation in the CDTI low-interest loan system for Technological Development Projects, Technological Innovation Projects and Joint Industrial Research Projects. The second analyzes the determinants of the firm's decision to invest in R&D, self-financing the expenditure at least partially.

It is also taken into account that the spending decision could present some persistence, i.e., firms with positive expenditures the previous year have a higher probability of investing again. This could be attributed to either the existence of sunk costs associated with R&D activities or to the learning process. If this is the case, we would talk about real state dependence as the expenditure itself causes the next period's higher probability. However, persistence could be due to some firms' characteristics (size, activity, technological opportunities and attitude towards risk) that make them keener to have R&D expenditures. If those characteristics are persistent over time, this would induce persistence also in the decision of R&D spending. In this case, we would talk about spurious state dependence. To correct the problems introduced by the presence of persistence, Wooldridge's (2005) methodology is applied.

For the first equation, some results can be highlighted. The probability of participating in the CDTI loan system is increased with the firm's technological profile. Other variables affecting this probability positively are sectorial financial constraints (either because of a lack of internal and/or external funds or as a consequence of large innovation costs), the presence of the firm in foreign markets and its recent experience in other public aid programs, especially CDTI programs. Sectorial difficulties related to the lack of market information, the existence of dominant firms and the uncertainty or lack of demand for innovations reduce the propensity to participate, maybe because these sectors have fewer incentives to conduct and finance R&D activities. Nevertheless, this result can also be due to the high correlation among sectoral indicators of innovation difficulties. Finally, a firm's size affects the probability of being awarded aid positively, although at a decreasing rate, suggesting the existence of entry costs when applying for public aid.

Regarding the decision to invest in R&D, our estimates show a significant and positive impact of CDTI loans, suggesting the effectiveness of this aid system. Moreover, if the selection problem is not considered, the impact of participation is underestimated; once correcting for this bias, the stimulus effect is larger for SMEs than for large firms and also higher for manufacturing than for services.

Finally, our results provide empirical evidence of the persistence in the R&D expenditure decision, reflecting true state dependence. More in detail, firms investing one year have around 50% more chances of investing in the next year. The impact of low-interest loans varies from 20 to 30 percentage points depending on the sample analyzed, except for services firms, where it is reduced to 9.6 percentage points. This effect is particularly important when there is persistence in R&D spending, suggesting that it is possible to induce firms to conduct R&D activities permanently by just awarding timely low-interest loans.

This result points out the relevance of public support to achieve the European Commission's target of investing 3% of GDP in R&D, as far as Spanish business R&D is concerned. Given that Spain belongs to the group of Moderate innovators (European Commission, 2010), with innovation performance below the EU27, fostering Spanish firms' technological activities should require not only an increase in the R&D intensity of actual R&D performers (intensive margin), but also of a rise in the share of R&D performers (extensive margin).

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APPENDIX: DEFINITIONS OF VARIABLES

Experience with CDTI funding: Dummy variable which takes the value 1 if the company was awarded with other CDTI aid in the recent past.

Experience with other agencies' funding: Dummy variable which takes the value 1 if the company was awarded with other organizations' aid in the recent past.

Exporter: Dummy variable which takes the value 1 if the company exported during the period.

Exports: Exports volume (millions of Euros) during the year (logarithms).

Foreign capital: Dummy variable which takes the value 1 if the company has a share of foreign capital of at least 50%.

Group membership: dummy variable which takes the value 1 if the firm belongs to a group.

High and medium-tech manufacturing: Dummy variable which takes the value 1 if the company belongs to any high or medium-tech manufacturing sector (NACE2 codes 24, 29, 30, 31, 32, 33, 34, 35).

High-tech services: dummy variable which takes the value 1 if the firm belongs to any high-technology service sector (NACE-2 digits code: 64, 72, 73).

Innovation difficulties:

- **Knowledge:** sectorial indicator of the degree of importance given by firms during this year to the lack of qualified staff or information on technology as factors making their innovation activities difficult. It is computed as the average for each CNAE2 of the values assigned by each firm inside this sector during the year (values between 1=not relevant and 4=high).
- **Financial:** sectorial indicator of the degree of importance given by firms during this year to the lack of funds in the firm or group, lack of external financing or high innovation costs as factors making their innovation activities difficult. It is computed as the average for each CNAE2 of the values assigned by each firm in this sector during the year (values between 1=not relevant and 4=high).
- **Market:** sectorial indicator of the degree of importance given by firms during this year to the lack of market information, the dominance of market by established firms, uncertain demand of innovative goods and services or lack of demand of innovations as factors making their innovation activities difficult. It is computed as the average for each CNAE2 of the values assigned by each firm in this sector during the year (values between 1=not relevant and 4=high).

Internal R&D expenditures per employee: Total expenditure on internal R&D over total employment (logarithms).

Manufacturing: Dummy variable which takes the value 1 if the company belongs to any manufacturing sector (NACE2 codes: 10 - 37).

Participation: dummy variable which takes the value 1 if the firm has been awarded with a CDTI soft loan during the year.

Patent application: dummy variable which takes the value 1 if the firm applied for patents during the period.

R&D with own resources: Dummy variable which takes the value 1 if the company devoted **its** own resources to invest in R&D during the year.

Services: dummy variable which takes the value 1 if the firm belongs to any service sector (NACE2 code: 50 - 74).

Size: number of employees during the current year (data in log.).
- **10-49 employees** : dummy variable which takes the value 1 if the firm has between 10 and 49 employees.
- **50-99 employees**: dummy variable which takes the value 1 if the firm has between 50 and 99 employees.
- **100-199 employees**: dummy variable which the takes value 1 if the firm has between 100 and 199 employees.
- **200-499 employees**: dummy variable which the takes value 1 if the firm has between 200 and 499 employees.
- **>500 employees**: dummy variable which the takes value 1 if the firm has more than 499 employees.

Start-up: dummy variable which takes the value 1 if the firm was created during the last three years.

Technological cooperation: Dummy variable which takes the value 1 if the company established technological cooperation agreements during the last three years with other partners.

Year of the application: Set of time dummy variables which take the value 1 when the proposal was presented this year.