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# Impact of low-interest credits on business R&D expenditures:

Spanish firms and CDTI loans for R&D projects

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## Abstract

Our objective is to estimate the effect of low-interest loans for R&D projects on business R&D. We take into account that the participation of firms in this kind of public programme probably depends on the same characteristics that determine their investment decisions. We also consider the possibility of persistence in R&D expenditures over time. The estimations provide evidence of the effectiveness of low-interest loans, being the stimulus effect larger for SMEs than for large firms and also higher for manufacturing than for services. Participants 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*: Low-interest credits, R&D projects, impact analysis.

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# 1. INTRODUCTION

At present, it is well known that public support for R&D is ex-ante justified by market failures that characterize this kind of activity. In fact, private investment in R&D is below the optimum social level (Arrow, 1962). However, as public funds for R&D have grown in the recent past, evaluating the effect of this aid on a firm's decisions and performance has become a priority.

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. 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. Econometric evidence about this relationship is ambiguous (García-Quevedo, 2004). Among the reasons behind this multiplicity of results, we can highlight the following: firstly, there is an absence of a generally accepted model that can be used when proposing econometrically testable hypotheses (David et al., 2000). Secondly, there are not any publicly available databases, making it difficult to compare different papers that use heterogeneous information. In addition, public programs differ in their objectives, funding schemes and methodology, so it seems reasonable that their evaluation also provides different results (Blanes and Busom, 2004).

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 CDTI on the firm's decision to self-finance R&D. Among the typology of funding programs managed by the CDTI between 2003 and 2005, we focus on the following: Technological Development Projects (TDP), Technological Innovation Projects (TIP) and Joint Industrial Research Projects (JIRP). 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 taken into account to apply for a low-interest loan 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. That is, firms with expenditures one year could be more likely to continue investing the next period. We use the method proposed by Wooldridge (2005) to control for this possibility. Our results confirm 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. PREVIOUS EMPIRICAL EVIDENCE

From an empirical point of view, evidence about the impact of public aid on private R&D has increased quickly and is mostly related to subsidy programs for R&D projects. For example, we have the papers by Walsten (2000) analyzing US firms, Lach (2002) for Israeli companies, Busom (2000) and Gonzalez et al. (2005) for Spain, Czarnitzki and Licht (2005) for innovative German firms, Duguet (2004) about French firms' spending on R&D, Clausen (2007) for Norway, and Takalo et al. (forthcoming) applied to Finnish firms.

Most of them 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 granted, 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 overestimating 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.

Among the papers which deal with these problems, noteworthy is Wallsten (2000), who considers a simultaneous equation model with R&D expenditures and subsidies as endogenous variables, using data from American firms in the *Small Business Innovation Research Program* from 1990 to 1992. Once controlling for the endogeneity of subsidies, Wallsten does not obtain any effect of them on the innovative effort. Moreover, he finds out a complete crowding-out effect of public funds on private ones.

Another outstanding paper is Lach (2002), conducted with a panel of Israeli firms, where the increase in participants´ R&D expenditure is estimated and compared with that of non-participants, not only for the year the subsidy is granted but also for the following ones. A positive dynamic effect, which needs some time to be achieved, is found especially for small firms.

A more recent paper by Clausen (2007) makes a key contribution by differentiating subsidy programs which finance projects “far from the market” from those financing the less uncertain, “close to the market”, projects. The impact is analyzed by splitting internal R&D into their different components. The impact on R&D quality is a concern as well. Available information allows removing firms which conduct R&D only when subsidized (firms without positive internal R&D expenditures). The results obtained through the instrumental variables methodology show that subsidies financing “far from the market” projects have a positive and significant impact on private R&D expenditures, giving extra incentives to innovate. This kind of aid affects R&D quality positively, too. On the contrary, for projects “close to the market,” private R&D expenditure is substituted with subsidies, mainly reducing the entry devoted to development activities. Actually, estimated elasticity of internal R&D expenditures to subsidies is 0.36 for “far from the market” projects while it is -0.66 for “close to the market” projects.

Noteworthy among the studies carried out for Spain are Busom (2000) and González, Jaumandreu and Pazó (2004). 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 database 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 database 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.

Recently, many papers have employed matching estimators as a methodological alternative. 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[1], 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, and Duguet (2004), for French firms with R&D expenditures, are examples of this approach. They all find evidence against total crowding-out effects, although only Duguet can also reject partial substitution[2].

Also with this methodology, two papers by Herrera and Heijs (2007) and González and Pazó (2008) study the Spanish case with the ESEE dataset. Herrera and Heijs (2007) use information about firms with R&D expenditures during the period 1998-2000, suggesting three groups of variables as potential determinants of the aid allocation: a) the firm’s characteristics (size, activity, age, location, property structure, diversification degree and financing barriers); b) market pressure (evolution, investment capacity, export-import trends) and; c) technological indicators (R&D culture, cooperative attitude, technology exports/imports). Their results show both an absence of crowding-out and a higher R&D intensity among supported firms (on average, they are 1.85% more intense).

González and Pazó (2008) analyze a longer period, 1990-1999. Panel data allow them to analyze persistence in innovation activities. 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.

Unlike the papers described before, Takalo et al. (forthcoming) specifically model the decisions made by the agents involved in the process. They develop a structural model of optimal treatment with heterogeneity of results where the treatment (subsidy) depends on the applicant’s investment. The model takes into account the heterogeneity of application costs. Estimations for Finland R&D projects show a social

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[1] 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.

[2] Aerts and Schmidt (2008) also reject total crowding out for Flanders and Germany with both matching estimators and CDiDRCS (Conditional difference-in-differences estimator with repeated cross-sections).

rate of return of subsidies between 30 and 50%, being spillover effects of subsidies smaller than effects on firm profits.

Finally, we can highlight the paper by Arqué-Castells and Mohnen (2012), 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 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.

## 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. Among the most usual alternatives, we find Heckman’s (1978) 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) [3]. 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 credit system during year $t$ $(t = 1,...,T)$ and is given by:

[3] 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).

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

where $y^*_{it}$ is a latent dependent variable, $x_{1it}$ represents the set of explanatory variables, $\beta_1$ is the vector of coefficients and $u_{it}$ is the error term. Firm *i* will be a participant if $y^*_{it}$ is positive[4].

In order to measure the stimulus effect of the credit 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:

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

where $z^*_{it}$ is a latent variable, $\hat{y}^*_{it}$ represents the participation in the low-interest loan system, $\alpha$ 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.

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 et al., 1997). That is, investing in R&D in one period increases the probability of

[4] A more rigorous estimate of the probability of participation should require the separate estimation of two decisions: the firm's decision to apply for the credit and the agency's decision to award it. Huergo and Trenado (2010) follow this method for the same CDTI aid scheme. This cannot be done in this paper as it is not possible to match CDTI and INE databases for rejected proposals.

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.

Taking into account the existence of persistence, we follow Wooldridge’s (2005) methodology, estimating a random effects dynamic Probit model[5]. 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 $\mu_i$. Following Wooldridge, we specify the distribution of $\mu_i$, assuming unobservable heterogeneity depends on the initial condition $z_{i0}$ and some strictly exogenous variables in this way:

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

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

where $\bar{y}_i^*$ and $\bar{x}_{2i}$ 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 $z_{it-1}$, $\hat{y}_{it}^*$, $x_{2it}$, $z_{i0}$, $\bar{y}_i^*$ and $\bar{x}_{2i}$ are the explanatory variables. Obtaining a statistically positive estimate for $\gamma$ would confirm the hypothesis of persistence due to true state dependence. Additionally, once the persistence effect has been discounted, parameter $\alpha$ 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.

## 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 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 credits: 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.

This information has been completed with records from the INE Technological 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; 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.

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.

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.

## 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 *et al.*, 2005; Heijs, 2005; Czarnitzki and Licht, 2005; Clausen, 2007; Huergo and Pereiras, 2010; Takalo *et al.*, forthcoming).

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[6]; 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,

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

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.

Table 2: Descriptive statistics

| | | *Non-participants* | | *Participants* | |
|---|---|---|---|---|---|
| Foreign capital (%) | | 17.3 | (37.9) | 16.0 | (36.7) |
| Technological cooperation (%) | | 38.4 | (48.7) | 67.5 | (46.9) |
| Innovation difficulties | Financial | 1.43 | (0.28) | 1.61 | (0.17) |
| | Knowledge | 1.07 | (0.18) | 1.18 | (0.13) |
| | Market | 1.10 | (0.12) | 1.16 | (0.08) |
| Size (number of employees) | | 416.6 | (1,175.6) | 293.76 | (801.3) |
| 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) |
| Exports (logs.) (t-1) | | 7.1 | (7.5) | 11.9 | (6.8) |
| Internal R&D expenditures per employee (logs.) (t-1) | | 3.6 | (4.0) | 6.7 | (3.3) |
| R&D performer with own resources (%) | | 44.0 | (49.7) | 83.6 | (37.1) |
| Start-up (%) | | 3.2 | (17.7) | 4.0 | (19.6) |
| Patent application (%) | | 21.9 | (41.4) | 43.3 | (49.6) |
| Group membership (%) | | 41.8 | (49.3) | 50.3 | (50.1) |

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.

Variables reflecting a firm's financial situation are also commonly considered, particularly when financial constraints are present. As is well known, 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, Hall *et al.* (1999) find that R&D activities in the high technology sector are sensitive to cash flow during the period 1978-1989 for the USA, while the relationship is not so clear for France and Japan. In turn, Bond *et al.* (2003) point out that, for British firms, cash flow has an impact on R&D investment decisions rather than on the quantities invested. However, financial aid received by awarded firms may imply a significant incentive for financially constrained firms, increasing their probability of performing technological activities and, therefore, of asking for these credits.

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 et al., forthcoming). 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 et al. (forthcoming) 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.

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 last year[7].

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.

[7] 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. To study the effect over the intensity of R&D investment, we first need to calculate the equivalent subsidy corresponding to the low-interest loan awarded.

The results are summarized in Table 3, 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[8].

The first fact that can be highlighted from Table 3 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.

[8] The whole sample also includes micro-firms (with fewer than 10 employees) and firms that are neither manufacturing nor services firms (agricultural, construction and public services).

Table 3: Probability of participation in the CDTI low-interest credits 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.

Another interesting result in Table 3 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.

### 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 4, 5 and 6 show estimates for the whole sample, distinguishing, as before, by size and sector. In each table, column (1) shows the results when observed participation is included as an explanatory variable, while column (2) gathers the alternative results when the predicted probability of participation from the first stage is considered. 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 4, 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 5), 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[9]. 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.

Table 4: Probability of performing R&D

| | | (1) | | | (2) | | | (3) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *dy/dx* | | D. E. | *dy/dx* | | D. E. | *dy/dx* | | D. 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) | | |

See notes to Table 3.

The selection bias is also positive for manufacturing firms (Table 6). 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 ef-

[9] The whole sample also includes micro-firms with fewer than 10 employees.

fect 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 4, 5 and 6 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 5: Probability of performing R&D by size

| | | SMEs | | | | | | | | | Large firms | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1) | | | (2) | | | (3) | | | (4) | | | (5) | | | (6) | | |
| | | *dy/dx* | | D.E. | *dy/dx* | | D.E. | *dy/dx* | | D.E. | *dy/dx* | | D.E. | *dy/dx* | | D.E. | *dy/dx* | | D.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) | | |

See notes to Table 3.

## Table 6: Probability of performing R&D by activity

| | | Manufacturing firms | | | | | | Services | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
| | | *dy/dx* | D.E. | *dy/dx* | D.E. | *dy/dx* | D.E. | *dy/dx* | D.E. | *dy/dx* | D.E. | *dy/dx* | D.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) | |

See notes to Table 3.

## 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, the first describing firms' participation in the CDTI low-interest loan system~~;~~ and the second one analyzing 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.

In the analysis, three data sources for the period 2002-2005 were used: the CDTI database, the EIT conducted by the INE and the PITEC database also collected by the INE under FECYT and Cotec's sponsorship. After merging them, the final sample consists of 5,689 observations, 2,429 firms and 499 supported projects from these typologies: Technological Development Projects, Technological Innovation Projects and Joint Industrial Research Projects.

As available data have panel structure and dependent variables are dummies, the estimation of each equation is obtained through a random effects Probit model. 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. 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.

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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.