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THE EFFECT OF R&D SUBSIDIES ON PRIVATE R&D: EVIDENCE FROM ITALIAN MANUFACTURING DATA

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Titolo: THE EFFECT OF R&D SUBSIDIES ON PRIVATE R&D: EVIDENCE FROM ITALIAN MANUFACTURING DATA

The Effect of R&D Subsidies on Private R&D: Evidence from Italian Manufacturing Data[1]

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Abstract

This paper uses a comprehensive firm level data set for the manufacturing sector in Italy to investigate the effect of government support on privately financed R&D expenditure. Estimates from a two-step equation model suggest that public assistance has a positive effect on private R&D investment. A non parametric matching procedure is also used to investigate the same effect. Here again the results suggest that the recipient firms achieve more private R&D than they would have without public support. The paper also examines whether public funding effects the financial sources available for R&D and finds that grants encourage credit financing for R&D. The effects on the use of internal sources are not conclusive.

Keywords: Applied Econometrics, matching, public subsidies, R&D investment

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

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1. Introduction

Government financial support for R&D has become common in industrialized countries. It is hoped that public subsidies will result in additional private investment that would not have occurred without public support. Market failures in real and financial markets offer scope and justification for public support, as the return may be not sufficient to justify private investment. The broad consensus on the use of public support is based on the inefficiencies of the market. These create a gap between private and social return on R&D, and as a result less than optimal levels of research. Incomplete appropriability of research output and externalities deriving from the public good nature of R&D are at the base of this (Nelson, 1959; Arrow, 1962). There is also asymmetric information about the expected outcome of R&D investments and sunk costs in R&D investment. Moreover investment in R&D is riskier than investment in physical assets, and as a result there are likely to be more financial constrained (Hyytinen and Tovainen, 2005; Czarnitzki, 2006).

Public investment is designed to encourage firms to carry out R&D by lowering marginal costs and decreasing the uncertainties that are typically connected to this activity. In addition to these direct effects at the firm level, positive indirect impacts are also expected to spill over to other firms in the system. There may also be an effect on the financial resources available to the firms. If these increase, the incentive has a positive effect on investment, but if they decrease subsidies turn into simple substitution of financing, with little effect on investment. The latter implies that the subsidized firms would have invested in research even if there had been no public support. R&D spending is only enhanced if the grants stimulate firms to undertake R&D projects that would be unprofitable in the absence of public support (Jaffe, 2002; Wallsten, 2000; Klette et al, 2000). Seen from this perspective, it becomes necessary to demonstrate that the programmes are effective in increasing R&D.

One of the problems in assessing the effectiveness of most public R&D financial programs is determining whether they might crowd out private financing of R&D. Since government grants are likely to be cheaper than funds from the capital markets, firms are encouraged to apply for public support for R&D even when private funds are available (Jaffe, 2002; Blanes and Busom, 2004). In such cases public subsidies are simply a substitute for private capital. This is particularly true when policy-makers support the potentially most profitable R&D projects in order to avoid wasting public funds. Nevertheless, there are also counteracting effects. Even though it is possible that such substitution occurs at firm level, at aggregate level the fact that certain firms obtains subsidies implies that others did not, and this makes it rather difficult to determine the net final effect (Hujer and Radic, 2005).

Considerable effort has been devoted to evaluating the efficiency of public support for R&D. Despite the quantity of literature on evaluation of public R&D policies, there is no consensus and the results are rather controversial (David & Hall, 2000; David et al.; 2000; Klette et al.2000; Hall, 2005) and there are important methodological issues which still have to be investigated. Meta-analysis by Garcia-Quevedo (2004) found that conclusions may depend on the level of analysis, where there is weak evidence that micro-level studies show the existence of crowding out effects.

One of the methodological problems in most studies is that estimations may suffer from potential selection problems. Firms given grants may have been be chosen by public agencies because they are likely to carry out successful research projects. Agencies are, indeed, likely to "pick the winners" and support attractive project proposals (Wallsten, 2000). If the criteria for allocating public funds are linked to high expected rates of return on private R&D funding (David et al 2000; Lach, 2002), then the probability of been chosen depends on current R&D spending. If this is the case, then public funding becomes endogenous, and estimates will be biased and inconsistent if they are not addressed in an econometric framework.

The literature on the econometrics of evaluation offers different ways of tackling the existence of an endogenous subsidy variable in policy evaluations. These include: (i) regressions with controls, (ii) fixed effects or difference-in-difference models, (iii) sample selection models, (iv) instrument variable estimators, and (v) non-parametric matching of treated and untreated firms.

This work analyzes a sample of 1233 manufacturing firms in Italy and adds a new piece of empirical evidence to the ongoing debate about the effectiveness of public support for R&D. Although there is common consensus about the importance of R&D in maintaining the competitiveness and aggregate growth of firms and countries, Italy has been consistently backward in terms of national R&D spending with respect to other OECD countries. R&D in Italy represents roughly 1.1% of GDP compared to an average of 2% in the UE-15 in the period 2001-2003. This becomes even more evident if the private R&D spending is considered (Capitalia Bank, 2005).

A parametric approach is employed to estimate the effect of public grants on R&D. In order to take into account potential self-selection in participation in the public funding schemes a two-step selection procedure is used in the model (Buson, 2000; Hussinger, 2006).

Secondly, this paper contributes to the treatment empirical literature by applying a non-parametric matching estimation for the average treatment effect to measure the impact of subsidies on R&D adoption. The basic idea is to determine whether the supported firms would have invested the same amount of ICT if they had not received assistance by comparing the results for participants in national support programmes with those of an appropriate control group of non-participants. Using a set of covariates the propensity score method (PSM) is employed to determine the probability of receiving support and to find counter-factuals for each recipient firm. Each subsidised firm is matched with a "twin" non-subsidised counterpart, which has the same probability of being subsidised. The computed difference is then linked to the effects of subsidy on the performance of firms (Busom, 2000; Czarnitzki and Fier, 2002; Almus and Czarnitzki, 2003; Aerts and Czarnitzki, 2004; Czarnitzki and Hussinger, 2004; Duguet, 2004; Czarnitzki et al., 2007; Atzeni and Carboni, 2008).

The regression results indicate that grants have significant positive effects on the level of private R&D spending. The non-parametric procedure confirms this result, since firms receiving public support would have invested less in research if they had they not been given a grant. These firms obtain more additional external financing for research than do their similar but non-subsidised counterparts. This suggests that public policy may be an effective tool for helping firms to overcome their financial constraints.

The remain of the paper is structured as follows. characteristics of the data and the descriptive statistics. Section III describes the contains the regression method used and the results. Section IV describes the matching procedure. Section V outlines the conclusions.

2. Data and variable description

The data used in this paper comes from the Survey of Manufacturing Firms (SMF) carried out by the Area Studi of Capitalia Bank (2003). The SMF surveyed a stratified sample of Italian firms with 11 to 500 employees. It also included all manufacturing firms with more than 500 employees. The data was stratified according to the number of employees, the sector, and the geographical location. It used the Census of Italian Firms as a benchmark. The SMF contains questionnaire information about firms' structure and behaviour, and fifteen years of data on their balance sheets (1989-2003). Since only a small fraction of the observations overlap, only the 2001-2003 survey is used in the empirical application.

The questionnaire also supplies information on the way total R&D is financed, namely venture capital, self-financing, credit, free grants and tax reductions. Self-financing is by far the most important and covers more than 80% of total R&D expenditure. In this paper firms are considered to be subsidised if they received free R&D grants or tax reductions for R&D, or both. There are four main types of incentive for R&D in Italy. These are as follows:

a) Law 46/1982 and Law 297/1999: public funds to support R&D through free grants or reductions in interest rates, or tax reductions.
b) Law 598/1994: grants for innovations, R&D activities and environment oriented investment.
c) Law 140/97: automatic incentives to invest in R&D through tax breaks, particularly for new products and processes.

There are three questions in the survey that can be used to directly evaluate the firm's access to the credit market: 1) whether at the current market interest rate the firm wants additional credit; 2) whether the firm is willing to pay a higher interest rate to obtain that additional credit; 3) whether the firm has applied for this credit but been refused. If the firm answers "yes" to the second or third questions, it is considered to be credit rationed (*RATION* =1). In this work this variable is used as a proxy for firm financial distress.

Table 1 shows the descriptive statistics for non-granted (controls) and granted firms (treated). There are a total of 1233 companies which invest in research. There are some interesting differences between the two groups. Firms which receive grants are larger than non-subsidised firms, both in terms of added value and in number of employees. They invest more in R&D per worker, employ relatively more research workers and their capital per worker ratio is appreciably lower. They also use more external credit and more internal financing, are more innovative and use more additional sources of public incentives.

The relevance of micro analysis is supported by huge differences in behaviour, productivity, size and performance across firms and industries (e.g. R&D is not normally distributed). Firm level data is better for measuring specific aspects that are very difficult to capture at the aggregate level, such as size, industry, age, location, etc. Unfortunately, access to longitudinal data is limited. In particular there is not regular information on the outcome decision and on the treatment since only a small fraction of the observations overlap in the various waves. This prevents the analysis to be addressed to important issues such as long-term effects of public.

Before proceeding further, I briefly highlight several groups of factors that are considered in this work. These may influence a firm's decision on whether or not to engage in privately financed R&D at a certain time. The variable of interest is the amount of private R&D expenditure (i.e. the firm's total R&D expenditure minus the total governmental R&D grant). R&D expenditure includes the cost of both internal and external R&D and is divided by the number of workers. This allows us to estimate the net effect of public grants on a firm's own research. Unlike many other studies, this work uses the amount of subsidy each firm receives to finance their R&D expenditure.

An important determinant in firm level R&D is firm size (measured by the number of employees). Size can affect R&D decisions in several ways, such as better organization, easier use of the financial markets, specialization of activities and routines, and investment in complementary activities to R&D. Moreover, since size can help to overcome the fixed cost barrier, it becomes an important factor in determining whether or not the firm invests in R&D.

Capital intensity is important, since more capital-intensive firms may have higher commitments to innovation than more labour-intensive ones. The number of researchers as a percentage of the total number of employees is used in the analysis as an indicator of internal technological capabilities, the state of technology and the structured (stable) firms' R&D commitment. A measure of indebtedness is also considered in order to control for firm financial potentiality to find sources to support R&D cost. Internal and credit (external) financing for research are considered, since they directly affect the total amount of resources devoted to R&D.

A measure of the financial constraints is also considered. Such constraints are in general good at explaining under-investment in technology and in R&D expenditure. The measure of financial constraints also provides an approximate proxy of credit market efficiency. The final cost of doing research may vary across firms due to differences in the availability and cost of financial resources. Arguments that R&D investment are generally more risky, sunk costs and other forms of market failures are commonly seen as having particularly severe effects in this field.

An export dummy is included since firms that compete in foreign markets might tend to be more innovative than others (Arnold and Hussinger, 2005) and hence more likely to apply for subsidies. Industry dummies are used to pick-up sector heterogeneity. There might be presence of significant cross-sectional differences in technological opportunity, appropriability conditions which may have also effects on innovation behaviour of individual establishments and competences. Moreover in some industries fixed costs will be lower than in others. Controls for fixed effects may be desirable in such cases, so that some of these unobservable effects can be captured.

3. The econometric framework and results

Two possible methods may be used to estimate the effects of public finance programmes on the level of private R&D. One is a structural model which can explain the factors which determine the decision to invest in R&D as well as the parameters which affect participation in the program. A second possibility is to obtain an estimate of the policy effect applying a quasi-experimental approach and comparing outcomes for a treated group of firms and a control group. I start specifying the structural model.

Empirical studies of the effects of R&D grants on firms typically regress some measure of firm productivity on the subsidy, along with other control characteristics. A positive coefficient for public R&D can be interpreted as meaning that there is complementarity between public and private R&D investment, while a negative coefficient is taken to imply that public R&D substitutes private R&D. The estimation typically takes this form:

$$y = \alpha + \beta(GRANT) + \delta X + \gamma Z + \varepsilon \qquad (1)$$

Where y is some measure of *R&D*, *GRANT* is the amount of public subsidy to firm i, X is a set of firm characteristics while Z represents dummies explaining other observables such as industry or location. ε is the error term. However, the main methodological caveat in this type of estimation is that firms self select into the grants project giving rise to inconsistent coefficients unless selection bias is considered.

One common way of tackling this problem is to apply a two-step selection estimate, with a selection equation describing the participation decision and an outcome equation describing the relationship between the outcome in which one is interested and a vector of covariates (Heckman, 1979). The rationale for this is that the decision to participate may depend on factors other than those in the regression model. If the random components are not distributed independently because some of the unobserved characteristics affecting *y* may also affect the selection process, observations in the sample will then be systematically different from those not in the sample. In such cases a more general two-stage model may be required.

The following variables are used in this study to estimate equation (1). The dependent variable is the amount of private internal R&D expenditure over the period 2001-2003 with the amount of the subsidy subtracted ($LogR\&D_{EMP}$). It is divided by labour units and log-transformed in order to avoid dimensional effects.[2] I believe that it is important to make this distinction in order to be able to distinguish clearly between the total amount of R&D (which implicitly includes the subsidies) and the firm's private commitment to research.

$LogGRANT_{EMP}$ is the amount of subsidy granted to firm *i* over the same period. $LogEMP_{2001}$ is the number of workers at the beginning of the period and this is used to measure firm size. Its squared term ($Log^2EMP_{(2001)}$) is included in order to check for possible size effects. $LogK_{EMPL(2001)}$ is capital intensity. The variable $LogEMP_{R\&D\text{-}EMPL(2001)}$ is the number of R&D workers as a percentage of total workers. These variables are divided by labour units so as to reduce collinearity with firm size and log-transformed in order to avoid dimensional effects. $DEBT_{BANK\text{-}PASS\ (2001)}$ is the ratio of debt to banks over total average debts as an indicator of the firm's financial structure.

INNOV, RATION, *EXPORT* and $GRANT_{OTHER}$ are dummies for innovation, credit constraints export and other grants, respectively. I also include among the regressors a dummy to check for grant awarded firms with zero private investment in research ($R\&D_{EMP\ (2001\text{-}2003)=0}$) and 15 industry dummies (ISTAT-ATECO classification) to control for potential fixed effects. The model is estimated as a cross-section.

The first specification of equation (1) is reported in Table 2 (column 1). Here the whole sample is considered and the treatment has a dichotomy status taking the value of one when firms receive the subsidy and zero otherwise. Although very crude, this supplies the first

[2] In order to avoid the dropping of observations when private financing was zero, for these firms the expenditure levels are arbitrarily set as 0.1€.

significant information. If the whole sample is considered, then the grant assisted firms have on average higher levels of private R&D spending (0.19 with 5% probability).

Column (2) shows the OLS results on the restricted sample of grant awarded firms only. The effect of subsidies on the recipient firms is positive and highly significant: this suggests that grants encourage private investment in R&D. However in the OLS regression the funding status is considered as exogenous and does not take into account potential selectivity. The next step is to tackle this problem by applying a two stage selection procedure.

Column (3) gives details of the results. The null hypothesis that the regression equation and the selection equation are independent cannot be rejected with 5% significance. The coefficient estimate on the grant variable is again statistically significant, suggesting that public support is a good predictor of private R&D spending. This confirms that subsidies produce higher R&D spending at firm level and that full crowding-out effects are not present in the sample.

However, another methodological caveat when this type of estimate is used is that the amount of the subsidy may be correlated with the error term (ε). Since participation and R&D expenditures may be simultaneously determined, estimates of the policy effects will be inconsistent unless selection bias and simultaneity are properly considered. To test for endogeneity I regressed the variable *GRANT* on the same set of covariates and including the total amount of industry grant per worker as a substitute for industry dummies (*Z*):

$$GRANT = \alpha_1 + \delta_1 X_1 + \phi_1 (IND_{j\ GRANT}) + \varepsilon_1 \qquad (2)$$

where for each sector (*j*) and firm (*i*):

$$IND_{j\ GRANT} = \sum_{2001}^{2003} GRANT_{(i,\ j)} \qquad (3)$$

Following Lichtenberg (1988) and Wallsten (2000), such a variable is constructed on an industry base in order to capture the potential grant available to the firm, depending on the type of research that it carries out. I then regressed the R&D equation on the same set of covariates but one, and on the residuals formed the *GRANT* equation (Davidson and MacKinnon, 1993):

$$y = \alpha + \beta GRANT + \delta X + \gamma Z + \theta_1 \varepsilon_1 + \varepsilon \qquad (4)$$

Since the coefficient of residuals is highly insignificant, the hypothesis that *GRANT* is correlated with unobserved factors can be rejected and the OLS is consistent (Table 3).

4. The matching procedure

The second objective of this work is to estimate the effect of participating in an R&D programme compared to non-participation. To evaluate the effects of government subsidies, one has to analyse what would have happened without the incentive program. Since neither the subsidized firms nor the non-subsidized firms can be considered random distributions, the challenge is to identify a reliable control group. Matching is a method which is often used (Heckman *et al*, 1998; Heckman and Navarro-Lozano, 2004). In the absence of experimental data, matching estimators have the convenient feature of approximating to a randomised *ex post* experiment.

Smith and Todd (2005) provide a detailed evaluation of the performance of different matching estimators such as nearest neighbour matching, kernel and local linear matching, and difference-in-differences matching. They also show that if the data is of high quality, matching is a good choice. The aim of this approach is to compare the outcome (R&D in this study) for participants in national support programmes with those of an appropriate control group of non-participants.

The most common evaluation parameter is the mean effect of treatment on the treated. This gives information about how much a treated firm (i.e. receiving the incentive: $D = 1$) benefits compared to how much it would have done if not treated (i.e. not receiving the subsidy: $D = 0$) given a set of characteristics X. The parameter is given by:

$$E(Y_1 - Y_0 \mid X, D = 1) \tag{5}$$

Moreover, Y_1 and Y_0 are observed only for participant and non-participant firms respectively. Evaluation then depends on the problem of missing data. The benefit of receiving the subsidy can be measured as the difference □ $= Y_1 - Y_0$ if the two outcomes for the same firm are available. Observed data does not contain sample counterparts for the missing counterfactual Y_0 for subsidised firms. This need to be inferred in some way from the sample. Using non-experimental data the parameter is estimated by assuming that conditioning on X, (Y_1, Y_0) and D are independent:

$$(Y_1, Y_0) \perp D \mid X \tag{6}$$

where $\perp$ denotes independence. This assumption is required so that, X, the non-subsidised firms' outcomes, have the same distribution as firms would have achieved if they had not participated in the public funding programme. This restriction, also known as "selection on observables" requires that the choice of participation is "purely random" for similar individuals. In terms of mean value, the implication of (6) is:

$$E(Y_0 \mid X, D=1) = E(Y_1 \mid X, D=0) \tag{7}$$

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) (Rosenbaum and Rubin, 1983). Hence, employing a probit model to estimate the conditional probability of participating in the program, the multi-dimensionality of the matching problem is reduced by matching on a mono-dimensional (scalar) propensity score:

$$Pr\{Di=1 \mid Xi\} = F(h(Xi)) \tag{8}$$

where $F(.)$ is the normal or logistic cumulative distribution, and $h(Xi)$ is a function of covariates. Once the probability of participation has been estimated, PSM matches each participant with a single "twin" non-participant. A metric criterion can also be imposed to ensure that the match is sufficiently close:

$$C(X_i) = \min_j |X_i - X_j|, \; i \in \{D=1\} \; j \in \{D=0\} \tag{9}$$

Two twins firms are matched by overlapping the propensity scores for treated and non-treated firms. The average difference in the outcome between subsidised firms and their non-subsidised twin counterpart will provide an estimator of the impact of the government's grant policy. [3]

This can be expressed formally as:

[3] The common case considered in the literature is just one binary treatment. However, Imbens (2000), Lechner (2001), Gerfin and Lechner (2002) Czarnitzki et al. (2007), Görg and Strobl (2007), extend the matching to allow for multiple programmes.

$$\hat{\psi} = \frac{1}{N}\left(\sum_{i=1}^{N} Y_1 - \sum_{j=1}^{N} Y_0\right),\ i \in \{D=1\},\ j \in \{D=0\} \qquad (10)$$

Finally an identification assumption is also required, because if all individuals with given characteristics choose to participate in the programme, there would be no observation on similar individuals that choose not to participate (Abadie and Imbens, 2002). Formally:

$$c < \Pr(D=1 \mid X = x) < 1-c \text{ for some } c > 0 \qquad (11)$$

In the terms first used by Rosenbaum and Rubin (1983), when both condition are satisfied the treatment is said to be 'strongly ignorable', so that the non-randomised experiment can be treated as if it were a randomised one. However, as pointed out by Abadie and Imbens (2002), these conditions are in many cases not satisfied, giving rise to some bias in the estimation.

In approximating a randomized *ex post* experiment we want to compare firms with grants with similar firms without grants. The problem is that there are mixed firms in this second group. Some did not ask for grants and others asked for, but did not receive, grants. If the latter are included in the matching, the selection cannot be considered akin to an ex post random one and the control group is biased, as it includes lower quality firms which have been refused the subsidy. Since the two groups cannot be considered random draws, the problem is to identify a reliable control group.

Evidence from table (1) in support of the random allocation hypothesis is not unequivocal. Treated firms invest more in research, are larger, have a lower capital per worker ratio and a slightly higher proportion of R&D employees. Such a group has a higher level of self-financing and uses about double the amount of credit for research per worker. They also have a higher propensity to innovate and use other forms of grants more. Interesting, firms engaged in R&D are not a self-selected group where financing constraints tend to be either less or more binding. Moreover, treatment and control groups may also differ in their unobservable characteristics and so the robustness of results would be undermined. However, there might be non-granted firms close to their control counterparts. In that case, despite group differences, it is possible to compare firms according to their characteristics (covariates).

The matching results

With this framework in mind, in order to account for potential selectivity bias, I first estimate the probability of a firm of receiving public funds, given a number of observable characteristics that potentially influence the probability of receiving public R&D support (Busom, 2000, Gonzalez et al., 2005 and Czarnitzki and Licht, 2006). Table 4 shows the probit estimation results (probability of participating in national-level programmes) based on data from a sample of 1224 firms that invest in R&D. The covariates are taken from regression (1). The dependent variable is a binary variable indicating participation in public R&D programs.

The following determinants are found to have significant influence on whether or not the firms receive public R&D funds. The probability of receiving public funds decreases with the amount of spending on R&D. The probability of receiving public funds increases with the size of the firms, though at a declining rate (the squared term of size is negative and significant at 5 percent). The percentage of R&D workers compared to total workforce is positive and highly significant. This suggests that firms' structured R&D strongly effects the probability of being subsidised. Surprisingly, there is no evidence that the ratio of external indebtedness influences the probability of receiving the award. The same is true for innovation and export dummies. Furthermore firms seeking additional external finance from the banking system do not receive subsidies more often than other firms.

The probit model is then applied to estimate a mono-dimensional propensity score for each observation. This measure is used to find counter-factuals for each subsidised firm and allows the sample to be divided up into those which participate in the public R&D schemes and a potential control group of non-subsidised firms. Using the propensity score value, each recipient firm is matched with a similar non-granted counterpart that has the same probability of being subsidised.[4] The matching of the two groups is considered as successful if there is no significant difference in the means of the probability of receiving R&D support and the means of determinants of receipt of subsidy. Given the matching assumptions (6 and 11), the only observable difference between the treated and the control group is grant receipt, and hence one can evaluate the effect of grants on R&D by estimating the difference in expenditure between the treated group and the matched control group, given the above assumptions.

The estimated propensity scores are divided into six blocks (Table 5). In each block there are a number of participants and the number of comparable non-participants. The region of common support is in the range (.02537076, .86902463.). This means that there are no participants with a predicted probability smaller than 0.02537, and no non-participants with a probability higher than 0.8690. For each participant it is selected a set of non-participants (control group) that have a similar probability to participate according to the observed characteristics. Moreover, to improve the quality of the matching, the region of common support is further restricted to less than 0.840 since no twins observations lie outside this threshold. 2 treated firms and 633 non treated firms are leftover for lack of match.

Figures 1 and 2 also show the estimated propensity scores for the treated and untreated firms and supply some preliminary insights about the two groups. From figure (1) it emerges that there is a considerable divergence between the two samples in the data set, confirming the initial worries about possible bias in the two groups. However once the sample has been "cleaned" of non-twin firms and only potentially matching firms are selected (Fig. 2), the nearest neighbours distributions for subsidised firms and the control group are sufficiently similar.

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4 However, there might be unobservable factors that induce non granted firms to invest their own funds in research and which make the selection of twin firms rather difficult. In such cases the comparison would be rather unreliable. Among unobservable factors the capability to implement an R&D project, for instance, strongly depends on the level of informal skills of the firm's employees and managers and experience may also be a relevant factor (Barker and Mueller, 2002).

The results of the matching procedure are then reported in Table (6). To corroborate the validity of the comparison, in the same table the matching diagnostic shows the mean value, differences and standard deviation of the firms matched in each group and sub-group. Since the outcome variable is expressed in euro per worker it is easy to interpret. The average effect of being given a subsidy is € 783.49 per worker, confirming that grants have a positive effect on private investment in R&D, as was found in the regression analysis. Given that the assumptions of this methodology, this would imply that subsidised firms would have invested considerably less if they had not been given the subsidy.[5] Such amounts becomes even more significant when one considers that the average amount of private R&D investment is € 2891. In the sample the public support program improves research of about 27 percent over the period considered.

A plausible justification of this results is that financially supported firms are more dependent on public aid in their R&D investment decision. In terms of policy it implies that public program is efficient since it supports *marginal* R&D projects which are expected to be privately low profitable and would be not pursued without a subsidy.

As a further step, to further focus on this argument and to shed some light on the complementarity or crowding-out issue, it might be useful to investigate whether grants effect the alternative sources of R&D financing that firms have access to, namely internal financing and external credit. This would allow to understand a little more about the relationships between public support, financing and the attitude towards R&D in the firms.

Table (7) shows the average effect of grants on the internal resources that the firms use to finance R&D. The results for firms with grants show that the support has a positive effect on the research program (more than € 400 per worker). However the result is not sufficiently significant hence, it does not allow a definite conclusion about potential additive effect from subsidies to this source of financing.

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[5] This result is in line with Busom (2000), Georghiou and Roessner (2000), Almus and Czarnitzki (2003), Czarnitzki and Hussinger (2004), Duguet (2004), Czarnitzki et al. (2007), Aerts and Czarnitzki (2005), Görg and Strobl (2007). All those matching studies reject a complete crowding out of private R&D efforts through public subsidies concluding that, on average, public funding stimulate private R&D spending.

The non significant coefficient simply suggests that differences between granted and non granted firms are not unequivocal.

The matching procedure is then applied to the amount of external credit, given the grant per employee as the treatment variable. The results reported in Table (8) are as expected. Given that public financing boosts private R&D expenditure and that the additional R&D is not financed through the firm's own resources, recipient firms make use of an additional € 347 external credit to finance their R&D expenditure compared to their non-granted counterparts. Again, given assumptions (6, 11), this implies that treated firms would have used (obtained) less credit if they had not entered the R&D program. This confirms the results in the general R&D matching. Subsidized firms invest more in private R&D than do non-subsidized ones. Furthermore it is particularly external credit financing that benefits from public support and this is complementary to private R&D investment.

Though the analysis in this paper does not allow us to identify causalities one straightforward conclusion is that firms awarded grants would have received less external credit for their research projects if they had not been in the public program. Since the results on the effects of the treatment status on internal funds are inconclusive, the total amount of private R&D would have been significantly lower. Hence, particularly when one considers the inefficiencies inherent in innovation, grants may be an important way of helping firms to overcome their financial constraints (Hall, 2002; Hyytinen and Toivanen, 2005; Czarnitzki, 2006; Binz and Czarnitzki, 2008).

There are various theoretical arguments on the effects of financial constraints on R&D (see Hall, 2002 for a review of the literature). These include incomplete appropriability of knowledge, information asymmetries due to the very nature of innovation processes, uncertainty on the returns of research (Arrow, 1962). These give rise to moral hazard and adverse selection problems. Information asymmetries result in financial constraints and credit rationing (Fazzari-Hubbard-Petersen 1988, Hoshi-Kashyap-Sharfstein 1992, Bond-Meghir, 1994). Credit markets are not likely to work efficiently and underinvestment in R&D is likely.

From the point of view of investment theory, R&D has a number of characteristics that make it different from ordinary investment (Binz and Czarnitzki, 2008). R&D activities can be considered as an investment in a firm's knowledge capital. In practice, a certain amount of R&D spending goes to paying the wages and salaries of highly educated researchers. Their efforts create an intangible asset which, particularly in the R&D field, tends to be both riskier and harder to give collateral value to. Unlike traditional investment, there is no capitalized value in firms' balance sheets which can be used as collateral in credit negotiations. The arguments about capital market imperfections and financing research programs are based on the investors' difficulty in distinguishing good projects from bad ones. Thus potential lenders like banks tend to be reluctant to finance R&D. As a result this has to be mostly financed from internal resources (the "financing gap" hypothesis).

Furthermore, as the rate of return required by an external investor may be consistently higher than that required by the company investing its own resources, external sources to finance R&D are likely to be difficult to obtain or costly, even when there are tax incentives or subsidies (Hall, 2002). Thus financial constraints on R&D are more likely to occur and these restrict the development of hi-tech firms, which may have to abandon crucial innovative projects. In such cases public policy may help firms to overcome in part their financial constraints and to mitigate potential underinvestment in R&D.

From a policy perspective all these arguments justify the social desirability of public schemes designed to reduce the costs for firms of investing in R&D. The rationale of such a policy is based on the fact that the cost of R&D capital is relatively high when compared to other types of investment and the subsidy program tries to mitigate this.[6] Hyytinen and Toivanen (2005) provide evidence that government funding helps firms from industries that are dependent on external finance. Czarnitzki and Toole (2007) find that R&D subsidies mitigate the effect of product market uncertainty on R&D investment and suggest ways in which public policies can increase R&D investment. Together with Czarnitzki (2006), these studies combine discussions about financial constraints and R&D subsidies and conclude that subsidies reduce the problem of underinvestment in R&D.

6 There is, however, an alternative approach, which relies on the private sector, that attempts to close the financing gap by reducing the degree of asymmetric information and moral hazard rather than simply subsidizing the investment (Hall, 2002).

5. Concluding remarks

This paper provides empirical evidence on the effects of public R&D funding on firms' R&D investment per employee in the Italian manufacturing sector. Given the critical importance of investment in research and development as a factor which drives innovation and economic growth, it is important to explore how public policies such as R&D subsidies influence private R&D investment. Public R&D programs are generally aimed at supporting R&D projects with large expected social benefits but with low expected private returns. An efficient technology program would not fund *inframarginal* projects. These are expected to be privately profitable and would be carried out without a subsidy. This is a typical policy exercise.

When evaluating public funding for R&D, it is of interest to investigate the firms' response to subsidies. The issue is then whether public financial support complements or substitutes R&D spending. If the latter is the case, then firms simply replace private sources with public ones, leaving the final level of research spending unchanged. Grants are clearly inefficient since it is very likely that the R&D project would have been carried out even without public support. Given that public resources are raised via socially costly revenue mechanisms, the end result will be that the whole economy is worse off.

The results of this work are consistent with the hypothesis that public funds have a positive effect on private R&D expenditure. Firms given grants achieve levels of private R&D investment that are greater than they would have been without public support. In terms of policy, it also suggests that public programs are efficient since they support marginal R&D projects which are expected to be low in profit and which would be not pursued without a subsidy.

When exploring the effect of public grants on the financial sources of R&D, the analysis provides primary evidence that public policy complements the capital markets. According to the results of this work, firms given grants would have received less external credits for their research projects if they had not been in the public program. One possible interpretation of this may be that since the financial constraints are quite similar for firms with or without grants, there is the same "desire" for additional external credit in the two sub-samples. However, grant-assisted firms make use of consistently more credit than do those without grants, and this additional credit is invested in R&D. This explains why such firms carry out more private (non-subsidised) R&D than their non-subsidised counterparts.

These findings are consistent with the view that that government funding can alleviate financial constraints and have positive effects on the borrowing capacity of firms. It is well-known that R&D investment usually involves higher risks than investment in tangible physical assets, and that asymmetric information between borrowers and lenders has particularly severe effects in this case. There are likely to be negative effects on firms' abilities to pursue R&D projects and this also damages their technological development and growth.

Table 1. Descriptive statistics: mean comparison treated and controls

	Controls obs: 879		Treated obs: 354	
Variable	Mean	Std. Dev.	Mean (€)	Std. Dev.
R&D per employee (triennium average)	2384.87	3479.00	2875.18	3649.62
Subsidised R&D investment per worker (triennium average)	0.00	0.00	1258.65	1943.73
Value added (triennium average)	8386.92	23091.99	10279.65	40884.35
Employees (2001)	148.41	373.53	167.34	673.42
Fixed capital per worker (2001)	50.24	59.21	46.05	49.73
R&D employees over total employees (2001)	0.06	0.06	0.09	0.09
Bank credit over total debt (2001)	0.20	0.18	0.22	0.18
Internal financing to R&D per employee (triennium average)	2071.48	3248.78	2313.76	3240.45
External credit to R&D per employee (triennium average)	248.57	1232.19	516.16	1648.07
INNOVATION=1 if firm has innovated	0.84	0.36	0.90	0.31
RATION =1 if firm is credit rationed	0.06	0.24	0.07	0.26
EXPORT=1 if firm has exported	0.89	0.31	0.89	0.31
OTHER SUBSIDIES=1 if firm has received other types of public grants	0.15	0.35	0.23	0.42

Table 2. Effect of public grants on private R&D spending

	(1) All sample	(2) Granted firms	(3) Granted firms
Dependent: log private R&D per employee (triennium average)	OLS: obs. 1233	OLS: obs. 354	Two stage estimation Obs:1237 Censored: 354
	Coef.	Coef.	Coef.
$LogGRANT_{EMP\ (2001\text{-}2003)}$	0.19**	0.33***	0.33***
$LogEMP_{(2001)}$	0.06	-0.31	-0.35
$Log^2EMP_{(2001)}$	0.01	0.04	0.03
$LogK_{EMPL(2001)}$	0.12***	0.06	0.05
$LogEMP_{R\&D\text{-}EMP(2001)}$	0.52	0.26***	0.03
$DEBT_{BANK\text{-}PASS\ (2001)}$	-0.15	-0.29	-0.55
RATION	0.03	0.24	0.15
INNOV	0.08	-0.03	-0.13
EXPORT	0.14	0.08	0.07
$GRANT_{OTHER}$	-0.03	0.01	-0.27*
$R\&D_{EMP\ (2001\text{-}2003)=0}$	-7.16***	-7.72***	-7.72***
Constant	7.07***	5.60***	7.34***
15 industry dummies (results not reported)	-	-	-
*** significant at 1%, ** significant at 5%, * significant at 10%	R^2=0.61 Adj R^2= 0.60	R^2=0.89 Adj R^2 = 0.88	LR test of indep. eqns. (rho=0): $chi^2(1)$=3.06 Prob>chi^2=0.08

Table 3. Durbin–Wu–Hausman (augmented regression test) for endogeneity:

Equation	Estimated coefficient of residuals	t value
R&D	.71	0.31
Hy: coeff. residuals = 0		
F (1, 330) = 0.10 Prob > F = 0.7538		

R&D equation is regressed on all exogenous variable but one, one including the total amount of industry grant per worker as a regressor as a substitutes of industry dummies. Since the coefficient of residuals is highly insignificant the hypothesis of exogeneity cannot be rejected.

Table 4. Probit parameter estimates of determinants of receipt of public R&D grants

Dependent: Grants to R&D investment obs: 1226		
	Coef.	Z
$LogR\&D_{(2001)}$	-0.07***	-6.27
$LogEMP_{(2001)}$	0.71**	2.99
$Log^2EMP_{(2001)}$	-0.05***	-2.07
$LogEMP_{R\&D\text{-}EMP(2001)}$	0.45***	9.01
$LogK_{EMPL(2001)}$	0.02	0.35
$DEBT_{BANK\text{-}PASS\ (2001)}$	0.39	1.65
RATION	0.12	0.72
INNOV	0.16	1.3
EXPORT	-0.16	-1.17
$GRANT_{OTHER}$	0.46***	4.39
Constant	-1.07*	-1.85
15 Industry dummies (results not reported)	-	-

*** significant at 1%, Pseudo R^2=0.1053
** significant at 5%, Prob>chi² =0.0000
* significant at 10%

Tab. 5. Number of blocks of treated and controls for participation in national programmes

Inferior of Prob (participating)	Number of Controls (non-participants)	Number of treated (participants)	Total
.009	374	57	431
.2	226	67	293
.3	140	80	220
.4	113	109	222
.6	16	37	53
0.8	1	45	46
Total	870	354	1224

Note: the common support option has been selected. The region of common support is [.02537076, .86902463]. The final number of blocks is 6. This number of blocks ensures that the mean propensity score is not different for treated and controls in each block.

Fig. 1 - Estimated Propensity Score

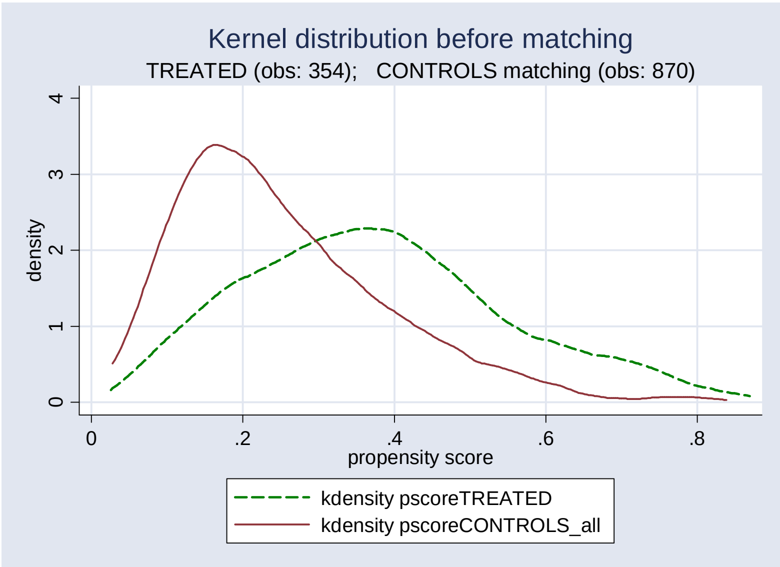
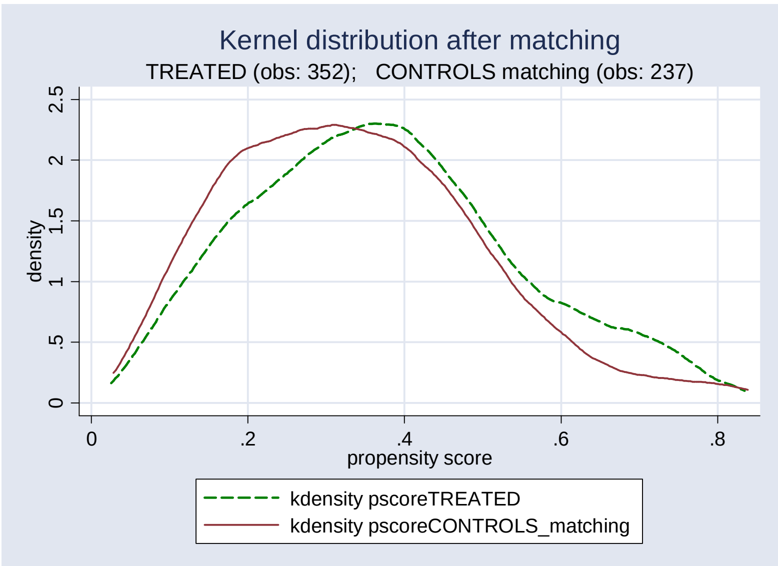


Fig. 2 - Estimated Propensity Score



Tab. 6 Average Treatment Effect (ATT) of Grants on private R&D

Outcome variable: private R&D spending (€ per worker).

Treatment variable: GRANT (0,1).

Estimation of the ATT with the Nearest Neighbour Matching method (random draw version)

Obs.	ATT (€)	Std. Error	t
Treated: 352 Control: 237	783.49	287.56	2.72

Matching diagnostic

	Mean (€)	Std. Dev.
Average outcome of the matched treated	2891.51	3653.52
Average outcome of the matched controls	2108.02	2566.52
Average absolute p-score difference between treated and controls	.0013	.0035

Tab. 7. Average Treatment Effect (ATT) of Grants on Internal Financed R&D

Outcome variable: R&D spending financed by internal funds (€ per worker).

Treatment variable: GRANT (0,1)

Estimation of the ATT with the Nearest Neighbour Matching method (random draw version)

Obs.	ATT (€)	Std. Error	t
Treated: 352 Control: 237	417.46	270.57	1.543

Matching diagnostic

	Mean (€)	Std. Dev.
Average outcome of the matched treated	2326.90	3244.95
Average outcome of the matched controls	1909.44	2533.59
Average absolute p-score difference between treated and controls	.0013	.0035

Tab. 8 Average Treatment Effect (ATT) of Grants on Credit Financed R&D

Outcome variable: R&D spending financed by credit (€ per worker).

Treatment variable: GRANT (0,1).

Estimation of the ATT with the Nearest Neighbour Matching method (random draw version).

Obs.	ATT (€)	Std. Error	t
Treated: 352 Control: 237	347.670	106.822	3.255

Matching diagnostic

	Mean (€)	Std. Dev.
Average outcome of the matched treated	519.09	1652.29
Average outcome of the matched controls	171.4211	709.23
Average absolute p-score difference between treated and controls	.0013	.0035

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