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The Effect of R&D Subsidies on Private R&D

by

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Abstract

This paper investigates the relationship between government support for R&D and R&D expenditure financed privately by firms using a comprehensive plant level data set for the manufacturing sector in the Republic of Ireland. Our empirical strategy combines a non-parametric matching procedure with a difference-in-differences estimator in order to deal with the potential selection problem inherent in the analysis. We find that for domestic plants small and medium sized grants serve to increase private R&D spending, particularly for the former where it can induce R&D spending even beyond the subsidy, while too large a grant may crowd out private financing of R&D. In contrast, evidence for foreign establishments suggests that grant provision causes neither additionality nor crowding out effects of private R&D financing, regardless of the size of the subsidy.

JEL classification: L2, H2, F2, O3

Keywords: research and development (R&D), subsidies, matching, difference-in-differences

Outline

Non-Technical Summary

Nowadays almost all OECD countries offer some sort of grants or subsidy schemes to encourage private research and development (R&D) activity. As a matter of fact such incentives represent on average the second highest form of support to industry. It is a priori not clear whether public support will be an effective means to stimulate private R&D activity. Ideally, government subsidisation of R&D should invoke what is commonly known as 'additionality' effects. Accordingly, an R&D subsidy may, by lowering private costs, turn a previously unprofitable project into a profitable one or speed up the completion of a current project and thereby encourage private R&D activity. Also, if it can reduce the fixed costs of other current or potential projects by the creation or upgrading of research facilities, it may further stimulate the spending on other non-subsidised R&D projects.

However, there is also the possibility that public funding will 'crowd out' private financing of R&D. Since it is likely to be cheaper for firms to apply for a government grant than raise funds in the capital market, some projects may be funded that would have been undertaken even without the receipt of government support.

Whether additionality effects of government subsidies outweigh any crowding out of private R&D activity in reality clearly requires an empirical investigation using appropriate data and estimation techniques. One crucial issue in the empirical literature has been how to deal with the problem of what privately financed R&D activity would have been without government support. Ideally, the researcher would want to observe what would have happened to R&D activity in the firm if it had not received a subsidy. Clearly, however, this is unobservable; one can only witness a funded firm's actual expenditure and not what it would have spent without a subsidy. This leaves as control group only those firms that were not subsidised. The use of non-recipients as a comparison group, however, would only be justified if the provision of grants were a completely random process, otherwise the analysis would suffer from selection bias. In reality, of course, this is unlikely to be the case as authorities will select recipients among the pool of candidates according to some selection criteria.

In this paper we re-examine the issue of whether government support stimulates or crowds out privately financed R&D expenditure. In terms of methodological innovation, we contribute to the literature by combining a non-parametric matching approach and the difference-in-differences estimator as suggested by Blundell and Costa Dias (2000). The empirical analysis is carried out using a large and extensive panel data set of manufacturing plants in the Republic of Ireland. Ireland arguably presents a good case study in that it has implemented an extensive policy of directly supporting industry, in particular with regard to technology intensive activity. The data set provides us with exhaustive information on plants' receipts of grants for R&D purposes.

Our results suggest that for domestic plants while grant provision at a small or medium scale does not `crowd out ' private spending, and in the case of small amounts may even create additionality effects, too large grants may act to finance R&D activity that would have been taking place anyway. In contrast, we find that there is no evidence of such additionality or crowding out effects for foreign multinationals regardless of grant amount size.

Section I: Introduction

Nowadays almost all OECD countries offer some sort of grants or subsidy schemes to encourage private research and development (R&D) activity. As a matter of fact such incentives represent on average the second highest form of support to industry; see Mowerey (1995) and Pretschker (1998). The commonly appealed to underlying economic rationale for this is that R&D activity inherently entails some market failure. More specifically, as argued by Arrow (1962), the incomplete appropriability of the results of R&D means that private returns will be lower than social returns and hence that firms will produce R&D below the socially optimal level. Also, it is frequently shown that R&D investment is financially constrained, i.e., external finance is difficult to obtain due to the inherent risk in R&D activity (Hall, 2002). Government funding may thus act to increase R&D activity to move closer to the social optimum.

Nevertheless, even though market failure is generally accepted as a feature of R&D, it is a priori not clear whether public support will be an effective means to stimulate private R&D activity. Ideally, government subsidisation of R&D should invoke what is commonly known as 'additionality' effects. Accordingly, an R&D subsidy may, by lowering private costs, turn a previously unprofitable project into a profitable one or speed up the completion of a current project and thereby encourage private R&D activity. Also, if it can reduce the fixed costs of other current or potential projects by the creation or upgrading of research facilities, it may further stimulate the spending on other non-subsidised R&D projects. Moreover, the funded project may stimulate spillovers of know-how and learning to other ones.

However, there is also the possibility that public funding will 'crowd out' private financing of R&D. Since it is likely to be cheaper for firms to apply for a government grant than raise funds in the capital market, some projects may be funded that would have been undertaken even without the receipt of government support. While this may be due to informational deficiencies between the government and the firm, it could very well also be the result of policy makers supporting those projects that are privately the most profitable in order to avoid being seen as wasting public funds. Additionally, if the supply of R&D inputs, such as R&D personnel, is inelastic (as argued by Goolsbee, 1998), then the commencement of the publicly funded project may crowd out other non-subsidised ones.

Whether additionality effects of government subsidies outweigh any crowding out of private R&D activity in reality clearly requires an empirical investigation using appropriate data and estimation techniques. However, although the number of relevant studies is now relatively numerous and growing, the evidence itself is rather mixed. For example, in their discursive review of the literature David et al (2000) conclude that the evidence seems "to be running in favour of finding complementarity of public and private investments " (p. 500). However, using a more quantitative review in terms of a meta-analysis, Garcia-Quevedo (2004) finds 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 crucial issue in the empirical literature has been how to deal with the problem of what privately financed R&D activity would have been without government support.[1] Ideally, the researcher would want to observe what would have happened to R&D activity in the firm if it had not received a subsidy. Clearly, however, this is unobservable; one can only witness a funded firm's actual expenditure and not what it would have spent without a subsidy. This leaves as control group only those firms that were not subsidised. The use of non-recipients as a comparison group, however, would only be justified if the provision of grants were a completely random process, otherwise the analysis would suffer from selection bias. In reality, of course, this is unlikely to be the case as authorities will select recipients among the pool of candidates according to some selection criteria.[2] Thus, properly identifying the effects of public funding on privately financed R&D activity requires generating the appropriate counterfactual in order to deal with the possible selection bias.

A number of econometric approaches have been applied to deal with this issue. For example, the most common approach has been to model simultaneously a selection equation as well as an R&D outcome equation; see Wallsten (2000), Busom (2000), and Hussinger (2003) for studies for the US, Spain and Germany, respectively. In contrast, Lach (2002) applies a difference-in-differences estimator to firm level data for manufacturing industries in Israel, while Almus and Czarnitzki (2003) use a matching procedure and evaluate the effect of grants on R&D spending in East Germany using a simple matching estimator. All of these approaches go some way towards addressing the selectivity problem at hand, however, all have their advantages and disadvantages. In this regard, in their survey of the various estimation methods that can be used for this type of

[1] This problem was pointed out as early as by Lichtenberg (1984).

[2] Moreover, awareness of these criteria may mean that plants will self select themselves into the application process.

evaluation in non-experimental data Blundell and Costa Dias (2000) conclude, however, that a combination of the non-parametric propensity score matching with the difference-in-differences estimator is likely to improve the accuracy of such an evaluation study considerably. This combined technique has, however, as of date not been applied to the study of the effect of grants on R&D expenditure yet.

In this paper we re-examine the issue of whether government support stimulates or crowds out privately financed R&D expenditure. In terms of methodological innovation, we contribute to the literature by combining a non-parametric matching approach and the difference-in-differences estimator as suggested by Blundell and Costa Dias (2000). The empirical analysis is carried out using a large and extensive panel data set of manufacturing plants in the Republic of Ireland. Ireland arguably presents a good case study in that it has implemented an extensive policy of directly supporting industry, in particular with regard to technology intensive activity.[3] As a matter of fact, in terms of funding R&D activity relative to other OECD countries, Ireland stands second in terms of the percentage of R&D expenditure due to government support.[4] The data set provides us with exhaustive information on plants' receipts of grants for R&D purposes. Hence, in contrast to studies such as Wallsten (2000) which only use data for a particular support programme, our data cover all R&D grants. One particular feature of Ireland's industrial structure is the importance of foreign multinational companies (MNCs), which accounted for roughly one half of manufacturing employment in 2000. Given the importance of financial constraints for investment in R&D and the empirical findings that financial constraints are likely to be different for MNEs (see Harrison and McMillan, 2003), we make a point of focusing on differences across nationality of ownership in our analysis, an aspect that remains as of yet unexplored.

The remainder of the paper is organised as follows. In the following section we outline grant provision in Ireland. Section III describes our data set and provides some preliminary empirical analysis. We outline the matching procedure combined with the

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[3] Prior to the 1980s technology intensive industry was virtually non-existent in Ireland. It has been shown that part of its spectacular growth process has been due to grant support; see Cassidy and Strobl (2004). Also Cassidy et al (2005) have shown that R&D has raised productivity in Irish manufacturing.

[4] See Toivanen and Niinien (2000). One should note, however, that Ireland still ranks low in terms of overall R&D activity. For example, figures from OECD's BERD database show that in Ireland in 1999 R&D was only 0.8 per cent of total output in manufacturing, relative to the 2.4 per cent OECD average.

difference-in-difference estimator in Section IV. Section V contains our main results and we provide a summary and some concluding comments in the final section.

Section II: Grant Provision in Ireland[5]

The agency primarily responsible for the provision of grant assistance in manufacturing in the modern era has been the Industrial Development Agency (IDA) until 1994, after which it was split into IDA Ireland and Forbairt. The former is now responsible for the grant provision to foreign owned firms while the latter presides over assisting indigenous plants.[6] The range of grants that have been available to firms include capital grants, training grants, rent subsidies, employment grants, feasibility study grants, technology acquisition grants, loan guarantees and interest subsidies, and, most importantly from the standpoint of this paper, research and development grants.

While there have been some changes in the provision of grants over time, provision within the time period examined in our empirical analysis can be safely summarised as follows (see KPMG, 2003). Projects suitable for assistance had to either involve the production of goods primarily for export, be of an advanced technological nature for supply to international trading or skilled self supply firms within Ireland, and/or be in sectors of the Irish market that are subject to international competition. In order to be eligible the applicant has to generally show that the project required financial assistance, is viable, has an adequate equity capital base, and, through financial assistance, will be able to generate new employment or maintain existing employment in Ireland, thereby increasing output and value added within the Irish economy. Additionally, there is also a generally more favourable view of more technology intensive projects and those of a more entrepreneurial nature. The actual grant level is generally very project specific and subjected to a cost-benefit analysis. Additionally, total grant levels can generally not exceed certain capital cost thresholds, usually between 45 and 60 per cent. Grants are usually paid in pre-specified instalments such that further payment is often subject to periodic reviews.

Section III: Data and Preliminary Empirics

Data

[5] See Meyler and Strobl (2000) for a more detailed discussion.

[6] After 1998 Forbairt become Enterprise Ireland as a consequence of a merger with the Irish Trade board.

We utilise information from two data sources collected by Forfás, the Irish policy and advisory board with responsibility for enterprise, trade, science, and technology in Ireland. Our first data source is the Annual Business Survey, collected from 1999 until 2002. This is an annual survey of plants in Irish manufacturing with at least 10 employees, although a plant, once it is included, is generally still surveyed even if its employment level falls below the 10 employee cut-off point. Over its four year existence the survey has covered around 50 per cent of all manufacturing plants with 10 or more employees. The information available from this source that is relevant to the current paper are the nationality of ownership, sector of production, output, employment, exports, wages, total and domestically purchased inputs, and total R&D expenditure.[7] One should note that Forfás defines foreign plants as plants that are majority-owned by foreign shareholders, i.e., where there is at least 50 per cent foreign ownership. While, arguably, plants with lower foreign ownership should still possibly considered to be foreign owned, this is not necessarily a problem for the case of Ireland since almost all inward foreign direct investment has been greenfield investment rather than acquisition of local firms (see Barry and Bradley, 1997).

Importantly, Forfás also has an exhaustive annual database on all grant payments that have been made to plants in Irish manufacturing since 1972. Specifically, there is information on the level of payment, the year of payment and the (aforementioned) explicit scheme under which it was paid. For our empirical analysis we can thus isolate R&D grants from all other grant payments made to the firm.

In terms of using these two data sources in conjunction with each other one should note that Forfás provides each plant with a unique numerical identifier, which allows one to link information across plants and years. For the analysis here we use the grant data for classifying plants as grant recipients, and the ABS for all other plant level variables used in the analysis. One should note that by linking information across data sources our sample consists of plants of generally at least 10 employees.

We calculate a measure of private R&D expenditure in any year as the value of total R&D expenditure net of R&D grant payments made to that plant in that year. Also, given that the matching procedure described in the following section utilises lagged values we supplemented our ABS data with information from the Irish Economy Expenditure, the

[7] All nominal variables are appropriately deflated by the consumer price index.

earlier form of the ABS that was ceased in 1998.[8] This allows us to maximize the number of observations in our empirical analysis.

Preliminary Empirics

As stated in the Introduction, R&D grants now constitute an integral part of the overall grant schemes offered in Ireland. In Figure 1 we graph the share of R&D related subsidies relative to total government support since the early 1970s. Accordingly, at the start of the 1970s less than one per cent of the grants were offered under the R&D scheme. This share has since, however, grown drastically, with notable increases in the early 1980s, mid 1990s and the start of this century. As a matter of fact, by 2002 more than 16 per cent of total government grants to industry was allocated to R&D activity.

[Figure 1 here]

Table 1 shows that, nevertheless, R&D spending remains low in Irish manufacturing relative to output, standing at 0.93 per cent. There are some sectoral differences with the Furniture sector, surprisingly, being the most, while the Drinks and tobacco industry is characterised by the least amount of R&D activity. One should note, however, that these two sectors are small relative to total manufacturing activity. Of the three most important sectors in Irish manufacturing, i.e., Chemicals, Food, and Metals and Engineering, only Metals and Engineering is characterised by above average R&D activity.

The R&D intensity compared across sectors may seem somewhat contrary to a priori expectations. However, one should note that the sectoral distribution of multinational activity is unevenly distributed across sectors and that, contrary to domestic plants, these may conduct much of their R&D activity outside of the host economy. This may be particularly important for some sectors given that output in Irish manufacturing in our sample is predominantly by foreign multinationals (over 76 per cent). In comparing R&D activity across ownership we find in this regard that the indigenous industry is nearly 50 per cent more active in R&D compared to foreign multinationals.

In examining the subsidy intensity in R&D, proxied by grant levels relative to total R&D expenditure, one discovers that only 1.93 per cent of R&D spending is financed by the government in Ireland.[9] Moreover, the support of domestic plants is nearly five times

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[8] The ABS is a more expanded version of the original Irish Economy Expenditure Survey, which only covered firms of at least 20 employees. However, the ABS, in contrast to the latter, contains information on the R&D expenditure of the plant.

[9] This is not unusual by OECD standards. For instance, according to Pretschker (1998) total support to industry in the OECD in 1993 was only about 1.15 if measured in a similar fashion.

that of their foreign counterparts. In terms of sectoral averages, our summary statistics show that grant provision in R&D is particularly high in the furniture and wood and wood products industries, and relatively low in Chemicals and Drink and Tobacco. A simple correlation coefficient would suggest some positive, but statistically insignificant correlation (0.49) between this and the intensity of R&D activity.

We also calculated grant receipt relative to output, as shown in the last column of Table 1. Here one finds that while grant provision is still high in the Furniture and Wood and Wood Products sectors and relatively low in the Chemicals and Drink and Tobacco sectors, the measure of grant intensity is sensitive to the choice of denominator. For instance, using output Miscellaneous Manufacturing ranks third as support recipient compared to ninth when we used R&D activity as denominator.

[Table 1 here]

Section IV: Econometric Methodology

The major problem in evaluating the effect of government grants on R&D is that grant receipt is most likely not random. Rather, certain types of firms may self select into the application process and the government may consciously select certain types of recipients among the applicants. The previous literature has dealt with this selectivity problem in a number of different ways. Wallsten (2000), for example, estimates simultaneously a selection equation as well as an R&D outcome equation. In order to obtain reliable estimates of the treatment effect, this approach rests on the assumption that there is at least one additional regressor that enters into the selection equation but not in the outcome equation. Wallsten (2000) calculates a variable equal to the “potentially awardable” grants for each firm, based on the total budget available to the grant giving agency. This may be a reasonable identifying variable in his case, however, in general, such a variable is difficult to come by in most data sets used to study this issue.

Lach (2002) uses a different methodology which does not rely on such exclusion restrictions being imposed. He employs a difference-in-differences (DID) estimator to identify the effect of grants on firm performance. This strategy relies on the assumption of common trends of macro variables on both groups, i.e., both groups are assumed to react identically to common macro shocks. This assumption may be problematic if very different types of firms are included in both groups. A second weakness of the DID estimator is that it does not guarantee that, in terms of observables, similar plants are being compared since OLS estimation implicitly assumes a linear effect across any range of values of a covariate. However, for instance, it may be that most grant recipients are young while non-recipients tend to be older and thus that one is not comparing like with like – an aspect known as the common support problem. Finally, the DID estimator still fails to control for unobserved temporary individual specific components which impact on the participation decision. As an example, suppose that firms anticipate receiving grants and therefore reduce their R&D expenditure just before the treatment. In this case, one may expect a faster growth of R&D expenditures for such firms even if they fail to receive a grant.[10] If that is the case, a DID estimator is likely to overestimate the effect of treatment.

Yet another approach is to use propensity score matching, as done by, e.g., Almus and Czarnitzki (2003), which specifically deals with the potential common support problem. Under the matching assumptions, the only difference between the treated and control group on observables 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.[11] One crucial assumption of this approach though is that of conditional independence, i.e., controlling for observables, the outcomes of the non-treated control group are independent of grant receipt.

As becomes apparent, matching and DID on their own require some arguably strong assumptions, while combining the two methods allows one to overcome those shortcomings. Indeed, as argued by Blundell and Costa Dias (2000) a combination of matching and difference-in-differences analysis arguably improves the accuracy of an evaluation study and we follow this approach here. The specifics of the methodology within our context is outlined below.

Traditionally the evaluation approach has been applied to single treatment frameworks, as, for instance, in Almus and Czarnitzki (2003). Arguably in the case of the effect of grant provision on own R&D spending, however, it is not only whether a plant receives a grant but how much it receives that may matter. Fortunately the evaluation approach has recently also been extended to multiple-treatment cases, see Imbens (2000) and Lechner (2001), and we utilise this extension to allow us to investigate how different grant amounts have affected private R&D spending. In this regard let there be $K+1$ different states, where these consist of K pre-specified categories of mutually exclusive

[10] This argument would be similar to "Ashenfelter's dip" in the labour economics literature (Heckman and Smith, 1999).

[11] See, for example, Imbens (2004) for an excellent survey of matching methods.

grant amounts and the case of no grant receipt (*k*=0). If we denote private R&D spending by *Y*, then the number of potential outcomes associated with each state for each plant *i* is $Y_i^0, Y_i^1, ..., Y_i^K$. Letting $T_i=k$, where $T \in \{0,1,\ldots K\}$, be the actual occurrence of the state of plant *i*, then all other elements in *T* are not observed for that plant.

One can use this framework to define what has become known as the 'effect of treatment on the treated'. More precisely, for $(K+1)K$ pair-wise comparisons of the average effect of grant amount type *k* relative to grant amount type *k'* conditional on receipt of grant amount type *k*, the `effect of treatment on the treated' is:

$$E(Y^k - Y^{k'}|T=k) = E(Y^{k'}|T=k) - E(Y^{k'}|T=k) \text{ for } k, k' \in \{0,1,\ldots K\}, k \neq k' \qquad (1)$$

One should note, while the first term is observed in the data, none of the other pairwise combinations are. In the evaluation literature one common estimator of these other counterfactuals is:

$$E(Y^{k'}|T=k) = E_X[E(Y^{k'}|T=k', X)|T=k] \qquad (2)$$

for some set of observable characteristics X. There are two important aspect to note with regard to (2). First, in order for the inner expectation of (2) to hold one needs to invoke what is commonly known in the literature as the conditional independence assumption, which requires that conditional on the value of the set of observable characteristics X, which themselves need to be unaffected by the treatment, the treatment indicator *T* is independent of all potential outcomes. Second, in order to evaluate the outer expectation it is pertinent that all participants in *k* have a counterpart in the *k'* comparison group for each X for which on seeks to make a comparison. In other words, one needs to find a 'common support' region.

The propensity score matching estimator (PSM) specifically addresses the potential problem of 'common support'. More precisely, the PSM estimator can help eliminate the bias due to differences in the supports of *X* in the treated and non-treated groups and the bias due to differences in the two groups in the distribution of *X* over its common support by 'matching' similar individuals across these two groups. In terms of implementing this estimator one normally would like to match individual units across a number of observable characteristics. However, in this regard it would be difficult to determine along which dimension to match the plants, or what type of weighting scheme to use. To overcome this dimensionality problem, Rosenbaum and Rubin (1983) suggest the use of a propensity score generated from modeling the probability of the treatment and this method can be easily extended within a multiple treatment framework of pair-wise comparisons. One should note in this regard that Lechner (2001) pointed out that when comparing two 'treatment groups' the existence of multiple treatments can be ignored since these other individuals are not needed for identification.

Accordingly, we first identify the probability of grant amount type *k* receipt compared to grant amount type *k'* receipt (or 'propensity score') conditional on a set of observables ***X*** using the following probit model:

$$P(T_{it}=k|T\ T_{it}=k, k') = F(\boldsymbol{X}) \tag{3}$$

A *k'* grant amount type plant *j*, which is 'closest' in terms of its 'propensity score' to a *k* type grant amount plant *i*, is then selected as a match for the latter using the 'caliper' matching method.[12] More formally, for each grant type *k* receiving plant *i*, a grant type *k'* plant *j* is selected such that for the predicted probability, P_{it}, of receiving a *k* type R&D grant at time *t* of grant recipient plant *i* and the predicted probability, P_{jt}, of receiving a *k* type R&D grant at time *t* for k' type grant recipient plant *j*:

$$\lambda > \left|P_{it} - P_{jt}\right| = \min_{j\in\{k'\}}\{|\ P_{it} - P_{jt}\ |\} \tag{4}$$

where λ is a pre-specified scalar which defines the boundary for the neighbourhood where matching is allowed. If none of the *k'* grant type recipients plants is within λ of the *k* type recipient *i*, it is left unmatched. This procedure is done for all *(K+1)K* type combinations.

Despite its appeal in addressing the 'common support' problem, the PSM estimator still crucially rests on the conditional independence assumption. In other words, in using the PSM it is pertinent that one can convincingly argue that the data at hand is sufficiently rich for this to be reasonable and/or that one supplements the PSM with another estimator to overcome this strong assumption. We thus combine our PSM matching procedure with a difference-in-differences estimator, which compares the change in the outcome variable for the *k* treated groups with the change in the outcome variable for all none k type grant amount recipients. Accordingly, let $\Delta^k Y$ be the difference in private R&D spending before and after receiving an R&D grant of amount *k*, and difference this with respect to the before and after differences for all comparison control groups, say $\Delta Y^{k'\neq k}$. One then obtains the difference-in-differences estimator $\delta = \Delta Y^k - \Delta Y^{k'\neq k}$. In terms of practical implementation this amounts to estimating:

$$\Delta\ Y_{it} = \alpha + \partial\sum_{1}^{k}\Delta G_{it}{}^{k} + \varepsilon_{it} \tag{5}$$

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12 The matching is performed in STATA Version 8 using the software provided by Sianesi (2001).

where Δ is a time differencing operator over $t-1$ to t and G^k are a k set of grant amount category dummies. Essentially this DID estimator combined with PSM allows us to purge all time invariant unobservables from our relationship of interest in the matched sample. However, even this combined estimation approach might leave one with a potential problem of unobserved effects. For example, firms may get a good idea, apply for a grant and also increase their R&D expenditure even in the absence of a grant (e.g., Kauko, 1996, Jaffe, 2002). If this is the case for both successful and non-successful applicants then this should not cause a problem in our approach. If, however, this is more likely to be the case for successful applicants, then our approach would likely overstate the potential additionality of grant receipt. Unfortunately, we cannot completely rule out this possibility, but instead need to make the argument that our data is rich enough so that no other time varying unobservables that may be correlated with grant receipt and own R&D spending remain.

Section V: Empirical Results

Propensity Score Matching Results

Importantly our information on grant receipt provides us with the actual amount of grant and thus allows to examine the impact beyond grant receipt incidence. However, taking grant size into account and using the propensity score matching simultaneously necessarily restricts us to grouping grant amounts into pre-defined categories. In this regard, the more categories we allow for, the less we are assuming away within-heterogeneity in the sense that different grant amounts within categories may have different impacts on private R&D financing. But, the greater the amount of categories one chooses the more unfeasible in terms of our sample size and implementation will PSM be, since K categories require the matching of $(K+1)K$ different combinations. Moreover, the choice of categories is to some extent arbitrary unless one has a clearly grounded a priori expectations of what amount `thresholds' would be reasonable. With these aspects in mind and after considerable experimentation we proceeded with using three different grant size categories - for convenience sake termed small, medium, and large – defined as, respectively, the amounts that fall below the 33.3 per centile, within the 33.3 to 66.6 percentile, and above the 66.6 percentile of the entire distribution of R&D grant payments over our entire sample period. We thus are slicing the entire distribution of grants into three equally probable groups. In terms of actual amounts this corresponded to categorizing grants less than 12,500 Euros as small, between 12,500 and 55,000 Euros as medium, and those above 55,000 Euros as large.

In implementing PSM on our three grant categories one would ideally like to use a set of covariates **X** that capture, or are correlated with, the factors that the IDA may take into account when deciding on handouts of grants as discussed above in Section II. As noted, the IDA was keen on supporting firms that were export oriented, entrepreneurial, technology intensive, skill intensive, linked to the local economy, and likely to be financially constrained. In terms of the information that our data sets provides we identified the following factors that may be important in this regard: size (employment), export intensity, domestic input use, average wage, labour productivity, foreign ownership, and age. We also included a dummy indicating the receipt of other (than R&D) type grants to capture other aspects that our, admittedly limited, set of controls may not capture.[13] We use lagged values of these variables in order to ensure our covariates are unaffected by grant receipt (or the anticipation of it); see Caliendo and Kopeinig (2005). Finally, we also included a dummy variable indicating whether the plant received a R&D grant in the previous year.

We provide some summary statistics of a number of relevant variables, broken down by grant amount type and ownership in Table 2. Accordingly, foreign plants are much more prominent in the large and medium than in the small grant receipt category. However, they also make up one fifth of the observations in the non-grant group. We also find that R&D grant recipients are more likely to have received other grant types compared to non-recipients, particularly the medium and large groups. While there is little detectable pattern across groups in terms of domestic input share, average wage, and age, one finds that large R&D grant recipients are much more export intensive than small grant or non- recipients, although a large part of this is due to the indigenous industry. Notable are also the greater size and greater labour productivity of large recipients compared to all others. The summary statistics additionally indicate that grant recipients have higher R&D per employee spending than non-recipients, although, importantly, this is only true for those that receive medium to large sized grants. Moreover, the same pattern is true if we only examine privately financed R&D expenditure.

[Table 2 here]

[13] Ideally we would have liked a more direct measure of technological intensity, but no such information was available to us. Also, one should note that unfortunately there is no direct measure of financial constraints available in the data.

As a next step we calculated propensity scores and used the matching estimator as previously outlined to create our control and treatment groups using a value of λ equal to 0.1. [14, 15] In doing so, from a total amount of 5422 non-recipients, 321 small grant recipient, 317 medium grant recipient, and 318 large grant recipient observations were able to match 381, 118, 171, and 168 observations, respectively. We assess the matching quality of this procedure using a variety of indicators shown in Table 3. For instance, as can be seen the pseudo R-squared of running the same probits with only the matched sample is considerably lower in all cases except where non-grant receipt is used as the treatment group. This only marginal reduction for the latter cases is arguably mostly due to the fact that the size of the non-recipient group is much larger than the other three and thus making it difficult to predict non-receipt (relative to receipt). One would also like those in the treatment group to be those predicted to be 'treated' according to the estimated propensity scores. In this regard one should note from Table 3 that the average estimated propensity scores of the treatment group in question always has an average propensity score above 0.5, except for when non-recipients are used as a control group. For the latter cases we can again invoke the likely reason to be due to relative sample size considerations. Finally, we also, as suggested by Rosenbaum and Rosin (1985), calculated the standardized bias of the propensity scores for our individual matching pairs as:

$$SB = 100 * \frac{abs(\bar{P}_1 - \bar{P}_0)}{\sqrt{0.5 * (V_1(P) + V_0(P)}} \tag{6}$$

where P is the propensity score, $\bar{P}$ represents its average, and V its variance. One finds from the resulting figures in Table in this regard that, except again for where non-recipients are used as the treatment group, bias reduction is considerable, ranging anywhere from 47 to 78 per cent. Thus, except when non-grant recipients are used as control or treatment groups, the matching quality indicators are clearly supportive of our underlying matching procedure.

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[14] In our case, λ is set equal to 0.1 We also experimented with lower and higher values. Marginal changes (for example reducing or increasing λ by 0.05) seemed to make relatively little difference in terms of the matched sample. However, increasing λ by a further 0.1 increased sample size substantially and clearly reduced matching quality, while decreasing it by a further 0.1 resulted in unfeasible sample sizes. Detailed results are available from the authors.

[15] We also experimented with doing the matching on propensity scores where we did not include some of the insignificant variables, in particular those that change signs over the sample period (such as age, employment, and domestic inputs). However, this generated little difference in the matched sample and our subsequent DID estimates. Results are available from the authors upon request.

In order to ensure that the lower performance of the matched pairs involving non-recipients was indeed due to their dominance in these pooled samples, we thus also experimented with using random samples of 317 observations from the non-recipient group in the relevant pooled samples. The results of this exercise are shown in the last six rows of Table 3. The matching quality indicators now show results considerably more in line with the pairs where there were much less sample size differences and we thus can conclude with reasonable confidence that our matching even where non-recipients were used as either the control or treatment group was relatively successful. [16]

Econometric Results on the Treatment Effect

In order to estimate the effect of grant provision on private R&D spending we started with the benchmark specification:

$$Y_{it} = \alpha + \beta_S SMALL_{it} + \beta_M MEDIUM_{it} + \beta_L LARGE_{it} + \varepsilon_{it} \qquad (7)$$

where *SMALL*, *MEDIUM*, and *LARGE* are zero-one type dummies indicating whether a plant received a small, medium, or large sized R&D subsidy, *Y* measures the logged value of privately financed R&D, and ε is a random error term.[17] One should note that $\beta_i>0$ indicates additionality effects, $\beta_i<0$ suggests crowding out effects, while a β_i not significantly different from zero implies neither of these for private R&D financing for any grant category *i*.

We first estimated (7) using the total sample (unmatched) with simple OLS as our benchmark case of the effect of government subsidies on privately financed R&D.[18] The resultant coefficients, shown in the first row of Table 4, are positive and significant, indicating that all sizes of grants act to create additionality effects on private R&D spending. Moreover, comparing the size of the coefficients across categories would suggest that such additionality effects are greater the larger the subsidy provided.

As noted earlier, one particular feature of the Irish economy is the large presence of foreign multinationals. A large literature now argues that multinationals can serve as an important stimulus to the domestic sector by enabling technology spillovers; see, for instance, Görg and Strobl (2001). As a matter of fact, several empirical studies for Ireland

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16 Nevertheless we proceed with our matched samples from the total sample given that one is likely to achieve better matches because there is a greater possible sample to match to.

17 We use the logged value in order to take account of outliers. In order to avoid in this regard the dropping of observations where privately financing was zero, we set expenditure in levels equal to one Euro for these.

18 While we used the unmatched sample, one should note that we reduced the data to include only observations for which we could also run a first differenced version of (7) in order to keep our sample size consistent across unmatched estimation types.

provide indirect evidence for this (Ruane and Ugur, 2005; Görg and Strobl, 2003). Thus, an important question is whether the policy maker can potentially increase such spillover effects by subsidising R&D activity by foreign multinationals within the host country. However, in considering whether potentially stimulating effects exist one has to also take into consideration that multinationals are less likely to face the same financial constraints as domestic firms. After all, they have many means of financing their operations, not least foreign direct investment, i.e., capital transfers to the parent company (see Harrison and McMillan, 2003). Hence, they are less likely to be reliant on the domestic capital market for funds for R&D funding. However, it must also be noted that multinational plants are by definition part of a greater multi-plant corporation, so R&D activity in Ireland may only be a small part of total R&D expenditure by the entire operation. The availability of R&D subsidies in Ireland may hence simply encourage the movement of some of this total activity to Ireland and away from headquarters and/or other plants located outside of Ireland, in particular for larger foreign owned plants.

To gain some insight into these issues we also divided the sample into foreign multinationals and domestic plants and estimated equation (7) separately for these two sub-grous.[19] As can be seen, from the second and third row of Table 4 additionality effects are not only present, but also are increasing with grant size for both types of plants. In examining the size of the coefficients across the groups one may note that the marginally greater values for foreign plants indicates that additionality effects may be larger for these, although, as just argued, one may need to be cautious in terms of interpreting additionality effects for both groups in the same way.

Clearly, there are many other factors that affect both grant receipt and R&D activity financed from private funds, thus potentially biasing our estimates. If these are assumed to be time invariant then they can be purged by simply first differencing equation (7). Our estimates from this exercise are shown in the fourth to sixth rows of Table 4. As can be seen, this dramatically changes any conclusions drawn from the coefficients. For the overall sample one finds that there are now only additionality effects for plants receiving small grants, but neither additionality nor crowding out effects for medium and large subsidy recipients. Breaking down the sample into nationality of ownership type

[19] Ideally, we would like to identify also domestic multinationals, as these may be less likely to be hampered by financial constraints. However, this information is not available to us in our data sets.

shows that this result is largely driven by domestic plants – for foreign plants even small grant recipients now no longer are subject to additionality effects.

In order to assess whether our results may thus far have been driven by the potential problem of 'common support', as discussed in Section IV, we then proceeded to use our matched sample in order to estimate a first differenced version of (7).[20] One should note that this is precisely the combined matching difference-in-difference estimator of equation (5), and the estimated coefficients clearly indicate that employing this can have substantial effects on any conclusions drawn. More precisely, while the results for the overall and foreign samples are consistent with those using the total sample, there are stark differences for domestic plants. First, one finds slightly larger additionality effects for small grant recipients than for the unmatched first differenced specification. Importantly, however, in contrast to the unmatched sample, there are now crowding out effects for those plants that receive relatively large grant amounts.

One possible concern with the estimations thus far may be that, given that our dependent variables is in logged levels, our results even after matching could be driven by the possibility that larger plants spend more of their own money on R&D and are also more likely to receive a grant. Such a size effect can be argued to be potentially important on a number of grounds. First, the traditional 'Schumpeter hypothesis' argues that larger firms have more incentives to undertake R&D because of economies of scale (see, Schumpeter, 1943, Kohn and Scott, 1982). Second, large firms are less likely to be financially constrained (e.g., Carpenter and Petersen, 2002) and therefore have better access to funds for R&D. Although our matching procedure is intended to create samples of 'similar' plants across all relevant characteristics, including size, and we have in this regard included employment as an indicator of size, the use of the summary score in the face of multi-dimensionality of characteristics may feasibly result in less than perfect matching in this regard. To investigate this we thus also redefined our dependent variable as privately financed R&D intensity, measured as the log of private expenditures on R&D per employee – the results of this are shown in the final three rows of Table 4. As can be seen, reassuringly our conclusions from the difference-in-differences PSM estimator is robust to this alternative dependent variable.

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[20] One should note that for this specification we have calculated bootstrapped standard errors (using 500 replications) as suggested by Lechner (2002) since the use of a matching further complicates the calculation of the actual estimation variance.

Section VI: Concluding Remarks

We investigated the relationship between government support for R&D and R&D expenditure financed privately by plants. To this end we used a unique rich data set on Irish manufacturing plants and employed an empirical strategy that combined a non-parametric matching procedure with a difference-in-differences estimator in order to deal with the potential selection problem inherent in the analysis. Our results suggest that for domestic plants while grant provision at a small or medium scale does not `crowd out ' private spending, and in the case of small amounts may even create additionality effects, too large grants may act to finance R&D activity that would have been taking place anyway. In contrast, we find that there is no evidence of such additionality or crowding out effects for foreign multinationals regardless of grant amount size.

One possibility for the differences in results across nationality of ownership may be that for foreign multinationals may not necessarily be affecting their total amount of privately financed R&D but rather result in shifting spending across locations. More precisely, while multinationals may be expected to carry out most of their R&D in the home country (Markusen, 1998), the availability of R&D subsidies in Ireland may encourage the relocation of some of this R&D activity to Ireland and away from the headquarter or other facilities located outside of Ireland. Although we cannot test this hypothesis with the data set at hand, the analysis of global R&D activities of multinationals could arguably provide further insight in this regard.

Table 1: R&D Summary Statistics by Sector

SECTORS:	*Output*	*RD/output*	*Grant/RD*	*Grant/Output*
Chemicals	24.7	0.56	0.72	0.01
Cloth., Foot. & Leath.	0.5	1.45	3.12	0.05
Drink & Tobacco	5.8	0.19	1.38	0.01
Food	14.5	0.65	3.04	0.04
Furniture	0.5	2.04	10.49	0.19
Metals & Engineering	45.8	1.39	1.66	0.03
Misc. Manufacturing	0.6	1.04	1.44	0.10
Non-Metallic Minerals	2.6	0.52	2.55	0.04
Paper & Printing	1.4	0.47	2.83	0.03
Plastics & Rubber	1.9	1.74	4.11	0.08
Textiles	0.9	1.08	3.07	0.07
Wood & Wood Pr.	0.9	1.10	12.73	0.18
Total Manufacturing	---	0.93	1.93	0.03
Domestic	23.7	1.23	4.77	0.09
Foreign	76.3	0.86	0.82	0.01

Note: (1) Authors' own calculation using data sources described in Section III. (2) All figures are in percentages. (3) Percentages concerning output are relative to total manufacturing output.

Table 2 – Summary Statistics by Grant Categories

SAMPLE	***Grant***	**Other Grants**	**Export Intensity**	**Domestic Input Share**	**Avg. Wage**	**Labour Prod.**	**Foreign**	**Avg. Age**	**Employment**	**R&D \ Empl.**	**Own R&D \ Empl.**
Total:	**None**	0.38	0.44	0.57	28.05	171.70	0.20	24	133.30	2.90	2.90
	Small	0.55	0.34	0.63	26.48	121.52	0.06	27	83.05	2.47	2.30
	Medium	0.63	0.47	0.57	33.23	136.83	0.17	23	81.40	4.18	3.32
	Large	0.63	0.67	0.53	33.22	237.22	0.33	23	203.85	9.66	7.86
Domestic	*None*	0.41	0.33	0.61	26.62	132.51	---	25	84.39	2.59	2.59
	Small	0.56	0.33	0.63	26.45	121.42	---	26	78.26	2.51	2.34
	Medium	0.65	0.41	0.61	26.28	134.36	---	23	68.10	4.47	3.54
	Large	0.68	0.57	0.58	31.11	162.16	---	24	144.70	8.48	6.25
Foreign	*None*	0.28	0.86	0.42	33.65	324.80	---	21	324.36	4.14	4.14
	Small	0.33	0.67	0.53	27.21	123.68	---	34	182.00	1.38	1.28
	Medium	0.52	0.77	0.38	67.67	149.07	---	23	147.30	2.77	2.23
	Large	0.51	0.89	0.43	37.68	395.20	---	19	328.36	12.15	11.25

Table 3 – Indicators of Matching Quality

Treat.	Control	Sample	Treat. Obs.	Control Obs.	Pseudo R^2 before	PseudoR^2 after	Avg. P-Score of Treat.	BiasRed. (%)
SMALL	*No Grant*	Total	321	5422	0.22	0.01	0.19	78.48
MEDIUM	*No Grant*	Total	317	5422	0.16	0.01	0.15	75.60
LARGE	*No Grant*	Total	318	5422	0.27	0.02	0.24	76.22
SMALL	*MEDIUM*	Total	321	317	0.10	0.02	0.57	52.91
SMALL	*LARGE*	Total	321	318	0.24	0.06	0.65	53.63
MEDIUM	*LARGE*	Total	317	318	0.17	0.06	0.60	46.81
No Grant	*SMALL*	Total	5422	321	0.22	0.19	0.95	7.60
No Grant	*MEDIUM*	Total	5422	317	0.16	0.14	0.95	6.80
No Grant	*LARGE*	Total	5422	318	0.27	0.21	0.96	15.63
MEDIUM	*SMALL*	Total	317	321	0.10	0.03	0.56	48.73
LARGE	*SMALL*	Total	318	321	0.24	0.06	0.64	55.53
LARGE	*MEDIUM*	Total	318	317	0.17	0.04	0.60	51.29
SMALL	*No Grant*	Random	321	317	0.32	0.08	0.49	54.23
MEDIUM	*No Grant*	Random	317	317	0.24	0.07	0.50	51.52
LARGE	*No Grant*	Random	318	317	0.34	0.13	0.50	43.74
No Grant	*SMALL*	Random	317	321	0.32	0.06	0.52	63.10
No Grant	*MEDIUM*	Random	317	317	0.24	0.04	0.50	60.56

No Grant	*LARGE*	Random	317	318	0.34	0.06	0.54	62.36

Table 4 – Regression Results of Effect of Subsidy on Private R&D Spending

Sample	Matched	Dep. Var.	First Diff.	SMALL	MEDIUM	*LARGE*	Obs.
Total	***No***	***Level***	***No***	1.835**	2.349**	3.935**	4192
				(0.230)	(0.194)	(0.192)	
Foreign	***No***	***Level***	***No***	2.754*	2.580**	4.376**	1294
				(1.371)	(0.595)	(0.411)	
Domestic	***No***	***Level***	***No***	1.880**	2.365**	3.728**	2898
				(0.209)	(0.188)	(0.206)	
Total	***No***	***Level***	***Yes***	0.237**	-0.018	-0.093	4192
				(0.084)	(0.081)	(0.084)	
Foreign	***No***	***Level***	***Yes***	-0.016	0.089	0.030	1294
				(0.349)	(0.194)	(0.135)	
Domestic	***No***	***Level***	***Yes***	0.240**	-0.051	-0.180	2898
				(0.086)	(0.089)	(0.108)	
Total	***Yes***	***Level***	***Yes***	0.266*	0.012	-0.125	828
				(0.092)	(0.097)	(0.092)	
Foreign	***Yes***	***Level***	***Yes***	-0.092	0.186	0.003	144
				(0.189)	(0.284)	(0.181)	
Domestic	***Yes***	***Level***	***Yes***	0.264**	-0.031	-0.204**	684

				(0.101)	(0.106)	(0.087	
Total	***Yes***	***Intensity***	***Yes***	0.717*	0.309	-1.438**	828
				(0.336)	(0.487)	(0.461	
Foreign	***Yes***	***Intensity***	***Yes***	-0.071	-0.342	-0.825	144
				(0.302)	(0.404)	(0.615	
Domestic	***Yes***	***Intensity***	***Yes***	0.726*	0.372	-1.763**	684
				(0.369)	(0.594)	(0.629	

Notes: (1) Standard errors in parentheses. (2) For the matched sample standard errors are generated via bootstrapping (500 replications). (3) ***, **, and * represent one, five, and ten per cent significance levels.

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