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The Effects of Fiscal Incentives for R&D in Spain "*

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Abstract

This paper explores the effect of fiscal incentives for R&D on innovation. Spain is considered one of the most generous countries in the OECD in fiscal treatment of R&D, yet our data reveal that tax incentives are little known and, especially, seldom used by firms. Restricting our empirical analysis to those firms that do report knowing about such incentives, we investigate the average effect of tax incentives on innovation, using both nonparametric methods (matching estimators) and parametric methods (Heckman's two-step selection model with instrumental variables). First, we find that large firms, especially those that implement innovations, are more likely to use the tax incentives, while small and medium enterprises (SMEs) encounter some obstacles to using them. Secondly, the average effect of the policy is positive, but significant only in large firms. Our main conclusion is that tax incentives increase innovative activities by large and high-tech sector firms, but may be used only randomly by SMEs.

***Keywords**:* R&D fiscal incentives, matching methods
***JEL Classification**:* O31, H25, H32.The Effects of Fiscal Incentives for R&D in Spain♣

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I. Introduction

Private firms spend less on R&D than is socially optimal because the presence of externalities creates a gap between private and public profitability (Arrow 1962; Nelson 1959). In most OECD countries governments try to solve this problem through various measures, such as subsidies or fiscal incentives for R&D, in order to stimulate innovation. The effectiveness of these instruments depends on each country's fiscal system and the purposes of its programs (European Commission 2003).

Spain is considered the most generous country in the OECD in tax treatment of R&D (Warda 2001 and 2002). Fiscal benefits act either on the tax base (free depreciation) or on the corporate income tax liability (tax credits for R&D and technological innovation) and apply to all firms that carry out R&D activities, independently of the success or failure of the project.[3] Given these tax incentives, the price of R&D is minor (Marra 2004; Corchuelo 2006), so these instruments should in theory stimulate innovation activities and correct for suboptimal R&D funding in firms.

However, empirical evidence reveals that these generous tax incentives are rarely used by Spanish firms (Corchuelo and Martínez-Ros 2008). Accordingly, the main goal of this paper is to evaluate the effectiveness of tax incentives for R&D in Spain. The success of this tax policy is based on the government's ability to design it and on the use of firms' expected profit. Therefore, it is very important to understand the design of the tax benefits and the characteristics of the firms that use them. This means that the variable that explains the financial-economic profitability of the incentives (generally measured by the marginal effective tax credit, B-index or cost of R&D capital) is endogenous. We assume also that there may be a selection problem—that is, the design of the tax incentives may make some kinds of firms more likely to use them than others.

Empirical studies that have analyzed the effectiveness of tax incentives for R&D have

[3] Fiscal incentives for R&D in Spain are governed by articles 11.2, 16.4, 35, 36 and 40.3 of the Revised Text of the Corporate Income Tax Law (RD-L 4/2004).

usually employed parametric techniques of econometric estimation. This paper uses a nonparametric approach (matching methods) to take into account the problems of selection and endogeneity. We also present a parametric approach (Heckman's two-step selection model) to compare our results with those from the standard approach.

The matching approach has been widely used in the evaluation of public policies, especially policies oriented to the labour market (Heckman, Ichimura and Todd 1997; Heckman, LaLonde and Smith 1999; Lechner 2002; Dehejia and Wahba 1999 and 2002; Hotz *et al*. 2006). In the evaluation of innovation policies, this method has been used, essentially, to analyse the effects of direct subsidies on R&D activities; little research has addressed the effects of tax incentives (Czarnitzki *et al*. 2004; Heijs *et al*. 2006). Also, only Marra (2004) and Corchuelo (2006) have studied the effects of tax incentives on innovation in Spain.

Our data come from the *Spanish Business Strategy Survey* at the firm level. Since 2001, this survey has included some questions related to firms' knowledge and use of tax incentives for R&D. Our analysis is focused on a single year, 2002, because of problems with answers to some of the questions in 2001, although we use variables covering the period 1998-2002.

Our results are presented in three parts. First, we isolate the factors that affect the probability that a firm will take advantage of tax incentives for R&D; second, we estimate the average effect of the tax policy on user and non-user firms, using a nonparametric approach (matching estimators); and third, we analyse the effects of tax benefits on R&D technological effort, using a parametric approach (Heckman's two-step selection model) in order to compare the results with those from the nonparametric method.

In summary, we find that firms with higher capacity for innovation, with a stable financial position, and that have also received R&D subsidies (especially SMEs) are more likely to take advantage of the tax benefits. However, SMEs encounter important obstacles to using them. Otherwise, on average, tax policy fosters technological effort, but the increase is only significant in large firms. Results from the Heckman's selection model confirm that tax policy has a significant and great effect only in large firms and firms that belong to high-technological intensity sectors and it is not significant for SMEs which they do not suffer selection problem.

We conclude that tax incentives for R&D are randomly distributed in SMEs because those firms are not aware of their benefits. In contrast, large firms accept the minor cost that fiscal incentives take for granted, and the policy has a positive effect on their technological effort.

The rest of the paper is organized as follows: Section 2 reviews the literature evaluating innovation policies, Section 3 introduces the data sources, and Section 4 discusses the methods used for the empirical assessment of the effects. The empirical results are presented in Section 5, and Section 6 concludes.

II. Literature review

There is abundant empirical literature related to the effects of financial public policies—either subsidies or tax incentives—on R&D spending. Studies of tax incentives aim mainly at measuring the additional private R&D spending and the cost-effectiveness of the incentives, that is, whether the additional R&D spending is greater than the government's tax revenue losses.

Most studies have used a micro-econometric framework because more and better micro-data are available, and most studies have focused on the American and Canadian economies (Hall and Van Reenen 2000). Nevertheless, there are also studies focused on other countries.[4] Studies using a macro-econometric framework are scarce but not irrelevant, since macro-data allow capturing the indirect effects caused by the incentives, for example, the spillover effects of innovation between countries (Guellec and van Pottlesberghe 2003; Falk 2004), or other macro-economic factors that affect R&D decisions (the culture of innovation, the fiscal system, etc.) (Bloom *et al*. 2002).

The methodology used in the literature on R&D fiscal incentives combines event studies comparing behaviour before and after a change in the policy (Collins 1983); questionnaire surveys and interviews attempting to determine how individual firms respond to a policy change (Mansfield 1986); and econometric estimation using two types of parametric methods: impact models (Berger 1993) in which a binary variable shows the impact of the tax incentive, and demand models (Hall 1993) that directly obtain the price-elasticity of R&D investment. Although results are mixed, the most recent studies confirm the effectiveness (Hall and van Reenen 2000)[5] and cost-effectiveness (Finance Department of Canada 1998) of tax incentives for R&D. In Spain, there is little evidence of the impact of this tax policy, except for studies by Marra (2004), who concludes that tax incentives affect the firm cost structure and improve the private demand for R&D, and Corchuelo (2006), who finds that incentives increase the probability of innovation and R&D effort.

Recently, parametric approaches have been combined with nonparametric ones in the evaluation of public policies. This approach has been widely used to determine whether R&D direct subsidies complement or crowd out private spending on R&D. In these studies, the recent concern about endogeneity and selection problems has led researchers to identify patterns in the distribution of public support and to estimate counterfactual status (Herrera and Heijs 2006).

Using a matching approach, Czarnitzki (2001), Fier (2002) and Almus and Czarnitzki (2003) have concluded that, in Germany, R&D subsidies do not fully crowd out private financing. Czarnitzki and Fier (2002), using data from German innovative firms in the service sector, obtain evidence of additionality as well, and argue that the reason may be that the service sector experiences more problems in protecting

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[4] Some examples: Lattimore (1997) in Australia, Asmussen and Berriot (1997) and Mulkay and Mairesse (2003) in France, van Pottlesberghe et al. (2003) in Belgium, and Parisi and Sembenelli (2003) in Italy.

[5] In general, the median of the elasticity is –0.85, and the average is -0.81 (European Commission 2003).

intellectual property than does the manufacturing sector. In France, Duguet (2004), working with a panel of innovative manufacturing and service sector firms and controlling for past R&D subsidies, shows that on average, public funds add to private funds rather than crowding them out. However, there might be a partial crowding-out effect if the amount of the subsidies could be taken into account. In Sweden, Lööf and Hesmati (2005), using data on 770 manufacturing and service firms that conduct R&D, also find additionality, especially in SMEs. In Finland, Czarnitzki and Ebersberger (2006) find that innovation input increases with the reception of public subsidies, so they reject a full crowding out of private by public financing. Innovation activities are also more equally distributed as a consequence of public subsidies. In Spain, Herrera and Heijs (2006) show that R&D subsidies have increased R&D intensity, especially among firms with less chance of obtaining public funding. González and Pazó (2006), using a bias-corrected matching estimator and controlling (as in Duguet, 2004) for past R&D subsidies, reject either full or partial crowding out of private financing by R&D subsidies and conclude that some firms (especially SMEs and firms with medium-low technological intensity) would have not developed R&D activities in the absence of R&D subsidies. Czarnitzki and Hussinger (2004) and Herrera (2004), using this approach, observe additionality for subsidies not only in R&D input but also in output (patenting behaviour).

Other studies combine parametric and nonparametric techniques to evaluate public funding policy. Kaiser (2004) analyses the effect of public support on firms' R&D intensity using Heckman's two-step selection model and nearest neighbour matching estimator. He finds no evidence of crowding out, although he has some doubts about this conclusion because of some problems in the data. Görg and Strolb (2005), working with a sample of Irish plants and using parametric (DID) and nonparametric estimations (with Caliper matching estimator), find that medium-sized and small domestic plants increase their R&D spending as a consequence of the subsidies received, whereas large plants do not. For foreign-owned plants, the authors do not find complementary or substitution effects, independently of their size. In Belgium, Aerts and Czarnitzki (2006), combining matching estimators and instrumental variables and taking into account the amount of subsidy received rule out full crowding out of private R&D spending. In Spain, Duch et al. (2006), who use the matching and OLS approach to analyze the impact of various types of R&D subsidies received by Catalonian manufacturing and service sector firms, find improvements not only in their returns but also in the evolution of their business practices and their added value. Czarnitzki and Licht (2005) combine both approaches to study the input and output additionality of R&D subsidies in eastern and western Germany. They include in the sample firms that do not conduct R&D, in order to consider the inducement effect of the subsidies. They observe complementary effects and reject the existence of a crowding-out effect.

Recently, an increasing number of studies have used both approaches to analyse the effects of R&D subsidies on firms' R&D co-operation. Czarnitzki and Fier (2003) in Germany, Ebersberger and Lehtoranta (2005) in Finland, and Czarnitzki, Ebersberger and Fier (2006) in Finland and Germany find that funding for R&D co-operation increases the output of patents. In Spain, Busom and Fernández-Rivas (2005) and Busom (2006), using a sample of innovative manufacturing firms, find that the type of R&D collaboration chosen is associated with various firm characteristics and that R&D subsidies cause a behavioural change in firms' R&D strategic partnerships.

Similar conclusions have been obtained in studies that have used only parametric methods of estimation to evaluate the relationship between R&D subsidies and firms' R&D activities. The exceptions are Wallsten (2000), who (using simultaneous equation models) finds full crowding out of private R&D spending in firms benefiting from the U.S. Small Business Innovation Research (SBIR) programme; Busom (2000), in Spain, who (using Heckman's two-step selection model) rejects full crowding out of private funds but finds partial crowding out for 30 percent of the firms; Toivanen and Niininem (2000), in Finland, who show that the positive effect of R&D subsidies disappears in firms with higher cash-flow; and Suetens (2002), in Belgium, who (using instrumental variables) finds no significant effects of R&D subsidies. The rest of the studies we have analysed rule out full (or partial) crowding-out effects on innovation inputs or outputs. In a micro-econometric framework, these include Czarnitzki and Fier (2001) in Germany (using OLS and logit models); Lach (2002) in Israel (using various types of estimators); Hanel (2003) in Canada (using univariate and two-stage logit models); Lehto (2000), working with plant data, and Ali-Yrkkö (2005 a, b), both in Finland (using instrumental variable approaches); Hussinger (2006) in Germany (using two-step parametric and semiparametric models); González et al. (2005) in Spain (using simultaneous equation models with thresholds and instrumental variables); and Gelabert *et al.* (2006) in Spain (using instrumental variables and Heckman's two-step selection model). In a macro-econometric framework, Wolff and Reinthaler (2005), working with a panel of OECD countries (using instrumental variables), also find no crowding-out effects.

To summarize, the majority of studies that have used only parametric or only nonparametric approaches or both, controlling for the endogeneity of R&D subsidies and sample selection problems, have rejected full crowding-out effects. There is evidence that the increases in innovation input translate into increased innovation output, as well.

In contrast, there are only two papers, to our knowledge, that have analysed the effects of tax incentives on R&D using a nonparametric approach. In Canada, Czarnitzki *et al*. (2004), using data for 1999, show that tax credits increase a firm's probability of developing new products in domestic and foreign markets; they infer that firms perform more R&D activities because of the tax incentives. In Spain, Heijs *et al*. (2006) use the *propensity score matching* method to analyse the effect of tax incentives on Spanish manufacturing firms. They reject a crowding-out effect, although they conclude that fiscal incentives do not stimulate additional R&D investment.

III. Spanish data

We use data provided by the SEPI Foundation on behalf of the Spanish Ministry of Industry, Tourism and Trade.[6] This survey contains data from 1990 to 2002 on manufacturing firms with more than 10 employees, which are questioned about their strategies in the short and long run, including their R&D decisions. Since 2001, this survey has included some questions about the knowledge and use of tax incentives for R&D that allow us to distinguish between firms that merely are aware of these incentives and firms that actually use them. Because of some problems with answers in 2001, our research refers to the year 2002, although we measure some variables for the period 1998 to 2002. Our final sample includes 1708 observations at the firm level.

Tables 1 and 2 analyse the knowledge and use of tax incentives by firms of various sizes[7] and sectors.[8] Only a little more than half of the firms in the full sample are aware of the incentives; awareness is especially low among SMEs and in industries with medium-low technological intensity. And of those that know about the R&D tax credit, fewer than half use it. If we consider only firms that conducted R&D in 2002, the percentages increase, especially of SMEs and firms with medium-low technological intensity that report knowing about the tax incentives, but still, very few firms report using them. Finally, Table 3 analyses the average R&D technological effort (R&D spending over sales), which, in general, is higher in those firms that know about and,

[6] See Fariñas and Jaumandreu (1999) and www.funep.es for the survey's design and elaboration.
[7] We sort by sizes because of the special characteristics of the sample. Large firms (more than 200 employees) were fully selected, while small ones (>10 and ≤ 200 employees) were randomly selected.
[8] Sectors are classified into high-medium and medium-low technological intensity according to www.ine.es/daco/daco42/daco4217/lstsctcnae.doc.

especially, that use the tax incentives. Whether there is a causal connection is something to confirm by empirical study.

[Table 1]

[Table 2]

[Table 3]

IV. Methods

We examine the average treatment effects of R&D tax incentives on firms' R&D technological effort using two different approaches: matching estimators and Heckman's two-step selection model.

The matching approach is used when the data exhibit a selection bias. If R&D tax incentives were randomly distributed among firms, then we could simply compare the average R&D technological effort of the user and non-user firms in order to obtain the treatment effect.[9] But fiscal incentives for R&D are not granted randomly; they depend on the government's design. Moreover, firms at least are partly self-select into the treatment and their decisions whether or not to take advantage of these incentives may be related to the expected benefits. The matching method attempts to emulate an experiment where tax incentives are distributed randomly by comparing the outcomes of pairs of firms that are very similar in several characteristics. We can then compare the average R&D technological effort of the group of user firms with the group of matched similar non-user firms. The main advantage of this approach is that we need assume neither functional form nor distribution of the measurement error term. But this method also has some drawbacks: it allows us only to verify heterogeneity between the treated and not-treated firms (Czarnitzki *et al.* 2004); it assumes that selection depends on observable factors only, which in turn means that the researcher has to observe every relevant factor that could affect the probability of receiving the treatment (Hussinger 2006); and it relies strongly on the existence of common support (Heckman *et al.* 1996 and 1997).

Because the matching method allows only for a binary treatment, we compare the results using a second method. Selection models take into account selection on either observable or unobservable variables. A characteristic of these models is the additive separability of the unobserved components. A failure of common support is not as big a problem as for the matching approach, although this method has the cost of assuming a functional form.

In the empirical analysis, we first consider the full sample of firms that report knowing about the tax incentives (which includes firms not conducting R&D), and second, the subsample of only firms that perform R&D. We work with the full sample because we take into account firms' R&D status in order to evaluate the inducement effect of tax incentives on firms that do not conduct R&D (Aerts and Czarnitzki 2006; González and Pazó 2006). If we judged only those that did, we could underestimate the treatment effect because we could not test whether or not a firm would have performed innovation activities without the incentives.

In the matching method, we evaluate the effect of tax incentives on R&D technological effort (Y_1) for the firms that use them (treated group, A=1), and the potential outcome (Y_0) for the non-user firms (untreated group, A=0). The fundamental problem of causal inference is that it is impossible to observe the individual treatment effect. But, under some assumptions, we can estimate the average treatment effect for the sample. We calculate the average treatment effect on the treated as follows:

$$ATT = E(Y_1 - Y_0 | A = 1) = E(Y_1 | A = 1) - E(Y_0 | A = 1)$$

[1]

And we estimate the average treatment effect on the untreated as follows:

$$ATC = E(Y_1 - Y_0 | A = 0) = E(Y_1 | A = 0) - E(Y_0 | A = 0)$$

[2]

To carry out the evaluation, we need to construct the counterfactual $E(\hat{Y}_0 | A = 1)$ in equation [1], that is, the R&D technological effort users would have made, on average, had they

[9] Under the weaker assumption of mean independence, which supposes that firms' participation in the fiscal incentives system is random, we can estimate the output by simply averaging the treatment and non-treatment firms

not taken advantage of the tax incentives, selecting from the non-user firms a control group in which the distribution of observed variables is as similar as possible to the distribution in the treated group. We also need to construct the counterfactual $E(\hat{Y}_1 | A = 0)$ in equation [2], that is, the R&D technological effort non-user firms would have made, on average, had they taken advantage of the tax incentives, selecting from the user firms the control group with the most similar distribution of observed variables.

To construct the counterfactual, we assume that all relevant differences between user and non-user firms are captured by their observable characteristics, *X*. Then we select from the non-user (user) firms a control group in which the distribution of observed variables is as similar as possible to the distribution in the user (non-user) group. We use the propensity score (PS) proposed by Rosenbaum and Rubin (1977) instead of the vector of the observable characteristics *X* as the matching argument. Rosembaum and Rubin (1977) define the propensity score as the conditional probability of using tax incentives [$p(x) = \Pr\{A = 1 | X = x\}$. They show that if the exposure to treatment is random within cells defined by *X*, it is also random within cells defined by the values of a synthetic measure *p(x).*

After that, we pair each user firm with some group of "equivalent" non-user firms, and associate the R&D technological effort of the treated firms *i*, y_i with the weighted outcomes of their "neighbours" *j* in the untreated comparison group (A=*0*) to obtain [1]:

$$\hat{y}_i = \sum_{j \in A=0} w_{ij} y_j \ .$$

[3]

And we pair each non-user firm with the group of "more similar" user firms, and associate the R&D technological effort of the untreated firms *j*, y_j with the weighted outcomes of their "neighbours" *i* in the treated comparison group (A=*1*) to obtain [2]:

$$\hat{y}_j = \sum_{i \in A=1} w_{ji} y_i \ .$$

(Wooldridge 2001).

[4]

w_{ij} and w_{ji} $\in[0,1]$ with $\sum_{j\in A=0} wij = \sum_{i\in A=1} wji = 1$ are the weighted controls in forming a comparison with the other groups, untreated and treated, respectively.

We estimate two types of matching estimators to obtain the treatment effect for the treated (user) firms and the untreated (non-user) firms.[10] First, we find the outcome of the most similar control unit, that is, *nearest neighbour matching*[11]

$$j : \left| p_i - p_j \right| = \min_{k\in\{A=0\}} \left\{ \left| p_i - p_k \right| \right\} \qquad w_{ik} = 1(K = j)$$

[5]

to estimate the treatment effect on the treated firm *i*, and

$$i : \left| p_j - p_i \right| = \min_{k\in\{A=1\}} \left\{ \left| p_j - p_k \right| \right\} \qquad w_{jk} = 1(K = i)$$

[6]

to estimate the treatment effect on the untreated firm *j*.

Second, we use a weighted average of the outcomes of the untreated (treated) firms where the weight given to untreated *j* (treated *i*) firms is in proportion to the nearness of the observable characteristics of *i* (*j*) and *j* (*i*) (this is Kernel-based matching)[12]

$$w_{ij} = \frac{K\left(\frac{p_i - p_j}{h}\right)}{\sum_{j\in A=0} K\left(\frac{p_i - p_j}{h}\right)}$$

[7]

to estimate the treatment effect for the treated firms *i*, and

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[10] See Heckman, Ichimura and Todd (1997, 1998), Heckman, Ichimura, Smith and Todd (1998), Smith (2000), Becker and Ichino (2002) and Smith and Todd (2004) for a discussion of different types of matching estimators.

[11] Nearest neighbour matching has been used in Czarnitzki (2001), Fier (2002), Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), Czarnitzki and Hussinger (2004), Kaiser (2004), Czarnitzki, Ebersberger and Fier (2004), Lööf and Hesmati (2005), Czarnitzki and Licht (2005), Czarnitzki and Ebersberger (2006), González and Pazó (2006), Herrera and Heijs (2006) and Aerts and Czarnitzki (2006).

[12] Kernel-based matching has been used by Czarnitzki and Fier (2003), Duguet (2004), Kaiser (2004), Ebersberger and Lehtoranta (2005), Busom and Fernández-Ribas (2005) and Busom (2006).

$$w_{ij} = \frac{K\left(\frac{p_j - p_i}{h}\right)}{\sum_{i \in A=1} K\left(\frac{p_j - p_i}{h}\right)}$$

[8]

to estimate the treatment effect for the untreated firms j.

Finally, we consider the average difference between the actual and the estimated outcome (R&D technological effort) to be caused by the tax policy. To derive equations [1] and [2] we need two assumptions given the propensity score: first, the *balancing property,* that is, the balancing of pre-treatment variables given the propensity score

$$A \perp X \quad | \, p(X)$$

[9]

where A shows the treatment status (using or not using the tax incentives); and second, the *unconfoundedness assumption* given the propensity score

$$Y_1, Y_0 \perp A \,|\, p(x).$$

[10]

If the first assumption is satisfied, observations with the same propensity score must have the same distribution of observable characteristics independently of their treatment status (the second assumption). That is, for a given propensity score, exposure to treatment is random; therefore, user and non-user firms should be on average observationally identical.

We estimate the propensity score according to Becker and Ichino (2002),[13] considering the normal cumulative distribution

$$p(x) = \Pr\{A = 1 | X = x\} = F(h(X = x))$$

where *h(X)* is a function of covariates with linear and higher order terms. We restrict the sample to common support; that is, we delete all the observations on user firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. Also, for both

[13] The program *pscore.ado* proposed by Becker and Ichino (2002) estimates the propensity score and tests the balancing assumption.

samples (the full sample and those firms that perform R&D and know about the tax incentives), we estimate separate propensity scores for larger firms (more than 200 employees) and for SMEs, to evaluate the effects on the outcome (R&D technological effort) by size. So we estimate in total six propensity scores, and then we calculate the average treatment effects on the treated firms using nearest neighbour and Kernel-based matching as well as the average treatment effects on the non-treated firms using nearest neighbour matching.[14]

To estimate the propensity score we use a similar specification from Corchuelo and Martínez-Ros (2008), in which the dependent variable is a dummy with value 1 if the firm takes advantage of the tax incentives and 0 otherwise. The vector of the covariates includes variables classified in three groups. The first group considers binary variables for firms' characteristics: size (*D10-20, D21-50, D51-100, D101-200, D201-500, D>500*, with value 1 if the firm is in the given interval of number of employees), to take into account management abilities (Czarnitzki and Fier 2002; González and Pazó 2006); sector (*DM-HS*, with value 1 if the firm is in a high-medium tech sector), to capture technological opportunities; and a financial variable (*financial stability,* with value 1 if the firm's own equity over total debt is >0.5 and 0 otherwise), to account for differences in the way that firms finance their investment activities (Harhoff 1998; Hall 2002 and 2005).

The second group includes binary variables linked with firms' innovation activities: *stable R&D firm*, with value 1 if the firm has performed R&D activities in the period 1998-2000, and 0 if it has not performed R&D activities or has done so in only some of those years, to show the experience of the firms (Busom 2000; Blanes and Busom 2004); and *receive subsidies in 2002* to take into account that firms that participate in this type of program are also aware of other kinds of public support and have perfectly identified the R&D expenditures that qualify for the deductions.

Finally, we have considered some variables that assume that firms evaluate costs and benefits before choosing to take advantage of the tax incentives. The benefits are approximated

[14] We employ the method described in Becker and Ichino (2002) and Abadie and Imbens (2004).

by the variable *B-index,*[15] which represents the minimum profit that one firm expects to obtain from investing in R&D, allowing for tax incentives.[16] The costs are approximated by two binary variables that reveal the obstacles perceived by managers to using tax incentives: *lack of R&D personnel,* with value 1 if the firm did not dedicate any personnel to R&D in 2002; and *lack of importance of quality improvements in production*, with value 1 if the firm does not perform quality controls, quality is not the principal reason for price variation, the firm does not perform market and marketing research to commercialise its product, and the firm has no design activities, and 0 otherwise.

We test[17] that the variables *B-index* and *receive subsidies in 2002* are endogenous, and we use instrumental variables to take the endogeneity into account. Therefore, we include in the regressions the variable *B-index* for the previous year, and we use the estimated probability of the variable *receive subsidies in 2002* (a binary variable with value 1 if the firm obtained an R&D subsidy in 2002) with a set of covariates.[18]

Finally, the predicted probabilities (the so-called propensity scores) obtained from the probit models serve as argument in the matching procedure.

Results from this method are compared with results from a two-step Heckman's selection model in which, in a first step, we analyse the probability of using the tax incentives, and second, we analyse technological effort as a function of a set of variables that includes the *B-index* (expected profitability) that firms expect to obtain by participating in the tax incentive system.

V. Empirical results

1. Probability of using tax incentives

[15] The B-index is a synthetic index designed by McFetridge and Warda (1983) that allows comparing the generosity of different systems of fiscal incentives for R&D. It is also the fiscal component of the cost of capital of a marginal project of R&D.

[16] The variable B-index has been elaborated in a similar way of Corchuelo and Martínez-Ros (2008).

[17] We use the Blundell and Smith test for probit models to check for the potential endogeneity of these variables. Under the alternative hypothesis, we regress the suspected endogenous variables as a linear projection of a set of instruments. We then include the residuals obtained in the model and, under the null hypothesis, exogeneity can be rejected, so we test the endogeneity of the variables.

[18] See and Martínez-Ros (2008) for details about the model used.

First, we have estimated the predicted probability of using the tax incentives for the full sample (Table 4) and the sample of firms performing R&D (Table 5). In all the specifications, we have verified that the balancing property is satisfied.[19]

The participation probability increases with firm size when the full sample is considered, but not when we restrict the sample to those firms performing R&D. Technological opportunities are not significant in either the full sample or the subsample of innovative firms. One important factor in explaining the probability of using tax incentives is to obtain R&D subsidies. Firms that apply for R&D subsidies have perfectly identified the qualified expenditures and can support the administrative or other costs of applying for them, so, as expected, this factor influences the use of the tax incentives system. This result shows complementarities among the public instruments to promote innovation. Financial stability also increases the probability of participation, but it is significant only to SMEs showing the importance of not having financial constraints to investing in R&D. In contrast, although being a stable R&D performer increases, in general, the probability of participation, it is significant only in large firms, which shows that firms with higher capacity to innovate are also more likely to use tax incentives. Finally, results report that only large firms are aware of the benefits from the tax incentives, while SMEs emphasize on the obstacles to using them.

In sum, those Spanish firms that have higher capacity for innovation (Czarnitzki *et al.* 2004), participate in other types of public financing of innovation activities and have a stable financing position are more likely to take advantage of tax incentives for R&D.

2. Average treatment effects

Second, we present the average treatment effect on treated firms and the average treatment effect on untreated firms using different types of matching estimators. We have tested the full sample of firms knowing tax incentives (Table 6) and the subsample of firms that know about the tax incentives and perform R&D (Table 7), distinguishing by size. The first two rows show nearest neighbour matching (random draw version) and the Kernel matching proposed by

[19] Upon request, the authors will provide the number of blocks that ensures that the mean propensity score is not different for treated firms and control firms in each block (guaranteeing that the balancing property is satisfied) and

Becker and Ichino (2002), and the rest of the rows show the sample average effect of treatment on treated firms (SATT) and the sample average effect of treatment on controls (SATC) using the nearest neighbour estimator proposed by Abadie and Imbens (2004). Effect tests are usually carried out by means of simple t-statistics. However, the ordinary t-value is biased upwards because it does not capture that the mean of the outcome variable of the control group results not from a random sampling but from an estimation (via the propensity score and the matching procedure). To remove this bias, we apply a bootstrapping method that simulates the distribution of the mean outcome of the control group by repeated sampling. This empirical distribution can calculate a standard error and, thus, a t-statistic that is not biased. On the other hand, Smith (2000) considers that the nearest neighbour estimator can operate with more than one "nearest neighbour," and *with* or *without* replacement, that is, the untreated firm can act as counterfactual of more than one treated firm. This way, we can reduce the variance of the estimator (Smith and Todd, 2004), since the observations with insufficient "nearest neighbours" are ignored and the group of possible matching firms is larger and this can reduce biases (Abadie and Imbens 2006).

In Table 6 we observe that only the SATT procedure presents a positive and significant effect of tax incentives on R&D technological effort, either for the full sample or for any group of firms by size. Comparatively, the effect is higher in SMEs. However, the effect that tax incentives would have on non-user firms is not significant.

When only firms that conduct R&D are considered (Table 7), the positive and significant effect of tax incentives exists only in large firms. This result supports the idea that only large firms are aware of the benefits of the incentives and that SMEs, in contrast, perceive some obstacles that impede their access to these incentives. The hypothetical effect that tax incentives would have on non-users is positive and significant in the full sample of innovative firms: R&D technological effort could be increased if more firms took advantage of tax incentives.

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the number of treated firms and control firms for each block considering the common support (the table that shows the inferior block of the propensity score).

Finally, we present the results of the second step of Heckman's procedure (the structural equation) in Tables 8 and 9. The dependent variable in the regressions is the log of R&D technological effort, and we have used the log of *B-index* as an independent variable to obtain the elasticity of R&D effort due to the tax benefits. Results are similar to those from the matching procedure. Only the coefficients of the technological opportunities and *B-index* variables are significant and have the correct sign. R&D technological effort increases in high-tech firms and when the B-index is minor, but the former effect is significant only in large firms. Parametric estimation shows that only large firms and firms in high-tech industries seem to benefit from the tax incentives, and for those firms the tax policy is effective. As well, the Mill's ratio is not significant in SMEs, which shows that there is not a selection problem and that tax incentives are randomly distributed in firms of this size.

VI. Conclusions

Fiscal incentives for R&D are instruments used by governments to encourage innovation. Spain's tax policy is considered the most favourable among the OECD countries, but data report that it is little used by firms. To explore the effectiveness of these incentives, we have used both parametric (matching estimators) and nonparametric (selection model) approaches on a sample of Spanish manufacturing firms.

There are two main findings in our paper. (1) Among firms that perform R&D activities, size per se does not affect the probability of using tax incentives, but they are used especially by large firms that can guarantee the viability of the projects and those that are more heavily involved in innovation activities. Moreover, tax incentives are also employed by firms that receive additional public financial support (direct subsidies) for R&D investment, in particular, small and medium-sized enterprises [SMEs]. Only large firms evaluate the estimated returns caused by the tax incentives. We also find that the obstacles are important especially for SMEs. (2) In the estimation of the counterfactual situation, we show that on average tax policy fosters R&D technological effort, but the increase is significant only for large firms. We consider that, in the case of SMEs, a reduction of the obstacles might increase their probability of implementing innovations and therefore increasing their R&D spending. Finally, results of the structural equation in the Heckman's selection model confirm that the tax policy has a significant and great effect only in large firms.

Our main conclusion is that in Spain, tax incentives for innovation are effective only in high-medium tech sectors and large firms and those incentives do not have impact on SMEs, where the incentives are randomly distributed.

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TABLE 1

Firms That Know about and Use R&D Tax Incentives, by Size (2002)

	Full sample					
	Do not know		Know		Use	
	Observations	% total	Observations	% total	Observations	% Know
SMEs	610	52.1	560	47.9	102	18.2
Large firms	87	16.2	451	83.8	191	42.4
Total	697	40.8	1,011	59.2	293	29.0
	Firms that conduct R&D					
	Observations	% total	Observations	% total	Observations	% Know
SMEs	62	25.6	180	74.4	82	45.6
Large firms	41	10.3	357	89.7	177	49.6
Total	103	16.1	537	83.9	259	48.2

Source: ESEE and own elaboration

TABLE 2

Firms That Know about and Use R&D Tax Incentives by Sector (2002)

	Full sample					
	Do not know		Know		Use	
	Observations	% total	Observations	% total	Observations	% Know
Medium-low tech	93	26.4	259	73.6	110	42.5
High-medium tech	604	44.5	752	55.5	183	24.3
Total	697	40.8	1,011	59.2	293	29.0
	Firms that conduct R&D					
	Observations	% total	Observations	% total	Observations	% Know
Medium-low tech	25	11.7	188	88.3	106	56.4
High-medium tech	78	18.3	349	81.7	153	43.8
Total	103	16.1	537	83.9	259	48.2

Source: ESEE and own elaboration

TABLE 3

R&D Technological Effort of Firms That Conduct R&D (2002)

	Do not know	Know	Use
SMEs	1.5	2.3	3.0
Large firms	0.8	1.6	2.2
Total	1.2	1.9	2.5

Source: ESEE and own elaboration

TABLE 4

Probability of Using Tax Incentives, among Firms That Know about Them

[Dependent variable: *claim R&D deductions*]

	Total	SMEs	Large
Const.	**-1.80 (-5.4)**	-0.9 (-3.0)	-0.9 (-3.8)
D21-50*	**0.71 (2.4)**		
D51-100*	**0.69 (2.1)**		
D101-200*	**1.04 (3.4)**		
D201-500*	**0.94 (3.1)**		
D> 500*	**0.72 (2.4)**		
DM-HS*	0.11 (1.0)	0.08 (0.4)	0.07 (0.5)
Financial stability*	**0.30 (3.0)**	**0.43 (2.9)**	0.21 (1.5)
Stable R&D firm*	**0.62 (3.9)**	0.45 (1.8)	**0.66 (3.2)**
$\hat{P}$ (receive subsidies in 2002)	**0.69 (3.0)**	**1.73 (2.8)**	**0.51 (2.0)**
$\hat{B} - index_{t-1}$	**0.65 (2.3)**	0.57 (1.0)	**0.72 (2.2)**
Lack of R&D personnel*	**-0.49 (-3.1)**	**-0.80 (-3.2)**	-0.38 (-1.8)
Importance of quality improvements in production*	**-0.40 (-3.1)**	**-0.48 (-2.5)**	-0.34 (-1,8)
Number of obs.	914	518	396
Log-likelihood	-409.1	-181.9	-231.33
Region of common support	[0.018, 0.92]	[0.023,0.96]	[0.111,0.83]

TABLE 5

Probability of Using Tax Incentives, among Firms That Conduct R&D and Know about the Incentives

[Dependent variable: claim R&D deductions]

	Total	SMEs	Large
Const.	-1.30 (-2.7)	-0.80 (-2.3)	-1.10 (-3.9)
D21-50*	0.72 (1.5)		
D51-100*	0.88 (1.7)		
D101-200*	0.91 (1.8)		
D201-500*	0.81 (1.7)		
D> 500*	0.56 (1.1)		
DM-HS*	0.23 (1.7)	0.27 (1.1)	0.09 (0.6)
Financial stability*	**0.26 (2.2)**	**0.47 (2.2)**	0.14 (0.9)
Stable R&D firm*	-	0.13 (0.5)	**0.80 (3.4)**
$\hat{P}$ (receive subsidies in 2002)	**0.81 (3.5)**	**1.55 (2.4)**	**0.52 (2.0)**
$\hat{B}-index_{t-1}$	**0.79 (2.7)**	0.73 (1.2)	**0.75 (2.2)**
Lack of R&D personnel*	**-0.42 (-2.1)**	-0.05 (-0.2)	**-0.63 (-2.3)**
Importance of quality improvements in production*	-0.31 (-1.9)	-0.46 (-1.8)	-0.19 (-0,8)
Number of obs.	487	171	316
Log-likelihood	-307.2	-101.9	-194.6
Region of common support	[0.120, 0.92]	[0.169,0.97]	[0.062,0.83]

TABLE 6

Matching Estimators: Firms that Know about the Tax Incentives

	Total	SMEs	Large
ATT (NNM)	0.35 (0.9)[(1)]	0.56 (0.9)[(1)]	**0.84 (2.3)**[(1)]
N. Treated	283	101	182
N. Controls	149	61	84
ATT (Kernel)	**0.76 (3.2)**[(1)]	0.53 (1.2)[(1)]	**0.74 (2.6)**
N. Treated	283	101	182
N. Controls	149	390	188
SATT (NNM)	**0.67 (2.6)**	**0.87 (2.1)**	**0.68 (2.3)**
N. Treated	283	101	182
N. Controls	615	417	198
Percent of exact matching	100	100	100
Number of matches	4	4	4
SATC (NNM)	0.23 (1.1)	0.16 (0.7)	0.33 (1.2)
N. Treated	615	417	198
N. Controls	283	101	182
Percent of exact matching	100	100	100
Number of matches	4	4	4

Note: (1) Bootstrap standard errors (n. reps: 100)

TABLE 7

Matching Estimators: Firms that Conduct R&D and Know about the Tax Incentives

	Total	SMEs	Large
ATT (NNM)	0.12 (0.3)[(1)]	0.47 (0.8)[(1)]	0.68 (1.8)[(1)]
N. Treated	249	81	168
N. Controls	114	42	77
ATT (Kernel)	**0.75 (2.6)**[(1)]	0.63 (1.1)[(1)]	**0.79 (2.6)**
N. Treated	249	81	168
N. Controls	231	85	142
SATT (NNM)	**0.84 (2.6)**	0.76 (1.2)	**0.82 (2.3)**
N. Treated	249	81	182
N. Controls	220	87	131
Percent of exact matching	100	100	100
Number of matches	4	4	4
SATC (NNM)	**0.59 (2.0)**	0.71 (1.3)	0.44 (1.2)
N. Treated	220	87	131
N. Controls	249	81	168
Percent of exact matching	100	100	100
Number of matches	4	4	4

Note: (1) Bootstrap standard errors (n. reps: 100)

TABLE 8

Heckman's Second Step (Structural Equation). Firms that Know about the Tax Incentives

[Dependent variable: log (R&D technological effort)]

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	Total	SMEs	Large
D21-50*	0.51 (0.9)		
D51-100*	-0.09 (-0.2)		
D101-200*	-0.33 (-0.6)		
D201-500*	-0.60 (-1.2)		
D> 500*	-0.72 (-1.2)		
DM-HS*	**0.79 (4.2)**	**0.70 (2.2)**	**0.78 (3.0)**
Financial stability*	-0.18 (-1.0)	-0.48 (-1.6)	-0.08 (-0.4)
Stable R&D firm*	0.43 (1,2)	0.51 (1.7)	0.06 (0.2)
$\hat{P}$ (receive subsidies in 2002)	**0.63 (2.0)**	0.75 (1.2)	0.40 (1.0)
Ln($\hat{B} - index_{t-1}$)	**-0.43 (-2.1)**	-0.18 (-0.6)	**-0.78 (-2.4)**
Mill's ratio	**-0.97 (-3.3)**	-0.60 (-2.5)	**-1.71 (-5.2)**
Number of obs.	243	81	162
Wald chi (free degrees)	134.8(19)	56.0(9)	63.9(9)

TABLE 9

Heckman's Second Step (Structural Equation). Firms that Conduct R&D and Know about the Tax Incentives

[Dependent variable: log (R&D technological effort]

	Total	SMEs	Large
D21-50*	0.30 (0.6)		
D51-100*	-0.22 (-0.3)		
D101-200*	-0.41 (-0.7)		
D201-500*	-0.64 (-1.0)		
D> 500*	-0.7 (-1.0)		
DM-HS*	**0.75 (3.7)**	**0.67 (2.0)**	**0.77 (2.6)**
Financial stability*	-0.23 (-1.2)	-0.54 (-1.7)	-0.09 (-0.4)
Stable R&D firm*	**0.71 (2.0)**	**0.71 (2.0)**	0.25 (0.8)
$\hat{P}$ (receive subsidies in 2002)	0.49 (1.3)	0.67 (1.0)	0.32 (0.7)
Ln($\hat{B} - index_{t-1}$)	**-0.49 (-2.0)**	-0.02 (-0.1)	**-0.89 (-2.3)**
Mill's ratio	**-1.28 (-2.5)**	-0.56 (-1.2)	**-2.02 (-4.5)**
Number of obs.	243	81	162
Wald chi (free degrees)	104.0(19)	42.2(9)	47.3(9)

TABLE A.1

Descriptive statistics

Variables	Total		Firms That Perform R&D		Firms That Know Incentives	
	Media	s.d.	Media	s.d.	Media	s.d.
D10-20*	0.22	0.41	0.04	0.19	0.12	0.32
D21-50*	0.27	0.44	0.13	0.34	0.21	0.41
D51-100*	0.10	0.30	0.08	0.28	0.10	0.30
D101-200*	0.10	0.30	0.12	0.32	0.12	0.33
D201-500*	0.20	0.40	0.38	0.48	0.27	0.44
D > 500*	0.12	0.32	0.25	0.43	0.18	0.38
DM-HS*	0.21	0.41	0.33	0.47	0.25	0.44
Financial stability >0.5*	0.38	0.48	0.41	0.49	0.41	0.49
Stable R&D firms*	0.30	0.46	0.81	0.40	0.44	0.50
Receive R&D subsidies in 2002*	0.09	0.29	0.25	0.44	0.15	0.36
B-index $_{t-1}$ (1)	0.41	0.14	0.45	0.21	0.42	0.17
Lack of R&D personnel *	0.68	0.47	0.14	0.35	0.53	0.50
Importance of quality improvements in production*	0.43	0.50	0.17	0.38	0.31	0.46
R&D technological effort						

Note: In parenthesis, percentages over the total.