The Effect of Public R&D Subsidies on Private R&D Spending in Chilean Manufacturing Firms*

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Executive Summary

This study analyzes the existence of a complementary relationship between public and private spending on Research and Development activities. The results show that public funding does not produce a substitution effect on private spending. In fact, depending on the methodology used, public subsidies actually produce a crowding in effect of up to 49% on private spending.

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1. Introduction

Chile presently possesses a policy supporting innovation in firms. Its implementation rests largely in the hands of CORFO through its Innova Chile programme. The various funding lines have been essentially set up to complement private research and development investment and other innovative activities carried out by firms.

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The main justification for spending public resources on these activities is the presence of market failures. These lead to a potentially lower-than-desirable level of private sector funding and/or participation in these activities. Thus emerges the need for the State to stimulate the development of these activities, especially given that the international evidence reveals the positive impact of R&D and its innovations on productivity and ultimately on the growth of nations.

However, clearly economic resources are scarce and therefore must be allocated as efficiently as possible. In this particular context, efficiency implies that the public funds targeted at innovation and R&D must carry out the role for which they were devised. In other words, that they effectively constitute a complementary source of funds to the firms own efforts.

Therefore, one of the main objectives of public R&D policy schemes is to support projects that would not otherwise be undertaken by firms alone. This refers to investments with a high degree of uncertainty regarding the results and returns on the investment made (market failures), which are characteristic of this kind of activity.

The objective of this study is to look for evidence of the effects of public R&D policy schemes on the Chilean manufacturing sector. Through the use of matching techniques proposed by the empirical literature and using the results of the Fourth National Innovation Survey of 2005, the following question will be tackled: Does the public support for R&D activities complement or substitute private R&D spending in Chilean firms?

2. Review of the Literature

2.1. Conceptual framework

The market failures associated to innovation suggest an underinvestment in R&D projects given that firms will only carry out projects that are privately profitable. This implies that there are projects that offer significant benefits to society but that do not cover the private costs and will therefore not be carried out by firms.

This is the main reason for justifying public financing for private R&D. The subsidy allows firms to reduce investment costs and therefore increase investment in innovative projects. This will in turn raise the productivity level of firms.

However, there is a risk that firms will have an incentive to apply for public funding for their internal benefit alone, in other words, to fund privately beneficial projects that they would have undertaken anyhow without public funding. The substitution of private for public funding is known as crowding-out and must be taken into account by the authorities when evaluating the efficiency of public R&D funding policies.

Nevertheless, as Busom (2000) suggests, evidence of a negative relationship between public and private R&D spending is not necessarily implies a negative impact of public funding policy. The reason for this is that public programmes may selectively choose projects with high social returns and a high likelihood of generating spillovers, which due to problems of appropriability, do not encourage the private sector to add extra resources to the funding already provided by the State.

Projects with high spillovers and low appropriability levels are unlikely to attract much investment from the private sector, unless their additional input produces returns that they can adequately capture. As such, in certain cases, a high public spending accompanied by a low additional private contribution does not necessarily imply a negative impact of public financing policy.

Thus, to get a good picture of the effect of public R&D funding policies, an estimator is required that captures as accurately as possible the hypothetical effort that firms would have made in the absence of public subsidies. This is the key aspect in the study of causal effects.

2.2. Prior experience

With regard to the impact of public funding on private R&D, the literature follows various different tracks. The inconclusive findings of the empirical literature are essentially due to the difficulty in making this kind of analysis due to the potential selection bias.

In general, public funding recipients are probably chosen according to technical and economic feasibility of the project and the background information of the applicant firm. Therefore, public funding becomes endogenous which leads to inconsistencies in the estimators of interest when that variable is correlated with the error. Furthermore, as a result of political incentives for example, it is quite likely that the authorities act on a picking-the-winners basis. In other words, that the authorities will choose firms and projects that are "sure things" and that consequently would probably be funded by firms in any case. This would, in effect, produce an "intentional" substitution effect (crowding-out).

David, Hall and Toole (2000) provides an overview of the literature on the relationship between R&D subsidies and private R&D spending for various levels of aggregation. All the reviewed studies attempt to estimate the sign and magnitude of the net effect of public funding policies. At an industry and country level, 2 of the 14 studies reviewed reveal the existence of crowding-out, both corresponding to U.S. data. At a laboratory and industry level, 9 out of 19 studies reveal the existence of crowding-out, 7 of which are based on U.S. data.

Busom (2000) presents evidence on the effects of public financing on the innovation activity of Spanish firms. It also studies the characteristics of firms with a higher probability of participating in public financing programs. Through systems of equations, the author models the decision of firms when applying for funding, the decision rule of the authorities in allocating subsidies and the R&D

spending decision by firms in one or the other condition, that is, with or without public funding. The author finds that small firms are more likely to receive a subsidy than larger ones. This may be due to the specific characteristics of smaller firms, such as higher risk aversion or financial market restrictions, or financing policy orientation towards these kinds of firms. In terms of the impact of public financing policy, the author finds that in general public funding induces more private effort, with the exception of 30% of firms in which a crowding-out effect cannot be ruled out.

Lach (2000) uses data on manufacturing sector firms in Israel between 1990 and 1995 to estimate the impact of the subsidies provided by the Ministry of Industry and Commerce. Using different methodologies such as the Before-After estimator, difference-in-differences and various dynamic data panel models, the author finds different results depending on the methodology used. However, the conclusions of the article indicate that there is no crowding-out in the subsidized firms and that the long-run elasticity for R&D subsidies is 0.22.

Wallsten (2000) uses data from the SBIR Program implemented in the United States to estimate the impact of subsidies on the innovation performance of small high technology firms. The author indicates that "Empirical studies to measure the effect of these government grants typically regress some measure of innovation or firm productivity (e.g. R&D spending or employment) on the subsidy. Many of these studies find a positive correlation between government R&D funding and private R&D effort and employment. While this approach can establish a correlation between government grants and firm R&D, it cannot determine whether grants cause firms to do more R&D or whether firms that do more R&D receive more grants…" (Wallsten, 2000, p.82). Given this perception, the author proposes estimating a multi-equational model that allows the contrasts of the above hypothesis to be separated. His results indicate that firms with more employees and patents receive more funding from the SBIR but that the subsidies do not seem to affect the employment level of the beneficiary firms. In fact, through this methodology, the author finds evidence that the SBIR grants substitute private R&D funding dollar for dollar. In other words, he finds evidence of crowding-out in the grants provided by the SBIR program.

More recently, Almus and Czarnitzki (2002) suggest that, for the case of Germany, the innovation activity of firms that receive public funding increased by approximately four percentage points compared to firms that did not receive public financing. Although the Mannheim Innovation Panel (MIP) contains panel data, the authors estimate three cross-sections for the three available years (1994, 1996, and 1998). Using non-parametric matching methodology, they estimate the causal effect of public funding by comparing the results of interest between the firms that received subsidies and those that did not. The propensity score is estimated considering dummies by industry; dummies by cohort (relative to the year of the estimate, 1994, 1996 or 1998); number of employees to control for firm size; exports, imports and market share to control for competitiveness; age of the firm to control for the propensity to engage in innovative projects (it is expected that older firms will be more hesitant to invest in R&D and are therefore less likely to apply for R&D funding, while newer firms, when being set up, must invest in innovative activities and are therefore more likely to apply for public financing); intensity of capital to control for different technologies used in the production process; possession of an R&D department to control for innovation performance; legal structure of the firm to control for the firm's attitude to risk; market concentration; and the type of ownership of the firm, in other words, if it belongs to a foreign or a West Germany company. It uses the difference-in-differences methodology.

In the Chilean case, Benavente (2003) finds that during the 1995-1998 period, Chilean manufacturing firms that received public funding for R&D: a) had higher R&D spending, b) made more process innovations, and c) had productivity improvements, compared to similar firms that did not receive public funding. A crowding-in effect is also observed in R&D spending in firms that received public funding. He finds that for every dollar the government provides in subsidies, firms allocate 1.3 dollars. This suggests a crowding-in effect of 0.3 dollars. The author also finds that firms that have cooperated with universities and/or public R&D institutes present higher levels of R&D spending than firms that have not entered into formal contracts with these types of institutions.

Finally, Bérubé and Mohnen (2007) examine whether firms that received R&D subsidies, on top of tax incentives, have a better innovation performance compared to those that were only favoured with tax incentives. Using Canadian manufacturing firm data for the year 2005, and non-parametric matching estimators, the authors find that receiving R&D subsidies on top of tax incentives improves the innovation performance of firms.

3. Empirical Application

3.1. Data

The data used in this study comes from the Fourth Survey of Technological Innovation (INE, 2005). That survey is an essential tool for measuring the state and the dynamics of innovation in Chilean firms (Universidad de Chile, 2005). It has been progressively perfected over the years, always in line with international standards, in order to characterize the various aspects related to the innovation process of Chilean firms. It should be noted that, in contrast to previous years, this version incorporated a complete section on R&D spending and personnel following the guidelines of the OECD Frascati Manual.

The statistical unit considered in the following analysis is firms that invest in research and development. Thus, every company that indicated it invested its own resources in R&D activities, either basic, applied or experimental development, is part of the sample of this study. As indicated in the following table, the sample included 610 firms in 2004. As a result of the sampling procedure applied for the survey implementation (INE, 2005), when the corresponding sectoral expansion factors are applied, the expanded sample totals 2,523 firms.

TABLE 1

As the above table shows, most firms that carry out R&D activities are from the agricultural, livestock, hunting and forestry sector as well as the manufacturing sector, with a respective share of 31.9% and 30.1% of total firms. Further behind lies the transport, storage and telecommunications sector with 14% of the expanded total.

Considering only the firms that received government subsidies (12% of the universe), the following table shows that on average 39% of total R&D financing comes from the State (considering all funding sources) and 69% comes from private funding. This proportion varies from sector to sector. In some cases, such as fishing and education, subsidies outweigh private sector spending.

TABLE 2

Of the 294 firms that received subsidies (12% of the total), the following table shows that the share of the subsidy as a proportion of all R&D spending (public and private) varies according to the economic sector. The average subsidy in 2004 represented 43% of total public and private R&D spending in the firms studied albeit with significant differences between sectors. For example, in the case of education, subsidies accounted for 86% of total firm spending in that sector, while in transport subsidies represented 50% of total public-private spending. The average subsidy in the manufacturing sector totalled 41% of total public-private R&D spending.

TABLE 3

In order to better characterize the firms that undertook R&D activities in 2004, the following table summarizes some of their main production variables. The selection of the variables for analysis closely follows the suggestions made in the recent literature in terms that could be closely linked to their own R&D efforts (Benavente, 2002).

Concerning private sector R&D spending, the information presented in Table 4 suggests that the distribution of that spending is highly asymmetric since the mean of that distribution is significantly higher than the median indicating that a small group of firms spends disproportionately more than the rest. Therefore, the values are also presented in quartiles of the natural logarithm of private spending to prevent the extreme values from being excessively determinant on the mean of the spending distribution. In effect, once the logarithmic conversion is applied, the average and median values match better thereby revealing a more symmetrical distribution as shown in the second row of Table 4.

The above also applies for the subsamples presented in the following columns; groups that have been separated between firms that received public R&D financing and those that did not. The statistical significance of the differences in means (in logarithms) between these two groups is presented in the last column of the table.

In terms of size, either measured by total sales or number of workers, Table 4 indicates that firms that received public R&D subsidies are larger than those that did not. Firms that received subsidies also applied on average for more intellectual property patents and carried out more cooperation activities compared to those without subsidies, among other aspects of interest. However, a higher proportion of firms that did not receive these subsidies have R&D departments within the company.

TABLE 4

4. Effect Analysis

The empirical evaluation of the impact of policy measures or, in general terms, of any treatment faces well-recognized problems associated to the nature of the experiment and the type of data available. For example, we may want to evaluate the impact of an R&D support program comprising of a tax incentive for those investments. The impact of the participation of a firm in that program would be easy to calculate if we could observe the company in both states at the same point in time: "R&D spending with treatment", to measure the result of the firm that participated in the incentives program; and "R&D spending without treatment", to measure the result that the firm would have had had it not participated in the incentives program. Consequently, the impact of the incentives program on firm *k* is expressed by:

$$\tau_k = (Y_k^1 - Y_k^0) \qquad (1)$$

in $t = t_0$, where:

$Y_k^1 =$ R&D spending of firm *k* with treatment (subsidy) in t_0.

$Y_k^0 =$ R&D spending of firm *k* without treatment (subsidy) in t_0.

$\tau_k =$ Impact of the program (or treatment) on firm *k*, which captures the spending differential on R&D as a result of being in one state or the other.

The above expression cannot be estimated directly because it is impossible to observe the performance of the same company in two different states (with and without subsidy) over the same point in time. This is the main problem of program impact evaluations. As such, the literature that tackles these issues proposes alternative methods to create the contrafactual (the non-observable state of the firm or individual under study).

Another problem in program evaluations is that in general the allocation of the treatment (allocation of a subsidy to a given firm in this case) is not random, and randomness is an essential assumption for directly measuring the impact of the program. If it were not random, it would not be possible to generalize the impact of the program based on a calculation of the effect that it had on the participating group since that group has certain specific characteristics that determine its participation.

It is also possible that the allocation of the treatment is dependent on certain conditions preset by the authorities. For example, tax incentives are offered to firms that, in the opinion of the authorities, are more likely to successfully implement the project or whose R&D spending is above a given threshold.

Then, through program design or simply by self-selection (firms or persons that possess characteristics that determine their participation in a program) the assumption of randomness is not fulfilled. This, together with the non-observability of the contrafactual, makes it difficult to estimate the impact of a given program.

Four methodologies covered in the literature for measuring the impact of public funding policies on private R&D spending are described below. They are applied sequentially on the sample of 2,523 firms that indicated they invested in R&D with their own funds in 2004. The assumptions underlying each methodology are discussed as well as the corresponding results.

4.1. Average Treatment Effect (ATE)

Under certain conditions, experimental type data allow the contrafactual to be constructed thus eliminating the evaluation problem. The contribution of experimental data lies in the elimination of the problem of self-selection since the treatment is allocated randomly to individuals. Then, under the additional assumption of the absence of spillovers, the untreated group is statistically equivalent to the treatment group in all dimensions except the treatment status thus permitting the construction of an adequate control group. Under this assumption, the ATE estimator can be measured in the following manner:

$$\hat{\alpha}_{ATE} = (\overline{Y}_t^1)_i - (\overline{Y}_t^0)_j \qquad en\ t = t_0 \qquad (2)$$

In $t = t_0$, where $\overline{Y}_t^1$ and $\overline{Y}_t^0$ denote the average result of interest for group *i* of treated firms (T) and group *j* of untreated firms (NT) respectively in the same moment in time xxxx. Graphically, the estimator is represented as follows:

FIGURE 1

If for one moment, the assumption that R&D financing is allocated randomly were established, the estimator of the average impact of the treatment (ATE) described in (2) could be calculated to approximate the effect of public policy on private R&D spending.

Tables 6 and 7 present the results of the ATE estimator for the years 2003 and 2004 respectively. The estimator is applied to the universe of 2,523 firms that finance R&D with their own funds, and on the subsample of manufacturing firms, differentiating by sectoral patterns in the production of innovationdescribed in the previous section.

Column DIF (T-NT) captures the estimator described in (2). In other words, the difference in the average R&D spending of firms with subsidy relative to the average private spending of firms without subsidy measured in thousands of Chilean pesos. The following column reveals the proportion of that difference with respect to the average spending of firms without subsidy. Finally, the last column captures whether the estimated difference – ATE, is statistically significant.

TABLE 5

TABLE 6

The results suggest that while the difference of private spending reported by firms in both groups is positive, the corresponding statistical test does not indicate that that difference is significant. Part of this result may be due to the high level of heterogeneity existing among productive sectors, which is not controlled by this estimator.[1]

A sharper view is obtained by analysing the manufacturing sector in particular.[2] The results presented in the earlier tables indicate that in the years 2003 and 2004 manufacturing firms with subsidy spent more on R&D compared to those without subsidy. In 2003, the former spent 161% more than the latter while in 2004 the difference was 232%. This implies that public funding is leveraging private funding in manufacturing sector firms.

An analysis by sectoral pattern in the production of innovation within the manufacturing sector[3] seems to indicate that firms that received subsidies and are labour intensive and have large scale production, spend on average more on R&D than their counterparts without public funding, thus suggesting a leveraging effect for this group of firms.

[1] For the sectoral heterogeneity of returns to R&D see Goto and Suzuki 1989 for Japan and Benavente et al, 2006 for Chile.

[2] It also has the advantage that most studies on these issues have been based exclusively on manufacturing sector information.

[3] A detailed description on sectoral typification used in the manufacturing sector is available in the appendix section.

4.2. Difference-in-differences Estimator (DID)

As mentioned earlier, the consistency of the estimator above is heavily dependent on the assumption of randomness when allocating a treatment – receiving public support. It should be highlighted that public R&D and innovation financing programs for firms apply a selection process following previously established criteria, such as technical and economic feasibility, innovative merit and/or whether or not it belongs to an economic sector that is prioritized by the institution. Therefore, the chosen firms probably possess specific characteristics that make them different to those that did not apply for the subsidy or that were not selected.

This difference between the two groups does not allow an adequate control to be set up based on those that do not receive subsidies since the subsidy impact estimator would not only capture the effect of the subsidy itself, but also the effect of the specific characteristics of the groups. This implies that the subsidy impact estimator could well be over or underestimating the corresponding effect (depending on the effect of those specific characteristics on R&D spending).

An alternative to the ATE is to capture the effect of a treatment, in this case of an R&D subsidy, on the same individual or firm dynamically. This method consists of comparing the average result of firms with the treatment with the same firms before the treatment. By applying time differentials, the specific characteristics of the firm that remain constant over time are nullified and therefore the estimator will be free from its effect.

Nevertheless, the assumption of invariance over time is quite strong once the period of analysis is not too short. There are also changes than can affect both the treatment and non-treatment firms. If this is not taken into account, changes in the subsidy result impact variable could be erroneously attributed, when in fact what occurred is more due to changes in the context surrounding the firms – economic cycles – more than to changes in its R&D activities.

In order to control for transitory events that affect both treatment and non-treatment firms, and the specific characteristics of the treatment and control groups, the literature suggests calculating a difference-in-differences estimator defined by the following expression:

$$\tilde{\alpha}_{DIF-in-DIF} = \frac{\sum_{k=1}^{N_1} (Y_t^{01} - Y_{t-1}^{01})_k}{N_1} - \frac{\sum_{n=1}^{N_2} (Y_t^{00} - Y_{t-1}^{00})_n}{N_2} \tag{3}$$

$$\tilde{\alpha}_{DIF-in-DIF} = (\overline{Y}_t^{01} - \overline{Y}_{t-1}^{01})_i - (\overline{Y}_t^{00} - \overline{Y}_{t-1}^{00})_j$$

Where Y_t^{01} is the result of a firm *k* belonging to group *i* of treated firms that receive subsidies only in *t* and Y_{t-1}^{01} is the result of the same firm without treatment in *t*–1. Meanwhile, Y_t^{00} is the result in *t* of a firm *n* belonging to group *j* of non-treatment firms and Y_{t-1}^{00} is the result of the same firm in *t* – 1. N1 is the total of firms that were treated in *t* and non-treatment in *t* – 1, while N2 is the total of untreated firms in *t* and in *t* – 1. Graphically, the estimator is represented as follows:

FIGURE 2

As such, the first differences clean the effects of the specific characteristics of the groups on the result variable, in this case private R&D spending. Meanwhile, the second difference cleans the effect of the transitory events once they affected both the treatment and non-treatment groups. However, if those transitory events do not affect the private R&D spending of both groups equally, the estimator will be biased since it will be capturing that difference as well as the effects of the subsidy.

The results of the difference-in-differences estimator applied to the data sample are presented in Table 7.

TABLE 7

While the results tend towards the same direction as the ATE estimator, it is dangerous to infer a statistically significant positive impact. This is because the number of observations of the treatment group is too few compared to the control group. This occurs because the former have to fulfil the condition that during the base year 2003 they did not receive any State support, but in the year 2004 they did. Meanwhile, the control group is comprised of firms that did not receive public R&D financing in 2003 or 2004.

4.3. Matching using Propensity Score and Observables

Given the above situation and that the allocation of subsidies is not a random process, the literature suggests the application of matching techniques. This methodology produces a situation in which there are no statistically significant differences between subsidized firms (treatment group) and unsubsidized firms (control group) in terms of the characteristics that affect the probability of receiving public financing. This situation allows an adequate control group to be created to approximate the contrafactual of the subsidized firms and thereby estimate the causal effect of public financing on the R&D spending of firms.

The causal effect can be approximated in the following manner:

$$\theta^1 = E[Y^1 - Y^0 \mid D=1] = E[Y^1 \mid D=1] - E[Y^0 \mid D=1] \qquad (4)$$

Where Y^1 denotes the result variable of a firm that receives subsidies and Y^0 denotes the result variable of a firm that does not receive subsidies. *D* is a dummy variable that takes the value of 1 when the firm receives public financing. $E[Y^1 \mid D=1]$ is observed and can be estimated in an unbiased manner based on the mean of the result variable considering the firms that have received subsidies. However, the result $E[Y^0 \mid D=1]$, corresponding to the contrafactual, is by definition not observable, and therefore it is necessary to establish certain assumptions that can offer some approximation of its value.

It is clear that $E[Y^0 \mid D=1]$ cannot be calculated based on the mean of the result variable of those which have not received subsidies since:

$$E[Y^0 \mid D=1] \neq E[Y^0 \mid D=0] \qquad (5)$$

This condition is only fulfilled if the allocation of subsidies were random. However, this does not really happen, both due to firm self-selection and picking-the-winners type behaviour.

Rubin (1977) introduced the Conditional Independence Assumption (CIA) to overcome the problem of the expression in (5). This condition implies that the participation (subsidy recipients) and the potential result (for example R&D spending) are independent for individuals with the same group of exogenous characteristics, *X = x:*

$$(Y^0, Y^1) \perp D \mid X = x \qquad (CIA) \qquad (6)$$

This condition allows the problem of non-observability of the contrafactual to be overcome $E[Y^0 \mid D=1]$. As such, if CIA is fulfilled, then $E[Y^0 \mid D=0, X=x_i]$ can be used to approximate the potential result or contrafactual. However, CIA is only fulfilled when all variables that affect the result of interest Y^0 and Y^1 and the participation status *D* are known. Thus, it holds that:

$$E[Y^0 \mid D=1, X=x] = E[Y^0 \mid D=0, X=x] \qquad (7)$$

This means that the result of interest of the untreated group can be used to calculate the average result of the treated group in an unbiased manner. This is because there are no differences between the groups once the observables X = x are controlled for. Finally, the causal effect specified in equation (4) is redefined as:

$$\theta^1 = E\left[Y^1 \mid D=1, X=x\right] - E\left[Y^0 \mid D=0, X=x\right] \quad (8)$$

The expression in (8) can be estimated based on the mean of both groups (treated and untreated). The next step is to find appropriate pairs of subsidized and unsubsidized firms with the same characteristics in vector X in order to obtain (8).

A significant problem of the CIA is that it requires a large range of exogenous characteristics to ensure validity. The high dimensionality of vector x_i can make it impossible to finds pairs with exactly the same characteristics. Fortunately, the exogenous variables vector x_i can be condensed into a single scalar named the Propensity Score. In this case, this measure represents the probability that firm *i* receives public financing given the characteristics vector x_i, that is $\Pr(D_i = 1 \mid X = x_i)$.

Rosenbaum and Rubin (1983) show that if the CIA is fulfilled, it is enough to condition on the Propensity Score to ensure the independence of the potential result (in this case, private R&D spending) and the receipt of subsidies, as long as there is a common support between the probability distribution of the treated and untreated groups. This means that there must be treated and control firms with similar probabilities of receiving public financing.

Therefore, the matching procedure consists of choosing a firm with subsidy and to find a clone of the group of firms without public financing, conditional on that the probability of receiving public subsidies is sufficiently similar between both firms in order to correctly approximate the contrafactual of the treated firm based on the firm without subsidy.

Nevertheless, Lechner (1998) suggests a hybrid matching in which, apart from conditioning on the propensity score, the observables are also conditioned. This would make sense considering the possibility of finding, for example, for a subsidized firm of the mining sector a clone from the financial services sector, revealing that from the technological – non-observable point of view, they can have very different needs from R&D needs.[4]

Following Lechner (1998), a hybrid matching has been estimated, with one modification, as suggested by Abadie and Imbens (2006), that the matching has been done using only one continuous variable – the propensity score. The remainder of the variables on which the matching has been conditioned is discrete; that is: economic sector (when the sample includes all firms), sectoral pattern of the production of innovation (when only manufacturing firms are considered), possession of an R&D department within the company, region (whether the firm is in the capital Santiago or in the other regions) and the ownership of the firm (private versus the others).[5]

[4] Abadie and Imbens, 2006, show that using more than one continuous variable for the matching can produce problems of consistency in the estimators.
[5] The results of the econometric estimates are presented in Appendix II.

Based on these estimates, the sample included in the matching can be considered well-balanced. This implies that there are no observable differences between the treated and control firms, with the exception of the treatment condition of course. This means that a good random treatment allocation process has been simulated within the sample. The tests on means implemented indicate that the equality of means between groups cannot be rejected for each of the variables considered.[6] The results of the matching technique are presented here below in Table 8.

Considering the sample of manufacturing firms, the matching methodology allowed a clone to be identified for 31 of 89 subsidized firms of the sector. The average R&D spending of firms that received subsidies is 182 million pesos, while the same figure for the controls that did not receive funding is 54 million pesos. The difference in means of 132 million therefore captures the impact of subsidies on private R&D spending in manufacturing firms. This implies that on average they spend 262% more than their counterparts without subsidies. However, these results should be viewed with care since, as mentioned earlier, the distribution of R&D spending is highly asymmetrical.

Table 8 shows that the distribution of R&D spending of both treated and control firms is asymmetric. Moreover, the distribution of the difference of means of the 31 cases analysed is also highly asymmetrical. This is graphically confirmed in Figure 5. While the mean is 132 million, the median is only 34 million.

FIGURE 3

As a result of the distribution of the difference of means, which comes from the asymmetric distribution of R&D spending of treated firms, it is considered better to interpret the impact of subsidies in terms of the median of the distribution of means. As was discussed in Section III, firms are highly heterogeneous in terms of spending. Therefore, a single firm can shift the mean sharply to the right leaving the remainder of the observations to its left. Clearly, this is not very representative for the other firms; although the median should be representative in this particular case.

Considering the median of the distribution of the difference of the means, the R&D spending of manufacturing firms with public financing is 34 million pesos higher (85% more) than that of the control firms. A bootstrapping test[7] on the hypothesis that the median of the difference of means is equal to zero is rejected at the usual confidence levels.

Meanwhile, a sectoral pattern analysis of the production of innovation did not reveal significant differences between the spending by subsidized and not subsidized firms. This may be due to the few observations available in each group and the few matchings carried out within this already small sample.

[6] See Appendix.
[7] See Appendix II.

4.4. Interpretation of the results for manufacturing firms considered in the matching

As mentioned above, the results show that manufacturing firms with subsidies spend a median of 34 million pesos more than those that did not receive public financing. This result indicates that public financing for R&D activities has a positive impact on private R&D spending by stimulating the recipient firm to invest more resources than it would have spent in the absence of the subsidy.

This can be verified by comparing the result variable of the treated and control firms, in which the only observable difference between both groups is the condition of treatment. Therefore, the difference in R&D spending between both groups is solely the result of that condition. This positive impact of public financing is known in the literature as a crowding-in effect of private financing in R&D.

A more detailed analysis of the group of firms that were included in the estimates, whose results are presented in Table 11, sheds some interesting results. It reveals differences in the impact by sectoral pattern on the production of innovation. While average (and median) manufacturing firms present a crowding-in effect of public R&D financing, input intensive firms present the opposite effect – crowding-out; however it is not significant at the usual confidence levels.

TABLE 9

Meanwhile, Table 12 shows that most firms with a positive impact of public financing have an R&D department. Moreover, over half are exporters and they are mainly concentrated in the capital Santiago. While they do not carry out cooperation activities, most of them indicate they highly value internal sources for generating innovative ideas.

TABLE 10

4.5. Leveraging Measure

Once a positive impact of public financing on the private R&D spending of manufacturing firms is found, it is worthwhile determining the degree of leveraging of the subsidy. In other words, how many extra pesos were spent for every peso in subsidy that was received by manufacturing firms.

To this end, an explanatory model of private R&D spending in 2004 was created (measured in natural logarithm) considering the 31 manufacturing firms which showed signs of crowding-in. The subsidy received by the firms during 2004, the lagged R&D spending of the firm, sales, employment level and age of the firm, were included as explanatory variables, all measured in logarithms. The results are presented below:

TABLE 11

Table 11 shows the long-run elasticity of private R&D spending with respect to public financing, which is $\frac{0.63}{1-0.10} \approx 0.70$. This indicates that a 10% increase in the subsidy produces a 7% increase in the long-run R&D spending of the firm. If the elasticity is divided by the subsidy-private spending ratio taken at the mean (see Table 11), the level of the marginal effect can be captured, which is $\frac{0.70}{0.72} \approx$ 0.97.. This indicates that each additional peso of subsidy increases long-run private spending by an average of 0.97 pesos. Assuming matching grants of 50%, there would be no additional leveraging above the amount that the firm has to co-finance.

As mentioned earlier, when the distribution of a certain variable is not very symmetrical, the median may be more representative than the mean in order to characterize the range of observations in the study. As Figure 4 and Table 11 show the subsidy-private spending ratio is not symmetrical. Therefore, just as in the case of the difference in the spending means, considering the median is an alternative.

FIGURE 4

If the median of the subsidy-private spending ratio is considered, the marginal effect is expressed by $\frac{0.70}{0.47} \approx 1.49$. This implies that each additional peso of public subsidy increases long-run private spending by 1.49 pesos. If once again, we assume a one-to-one matching grant subsidy scheme, the additional leveraging on the compulsory co-financing of the firm is 0.49 pesos.

Finally and to conclude, the results indicate that there is a positive impact of public R&D financing on manufacturing firms and that the long-run leveraging of private R&D spending per peso of subsidy ranges between 0.97 and 1.49 pesos (in mean and median respectively). This implies that given a one-to-one matching grant subsidy scheme, the subsidy does not leverage additional funds over the private co-financing if the mean of the difference of R&D spending is considered. However, there is a leveraging effect of 0.49 pesos over the private co-financing when the median of that distribution is considered.

5. Conclusions

We have attempted to answer the following question by means of various methodologies proposed in the literature for determining causal effects: Do public incentives for R&D spending in Chilean firms stimulate or substitute private R&D spending?

In general, the results indicate that there is a positive and significant effect of public R&D financing policies on manufacturing firms. The impact of subsidies on R&D spending measured through the difference in the average spending of firms that received subsidies compared to those that did not, ranges between 87 and 133 million pesos depending on the methodology used.

The literature suggests that matching techniques overcome many of the problems affecting the simple impact estimators such as the Average Treatment Effect (ATE) and the Before-After estimator. This study applied a matching hybrid using the propensity score other binary observable variables following Rosenbaum and Rubin (1983), Lechner (1998), and Abadie and Imbens (2006).

Since the distribution of R&D spending is highly asymmetrical, the median is also considered as an additional impact indicator. This is because the sample includes a small group of firms that spend significant amounts on R&D thus producing a highly asymmetrical distribution.

Given this indicator, the impact of public subsidies on manufacturing firms is around 85%. In terms of pesos, this means that firms that received subsidies in 2004 spent an additional 34 million pesos compared to firms that did not receive subsidies. These results highlight the positive impact of public R&D financing on manufacturing firms that received R&D grants. This is known in the literature as a crowding-in effect.

The long-run leveraging of private R&D spending per peso of subsidy ranges between 0.97 and 1.49 pesos (in the mean and median respectively) for manufacturing firms considered in the matching. This implies that given a one-to-one matching grant subsidy scheme, in other words where for every peso in State subsidy, the firm agrees to contribute an equal amount, the subsidy does not leverage additional funds over the private co-financing if the mean of the difference of R&D spending is considered. On the other hand, there is a leveraging effect of 0.49 pesos over the private co-financing when the median of that distribution is considered.

6. Refrences

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Appendix

Table 1: Distribution of the sample under study by economic sector

Sector	Descripción	Número de firmas sin expandir	Porcentaje	Número de firmas muestra expandida	Porcentaje
A	Agricultura, ganadería, caza y silvicultura	52	8.5%	806	31.9%
B	Pesca	17	2.8%	59	2.3%
C	Explotación de minas y canteras (medianas y grandes)	20	3.3%	20	0.8%
D	Industria Manufacturera	321	52.6%	759	30.1%
E	Generación y distribución de energía eléctrica	24	3.9%	24	1.0%
F	Construcción	23	3.8%	87	3.4%
G	Comercio al por mayor y al por menor; reparación de vehículos automotores, motocicletas, efectos personales y enseres domésticos.	9	1.5%	9	0.4%
I	Transporte, almacenamiento y comunicaciones	27	4.4%	352	14.0%
J	Intermediación financiera	20	3.3%	87	3.4%
K	Actividades inmobiliarias, empresariales y de alquiler	44	7.2%	134	5.3%
L	Administración publica y defensa; planes de seguridad social de afiliación obligatoria	6	1.0%	8	0.3%
M	Enseñanza	23	3.8%	83	3.3%
N	Servicios sociales y de salud	17	2.8%	76	3.0%
O	Otras actividades de servicios comunitarios, sociales y personales	7	1.1%	19	0.8%
TOTAL		610	100.0%	2,523	100.0%

Table 2: Share of subsidies in R&D aggregates by economic sector (only considers subsidized firms)

Sector	Descripción	Gasto I+D Firma (1)	Subsidio a I+D (2)	Proporción subsidio (3)=(2)/(1)+(2)
TODAS	Todos los sectores	67,782.20	51,959.47	43%
A	Agricultura, ganadería, caza y silvicultura	41,375.04	17,393.35	30%
B	Pesca	46,975.64	41,275.50	47%
C	Explotación de minas y canteras	1,245,988.00	51,666.67	4%
D	Industria Manufacturera	47,850.82	33,044.99	41%
E	Generación y distribución de energía eléctrica	65,839.67	1,000.00	1%
F	Construcción	26,935.75	13,766.60	34%
G	Comercio al por mayor y al por menor; etc.	61,400.56	1,639.00	3%
I	Transporte, almacenamiento y comunicaciones	77,442.95	77,720.00	50%
J	Intermediación financiera	173,478.30	n.d.	n.d.
K	Actividades inmobiliarias, empresariales, y otros	119,597.50	10,880.13	8%
L	Administración publica y defensa, y otros.	138,938.30	n.d.	n.d.
M	Enseñanza	78,893.24	492,495.30	86%
N	Servicios sociales y de salud	34,128.92	6,000.00	15%
O	Otras actividades de servicios comunitarios, y otros	28,836.84	5,000.00	15%

En (1) se calculó el promedio del gasto privado en I+D considerando el total de firmas por sector que financian I+D con recursos propios.
En (2) se calculó el promedio del subsidio por sector, considerando firmas que recibieron financiamiento público a la I+D.

Cálculos consideran muestra expandida. n.d. : Implica que no hubo firmas del sector que recibieron financiamiento público.

Table 3: Private R&D spending and public subsidies by economic sector ($2004)

Sector	Descripción	Nº firmas que financian I+D con recursos propios	Nº Firmas con subsidio	Porcentaje de firmas que recibe subsidio	Promedio de la razón (subsidio/Total I+D) para firmas con subsidio>0	Promedio de la razón (subsidio/I+D financiada por la firma)
TODOS	Todos los sectores	2,523	294	12%	0.39	0.69
A	Agricultura, ganadería, caza y silvicultura	806	145	18%	0.36	0.57
B	Pesca	59	4	7%	0.51	1.76
C	Explotación de minas y canteras	20	3	15%	0.25	0.33
D	Industria Manufacturera	759	89	12%	0.20	0.26
E	Generación y distribución de energía eléctrica	24	2	8%	0.20	0.25
F	Construcción	87	10	11%	0.39	0.64
G	Comercio al por mayor y al por menor; etc.	9	2	22%	0.40	0.66
I	Transporte, almacenamiento y comunicaciones	352	4	1%	0.14	0.16
J	Intermediación financiera	87	0	0%	n.d.	n.d.
K	Actividades inmobiliarias, empresariales, y otros	134	15	11%	0.40	0.69
L	Administración publica y defensa, y otros.	8	0	0%	n.d.	n.d.
M	Enseñanza	83	18	22%	0.64	2.39
N	Servicios sociales y de salud	76	1	1%	0.40	0.67
O	Otras actividades de servicios comunitarios, y otros	19	1	5%	0.30	0.43

Cálculos consideran muestra expandida. n.d. : Implica que no hubo firmas del sector que recibieron financiamiento público.

Table 4: Descriptive statistics

Variable	A=Toda la muestra (N=2,523)					B=Firmas con subsidio (N=294)					C=Firmas sin subsidio (N=2,229)					Test dif. de medias (B y C)
	p25	p50	p75	media	desv. est.	p25	p50	p75	media	desv. est.	p25	p50	p75	media	desv. est.	
Gasto privado I+D en 2004 (miles de $)	2,000	6,000	31,000	67,782	513,957	2,000	10,000	63,900	75,676	227,632	2,000	6,000	31,000	66,741	540,541	
ln(Gasto privado I+D en 2004)	7.60	8.70	10.34	9.03	2.00	7.60	9.21	11.07	9.45	1.87	7.60	8.70	10.34	8.97	2.01	***
Gasto público I+D en 2004 (miles de $)	n.a.	n.a.	n.a.	n.a.	n.a.	5,000	7,125	30,000	51,959	219,172	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
ln(Gasto público I+D en 2004)	n.a.	n.a.	n.a.	n.a.	n.a.	8.52	8.87	10.31	9.49	1.35	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Ventas año 2004 (miles de $)	375,000	1,112,595	5,580,000	14,500,000	62,300,000	396,370	591,475	6,055,560	18,800,000	88,000,000	326,306	1,137,553	5,580,000	14,000,000	58,100,000	
ln(Ventas año 2004)	12.83	13.92	15.53	14.08	2.12	12.89	13.29	15.62	14.32	1.93	12.70	13.94	15.53	14.05	2.14	**
Ventas año 2003 (miles de $)	313,073	1,018,404	4,947,364	11,700,000	50,700,000	349,914	517,398	5,269,107	15,300,000	65,400,000	313,073	1,084,712	4,746,751	11,200,000	48,400,000	*
ln(Ventas año 2003)	12.65	13.83	15.41	13.89	2.33	12.77	13.16	15.48	14.18	1.94	12.65	13.90	15.37	13.86	2.37	***
Empleo año 2004	30	87	314	280	632	51	122	132	367	1023	30	79	340	268	560	***
ln(Empleo año 2004)	3.4	4.5	5.7	4.6	1.4	3.9	4.8	4.9	4.7	1.5	3.4	4.4	5.8	4.5	1.4	**
Empleo año 2003	22	85	281	252	573	50	180	180	368	967	22	75	300	236	496	***
ln(Empleo año 2003)	3.1	4.4	5.7	4.5	1.4	3.9	5.2	5.2	4.8	1.5	3.1	4.3	5.7	4.5	1.4	***
Exportaciones año 2004 (miles de $)	0	0	43,919	3,345,529	31,700,000	0	0	88,000	7,348,559	66,300,000	0	0	31,016	2,817,538	23,700,000	***
ln(Exportaciones año 2004)	0	0	10.69	3.81	6.15	0	0	11.39	4.22	6.39	0	0	10.34	3.76	6.12	
Exportaciones año 2003 (miles de $)	0	0	57,236	2,317,433	19,200,000	0	0	617,240	5,545,620	42,600,000	0	0	24,345	1,891,642	13,200,000	***
ln(Exportaciones año 2003)	0	0	10.95	3.91	6.20	0	0	13.33	5.76	6.77	0	0	10.10	3.66	6.08	***
Edad de la firma (años)	6	12	25	19	20	6	11	25	20	21	7	12	25	19	20	
ln (Edad de la firma)	1.8	2.5	3.2	2.5	1.0	1.8	2.4	3.2	2.5	1.0	1.9	2.5	3.2	2.5	1.0	
N°derechos Prop. Intelectual solicitados	0	0	0.0	0.8	6.9	0	1	1.0	1.9	7.8	0	0	0	0.7	6.8	***
ln (N°derechos Prop. Intelectual solicitados)	0	0	0	0.2	0.5	0	1	0.7	0.5	0.7	0	0	0	0.1	0.5	***
Firma en RM (dummy=1)			0.44					0.32					0.46			***
Firma Manufacturera (dummy=1)			0.30					0.30					0.30			
Firma posee departamento de I+D (dummy=1)			0.32					0.22					0.33			***
Firma es de propiedad privada (dummy=1)			0.86					0.89					0.85			**
Firma ha realizado acciones de cooperación (dummy=1)			0.08					0.11					0.07			**
Importancia fuentes internas para innovar (dummy=1 si importancia es alta o muy alta)			0.70					0.87					0.68			***

n.a.: No aplica

* Significancia al 10% - ** Significancia al 5% - *** Sigmificancia al 1%

Considera muestra expandida

Table 5: Average impact treatment estimator (ATE), 2003

ATE 2003	DIF (T-NT) (M$)	AUMENTO O DISMINUCIÓN PORCENTUAL	NUMERO EMPRESAS		SIGNIF.
			T	NT	
Toda la muestra	8,580	12%	160	1,820	
Manufactura	57,958	161%	92	639	**
Insumos	-11,685	-34%	52	266	**
Mano de Obra	256,338	1093%	11	160	**
Escala	115,053	202%	24	152	*
Especializada	33,095	146%	3	54	
Ciencia	17,761	100%	2	7	

* Significancia al 10% - ** Significancia al 5% - *** Significancia al 1%

Table 6: Average impact treatment estimator (ATE), 2004

ATE 2004	DIF (T-NT) (M$)	AUMENTO O DISMINUCIÓN PORCENTUAL	NUMERO EMPRESAS		SIGNIF.
			T	NT	
Toda la muestra	8,934	13%	294	2,229	
Manufactura	87,361	232%	89	670	***
Insumos	2,425	7%	56	276	
Mano de Obra	267,041	1027%	10	177	**
Escala	238,504	477%	21	147	**
Especializada	s/i	s/i	s/i	s/i	s/i
Ciencia	-13,995	-78%	2	6	**

s/i : No hay firmas subsidiadas en dicha categoría, por lo que no es posible calcular el estimador.

* Significancia al 10% - ** Significancia al 5% - *** Sigmificancia al 1%

Table 7: Difference-in-differences estimator (DIF in DIF)

A-D (2003-2004)	ANTES (NT)	DESPUÉS (T)	DIF (T-NT) (M$)	AUMENTO PORCENTUAL	NUMERO EMPRESAS	SIGNIF.
Toda la muestra	2003	2004	57,789	16%	14	**
Manufactura	2003	2004	133,364	77%	6	***
Insumos	2003	2004	67,292	95%	2	
Mano de Obra	2003	2004	s/i	s/i	s/i	s/i
Escala	2003	2004	166,400	74%	4	**
Especializada	2003	2004	s/i	s/i	s/i	s/i
Ciencia	2003	2004	s/i	s/i	s/i	s/i

s/i : No hay firmas subsidiadas en dicha categoría, por lo que no es posible calcular el estimador.

* Significancia al 10% - ** Significancia al 5% - *** Sigmificancia al 1%

Table 8: Matching estimator

DESCRIPCIÓN	TODA LA MUESTRA	MANUFACTURA
Media Tratados (M$)	53,889	182,341
Media Controles(M$)	27,944	50,415
Diferencia Medias DIF (M$)	**25,945**	**131,926**
Aumento Porcentual	93%	262%
Significancia	**	**
Muestra de firmas	198	31
Mediana Tratados (M$)	2,000	60,000
Mediana Controles (M$)	13,876	39,770
Mediana DIF (M$)	-11,876	33,844
Aumento Porcentual para mediana	-86%	85%
Significancia mediana DIF		**

* Significancia al 10% - ** Significancia al 5% - *** Sigmificancia al 1%. Notar que la mediana de la diferencia de medias no es igual a la diferencia de medianas de los grupos de tratamiento y control.

Table 9: Results of matching and other variables of interest

Variable	Firmas consideradas en el matching (N=31)			
	Mediana	Media	Desv. est.	N
Gasto privado I+D en 2004 (miles de $)	60,000	182,341	276,670	31
ln(Gasto privado I+D en 2004)	11.00	11.20	1.42	31
Diferencia de gasto privado en I+D en 2004 (entre firmas tratadas y de control)	33,844	131,926	262,571	31
Gasto público I+D en 2004 (miles de $)	30,000	53,821	75,911	31
ln(Gasto público I+D en 2004)	10.31	10.22	1.24	31
Razón subsidio-gasto privado en I+D año 2004	0.47	0.72	1.39	31
Diferencia de gasto privado en I+D en 2004 (entre firmas tratadas y de control) por patrón sectorial en la producción de innovación:				
Insumos	-13,369	-26,045	82,935	7
Mano de obra	20,230	223,542	377,245	10
Escala	82,792	174,393	193,975	12
Ciencia	-28,060	-28,060	29,577	2

Table 10: Characterization of sample considered in the matching

Firmas consideradas en el matching (N=31)	
Variable	**Proporción del total**
Firmas exportadoras en 2004 (dummy=1)	0.55
Firmas exportadoras en 2003 (dummy=1)	0.58
Firma en RM (dummy=1)	0.77
Firma posee departamento de I+D (dummy=1)	0.90
Firma es de propiedad privada (dummy=1)	0.97
Firma ha realizado acciones de cooperación (dummy=1)	0.10
Importancia fuentes internas para innovar (dummy=1 importancia alta o muy alta)	0.84
Patrón sectorial en la producción de innovación: Insumos (dummy=1)	0.23
Patrón sectorial en la producción de innovación: Mano de obra (dummy=1)	0.32
Patrón sectorial en la producción de innovación: Escala (dummy=1)	0.39

Table 11: Results of the explanatory model of private R&D spending, 2004

VARIABLE EXPLICADA: Ln (Gasto Privado año 2004)		
VARIABLES EXPLICATIVAS	**COEFICIENTE**	**SIGNIFICANCIA**
Ln(Gasto privado año 2003)	0.10	***
Ln(Subsidio público año 2004)	0.63	***
Ln(Ventas año 2003)	0.57	**
Ln(Empleo 2003)	-0.53	*
Ln(Edad de la firma)	-0.16	
Constante	-1.783	
Ajuste R-Cuadrado	0.79	
Número de Observaciones	31	

Figure 1: Sample considered for calculating the ATE estimator

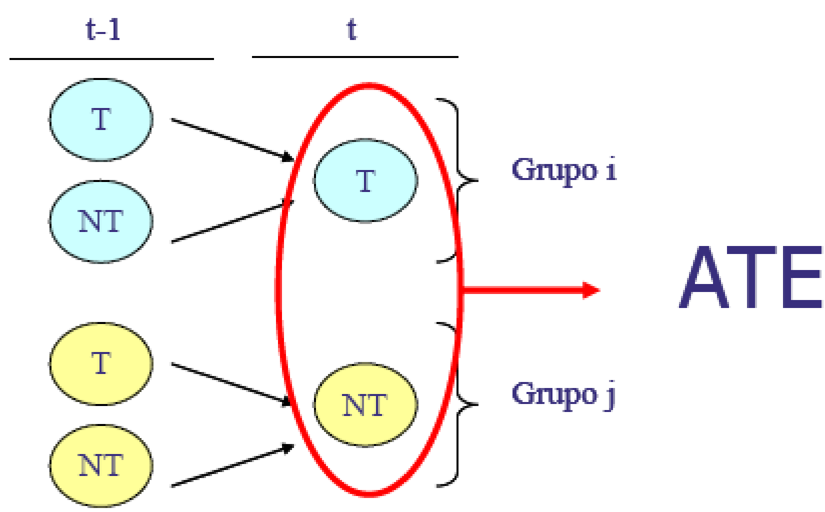

Figure 2: Sample considered for calculating the AD estimator

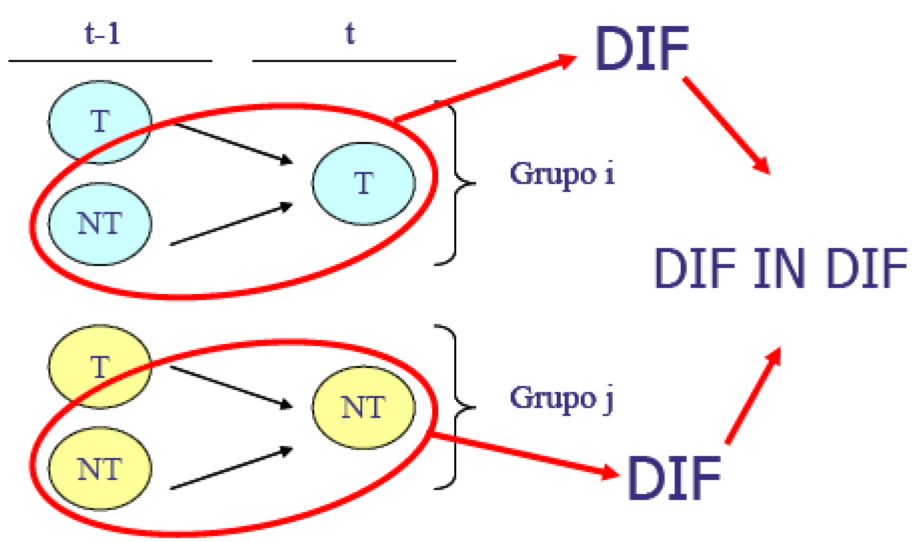

Figure 3: Distribution of the difference in R&D spending between treated and control firms

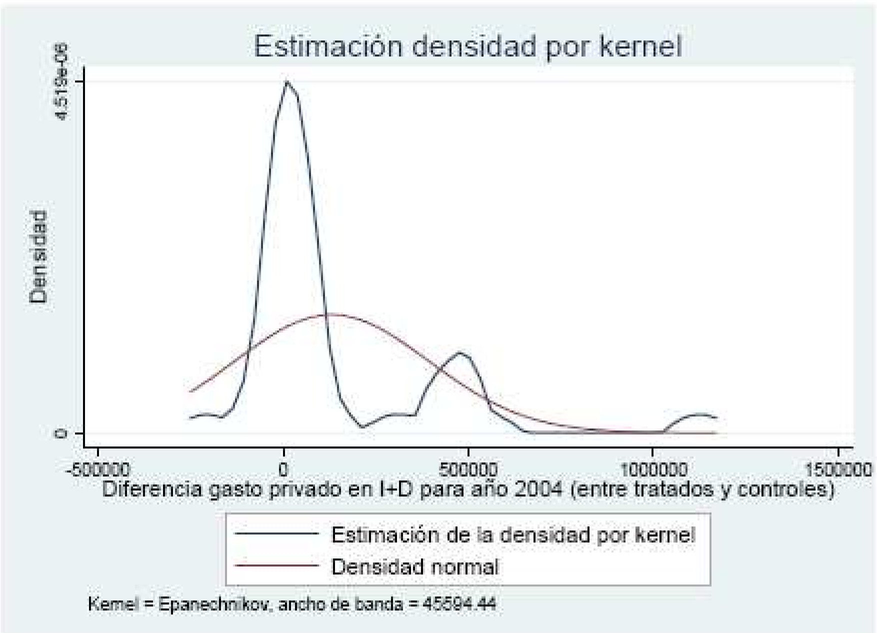

Figure 4: Density of the distribution of the subsidy-private spending ratio