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

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Abstract

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.

JEL: C23; L11;

Keywords: Public Financing, Private R&D Spending, Complementarity or Substitution, Chilean Manufacturing.

1. Introduction

In Chile, the public agency responsible of supporting innovation in firms is 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 mainly due to the presence of market failures. These lead to a potentially lower-than-desirable level of private sector funding and/or participation in these kind of 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, through the resulting 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 on the effects of public R&D subsidies 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 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 knolewledge and innovation production suggest an underinvestment in R&D projects given that firms will only carry out those that are privately profitable. This implies that there are projects that offer significant benefits to society but do not cover the private costs and will therefore not be carried out by firms.

This is the main reason for justifying public funding of R&D. The subsidy allows firms to reduce costs and therefore the investment in R&D and innovation projects increases, which in turn also raises firms' productivity.

However, there is a risk that firms will have incentives 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 R&D funding policies.

Nevertheless, as Busom (2000) suggests, evidence of a negative relationship between public and private R&D spending does not necessarily imply a negative effect of public funding policy. The reason for this is that public agencies may choose precisely to finance heavily R&D projects with higher spillover potential, where incentives for private funding may be small, basically due to problems of appropriability.

2.2. Prior experience

With regard to the effects of public funding on private R&D, the literature follows 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 chosen according to specific criteria, like technical and economic feasibility of the project and the background information of the applicant firm. Therefore, public funding becomes endogenous. Furthermore, as a result of political incentives for example, authorities may act on a picking-the-winners basis. In other words, agencies may choose projects with high private marginal rates of return and that consequently would probably be funded by firms in any case. This would, in effect, produce an "intentional" substitution effect.

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 funding 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 funding policy orientation towards these kinds of firms. In terms of the impact of public funding 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 panel data models, the author finds different results depending on the methodology used. However, the conclusions of the article indicate that there is evidence suggesting that the R&D subsidies granted by the Ministry of Industry and Trade stimulated long-run company-financed R&D expenditures: their long run elasticity with respect to R&D subsidies is 0.22. This implies that at the mean of the data, an extra dollar of R&D subsidies increases long-run company-financed R&D expenditures by 41 cents (total R&D expenditures increase by 1.41 dollars).

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.

Almus and Czarnitzki (2002) estimate the causal effect of public funding on innovation activities of firms located in Eastern Germany. Using non-parametric matching methodology and the Mannheim Innovation Panel (MIP), the authors estimate three cross-sections for the three available years (1994, 1996, and 1998). Their results suggest that, compared to the case where no public financial means are privided, it turns out that firms increase their innovation activities by about four percentage points.

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 a non-parametric matching estimator, they find that firms that benefited from both policy measures introduced more new products than their counterparts that only benefited from R&D tax incentives. They also made more world-first product innovations and were more successful in commercializing their innovations.

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. 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 a firm that invests 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 table 1, the sample included 610 firms in 2004. As a result of the sampling procedure applied for the survey implementation (INE, 2005), when expansion factors are applied, the expanded sample totals 2,523 firms.

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

Sector	Description	Number of firms (not expanded sample)	Percentage	Number of firms (expanded sample)	Percentage
A	Agriculture, hunting and forestry	52	8.5%	806	31.9%
B	Fishing	17	2.8%	59	2.3%
C	Mining and quarrying (median and big)	20	3.3%	20	0.8%
D	Manufacturing	321	52.6%	759	30.1%
E	Electricity supply	24	3.9%	24	1.0%
F	Construction	23	3.8%	87	3.4%
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	9	1.5%	9	0.4%
I	Transport, storage and communications	27	4.4%	352	14.0%
J	Financial intermediation	20	3.3%	87	3.4%
K	Real estate, renting and business activities	44	7.2%	134	5.3%
L	Public administration and defence; compulsory social security	6	1.0%	8	0.3%
M	Education	23	3.8%	83	3.3%
N	Health and social work	17	2.8%	76	3.0%
O	Other community, social and personal service activities	7	1.1%	19	0.8%
TOTAL		610	100.0%	2,523	100.0%

As table 1 show, most firms that carry out R&D activities are from the agricultural, 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 lays the transport, storage and communications sector with 14% of the expanded total.

Considering only the firms that received government subsidies (12% of the universe), table 2 shows that on average 39% of total R&D funding 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: Share of subsidies in R&D aggregates by economic sector (only considers subsidized firms)

Sector	Description	Nº of firms that finance R&D with own resources	Nº of firms with subsidy	Percentage of firms with subsidy	Average of the ratio (subsidy/Total R&D) for firms with subsidy>0	Average of the ratio (subsidy/R&D financed by the firm)
ALL	All Sectors	2,523	294	12%	0.39	0.69
A	Agriculture, hunting and forestry	806	145	18%	0.36	0.57
B	Fishing	59	4	7%	0.51	1.76
C	Mining and quarrying (median and big)	20	3	15%	0.25	0.33
D	Manufacturing	759	89	12%	0.20	0.26
E	Electricity supply	24	2	8%	0.20	0.25
F	Construction	87	10	11%	0.39	0.64
G	Wholesale and retail trade; etc.	9	2	22%	0.40	0.66
I	Transport, storage and communications	352	4	1%	0.14	0.16
J	Financial intermediation	87	0	0%	n.a.	n.a.
K	Real estate, renting and business activities	134	15	11%	0.40	0.69
L	Public administration and defence; etc.	8	0	0%	n.a.	n.a.
M	Education	83	18	22%	0.64	2.39
N	Health and social work	76	1	1%	0.40	0.67
O	Other community, social and personal service activities	19	1	5%	0.30	0.43

Calculations consider the expanded sample. n.a.: means there were no firms that received public funding in the sector.

Of the 294 firms that received subsidies (12% of the total), table 3 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: Private R&D spending and public subsidies by economic sector ($2004)

Sector	Description	Private R&D expenditure (1)	R&D subsidy (2)	Subsidy ratio (3)=(2)/(1)+(2)
ALL	All Sectors	67,782.20	51,959.47	43%
A	Agriculture, hunting and forestry	41,375.04	17,393.35	30%
B	Fishing	46,975.64	41,275.50	47%
C	Mining and quarrying (median and big)	1,245,988.00	51,666.67	4%
D	Manufacturing	47,850.82	33,044.99	41%
E	Electricity supply	65,839.67	1,000.00	1%
F	Construction	26,935.75	13,766.60	34%
G	Wholesale and retail trade; etc.	61,400.56	1,639.00	3%
I	Transport, storage and communications	77,442.95	77,720.00	50%
J	Financial intermediation	173,478.30	n.a.	n.a.
K	Real estate, renting and business activities	119,597.50	10,880.13	8%
L	Public administration and defence; etc.	138,938.30	n.a.	n.a.
M	Education	78,893.24	492,495.30	86%
N	Health and social work	34,128.92	6,000.00	15%
O	Other community, social and personal service activities	28,836.84	5,000.00	15%

In (1) the average of private R&D expenditure was calculated considering all firms in the sector that finance R&D with their own resources. In (2) the average subsidy by sector was calculated, considering firms that received public funding on R&D. Calculations consider the expanded sample. n.a.: means there were no firms that received public funding in the sector.

In order to better describe the firms that undertook R&D activities in 2004, table 4 summarizes some of their main characteristics. The selection of the variables for analysis follows the recent literature, particularly in terms of the factors that could be closely linked to R&D efforts in the firm (Benavente, 2002).

Concerning private R&D spending, the information presented in table 4 suggests a highly asymmetric distribution since the mean is significantly higher than the median, indicating that a small group of firms spends disproportionately more than the rest. Therefore, private spending is also presented in natural logarithm in order to smooth the 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 funding and those that did not. The statistical significance of the differences in means 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 rights 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: Descriptive statistics

Variable	A=All sample (N=2,523)					B=Firms with subsidy (N=294)					C=Firms without subsidy (N=2,229)					Mean diference test (B and C)
	p25	p50	p75	mean	st. dev.	p25	p50	p75	mean	st. dev.	p25	p50	p75	mean	st. dev.	
Private expenditure on R&D in 2004 (thousand $)	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(private expenditure on R&D in 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	***
Public expenditure on R&D in 2004 (thousand $)	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(public expenditure on R&D in 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.
Sales in 2004 (thousand $)	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(sales in 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	**
Sales in 2003 (thousand $)	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(sales in 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	***
Employment in 2004	30	87	314	280	632	51	122	132	367	1023	30	79	340	268	560	***
ln(employment in 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	**
Employment in 2003	22	85	281	252	573	50	180	180	368	967	22	75	300	236	496	***
ln(employment in 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	***
Exports in 2004 (thousand $)	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(exports in 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	
Exports in 2003 (thousand $)	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(exports in 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	***
Age of the firm (years)	6	12	25	19	20	6	11	25	20	21	7	12	25	19	20	
ln (age of the firm)	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° of IP rights requested	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° of IP rights requested)	0	0	0	0.2	0.5	0	1	0.7	0.5	0.7	0	0	0	0.1	0.5	***
Firm in the capital, MR (dummy=1)			0.44					0.32					0.46			***
Manufacturing firm (dummy=1)			0.30					0.30					0.30			
Firm owns an R&D department (dummy=1)			0.32					0.22					0.33			***
Private ownership of the firm (dummy=1)			0.86					0.89					0.85			**
Firm has carried out cooperation activities (dummy=1)			0.08					0.11					0.07			**
Importance of internal sources to innovate (dummy=1 if importance is high or very high)			0.70					0.87					0.68			***

n.a.: Does not apply. * 10% significance - 5% significance - *** 1% significance. Calculations consider the expanded sample.

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 data available. For example, we may want to evaluate the impact of an R&D support program consisting on a tax incentive. The impact of the participation of a firm in that programme would be easy to calculate if we could observe the company in both states at the same moment: "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 if it had not participated in the incentives program. Consequently, the impact of the program on firm *k* in $t = t_0$ is expressed by:

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

Where:

$Y_k^1 =$ R&D spending of firm *k* with treatment or tax incentive in t_0.

$Y_k^0 =$ R&D spending of firm *k* without treatment or tax incentive in t_0.

$\tau_k =$ Impact of the treatment (or tax incentive) 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. As such, the literature that tackles these issues proposes alternative methods to create the counterfactual (the non-observable state of the firm or individual under study).

The main problem in program evaluation is that in general the allocation of the treatment (allocation of a tax incentive or 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, subsidies are awarded 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 that have specific characteristics choose to participate in a public programme) the assumption of randomness is not fulfilled. This, together with the non-observability of the counterfactual, makes it difficult to estimate the impact of a given program.

Three methodologies covered in the literature for measuring the impact of public funding policies on private R&D spending are described below. 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 counterfactual 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:

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

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 (UT) respectively in the same moment in time t_0. Graphically, the estimator is represented in figure 1.

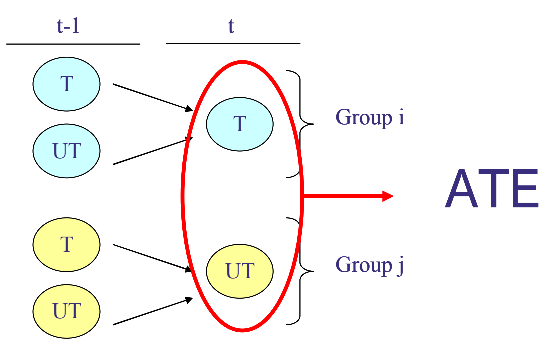

Figure 1: Sample considered for calculating the ATE estimator

If for one moment, the assumption of randomly assignment of R&D funding 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 5 and 6 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 their sectoral innovation pattern[1].

Column DIF (T-UT) 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: Average impact treatment estimator (ATE), 2003

ATE 2003	DIF (T-UT) (M$)	INCREASING OR DECREASING PERCENTAGE	NUMBER OF FIRMS		SIGNIF.
			T	UT	
All the sample	8,580	12%	160	1,820	
Manufacturing	57,958	161%	92	639	**
Resource-intensive	-11,685	-34%	52	266	**
Labor-intensive	256,338	1093%	11	160	**
Scale-intensive	115,053	202%	24	152	*
Specialized	33,095	146%	3	54	
Science-intensive	17,761	100%	2	7	

* 10% significance - 5% significance - *** 1% significance.

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

ATE 2004	DIF (T-UT) (M$)	INCREASING OR DECREASING PERCENTAGE	NUMBER OF FIRMS		SIGNIF.
			T	UT	
All the sample	8,934	13%	294	2,229	
Manufacturing	87,361	232%	89	670	***
Resource-intensive	2,425	7%	56	276	
Labor-intensive	267,041	1027%	10	177	**
Scale-intensive	238,504	477%	21	147	**
Specialized	n/i	n/i	n/i	n/i	n/i
Science-intensive	-13,995	-78%	2	6	**

n/i : There are no firms in this category. * 10% significance - 5% significance - *** 1% significance.

[1] Following Berube and Mohnen (2007).

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.[2]

A sharper view is obtained by analysing the manufacturing sector in particular.[3] The results presented in tables 5 and 6 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 may imply that public funding is leveraging private funding in manufacturing sector firms.

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

4.2. Difference-in-differences Estimator (DID)

As mentioned earlier, the consistency of the above estimator is heavily dependent on the assumption of randomness when allocating a treatment – in this case, receiving public support. It should be highlighted that public R&D and innovation funding programmes 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 agency. Therefore, the chosen firms probably have 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 treated firms with themselves before the treatment was assigned. By applying time differentials,

[2] For the sectoral heterogeneity of returns to R&D see Goto and Suzuki 1989 for Japan and Benavente et al, 2006 for Chile.
[3] It also has the advantage that most studies on these issues have been based exclusively on manufacturing sector information.

estimator will be free from the effect of specific characteristics of the firm that remain constant over time.

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:

$$\alpha_{DIF-in-DIF} = \frac{\sum_{k=1}^{N_1}(Y_t^{01} - Y_{t-1}^{01})_k}{N_1} - \frac{\sum_{n=1}^{N_2}(Y_t^{00} - Y_{t-1}^{00})_n}{N_2} \tag{3}$$
$$\alpha_{DIF-in-DIF} = (\overline{Y}_t^{01} - \overline{Y}_{t-1}^{01})_i - (\overline{Y}_t^{00} - \overline{Y}_{t-1}^{00})_j$$

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 in figure 2.

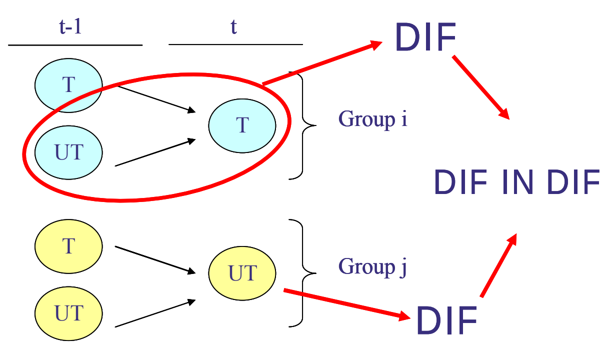

Figure 2: Sample considered for calculating the DIF-in-DIF estimator

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

DIF in DIF (2003-2004)	t-1	t	DIF in DIF (M$)	PERCENTAGE RISE	NUMBER OF FIRMS		SIGNIF.
					T	UT	
All the sample	2003	2004	55,522	2449%	14	1655	**
Manufacturing	2003	2004	129,342	3216%	6	577	***
Resource-intensive	2003	2004	60,402	877%	2	242	
Labor-intensive	2003	2004	n/i	n/i	n/i	n/i	n/i
Scale-intensive	2003	2004	164,390	8179%	4	128	**
Specialized	2003	2004	n/i	n/i	n/i	n/i	n/i
Science-intensive	2003	2004	n/i	n/i	n/i	n/i	n/i

n/i : There are no firms in this category. * 10% significance - 5% significance - *** 1% significance.

While the results tend towards the same direction as the ATE estimator, it is risky to infer a statistically significant positive impact because of the few observations available.

4.3. Matching using Propensity Score and Observables

Given the above situation and that the allocation of subsidies is not random, 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 funding. This situation allows an adequate control group to be created to approximate the counterfactual of the subsidized firms and thereby estimate the causal effect of public funding on firms R&D spending.

The causal effect can be approximated according to the following expression:

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

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 funding. $E\lfloor Y^1 \mid D=1 \rfloor$ 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 $E\lfloor Y^0 \mid D=1 \rfloor$, corresponding to the counterfactual, 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 $E\lfloor Y^0 \mid D=1 \rfloor$ cannot be calculated based on the mean of the result variable of those which have not received subsidies since:

$$E\lfloor Y^0 \mid D=1 \rfloor \neq E\lfloor Y^0 \mid D=0 \rfloor \qquad (5)$$

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 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 counterfactual $E\lfloor Y^0 \mid D=1 \rfloor$ to be overcome. As such, if CIA is fulfilled, then $E\lfloor Y^0 \mid D=0, X = x_i \rfloor$ can be used to approximate the potential result or counterfactual. 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:

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

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:

$$\theta^1 = E\lfloor Y^1 \mid D=1, X = x \rfloor - E\lfloor Y^0 \mid D=0, X = x \rfloor \qquad (8)$$

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* can make it impossible to find pairs with exactly the same characteristics. Fortunately, the exogenous variables vector *X* can be condensed into a single scalar named the Propensity Score. In this case, this measure represents the probability that firm *i* receives public funding given the characteristics vector *X*, 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 funding.

Therefore, the matching procedure consists of choosing a firm with subsidy and to find a clone of the group of firms without public funding, conditional on that the probability of receiving public subsidies is sufficiently similar between both firms in order to correctly approximate the counterfactual 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, it should also be conditioned on observables. 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. Here, the problem is that from a technological point of view, both firms may be very different.[4]

Following Lechner (1998), a hybrid matching has been estimated, with one modification, as suggested by Abadie and Imbens (2006): 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 innovation pattern (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 other).

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 indicate that the equality of means between groups cannot be rejected for each of the variables considered. The results of the matching technique are presented in table 8.

[4] Abadie and Imbens, 2006, show that using more than one continuous variable for the matching can produce problems of consistency in the estimators.

Table 8: Matching estimator

DESCRIPTION	ALL THE SAMPLE	MANUFACTURING
Mean of the treated T (M$)	53,889	182,341
Mean of controls C (M$)	27,944	50,415
Difference of means DIF (M$)	**25,945**	**131,926**
Percentage rise	93%	262%
Significance	**	**
Sample of firms	198	31
Median of the treated (M$)	2,000	60,000
Median of controls (M$)	13,876	39,770
Median of the difference in R&D expenditure per match (M$)	-11,876	33,844
Percentage rise in median	-86%	85%
Median on difference significance		**

* 10% significance - 5% significance - *** 1% significance. Consider that the median of the differences in R&D expenditure for each match is not the same than the difference of the medians between treatment and control groups.

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 for the controls that did not receive funding is 54 million pesos. The difference in means of 132 million therefore captures the effect 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 are asymmetric. Moreover, the distribution of the differences in R&D expenditure per match 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.

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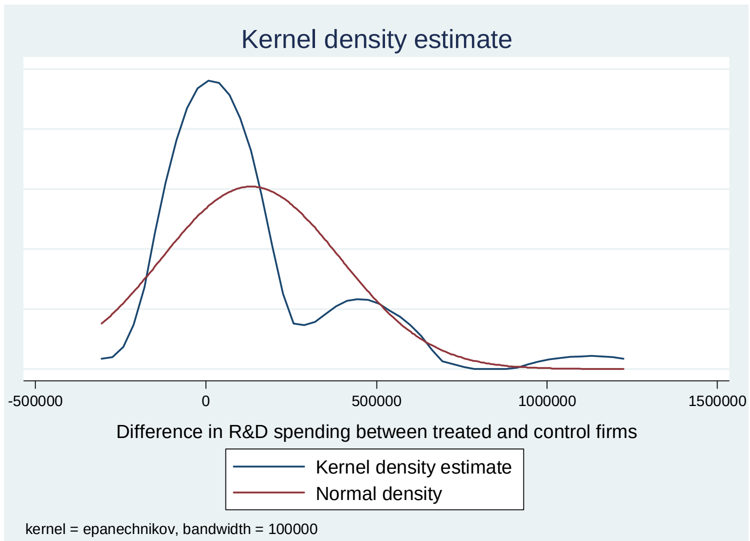

Figure 3: Distribution of the difference in R&D spending between treated and control firms

As a result of the distribution of the differences in R&D expenditures per match, which comes from the asymmetric distribution of R&D spending of treated firms, it is considered better to interpret the effect of subsidies in terms of the median of the distribution. 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 rest 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 differences in R&D expenditures per match, 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 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 innovation pattern analysis 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.

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, considering the median, 34 million pesos more than those that did not receive public financing. This result indicates that public funding on R&D activities has a positive effect 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.

A more detailed analysis of the group of firms in the matching sample, whose results are presented in Table 9, sheds some interesting results. For example, it reveals some differences in the effect by sectoral innovation pattern.

Table 9: Results of matching and other variables of interest

	Firms in matching sample (N=31)			
Variable	**Median**	**Mean**	**St. Dev.**	**N**
Private R&D expenditure in 2004 (thousand $)	60,000	182,341	276,670	31
ln(private R&D expenditure in 2004)	11.00	11.20	1.42	31
Diference on private R&D expenditures in 2004 (between treated and untreated firms)	33,844	131,926	262,571	31
Public R&D expenditure in 2004 (thousand $)	30,000	53,821	75,911	31
ln(public R&D expenditure in 2004)	10.31	10.22	1.24	31
Subsidy to private R&D spending ratio in 2004	0.47	0.72	1.39	31
Diference on private R&D expenditures in 2004 (between treated and untreated firms) by sectoral innovation pattern taxonomy:				
Resource-intensive	-13,369	-26,045	82,935	7
Labor-intensive	20,230	223,542	377,245	10
Scale-intensive	82,792	174,393	193,975	12
Science-intensive	-28,060	-28,060	29,577	2

Meanwhile, Table 10 shows that most firms of the matching sample for which a positive impact of public funding was found, 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: Characterization of sample considered in the matching

Firms in matching sample (N=31)	
Variable	**Percentage**
Exporting firms in 2004 (dummy=1)	0.55
Exporting firms in 2003 (dummy=1)	0.58
Firm in the capital, MR (dummy=1)	0.77
Firm owns an R&D department (dummy=1)	0.90
Private ownership of the firm (dummy=1)	0.97
Firm has carried out cooperation activities (dummy=1)	0.10
Importance of internal sources to innovate (dummy=1 if importance is high or very high)	0.84
Sectoral innovation pattern: Resource-intensive (dummy=1)	0.23
Sectoral innovation pattern: Labor-intensive (dummy=1)	0.32
Sectoral innovation pattern: Scale-intensive (dummy=1)	0.39

Once a positive effect of public funding on 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 developed (measured in natural logarithm) considering the 31 manufacturing firms identified in the matching procedure. 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 in table 11.

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

Dependant Variable: Ln(Private R&D expenditure in 2004)		
Control variables	**Coefficient**	**Significance**
ln(private R&D expenditure in 2003)	0.10	***
ln(public R&D subsidy in 2004)	0.63	***
Ln(sales in 2003)	0.57	**
Ln(employment in 2003)	-0.53	*
Ln(age of the firm)	-0.16	
Constant	-1.78	
R2 Statistic	0.79	
Nuber of observation	31	

Table 11 shows the long-run elasticity of private R&D spending with respect to R&D subsidies, 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 to private R&D spending ratio taken at the mean (see Table 9), 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 Table 11 show, the subsidy to private R&D spending ratio distribution is not symmetrical. Therefore, just as in the case of the differences in R&D expenditures per match, considering the median is an alternative.

If the median of the subsidy to private R&D spending ratio distribution 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 effect of public R&D subsidies 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-funding if the mean of the subsidy to private R&D spending ratio distribution is considered. However, there is a leveraging effect of 0.49 pesos over the private co-financing when the median is considered.

5. Conclusions

In this paper we have attempted to answer the following question: Does public support for R&D activities complement or substitute private R&D spending in Chilean firms?

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 Diference-in-Diference estimator. Following Rosenbaum and Rubin (1983), Lechner (1998), and Abadie and Imbens (2006) this study applied a hybrid matching using the propensity score and other binary observable variables as controls.

The matching results indicate that there is a positive and significant effect of public R&D funding policies on manufacturing firms. The effect of subsidies on private R&D spending measured through the difference in the average spending of firms that received subsidies compared to those that did not, is about 133 million pesos.

Since the distribution of R&D spending is highly asymmetrical, the median is also considered as an additional effect 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.

Considering the median of the distribution of differences in private R&D spending per match, the effect of public subsidies on manufacturing firms is around 85%. This means that firms that received subsidies in 2004 spent, on average, an additional of 34 million pesos compared to firms that did not receive subsidies. These results highlight the positive effects of public R&D subsidies 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 sample. This implies that given a one-to-one matching grant subsidy scheme, the subsidy does not leverage additional funds over the private co-funding if the mean of the difference of private R&D spending distribution is considered. On the other hand, there is a leveraging effect of 0.49 pesos over the private co-funding when the median is considered.

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