Private R&D and Public R&D subsidies: Microeconometric Evidence from Denmark[§]

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Abstract: Both fully parametric and nonparametric microeconometric evaluation methods show that public research subsidies do not have a significant effect on private Research and Development (R&D) expenditures of non–public Danish firms that perform R&D and have more than ten employees.

Keywords: selection models, R&D subsidies, matching models, Denmark

JEL classification: L2, C34

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1 Introduction

It is widely acknowledged by European economic policy makers that research and development (R&D) is a main ingredient of sustained economic growth and welfare. It is also generally accepted that private R&D needs to be publicly supported since the social returns to R&D exceed the private returns to R&D which is due to the fact that firms may not be able to fully reap the benefits of their research. This is so since whenever firms undertakes research, fractions of the newly generated knowledge leaks out to competitors, thus creating an external effect termed "research spillover" that justifies policy intervention from an economic theory point of view.

The leaders of the EU–15 countries agreed that the ratio of R&D expenditures to GDP should be at least 3 percent until 2012 on their March 2003 Barcelona summit. In order to me meet this goal, subsidization of R&D will probably increase since according to figures published by the OECD (OECD 2003), the average R&D/GDP ratio of the EU–15 countries was 1.8 percent in 2001 and thus well below the targeted 3 percent. The latest reported figure for Denmark is from 1999 when the R&D/GDP ratio was 2.2 percent.

A key question for economic policy to ask is whether public R&D support stimulates private R&D efforts (by equalizing private returns to R&D to the social returns to R&D) or if it crowds it out (since firms may free–ride on government subsidies). In this paper I try to identify the effects of public R&D support on private R&D efforts using data on a cross–section of 268 Danish service sector and 847 manufacturing firms observed in 2001 that export, conduct R&D and have more than ten registered employees.

While there is a quite broad agreement that tax incentives stimulate R&D (Bloom et al. 2000; Hall and van Reenen 2000; Warda 2002), existing studies on the effects of direct subsidization arrived at very mixed conclusions. For example Busom (2000) finds crowding–in effects of public R&D for a sample of Spanish firms using an econometric model that parametrically corrects for the potential endogeneity of R&D subsidies to private R&D expenditures (there might be a bi-causal relationship between R&D subsidies and private R&D expenditures); Lach (2002) reports insignificant effects of public R&D on private R&D for Israeli firms using difference–in–difference methods while Czarnitzki and Fier (2002), who use matching models, show that public R&D support decreases private R&D efforts of German firms. Surveys by David et al. (2000), Harhoff and Fier (2002) and Klette et al. (2000) also report a wide array of evaluation results.

The only existing econometric analysis for Denmark I am aware of is Sørensen et al. (2003). This macroeconometric study uses sector–level data on selected Danish manufacturing industries that spans the period 1974 to 1995. The authors find significantly positive effects of public research support on private R&D.

That differences between different evaluation studies exist is not very surprising. First, public subsidization programs differ across different countries and even within countries. Second, econometric evaluation methods widely differ as well. The fundamental evaluation problem is that the econometrician does not observe what would have happened had there been no subsidization program. The microeconometric approaches I use to handle this issue are fully parametric two–step regressions method I developed elsewhere (Kaiser 2002) and matching methods (Heckman et al. 1999, Section 7.4).[1]

The main empirical finding of this paper is that neither econometric method find statistically significant effects of R&D subsidies on private R&D intensity (R&D expenditures scaled by sales) which suggest that R&D stimulating and free–riding effects just balance out one another. Even though this result has to be viewed with much caution due to a multitude of data–related caveats (that I discuss in Section 2 below), it still provides evidence for a need to review Danish research subsidization policies. This review would ideally be based on large–scale econometric studies that are coupled with detailed case studies in order to make sure that governmental policy is based on firm quantitative grounds.

[1]Difference–in–difference estimation as in Lach (2000) is not applicable here since requires panel data which I do not have at my disposal. The data set I use has "some" panel data dimension since few questions are asked both for 2001 and retrospectively for 1999 as well. Difference–in–difference models require, however, at least three consecutive observation.

2 Caveats

Before proceeding I believe some words of caution with regard to this paper are in order. The paper suffers from five main potential problems with the most important one undoubtedly being that the number of observations is low and that the number of firms that received public R&D subsidies is even lower (86 in manufacturing and 43 in services). All inference is hence based on a fairly small sample.[2]

The other four potential flaws of my paper are the same as for other existing studies. First, I only estimate the effect of those firms that receive treatment. There might of course be positive or negative spillovers effects on non–treated firms that go unnoticed. Second, I do not have information on the exact support scheme (size, application requirements, easiness of access, non–pecuniary support such as counselling etc.) that the treated firms have benefited from. It might well be that different subsidization programs have different effects. What I estimate in this paper is the average effect of a bundle of support programs. Third, my study does not trace the long–run effect of public research subsidies and also does not estimate issues such as reductions in wasteful duplication of R&D efforts. It is possible that public R&D support does not have a significant effect on private R&D today but that it stimulates future private R&D. Fourth, my analysis is

[2] It is, however, not much smaller than that of other evaluation studies, for example the widely cited paper by Dehejia and Wahba (1999).

based on self–reported data and it cannot be ruled out that there is heterogeneity across the respondents' definition of R&D and R&D subsidies.

A last issue to note here is that my analysis is not concerned with the effect of public R&D on R&D *success* such as patent applications, patent grants, or the successful launch of a new production process or of a product innovation.

3 Empirical approach

My two methods of identifying the effect of public research support on private R&D are a (i) a fully parametric two–step estimator and (ii) propensity score matching approach.

3.1 Parametric model

The baseline idea behind my fully parametric model is to control for the potential endogeneity of treatment on private R&D using a instrumental–variables type technique. I first estimate a binary probit model for the probability to receive R&D subsidies ("treatment equation") and then estimate a ordinary least square (OLS) regression that controls for the endogeneity of treatment using Heckman–type (Heckman 1979) correction terms.[3]

[3]The corresponding variance–covariance matrix is inconsistent which is why I use block–bootstrapped standard errors with 10,000 replications.

The practical problem with this estimator is that it requires "exclusion restrictions", e.g. variables that are likely to affect the probability of receiving R&D subsidies but are "unrelated" ("orthogonal") to private R&D intensity. After having experimented and tested various different exclusion restrictions, my specification of the treatment equation includes the following six exclusion restrictions. My first four exclusion restrictions are dummy variables that are coded one (and zero otherwise) if a firm's fiercest competitor on foreign markets are (i) locally oriented firms, (ii) nationally oriented firms, (iii) multinationally oriented firms[4] and (iv) at least partly publicly owned firms.[5] The intuition behind their inclusion is that it might not matter for private R&D where the competition comes from (but rather that there is competition at all) while government might find it important to strengthen the technological competitiveness of domestic firms vis–a–vis foreign competition. My fifth and sixth exclusion restrictions are dummy variables for cooperation with external parters in the generation of new products or processes in general and with academia in specific. It is an explicit policy of the Danish government to encourage R&D cooperation, in particular between private firms and academia, so that it seems likely that such inter–firm coopera-

[4]This variable is left out in the specification for manufacturing industries since it proved to significantly affect R&D intensity as well.

[5]The latter variable is left out in the specification for manufacturing industries since perfectly predicts R&D subsidization.

tion is also rewarded by R&D subsidies.[6]

For exclusion restrictions to be valid they have to have two properties: they (i) must be highly correlated with the variable that is potentially endogenous and (ii) need to be orthogonal to the equation of core interest, the R&D intensity equation. Property (i) means that the exclusion restrictions need to have significant effects on the probability to receive treatment and can easily be tested by simple t–tests and Wald–tests for joint significance. As it is shown in Table 2, the exclusion restrictions are jointly significant and some of them are also separately significant. Property (ii) is informally tested by regressing the residuals from the R&D intensity equation on the exclusion restriction. They should have both separately and jointly insignificant effects on the residuals. It indeed turns out that the exclusion restrictions do neither have separately nor jointly significant effects on the residuals. I do not display these regression results for the sake of brevity.

The full specification of the binary probit model for the probability to receive R&D subsidies is described in Section 5.

[6]This variable is suspicious to also influence the private R&D intensity (as, e.g., in Kaiser 2002). The cooperation variable did, however, not turn out to be significant in the R&D intensity equation.

3.2 Nonparametric model

Propensity score matching is a way to "correct" the estimation of treatment effects by controlling for the existence of non–random selection into support programs. The baseline idea is to compare firms from the "treatment" group with observationally equivalent firms that did not receive public R&D subsidies. Firms, just like individuals, come with a large set of characteristics and many of those characteristics might influence the probability to receive treatment. Therefore, a one–to–one matching of firms according to their observed characteristics is often practically infeasible which is why propensity score matching aims at summarizing the characteristics of each firm in a linear index variable — the propensity score — which makes multidimensional matching feasible.

The propensity score is generated by a simple binary choice model, in the present case by a binary probit model. Once the propensity score is estimated, the data is split into several equally spaced intervals of the propensity score. Within each of these intervals the average propensity score of treated and control firms must not differ significantly — the "balancing property" is then satisfied. If they do, estimation of average treatment effects based on propensity scores is inconsistent since, intuitively, the estimation would then be based on comparing non–comparables.

Even if the propensity score is estimated and the balancing property is satisfied in each interval, a one–to–one matching based on the propensity score in each interval can not be performed since the probability of observing two firms with exactly the same value of the propensity score is zero since the propensity score is a continuous variable. This is why I use the following three methods to overcome this problem that have been proposed in the literature: Nearest Neighbor Matching (in the two versions frequency weights and random draw), Kernel Matching and Stratification Matching. At the bottom line, these methods numerically search for "neighbors" that have a propensity score of non–treated firms which is very close to the propensity score treated firms. I omit further details here for brevity and refer to Becker and Ichino (2002) who also provide the STATA software code I use in this paper.

4 Data

The econometric evaluation is based on survey data that was made available to me by the Danish Ministry of Economic and Business Affairs. It was collected by the Danish consultancy firm PLS Rambøll in March 2002; the survey questions relate to 2001. The population of the survey is all non–public exporting firms with a minimum of ten registered employees in Denmark. The data was collected in a combination of postal interviews, internet interviews and phone interviews. Before the data collection started, the sampling frame was divided up into nine different strata. A target number of firms in each strata was set and interviews were conducted until each strata was filled with the targeted number of firms. The total number of observations is 1,000. Further details on data collection methods are provided by Danish Ministry of Economic and Business Affairs (2002).

After correcting for item–nonresponse and deleting all firms from agriculture and fishery, my data consists of a total of 550 firms, of which 139 are from services and 411 are from manufacturing. Some of the survey questions, like those on R&D expenditures and R&D subsidies, were asked retrospectively for 1999 as well so that the total number of observation increases to 1,134.

It is in principle possible to estimate the treatment effects for 1999 and 2001 separately and/or to estimate the effect of treatment in both 1999 and 2001 on private R&D expenditures in 2001. The difficulty is, however, that this leads to a substantial reduction in sample size which is why I run "pooled" estimations.

My measure of private R&D is R&D intensity, the ratio of private R&D to total sales. By proceeding this way, I circumvent measuring sheer size effects and am consistent with existing studies (e.g. Busom 2000; Czarnitzki and Fier 2002).

Private R&D intensity is calculated from the two survey question "Please report the share of your R&D budget in total sales in 1999 and 2001" and "Please report how large the share of your R&D budget was that was financed by subsidies or public contributions". The data hence contains information on how much subsidies a firm received. By only differentiating between treatment and non–treatment firms I therefore discard potentially valuable information since treatment effects might differ across different treatment magnitudes.

Table 1 displays mean private R&D intensities, the share of public R&D in total R&D and the share of firms that received public support. The figures are provided for R&D performing firms only since non–R&D performing firms are excluded from the sample. A total of 43 percent of the firms in the sample did not conduct R&D in 1999, the corresponding figure for 2001 is 40.4 percent.

Table 1 contains good news for economic policy since R&D intensity has been raising between 1999 and 2001 in both manufacturing and services, with most of the growth being attributable to private R&D. The fraction of firms that received R&D subsidies increased in manufacturing industries while it decreased in services. Average private R&D intensity in manufacturing was 6.3 percent in 2001, it was slightly higher in services with 7.7 percent. The variation in R&D intensity and public funds is considerable as indicated by large standard errors.

The share of public R&D in total R&D differs very much from figures reported by OECD (2003). This is so because the OECD figures also include government support in the form of tax incentives and direct support to public–private research partnership institutions that play a very important role in Danish research policy (Sørensen et al. 2003; Hougaard Jensen et al. 2003).

5 Specification

In order for the propensity score estimator to be able to match comparable firms to one another, the binary probit model that generates the propensity score needs to have a "'good fit", it in particular needs to lead to a highly significant specification of the treatment equation. A reasonable fit of the binary probit model is of course also a prerequisite for the parametric model.

Apart from the exclusion restrictions that I described in Subsection 3.1, my specification consists of four sets of variables: (i) variables that represent firms' research activities, (ii) variables that represent the skill structure of the workforce, (iii) the degree of firms' internationalization and (iv) the "usual" control variables for observed firm heterogeneity; namely firms size (measured by the natural logarithm of the number of workers), a set of sector dummies and a year dummy variable for the year 1999.

Variables representing research activity

A firm's approach to R&D is a somewhat natural determinant of the probability to receive public research subsidies which is why I include a dummy variable for holding at least one patent, a dummy variable for cooperation with public research institutions or universities in innovation and a dummy variable for having introduced a new or markedly improved product in the past two years.

Variables representing skill structure

The skill structure of a firm's workforce is also an important determinant of research activity and also is likely to influence a firm's ability to attract public funding in a significant way. I therefore include the share of employees with (i) a more than four years long university education, (ii) a between three and four years long university or technical college education and (iii) no formal education.

The share of employees with less than a less than a three years long formal education is the comparison group.

Variables representing internationalization

The degree of internationalization of a firms might also affect its ability to attract public funding for example since government might want to support firms that are facing stiff international competition to a larger extent than firms that are more domestically oriented. My three variables representing internationalization are (i) the number of languages that were spoken during the last meeting the survey respondent participated in, (ii) a dummy variable that is coded 1 if the firms is involved in international activities[7] and (iii) the share of exports that is billed in Euros.

My specification for R&D intensity contains, except for the exclusion restrictions, the same variables as my specification for the probability of treatment.

6 Results

6.1 Treatment equation

Table 2 displays the estimation results of the probit models for the probability of public R&D support.

[7]This variable is omitted in the specification for services since it perfectly predicts governmental support.

The most important results from Table 2 from an econometric perspective is that (i) all specifications appear to give a reasonably good fit with all specifications being very highly significant and with pseudo R^2s of between 0.13 and 0.53 and (ii) that the balancing property is satisfied in all intervals which means that I indeed compare firms that are comparable to one another with respect to the set of variables I include in my specification.

Consistent with Denmark's past as a primarily agricultural country, the food industry is most likely to receive R&D subsidies. By contrast, the furniture industry is least likely to receive treatment, presumably since it is not a very R&D intensive industry. There are insignificant differences between the other sectors.

Firms that hold patents, that introduced new products — e.g. firms with a "good" innovation record — and that cooperate with academia are significantly more likely to receive public funds than "worse" performing firms.

The share of workers with an education longer than four years has a weakly significant (and positive) effect in the joint specification and in the specification for services only which means that firms with a formally more qualified workforce are more likely to receive public R&D support.

A firm's internationalization does generally not have a significant effect on public R&D subsidies.

The signs of the two firm size variables indicate an inverse U–shaped effect of firm size on the probability of receiving treatment meaning that both very small and very large firms are unlikely to receive R&D subsidies. The chance of receiving treatment is maximal if firm size is 143 employees in the joint specification, 116 in the specification for manufacturing and 162 in the specification for services.

Insert Table 2 about here!

6.2 Parametric model

Table 3 shows OLS estimation results for the private R&D intensity equation. The dummy variable for treatment does not directly translate into a percentage effect on private R&D intensity since it also hinges upon the two Heckman–type correction terms. This is why the percentage effect on private R&D intensity is displayed in Table 4.

The only information Table 4 contains is that there are insignificant effects of public R&D support the treated firms, both in the joint specification, the specification for services and the specification for manufacturing.

The results for private R&D intensity estimation, displayed in Table 3, suggest that private R&D is highest in the office machinery sector and lowest in furniture. Firms that own a patent spend about twice as much on R&D than firms that do not hold patents.[8] The skill structure variables indicate that the larger the share of highly qualified personnel is, the more firms spend on private R&D. This is unsurprising since the largest fraction in total private R&D expenditures are labor

[8]Due to the fact that this variable is likely to be endogenous to private R&D, the related coefficient should be interpreted as a correlation rather than a causality.

cost. Firms that face foreign competition from multinational firms spend significantly more on R&D than firms not confronted with that type of competition. The variables for internationality are ambiguous in sign: the more number of languages spoken at the last meeting is significantly positive, the "international" dummy variable is insignificant and the share of bills issued in Euros is negative. Firm size does not have a significant effect on private R&D intensity.

6.3 Nonparametric model

The main finding from the propensity score matching model is the same as for the parametric model: there are insignificant treatment on the treated effects. This is shown in Table 5 which displays propensity score matching estimation results for the effect of public subsidies on those firms that received public subsidies. The estimation results are not only insignificant, they are also very small in absolute magnitude.

6.4 Comparison to the study by Sørensen et al. (2003)

My finding of insignificant effects of treatment is somewhat in contrast to the results of Sørensen et al. (2003). There are many sources for this contradiction (in their order of importance): (i) the authors estimate an average effect on all firms, both treated and non–treated (ii) the estimation methods are completely different (iii) the data refers to a different time period and (iv) there might be aggregation problems in Sørensen et al. since sector–level data is used.

7 Conclusions

This paper analyzes the effects of public R&D subsidies on private R&D spending at the firm level. The empirical evidence is based on a sample of 1,101 R&D performing Danish firms from manufacturing and services that are involved in export activities observed in 1999 and 2001.

Fully parametric and propensity score matching methods are applied to estimate the effect of public R&D on private R&D, i.e. the effect of treatment on the treated.

The main result of this paper is that there is neither evidence provided for crowding–in nor for crowding–in effects of private R&D by public R&D.

These estimation results are based on a fairly small sample of firms, especially on a small set of firms that receive public research subsidies — 847 firms in manufacturing of which 86 received treatment and 268 in services of which 43 received treatment. This is why one needs to interpret my results with much caution. A lesson I believe to be definitely learned from this paper is that large–sample econometric studies, ideally supported by case studies, to estimate the effects of public R&D on private R&D are needed to enable policy to reach wise decision with respect to R&D policy.

Table 1: R&D intensity and research subsidization

	Total R&D intensity		**Private R&D intensity**		**Share publicly funded R&D**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Manufacturing						
1999	5.8	9.1	5.7	8.8	1.8	7.7
2001	6.3	9.4	6.1	8.1	2.1	8.3
Services						
1999	7.1	9.1	6.7	8.8	3.3	10.2
2001	7.7	9.4	7.5	9.1	2.6	8.8

Table 1 displays summary statistics for R&D intensity and research subsidization.

Table 2: Binary probit estimation results: probability to receive public funding

	Joint		Manufacturing		Services	
	Coeff.	**Std. err.**	**Coeff.**	**Std. err.**	**Coeff.**	**Std. err.**
Exclusion restrictions						
Local competition	0.3355**	0.1561	0.2620	0.1792	0.9993**	0.5127
National competition	-0.1281	0.1198	-0.2308*	0.1416	0.3844	0.3245
Competition from public firms	0.4053	0.3568	0.5242***	0.2035	3.6666***	1.0999
Cooperation with academia	0.6633***	0.1659	0.3203**	0.1619	1.4580***	0.4346
Cooperation	0.3217**	0.1421	-0.9014**	0.4247	0.4835	0.4076
Sector dummies						
Trade	0.0036	0.1911			-0.3374	0.3303
Furniture	-1.0746***	0.4228				
Office machinery	0.0280	0.2669	0.0760	0.2813		
Plastic and non–metals	-0.2132	0.2272	-0.0452	0.2399		
Motor and machinery	-0.0116	0.1656	0.1524	0.1860		
Wood	-0.2043	0.3208	-0.1708	0.3360		
Textile	-0.1234	0.3000	-0.0576	0.3208		
Food	0.4692**	0.1938	0.5561***	0.2151		
Variables representing research activity						
Patent holder	0.6489***	0.1300	0.3344**	0.1603	1.6916***	0.3266
New product introduced	0.2440	0.1702	0.1860	0.1883	1.5038*	0.9260
Variables representing skill structure						
Share more than 4 years education	0.5303*	0.2774	0.0642	0.3990	1.2835*	0.7257
Share 3–4 years education	-0.1337	0.2864	0.0396	0.3158	-0.4630	1.0038
Share 3 years education	-0.0356	0.2878	-0.1078	0.3291	0.4902	0.8790
Variables representing internationalization						
Competition from multinationals	-0.1407	0.1250	-0.1072	0.1480	-0.1260	0.3656
ln(# of languages)	0.3333**	0.1623	0.3405**	0.1804	0.8145*	0.4761
International	0.2122	0.3465	0.0244	0.3652		
Share bills in euro	0.0002	0.0020	0.0022	0.0022	-0.0075	0.0071
Year dummy, firm size and constant						
Year 1999	-0.0267	0.1107	-0.0331	0.1283	0.0067	0.2684
ln(# of employees)	0.5059**	0.2328	0.4515	0.2793	1.3342**	0.5869
ln(# of employees)^2	-0.0510**	0.0235	-0.0475*	0.0283	-0.1312**	0.0570
Constant	-3.4874***	0.6602	-3.0553***	0.7514	-7.8342***	2.0544
# of obs. and pseudo R^2						
# of obs.	1101		822		279	
Pseudo R^2	0.1783		0.1268		0.5265	
Tests for joint significance						
		p–val.	Wald–test stat.	p–val.	Wald–test stat.	p–val.
Entire spec.	138.21	0.0000	68.20	0.0000	122.62	0.0000
Excl. restrictions	37.95	0.0000	19.80	0.0005	28.72	0.0000

Table 2 displays the binary probit model estimation results that are used to generate the propensity score. The asteriks ***,** and * indicate statistical significance at the one, five and ten per cent marginal significance level.

Table 3: OLS with endogenous treatment estimation results, dependent variable: private R&D expenditures (in percent)

	Joint		Manufacturing		Services	
	Coeff.	**Std. err.**	**Coeff.**	**Std. err.**	**Coeff.**	**Std. err.**
Treatment effects						
Dummy R&D subsidies	-4.4342	2.8696	-2.5157	4.8134	-9.3476**	4.5145
Heckman–term 1	2.1568	1.7738	1.4095	2.8850	3.6303*	2.0369
Heckman–term 2	2.9516*	1.7331	4.4237*	2.4845	5.9255	4.3580
Sector dummies						
Trade	-1.3438**	0.6859			-2.9653***	1.1385
Furniture	-2.1366***	0.7886	-2.1920**	0.9173		
Office machinery	8.1649***	1.8299	8.2758***	1.7398		
Plastic and non–metals	-1.0412	0.7528	-0.8589	0.7763		
Motor and machinery	-1.1305	0.8288	-0.8488	0.8695		
Wood	-1.9840**	0.8540	-1.4822	0.9786		
Textile	-1.0784	0.9483	-0.9315	0.9436		
Food	-1.4143	0.9217	-1.2526	0.8976		
Variables representing research activity						
Patent holder	1.9052**	0.8115	1.3286	0.8433	6.5650*	3.9317
New product introduced	-0.2375	0.9419	0.9095	0.9604	-2.8160	2.0220
Variables representing skill structure						
Share more than 4 years education	10.9171***	1.6174	12.2745***	2.4001	8.5908***	2.5958
Share 3–4 years education	2.6189***	0.8367	1.7560**	0.8996	6.6168***	1.8449
Share 3 years education	0.4154***	1.2543	0.9218	1.4050	-1.8844***	2.2669
Variables representing internationalization						
Competition from multinationals	1.8918***	0.5197	1.6852***	0.6185	3.5984***	1.1038
ln(# of languages)	1.7500***	0.5908	2.4454***	0.6960	-0.2894	1.2103
International	0.6668	0.6004	0.3487	0.8532		
Share bills in euro	-0.0168**	0.0075	-0.0127	0.0092	-0.0321*	0.0168
Year dummy, firm size and constant						
Year 1999	-0.5053	0.4820	-0.3625	0.5659	-0.9146	0.9893
ln(# of employees)	-0.0772	0.6543	0.1250	0.7984	-0.2120	1.2349
ln(# of employees)^2	-0.0491	0.0640	-0.0739	0.0793	-0.0109	0.1304
Constant	3.2147***	1.9213	1.6180	2.1665	7.5580	3.6809
# of obs. and adj. R^2						
# of obs.	1,101		822		279	
Adj. R^2	0.1988		0.2123		0.2635	
Tests for joint significance						
	F–test stat.	p–val.	F–test stat.	p–val.		
Correction terms	4.55	0.1029	3.26	0.1958	3.67	0.1597
Treatment effects	4.85	0.1828	3.73	0.2920	5.18	0.1590
Entire spec.	10.72	0.0000	9.08	0.0000	5.68	0.0000

Table 3 displays OLS estimation results for private R&D intensity. The Heckman–type correction terms control for the endogeneity of receiving R&D subsidies on private R&D intensity. Standard errors are bootstrapped with 10,000 replications.

Table 4: Average treatment on the treated effect

	Average treatment effect (in %)	**Std. error**
All	-0.9201	1.6760
Manufacturing	-0.6573	1.2652
Services	-2.1156	7.4177

Table 4 displays average causal treatment effects of public R&D subsidies on private R&D intensity (private R&D relative to total sales) based on the parametric model. "NNM" is short for "Nearest neighbor matching". In cases where the number of control firms is smaller than the number of treated firms, some of the control firms have been used multiply in the matching.

Table 5: Average treatment on the treated effect

	# of intervals	**# treated**	**# controls**	**Average treatment effect (in %)**	**Std. error**
All					
NNM, equal weights	4	129	99	-0.3731	1.4072
NNM, random draw version	4	129	99	-0.3731	1.2363
Kernel Matching	4	129	1,005	0.0903	0.7855
Stratification	4	129	1,005	-0.2698	0.8429
Services					
NNM, equal weights	5	43	25	-6.6676	4.4970
NNM, random draw version	5	43	25	-6.6676	4.1161
Kernel Matching	5	43	244	-3.4951	2.1340
Stratification	5	43	225	-4.7274	2.7791
Manufacturing					
NNM, equal weights	4	86	64	0.1999	1.5692
NNM, random draw version	4	86	93	0.1999	1.3194
Kernel Matching	4	86	761	1.0027	1.0451
Stratification	4	72	731	0.8405	1.2346

Table 5 displays average causal treatment effects of public R&D subsidies on private R&D intensity (private R&D relative to total sales). For example, firms from the service sector that receive public subsidies have an on average 6.7 percent lower R&D intensity then firms that do not receive subsidies (standard error 4.5 percent). Standard errors are bootstrapped, 10,000 replications were used. "NNM" is short for "Nearest neighbor matching". In cases where the number of control firms is smaller than the number of treated firms, some of the control firms have been used multiply in the matching.

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