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# The Impact of Public Funds on Private R&D Investment: New Evidence from a Firm Level Innovation Study*

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## Abstract

This paper investigates the effectiveness of a public innovation policy aimed at stimulating private R&D investment. The research will examine whether public funding increases the total spending on research or merely displaces funding from private sources. The empirical analysis is based on the Community Innovation Surveydata merged with register data. It is an evaluation of whether firms receiving public funds have on average a higher R&D intensity compared to those not receiving any such support. In order to account for possible selectivity bias, and to improve comparability of firms, two different versions of a semi-parametric matching approach are employed. The two matching estimators result in somewhat different results. The Nearest Neighbour estimator is preferred to the Kernel estimator. The results support the hypothesis suggesting that there are additive effects of public R&D financing on private research expenditures, but the only beneficiaries are small firms.


**Keywords:** R&D investment, crowding out, public funding, matching, subsidies

**JEL Classification:** C24; L10; O30; O31; O38; 040

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## 1. INTRODUCTION

Due to the assumptions of market failures and the under-investment in R&D and innovation activities, all OECD countries are spending significant amounts of public funds on programmes intended to stimulate these activities. At the end of the 1990s, the share of government funding of the total R&D, in the respective economies, was approximately one third in the US and Europe and one fifth in Japan (OECD 2000). Nearly 10% of commercial firms' R&D expenditures in the OECD are publicly funded.

The theoretical literature on the economic benefits of innovative activities is vast. There is also a steadily growing empirical econometric literature and case studies verifying the importance of R&D and innovation at various levels of aggregation. Furthermore, it is widely accepted that, in the absence of policy intervention, the social rate of return on R&D expenditure exceeds the private rate, leading to a socially sub-optimal rate of investment in R&D (Guellec and Pottlesberge, 1997). The main channels of public support for individual firms are tax incentives, direct government funding, co-operation arrangements between firms, research institutes and universities, and loan guarantees.

Considerable effort has been devoted to the evaluation of the efficiency of public subsidies for R&D. Despite the prevalence of such programmes, there is little consensus about their effectiveness (Jaffe 2002 and Hall 2002), and there remain serious methodological issues about their findings, which are yet to be investigated.

Klette, Möen and Griliches (2000) report that most evaluation studies on governmental subsidies utilising microeconometric methods are based on the assumption that R&D subsidies, to a large extent, are allocated randomly to firms and projects. If the allocation process is haphazard then the challenging issue is to find sufficient comparative data for firms receiving R&D subsidies as for similar non-supported firms. The difference in performance between the two groups of firms could then be estimated, with public funds as a determinant.

There is overwhelming evidence that firms do not randomly participate in governmental R&D support programs. On the contrary many studies have concluded that, to a large extent, public R&D policy attempts to cherry-pick the winners in programs such as ATP, SEMATECH and SBIR (see Irwin and Klenow, 1996 and Lerner, 1998). Furthermore, small firms participate less frequently than larger firms in various support programmes and a larger proportion of beneficiaries and users of the support programs are in the more technologically advanced sectors (Hanel, 2003).

If the performance of the supported and non-supported firms ex ante differs systematically one difficulty in this type of evaluation is the potential selection bias. Jaffe (2002) describes a typical case, where firms funded by the government are liable to be those with the best ideas. This implies that these firms have more incentive to spend their own resources and are more likely to receive support from third parties. Hence, in a microeconometric analysis, public funding is an endogenous variable and its inclusion in the list of independent variables will result in inconsistencies.

The empirical analysis in this paper seeks to assess to what extent firms receiving subsidy would have invested had they not benefited from apublic policy scheme? In doing so we investigate whether firms that received public funds, have on the average, a higher R&D intensity compared to those that did not receive any public support.

In order to account for selectivity bias we initially estimate a firm's probability of receiving public funds given a number of observable characteristics. The sample is then divided with respect to a firm's participation in the public R&D schemes and a potential control group of non-subsidised firms. Each subsidised firm is matched with a similar non-subsidised firm, or a pair of similar firms, that have the same probability of being subsidised, and the difference in their performances is computed. The difference is then linked to the effects of subsidy on the performance of firms.

The remaining part of this paper is organised as follows. Section 2 reviews the theoretical background with a focus on recent studies evaluating the effects of government sponsored commercial R&D programmes. Section 3 delineates the data. Section 4 introduces the methodological approach used. Section 5 states the empirical results, and Section 6 concludes this study.

## 2. THEORETICAL BACKGROUND AND REVIEW OF RECENT STUDIES

The economic-theoretic support for state intervention in R&D activities begins with Schumpeter (1942), Nelson (1959) and Arrow (1962) and revolves around the conceptual idea that knowledge is a nonrival good. Therefore, the return on investment cannot be appropriated by the firm undertaking the investment, thus leading to an underprovision of R&D investment in the economy. To correct for this market failure and in an attempt to estimate the optimum level of public support for commercial firms, Gullec and Pottelsberghe (2003) suggest a threshold value of approximately 10%, on average, for the 17 OECD countries. Interestingly, this only slightly exceeds the reported average rate of subsidy for the OECD as a whole.

In their endogenous growth model Davidsson and Segerstrom (1998) differentiate between innovative R&D and imitative R&D. The former produces higher quality products, while the latter imitates other firms' products. Although both types of R&D activities create new knowledge, they find that only innovative R&D subsidies lead to faster economic growth. A governmental grant regime, stimulating a faster rate of imitation, makes the monopoly profits earned from successful innovation more short-lived. The consequence is a decrease in the rate of technical change, resulting in slower economic growth. Based on data from a typical OECD country, Davidsson and Segerstrom empirically show that all R&D expenditures increase the level of GDP, but only investments associated with new products for the market, new processes and development of knowledge have a positive impact on the GDP growth rate.

Most industrialised countries have publicly funded research-grant programmes that attempt to funnel public resources directly into R&D projects that are anticipated to have particularly large social benefits. Such research-grant programmes include those that support basic scientific research; R&D aimed at particular technical priorities to the state (e.g. defence, health and environment); "pre-competitive" R&D intended to generate large spill-over, often with a collaborative component; subsidies especially targeting the new technology based firms and early-stage financing to firms, particularly those in the high-technology field. Most of these grant programmes can be assumed to target innovative R&D along the Davidsson-Segerstrom definition.

The assessment of various governmental grant programmes is afflicted with fundamental measurement problems such as: (i) how to measure research output of supported research entities, (ii) how to measure the spill-over benefits of funded research enjoyed by entities other than those that are directly supported, and (iii) how to measure transformational impacts, whereby public support changes the nature of the research infrastructure, with possible long-lasting effects.

In evaluation studies several different measures of R&D output can be distinguished. First, if the R&D expenditure is aimed at early-stage technology development then the output can be technical and the activities that transform commercially promising innovation into a *business plan* can attract sufficient investment such that output enters a market successfully (see Branscomb et. al 1999). Second, when the objective of the R&D efforts is to develop a new science or technology that is protectable, then the best measure of output is *patents* or *copyrights*. Third, R&D investment intended to result in the successful entry of a new or significantly improved product into a particular market can best be measured as *innovation sales.*

A more recent discussion on the impact of state funding considers whether the public funding decision represents an endorsement of a project as being of high quality. The screening of proposals by the likelihood of success is a costly and uncertain process. Non-public sources of funding may piggyback on the public review process, or, even if they make their own assessments, they acknowledge that their assessment is uncertain and can be influenced by that of the government experts. This “certification” or “halo” effect is believed by research grants agencies in the USA to be an important factor in increasing the total spending of grant recipients (Diamond 1998, and Jaffe 2002).

It is also well documented in the literature that firms funded by the government are likely to be among those with the best ideas. Thus, they have more incentive to spend their own resources, and are more likely to receive support from third parties than firms not funded. As emphasised by Jaffe (2002), any regression analysis that compares the research expenditure of government supported firms to those that are not supported has to take into account the selectivity problem. A closely related assessment issue concerns *additivity* versus *crowding out* phenomenon. While the selectivity problem arises because public funding goes to proposals judged in advance as likely to succeed; the additivity and crowding phenomenon out refers as to whether public funding increases the total spending on research or merely displaces funding from other sources.[1]

In order to measure the impact of public funded R&D and to reduce the problem of selection bias, many recent assessment studies rely on one or more of the following methods: (i) regressions with controls, (ii) fixed effects or difference-in-difference models, (iii) sample selection models, (iv) instrument variable estimators, or (v) matched samples of treated and untreated firms. The treated firms are firms receiving public funds.

[1] Busom (2000) discusses the problem of complete crowding out versus partial crowding out and concludes that the latter often is difficult to measure due to lack of detailed information about the firms’ R&D expenditures.

In recent years there has been a surge in econometric works focusing on the effectiveness of public R&D policy at various levels of aggregation in many OECD countries.[2] This paper adds to the sub-branch of public R&D policy assessment, which focuses on the evaluation of the impact of governmental support on private research expenditures. Table 1 depicts the common methods used and the main results from selected recent related studies.

Table 1: Recent studies on the impact of R&D subsidies.

| Year | Data and period | Author(s) | Methods | Results |
|---|---|---|---|---|
| 1998 | Finnish data 1985-93 | Toivanen and Niininen | Regression with controls | R&D subsidies have no effect of private R&D for large firms but increase private funding by 5% for small firms. |
| 1999 | Spanish data 1998 | Busom | Regression with controls | For two firms out of three the subsidies increase private funding of R&D by 20%. For the remaining third of firms, there would be a complete crowding out. |
| 2000 | U.S. SBIR data 1990-92 | Wallsten | Instrumental variables approach | The R&D investment would have been made even without subsidies because governmental agencies tend to favor projects with the highest private return. |
| 2000 | Israeli data 1990-95 | Lach | Matched samples and Regression with controls | Using matching methods and a subsidy dummy variable suggest that subsidies add to private funding of R&D. Regression methods suggest that one additional dollar in R&D subsidy would increase private R&D by 41 cents. |
| 2001 | German data 1994-98 | Czarnitzki and Fier | Regression with controls | On the average one Euro of subsidy would increase private R&D by 1.3 to 1.4 Euros. |
| 2002 | German data from 1995, 1997 and 1999 | Almus and Czarnitzki | Matched samples | Firms in Eastern Germany that participated in governmental R&D schemes increased the private R&D-investments with an amount corresponding to 4% of their turnover. |
| 2003 | French data 1985-97 | Duguet | Matched samples | R&D subsidies add to the private R&D. |

The studies based on Israeli longitudinal data (Lach, 2000), German longitudinal and cross-sectional data (Czarnitzki and Fier, 2001, and Almus and Czarnitzki, 2003) and French longitudinal data (Duguet 2003) use both regressions with controls and matched samples. All these studies suggest that public funds stimulate private R&D activities. A Finnish longitudinal study (Toivanen and Niinen, 2000) and one Spanish cross sectional study (Busom 2000), both using regressions with controls, gave mixed results. Finally, Wallsten (2000) finds that public support within the framework of the U.S. SBIR-programme, does not increase private spending.

[2] For examples of such studies, see Klette and Möen (Norway), 1999; Lerner (USA), 1999; Guellec and Pottelsberghe (OECD), 1999; Czarnitzki (2000) Germany; Branstter and Sakakibara (2000) Japan; Hyytinen and Toivanen (Finland), 2003; Duguet (France), 2003; Almus and Czarnitzki (Germany), 2003; Motohashi (Japan),

The heterogeneous results from different assessment studies, shown in Table 1, confirm previous findings in the literature. Reviewing the body of available econometric evidence accumulated over the past 35 years, David, Hall and Toole (1999) conclude that conflicting answers are given as to whether public R&D spending increases or replaces private R&D expenditure. The authors suggest that a possible explanation to this ambivalent finding in the existing literature would be different and sometimes inadequate research methodologies applied to the data.

The methodology used in this paper, motivated by the data available, is a matching process, whereby subsidised firms are matched with the most similar but non-subsidized firms found in the sample. Our approach of matching samples is similar to the Rosenbaum and Rubin (1983) propensity score model. In this approach a group of firms that have the same probability of receiving public funds is considered as reference group. Each subsidized firm is matched with a non-subsidized firm that has the same characteristics and probability of being subsidized and the difference in their R&D performances is computed. This procedure is repeated for all the subsidized firms and the average of these differences will provide an estimator of the possible effect of public R&D support on the firms' R&D activities.

## 3. THE DATA

The data used in this study is obtained from the Community Innovation Survey (CIS) III for Sweden. The survey was collected in 2001 and it covers the period 1998 to 2000. The focus is on both the manufacturing sector and business services. The sample is restricted to only firms that reported a positive R&D and other innovation expenditure. The final sample consists of 770 firms of which 160 (20.8%) firms participated in public R&D schemes. The CIS data was merged with register data containing complete information on the firms' annual accounts.

Table 2 shows that the proportion of subsidised R&D-firms varies within the range of 8-30 % in each different industry class. The largest fraction of supported firms is found among recycling, business services, motor vehicles and food products. Publishing and raw material based production show the lowest proportion of firms utilizing governmental R&D programmes.

(2003), and Hanel (Canada) 2003). For recent surveys, see also Kette, Möen and Griliches (2000) and Hall and Van Reenen (2000).

Comparing different size classes, Table 3 reveals that the proportion of supported R&D firms is considerably smaller for medium-sized firms (50-499 employees) compared to the group of very small firms (10-49). In the largest size group (500 and more) one in four firms participated in public R&D programmes.

Descriptive statistics for the two sub-samples of non-funded and funded firms are presented in Table 4. The right section of the table presents results from a t-test on inequality of means between the two samples.

First, it shows that there is a large difference in R&D and other innovation expenditure, per employee, between the two samples. The t-test reveals that the average funded firm is significantly more R&D-intensive than the average non-funded firm. Second, Table 4 depicts that funded firms have considerably larger gross investment per employee compared to the non-funded firms. Third, the average funded firm has a large amount of equity capital, per employee, compared to its non-funded counterpart. Fourth, we also observe that a funded firm is on the average somewhat larger than the non-funded counterpart. The funded firm also has a relatively high degree of indebtedness per employee. However, the size based mean-values are not statistically different.

The lower section of Table 4 presents descriptive statistics for the 7 dummy variables, based on the CIS-survey. Here we find that one in four funded firms reported that financial constraints hampered their innovation activities compared to only one in ten non-funded firms. Our interpretation is that funded firms belong to a select group of firms with more ideas than non-funded firms. Non-funded firms have a greater propensity to be part of a group and to be foreign owned. For other variables, including demand pull R&D (a composite variable indicating if the intention of R&D is to extend the range of products, to increase market share or improve product quality), lack of skill as an obstacle to innovation, possession of patents or an export indicator; no significant difference can be established between the two samples.

In summation, our findings suggest that the group of funded firms is a selective one. The descriptive statistics show large differences between the two groups regarding firms' investment in R&D and physical capital, but also with respect to external financial sources in terms of equity and debt. It is to be noted that by not accounting for such systematic differences listed above, when assessing the efficiency of public R&D support to firms, will very likely result in selectivity bias.

## 4. THE METHODOLOGY

The fundamental research issue is to measure the effect of public R&D support on firms' innovation performances. A methodological challenge as defined in the statistics literature as the lack of *counterfactual evidence,* implies that we cannot forecast the result of the firms' innovation performances in the absence of subsidies.[3] Pursuing the literature on assessing the effect of a particular treatmentf, we will use the results of non-recipients, with similar characteristics, to estimate the possible effect on recipients had they not participated in public funded R&D-programmes. The first disparity in this literature lies in the use of experimental and non-experimental methods. In a non-experimental evaluation, as pointed out by Smith (2000); "statistical techniques are used to adjust the results of persons who choose to participate, in order to assess the result had they not participated. In contrast, an experimental method directly produces counterfactual evidence by forcing some potential participants not to participate."

The present study compares data on non-experimental groups of firms. The estimator we apply is a semi-parametric method of matching. More conventional methods in causality studies use parametric estimators, such as instrumental variable estimators; the two-step estimator of Heckman (1979) or the difference-in-difference estimator. The choice of a particular estimator is often motivated by the structure of the data available together with the research question.

Heckman *et al.* (1998) notes that pioneering matching studies were made by Fecher (1860). Traditional matching estimators pair each collaborator with an observable similar non-collaborator, and interpret the difference in their outcomes as the effect of collaboration. However, when the sample contains extensive control variables (X), it is difficult to determine which variables (or more correctly cells) to match with a unit. Moreover, for some values of (X) among participants, close matches will perhaps not be found among comparison members. A solution to this problem, based on statistical tests, is the "propensity score" matching, developed by Rosenbaum and Rubin (1983).[4]

Propensity score matching, rather than utilising a vector of observed characteristics (X), matches participants and non-participants based on their estimated probability of

[3] For a detailed discussion on the *problem with counterfactual evidence in assessment analyses,* see Holland 1986.

[4] Smith (2002) notices that this problem is reduced, but not eliminated when matching on a scalar P(X) compared to a vector X.

participation; known as *P(X).* Rosenbaum and Rubin (1983) show that matching on (X) produces consistent estimates, matching on P(X) also has the same effect. The propensity score matching estimation methods have become increasingly popular in medical trials and in the evaluation of economic policy interventions (Becker and Ichino, 2003). Many examples of the latter are found in the labour literature.

Several crucial conditions apply to the use of matching estimators.[5] Matching, whether on X or on P(X), relies on a *conditional independence assumption*. As emphasised by Smith (2002); making this conditional independence assumption plausible in practice requires access to very rich data. It also requires careful thought, guided by economic theory, about which variables do or do not affect participation and outcomes.[6] In addition, Smith and Tood (2004) suggest that evaluation estimators are only found to work effectively when they satisfy the following criteria: (a) in a particular treatment program the same data sources are used for all participants, and non-participants, (b) the data contains a rich set of variables relevant to modelling the participating decision, and (c) participants and non-participants reside in the same market.

In the present study, the conditional independence assumption states that once we condition on P(X), participation in public R&D programmes is independent of the outcome in the non-participation state. This requires that all the variables that affect the outcome, both in collaboration and in the absence of collaboration must be included in the matching. However, in our study, in common with most other evaluation analysis, no robust theoretical guidance exists as to how to choose the set of conditioning X-variables.

Although the assessment estimators discussed by Smith and Todd (2004) concern labour-market programs, we assume that the criteria can be transposed to other markets. Thus, we conclude that the Community Innovation Survey information fulfils criterion (a) and at least partly, criterion (c)[7]. In addition we find support for criterion(b) in Almus and Czarnitzki (2003), who argue that the CIS-data provides comprehensive information on the firms for identifying a similar control observation for each treated firm. However, in the present study

[5] Heckman, Ichimura and Todd (1997, 1998), Heckman, Ichimura, Smith and Todd (1998), Smith and Todd (2004), and Smith (2000), provide critical discussions on strengths and weakness of matching estimators.

[6] Partly at variance with Deheija and Wahba (1999), Heckman, *et al*. (1998), Heckman, Ichimura and Todd (1999), Lechner (2002) and Smith and Todd (2004) find that the matching estimates can be quite sensitive to the variables needed to construct P(X).

[7] This is applicable at the 2-digit level of industry classification.

we have supplemented the CIS data with financial information, from the annual accounts, on physical capital stock, equity and debt.

The matching estimation procedure we are using can be described as follows. Initially a probit model is applied in order to estimate the propensity score for each observation. The dependent variable is the decision whether, or not, to participate in public R&D programs. The vector of determinant variables contains the set of characteristics (13 explanatory variables and 15 dummies for industry classifications) that potentially influence the probability of receiving public R&D support. After the determinants to R&D subsidy are identified and the probit model is estimated, a mono-dimensional propensity score is calculated for every observation. This measure is used to find counterfactuals for each supported firm.

In the next step we conduct a non-parametric matching approach based on the propensity score. Here the procedure is as follows. Firstly, the observations are separated with respect to their status regarding public R&D support. Secondly, a firm *i* that receives subsidy is selected. Thirdly, we utilize the propensity score and calculate a correct measure of distance to find the nearest neighbors or *matched* firms for each subsidized firm. The matching procedure is regarded as successful if the means of the probability of receiving R&D support and the means of determinants of receipt of subsidy, among the two groups, do not differ significantly. Finally, the impact of public financial support in promoting innovation is evaluated by comparing the average R&D expenditures between the groups of subsidized and non-subsidized firms.

We now proceed to the more formal notation of the estimation approach applied in this study. Following Heckman, Ichimura, Smith and Todd (1998)[8], we denote the outcome conditional on R&D support by $Y_1$ and the outcome on non-support by Y0. Further, let U=1 to signify participation in public R&D schemes, otherwise U=0. Since we only observe $Y_0$ or $Y_1$ for each firm, but never both, without statistical techniques we cannot compute the causal effect of R&D-subsidies, $\Delta = Y_1 - Y_0$, for any firm.

The method of matching applied is aimed at identifying non-subsidized firms, with the same probability of receiving support, as those actually subsidized. That is, conditional on some X, $Y_0$ is independent of U:

[8] See also Fisher (1935), Roy (1951) and Quandt (1972)

$$Y_0 \perp U \mid X \tag{1}$$

where "⊥" denotes independence and the variables to the right of "|" are conditioning variables. This assumption generates a control group with the following characteristics: conditional on X, the distribution of $Y_0$, given U=1, is the same as the distribution of $Y_0$, given U = 0. Hence, considering mean value, the implication of (1) is:

$$E(Y_0 \mid X, U=1) = E(Y_0 \mid X, U=0) \tag{2}$$

Rosenbaum and Rubin (1983) prove that given that the $Y_0$ results are independent of collaboration participation, conditional on X, they are also independent of participation, conditional on the propensity score Pr(U=1|X). An important implication is as follows: provided that we can apply a probit model and parametrically estimate the conditional probability of participating in a joint research program, the multi-dimensionality of the matching problem is reduced by matching on a mono-dimensional (scalar) propensity score. Thus the formal notion for the applied probit model is:

$$\Pr\{U_i=1 \mid X_i\} = F(h(X_i)) \tag{3}$$

where F(.) is the normal or logistic cumulative distribution, and $h(X_i)$ is a function of covariates with linear and higher terms.

Traditional propensity score matching methods pair each participant with a single non-participant (a "twin"). Nearest neighbours may be far apart. For that reason a metric criterion can be imposed to ensure that the match is close enough:

$$C(X_i) = \min_j |X_i - X_j|,\ i \in \{U=1\}\ j \in \{U=0\} \tag{4}$$

Smith (2000) points out that nearest neighbour matching can be operationalised with more than one nearest neighbour, and with or without replacement; where "with replacement" means that a given non-participant observation can form the counterfactual for more than one participant. In this paper we use the two nearest neighbours. The main advantage of a larger number of neighbours, compared to pairwise matching, is a reduction in the variance of the estimators (Smith and Todd, 2004). Moreover, this method ignores observations with insufficient close neighbours. In the present study, we have utilised both the nearest neighbour (kernel) approach and an extension of this approach that includes two neighbours.

In the latter case, 4 per cent (or 6) of the subsidized firms lacking close neighbours are excluded from the matching procedure.

A successful matching process is defined to a large extent by overlapping of the propensity scores for collaborators and non-collaborators. Figure 1, in the appendix, displays the estimated propensity scores for the subsidized firms ("treatment group") and non-subsidized firms ("potential control group"). In particular, the left part of Figure 1 shows a considerable divergence between the two samples. Figure 2 presents the propensity scores for subsidized firms and the selected control group of nearest neighbours. In this case it is shown that the overlap between the treatment group and the control group is almost complete.

The average of the difference in R&D-intensity between subsidized firms and the control group of non-subsidized twin firms will provide an unbiased estimator of the importance of the governmental R&D-policy. Formally this can be expressed as:

$$\hat{\theta} = \frac{1}{N^1}\left(\sum_{i=1}^{N^1} Y_1 - \sum_{j=1}^{N^1} Y_0\right), \text{ i} \in \{\text{U=1}\}, \text{ j} \in \{\text{U=0}\} \qquad (5)$$

## 5. THE MATCHING RESULTS

In the first step of our assessment we investigate factors that influence the probability of receiving public R&D support. Table 5 displays the probit estimation results based on data from a sample of 770 innovative firms. The following determinants are found to have significant influence on the firms' receipt of public R&D funds.

Firstly, the probability of receiving public funds decreases with the firms' size. The small positive sign on the squared size variable reinforces, at a decreasing rate, the disadvantage of large firms in the allocation of public funds.

Secondly, it is likely that firms reporting lack of appropriate sources of finance as a hampering factor for innovation activities, more often receive subsidies than other firms. One explanation may be that highly innovative firms have more ideas than investment funds available to them.

Thirdly, for the Swedish sample of R&D-firms in this paper, membership of a group of firms has a negative influence on public R&D support.. This is interpreted as, membership of a group is an indication of the availability of alternative sufficient non-public pool of financial or R&D resources.

Fourthly, we find some fragile evidence that the amount of debt per employee is positively associated with R&D activities. Since debt is a positive function of profitability, this estimate indicates that successful firms with access to both internal and external financial resources have a greater probability of receiving public financial support.

Finally, possession of patents, as a proxy for recurrent R&D activities, and a firms current R&D-stock, have a positive impact on the receipt of R&D support at the 10% level of significance. A large R&D-stock is an indication of effective and successful use of research and development resources.

The non-parametric estimation results by matching are presented in Table 6. The left section of the table displays the results from the kernel matching and the right section depicts the nearest neighbour matching (NNM) estimates. Here we examine the effect of public grants on the R&D intensity, and indirectly, the subsidies' possible negative allocative distortions on productive resources. Given that public resources are raised via socially costly revenue mechanisms, then society will be worse off if the total R&D investment remains unchanged but public funded investment replaces privately funded investment (see Jaffe 2002).

The first column of both the left and the right hand sections of Table 6 display the mean values for the selected control group of counterfactual. The second column of each part shows the mean values for the subsidized firms. It should be noted, that the counterfactual group in the Kernel matching consists of one matched firm to each subsidized firm, while the corresponding group in the NNM-approach consists of two matched firms to each subsidized firm. The estimate of the target variable, R&D per employee, in the case of the non-subsidized firms represents the effect on the subsidized firms had they not received any support.

The unbiased estimator of the effectiveness of a public innovation policy, aimed at stimulating private R&D investment, shows that the average subsidized firm has significantly greater R&D expenditure per employee compared to a twin-firm without any public R&D support.

Before any conclusion can be drawn from this study, there remains an important methodological issue to be addressed. It concerns the construction of a relevant and valid control group (Klette et. al 2000).

Examining the estimated probability of receiving funding, the results from the Kernel matching reveal a difference between the two samples. The two-sample test of inequality, though, suggests that the difference is not statistically significant. When utilising the NNM-approach, we find no evidence of disparity in the likelihood of participating in public R&D programmes.

The results from the Kernel matching show no evidence of disparity in the means, for 25 out of the 27 control variables. The exceptions are debt and firm size. Subsidized firms have on average a greater ratio of debt per employee than non-subsidized firms and are also somewhat larger. The estimate from the NNM-approach, however, reveals no significant differences between the subsidized firms and non-subsidized firms in the selected control group regarding the 12 variables controlling form different firm characteristics and the 15 industry dummies as well.

In order to make a sensitivity test of the main results, we repeat the semi-parametric estimation procedure, but drop the small firms in the sample. These include firms with 10-50 employees. Using the Kernel-approach, the left section of Table 7 indicates that the productive effect of R&D subsidies is significantly different from zero, i.e. the participation in government sponsored R&D-programmes resulted in increased private R&D investment. However, looking at the results from the NNM-matching (see the right section of Table 7) we find that the impact of public R&D is only marginally different from zero. Hence, the conclusion that can be drawn from the Swedish data is that the hypothesis on the additive impact of R&D support on private research expenditure can be supported only for small sized firms.

## 6. SUMMARY

Technological change, and the growing significance of R&D investment, are often cited as the primary driving force of economic growth; and it is widely accepted that the social rate of return on R&D expenditure exceeds the private rate. In the absence of policy intervention, the latter may lead to low R&D activity in the society and to a sub-optimal rate of economic growth. The industrialized countries have all, to varying degrees, publicly funded R&D-projects that are believed to have particularly large social benefits. The total amount of public R&D-support is considerable. On average, within the OECD nearly 10% of the commercial firms' R&D expenditure are publicly funded..

An important issue to evaluate is whether public funding increases the total spending on research or merely displaces funding from other sources. Given that public resources are raised via socially costly revenue mechanisms, then the total economy will be worse off if society's total R&D investment remains unchanged but public research-grant programmes, by crowding out, replace privately funded investment.

One important methodological challenge in the evaluation of public R&D funding is discussed in the statistics literature as the lack of counterfactual evidence. This limitation is manifest by the fact that we can have no knowledge of the result on the firms' R&D-expenditure in the absence of subsidies. In this paper, in concurrence with the tradition in the labour literature, we have used the outcomes on non-subsidized R&D-firms to estimate the effect on subsidised firms , had they not participated in public R&D-programmes.

By applying a semi-parametric matching approach we initially established that subsidised firms are a select group of R&D-firms. These firms invest more in both R&D and physical capital compared to other R&D-firms; they have relatively more equity-capital; they are somewhat larger and more debt-financed. To correct for this potential selectivity bias, initially a probit model is applied to estimate the propensity score. The dependent variable is the decision whether or not to participate in public R&D programs. As a result a mono-dimensional propensity score was calculated for every observation, which was used to find non-supported counterfactual for each supported firm.

Next, we conducted a non-parametric matching estimation based on the propensity score. These observations were separated with respect to their status of public R&D support. Then, firms receiving funds are individually selected and we utilized the propensity score to find the nearest neighbors, or *matched* firms, for every subsidized firm. The matching procedure was regarded as successful since the means of the probability of receiving R&D support and the determinants of subsidy, in both groups, did not differ significantly. Finally the impact of public financial support on private R&D-investment was evaluated by comparing the average R&D-intensity between the groups of subsidized and non-subsidized firms. The results, based on a large sample of Swedish firms, showed that the average subsidized firm has significantly greater R&D expenditure per employee compared to a twin-firm without public R&D support. However, this difference is relatively insignificant and applicable only for medium and large sized firm with more than 50 employees.

Given the results presented here, the interpretation is as follows. Having used a matching process and controlling for the differences between funded and non-funded firms, we find that public funds contribute to an increase in the total R&D efforts in Sweden, but the only beneficiaries are small manufacturing and services firms. The results rejected the crowding out hypothesis but they did support the hypothesis on the additive effect of public R&D support on private research expenditure, among small firms with 10-50 employees. We found some variance in the results depending on which alternative unbiased matching estimator is employed. Our results based on Community Innovation Survey data merged with register data suggest that the Nearest neighbour estimator is preferred to the Kernel estimator.

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Table 2. Distribution of firms by industrial sector and the percentage of firms subsided.

| Industry Code | Nace 2 | Industrial sector | Firms with R&D investment | percentage of firms subsidized |
|---|---|---|---|---|
| Nc14 | 36-37 | Manufacture of furniture; manufacturing n.e.c; Recycling | 33 | 30.3 |
| Nc15 | 72-73, 742-743 | Computer and related activities; Research and development; Architectural and engineering activities and related technical consultancy; Technical testing and analysis | 111 | 27.9 |
| Nc13 | 34-35 | Motor vehicles, trailers and semi-trailers; transport equipment | 54 | 27.8 |
| Nc1 | 15-16 | Food products and beverages; tobacco | 40 | 27.5 |
| Nc2 | 17-19 | Textile, apparel and leather | 36 | 22.2 |
| Nc3 | 20 | Wood and of products of wood and cork, exc. furniture; art. of straw and plaiting materials | 34 | 20.6 |
| Nc10 | 29 | Machinery and equipment | 79 | 20.3 |
| Nc7 | 25 | Rubber and plastic | 45 | 20.0 |
| Nc12 | 33 | Medical, precision and optical instruments | 48 | 18.8 |
| Nc11 | 30-32 | Office machinery and computers; Electrical machinery and apparatus n.e.c.; Radio, television and communication equipment and apparatus | 76 | 17.1 |
| Nc9 | 27-28 | Basic metal and fabricated metals; Fabricated metal products, except mach. and equipment | 68 | 16.2 |
| Nc6 | 23-24 | Coke, refined petroleum products and nuclear fuel; Chemicals and chemical products | 48 | 14.6 |
| Nc4 | 21 | Pulp, paper and paper products | 35 | 14.3 |
| Nc8 | 26 | Non-metallic mineral products | 26 | 13.9 |
| Nc5 | 22 | Publishing, printing and reproduction of recorded media | 37 | 8.1 |
| Total | | | 770 | 20.8% |

Table 3. Distribution of subsidized firms by size-classes.

| Number of employees | Firm with positive R&D investment | Share of subsidized firms |
|---|---|---|
| 10-25 | 239 | 23.8 |
| 26-50 | 127 | 19.7 |
| 51-100 | 100 | 13.0 |
| 101-200 | 79 | 20.2 |
| 201-500 | 125 | 14.4 |
| 501- | 100 | 31.0 |

Table 4. Summary statistics and result from a two-sample t-test on inequality of means between non-funded and funded firms.

| | Non-funded firms Number of observations: 610 | | | | Funded firms Number of observations: 160 | | | | Two-sample t-test on inequality of means |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev | Min | Max | Mean | Std. Dev | Min | Max | |
| R&D/emp[a] | 3.254 | 1.671 | -3.759 | 7.197 | 3.941 | 1.645 | -1.385 | 7.545 | -4.68*** |
| Firm size[a] | 4.337 | 1.461 | 2.302 | 8.891 | 4.446 | 1.828 | 2.302 | 9.753 | -0.69 |
| Gross inv/emp[a] | 3.719 | 1.262 | -0.753 | 9.353 | 4.025 | 1.294 | 0 | 8.290 | -2.67*** |
| Cap stock/emp[a] | 4.947 | 1.384 | -0.844 | 8.417 | 4.982 | 1.458 | 0.356 | 8.323 | -0.27 |
| Equity/emp[a] | 5.023 | 1.560 | -0.433 | 9.299 | 5.245 | 1.421 | -1.343 | 8.612 | -1.71* |
| Debt/emp[a] | 6.184 | 0.950 | -1.954 | 9.034 | 6.318 | 0.996 | 3.988 | 10.127 | -1.53 |
| Financial const. | 0.101 | 0.302 | 0 | 1 | 0.243 | 0.430 | 0 | 1 | -3.92*** |
| Skill const. | 0.150 | 0.358 | 0 | 1 | 0.143 | 0.351 | 0 | 1 | 0.22 |
| Export indicator | 0.885 | 0.318 | 0 | 1 | 0.868 | 0.338 | 0 | 1 | 0.55 |
| Foreign owned | 0.249 | 0.432 | 0 | 1 | 0.181 | 0.386 | 0 | 1 | 1.92* |
| Part of a group | 0.675 | 0.468 | 0 | 1 | 0.525 | 0.500 | 0 | 1 | 3.42*** |
| Recurrent R&D | 0.437 | 0.496 | 0 | 1 | 0.506 | 0.501 | 0 | 1 | -1.54 |
| Demand pull R&D | 0.480 | 0.500 | 0 | 1 | 0.443 | 0.49 | 0 | 1 | 0.82 |

Notes: (a) in logarithmic form.

Significant at the <1% (***), 1-5% (**) and 5-10% (*) levels of significance.

Table 5. Probit parameter estimates of determinants of receipt of public R&D subsidies.

| | Coefficient | t-value |
|---|---|---|
| **Number of observations 770** | | |
| Firm size (employment)[a] | -0.536 *** | -2.61 |
| Firm size squared [a] | 0.059 *** | 2.99 |
| Gross inv/emp[a] | 0.060 | 1.28 |
| Cap stock/emp[a] | -0.050 | -0.92 |
| Equity/emp[a] | 0.056 | 1.38 |
| Debt/emp[a] | 0.125 * | 1.69 |
| Financial const. | 0.572 *** | 3.87 |
| Skill const. | -0.071 | -0.46 |
| Export indicator | -0.081 | -0.45 |
| Foreign owned | -0.108 | -0.71 |
| Part of a group | -0.386 *** | -2.87 |
| Recurrent R&D | 0.237 * | 1.82 |
| Demand pull R&D | -0.089 | -0.82 |

Notes: Significant at the <1% (***), 1-5% (**) and 5-10% (*) levels of significance.
Industry dummies are included.

Table 6. Two sample t-tests results of inequality of means after the matching process.

| | Kernel matching | | | Nearest neighbour matching | | |
|---|---|---|---|---|---|---|
| Determinant variables | Non-subsidised firms | Subsidised firms | t-test value | Non-subsidized firms | Subsidised firms | t-test value |
| Observations | 160 | 160 | | 308 | 154 | |
| Prob to receive fund | 0.269 | 0.291 | -1.21 | 0.272 | 0.272 | -0.05 |
| R&D/employee [a] | 3.232 | 0.3941 | -4.94*** | 3.270 | 3.897 | -3.72*** |
| Firm size (emp)[a] | 4.165 | 4.446 | -1.78* | 4.211 | 4.303 | -0.56 |
| Gross inv/emp[a] | 3.982 | 4.025 | -0.34 | 4.011 | 3.985 | 0.20 |
| Cap stock/emp[a] | 4.818 | 4.982 | -1.23 | 4.734 | 4.971 | -1.58 |
| Equity/emp[a] | 5.069 | 5.245 | -1.32 | 5.175 | 5.215 | -0.28 |
| Debt/emp[a] | 6.082 | 6.318 | -2.09** | 6.162 | 6.271 | -1.15 |
| Financial const. | 0.238 | 0.243 | -0.13 | 0.253 | 0.240 | 0.30 |
| Skill const. | 0.143 | 0.143 | -0.01 | 0.152 | 0.142 | 0.27 |
| Export indicator | 0.830 | 0.868 | -1.28 | 0.834 | 0.863 | -0.83 |
| Foreign owned | 0.173 | 0.181 | -0.25 | 0.204 | 0.181 | 0.58 |
| Part of a group | 0.504 | 0.525 | -0.45 | 0.519 | 0.519 | 0.00 |
| Recurrent R&D | 0.460 | 0.506 | -1.10 | 0.496 | 0.500 | -0.06 |
| Demand pull R&D | 0.442 | 0.443 | -0.02 | 0.422 | 0.448 | -0.52 |
| Nc2 | 0.046 | 0.050 | -0.19 | 0.045 | 0.051 | -0.30 |
| Nc3 | 0.049 | 0.043 | 0.33 | 0.035 | 0.045 | -0.48 |
| Nc4 | 0.029 | 0.031 | -0.09 | 0.064 | 0.032 | 1.61 |
| Nc5 | 0.019 | 0.018 | 0.023 | 0.022 | 0.019 | 0.23 |
| Nc6 | 0.052 | 0.043 | 0.54 | 0.045 | 0.045 | 0.00 |
| Nc7 | 0.046 | 0.056 | -0.54 | 0.042 | 0.058 | -0.73 |
| Nc8 | 0.030 | 0.031 | 0.03 | 0.048 | 0.032 | 0.86 |
| Nc9 | 0.066 | 0.068 | -0.11 | 0.071 | 0.071 | 0.00 |
| Nc10 | 0.115 | 0.100 | 0.63 | 0.136 | 0.103 | 1.03 |
| Nc11 | 0.070 | 0.081 | -0.46 | 0.058 | 0.077 | -0.76 |
| Nc12 | 0.055 | 0.056 | -0.02 | 0.042 | 0.058 | -0.73 |
| Nc13 | 0.074 | 0.093 | -0.83 | 0.061 | 0.077 | -0.63 |
| Nc14 | 0.063 | 0.062 | 0.03 | 0.051 | 0.064 | -0.55 |
| Nc15 | 0.175 | 0.193 | -0.56 | 0.211 | 0.194 | 0.41 |

Note: Significantly unequal at the <1% (***), 1-5% (**) and 5-10% (*) levels of significance.

Table 7. Two sample t-tests results of inequality of means after the matching process. Only firms with 51 or more employees are included.

| | Kernel Matching | | | Nearest neighbour matching | | |
|---|---|---|---|---|---|---|
| Determinant variables | Non-subsidised firms | Subsidised firms | t-test value | Non-subsidised firms | Subsidised firms | t-test value |
| Observations | 78 | 78 | | 144 | 72 | |
| Prob to receive fund | 0.272 | 0.315 | -1.42 | 0.274 | 0.276 | -0.10 |
| R&D/employee [a] | 3.348 | 3.966 | -2.67*** | 3.413 | 3.895 | -1.97* |
| Firm size (emp)[a] | 5.587 | 5.990 | -1.71* | 5.793 | 5.794 | 0.00 |
| Gross inv/emp[a] | 3.898 | 4.163 | -1.61 | 4.071 | 4.129 | -0.38 |
| Cap stock/emp[a] | 5.240 | 5.549 | -1.53 | 0.589 | 0.523 | 0.37 |
| Equity/emp[a] | 5.273 | 5.551 | -1.23 | 5.453 | 5.512 | -0.27 |
| Debt/emp[a] | 6.329 | 6.766 | -2.09** | 6.740 | 6.706 | 0.24 |
| Financial const. | 0.152 | 0.205 | -0.98 | 0.194 | 0.194 | 0.00 |
| Skill const. | 0.121 | 0.141 | -0.46 | 0.152 | 0.138 | 0.27 |
| Export indicator | 0.904 | 0.961 | -1.69* | 0.965 | 0.958 | 0.24 |
| Foreign owned | 0.291 | 0.320 | -0.51 | 0.354 | 0.333 | 0.30 |
| Part of a group | 0.719 | 0.756 | -0.65 | 0.763 | 0.763 | 0.00 |
| Recurrent R&D | 0.653 | 0.730 | -1.36 | 0.618 | 0.722 | -1.55 |
| Demand pull R&D | 0.443 | 0.461 | ´-0.28 | 0.388 | 0.472 | -1.15 |

Note: Significantly unequal at the <1% (***), 1-5% (**) and 5-10% (*) levels of significance.
Industry dummies are included.

Figure 1. Estimated propensity score based on 160 R&D subsidized firms and a potential group of 600 non-subsidized firms.

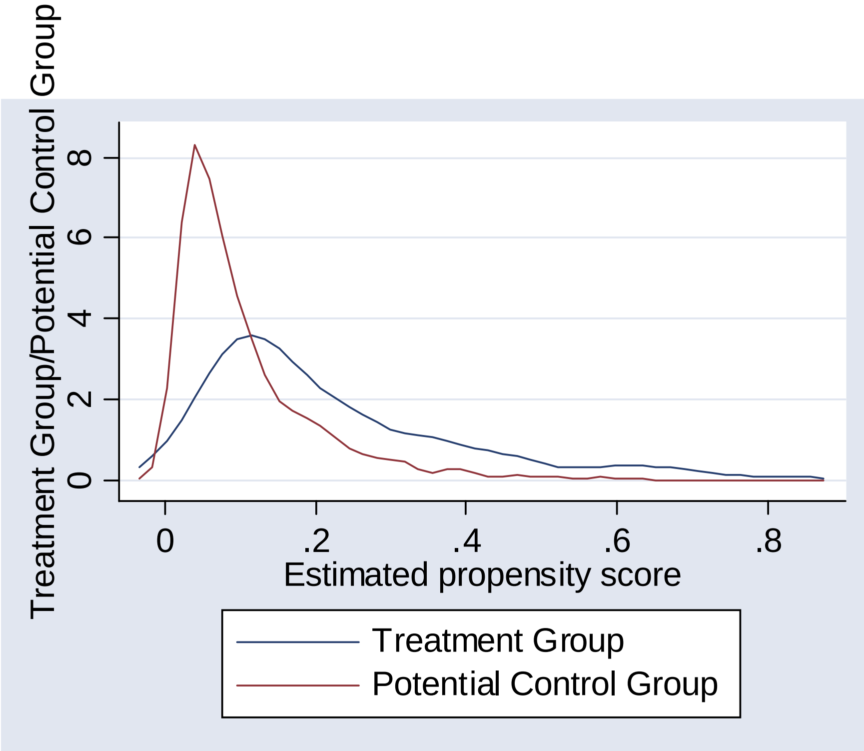
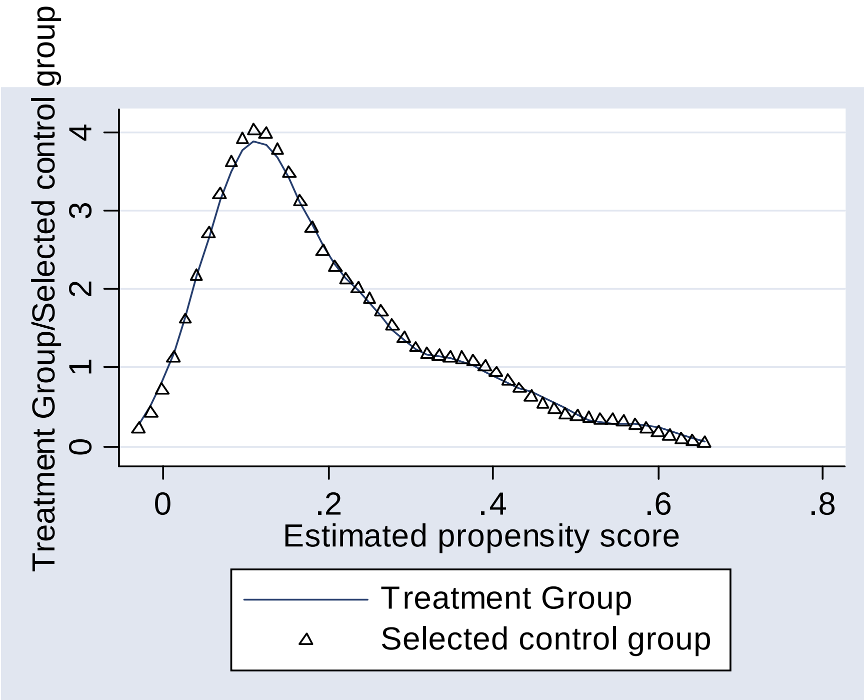



Figure 2. Estimated propensity score based on 154 R&D subsidized firms and a selected group of 308 non-subsidized firms.



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