Grant Support and Exporting Activity: 
Evidence from Irish Manufacturing

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Abstract

This paper investigates whether government support can act to increase exporting activity. To this end we use a rich plant level data set for Irish manufacturing. Results show that grants, if sufficiently large, can act to increase the export intensity of firms that are already exporters, but we find no evidence that they can turn non-exporters into exporters.

Keywords: exporting, subsidies, matching, difference-in-differences

JEL classification: L2, H2, F2, O3

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Section I: Introduction

Most governments seem to take the view that exporting is a good thing, so that the more firms in the economy export, the better. In this regard it is not surprising that most governments seem to have taken some initiative over the last decade in encouraging firms to export. This may take the form of direct support encouraging firms to export. For example, Bernard and Jensen (2004) note that all fifty US states have offices to assist firms in selling goods and services abroad. Government support may also indirectly encourage exporting activity by supporting other aspects of firm behaviour, such as productivity, that will enable firms to compete better on the international market. Examples of such relevant support programmes include arguably subsidies such as for R&D, training, amongst others.¹

Despite the potential importance of government support programmes in ultimately encouraging firms to export, there are few empirical studies to have investigated this issue. One exception is the recent study on the determinants of exporting activity in the US by Bernard and Jensen (2004). Specifically, the authors examine the various possible determinants of the incidence to export using data for US manufacturing. Amongst these they investigate how export promotion expenditures at the state level have influenced the decision to export or not. Their findings, however, suggest little evidence of these encouraging participation on the global market in US manufacturing. Arguably, however, there may a number of reasons for their lack of support in this regard. Firstly,

¹ Well known examples include the Small Business Innovation Program in the US (Wallsten, 2000), R&D support available from the Office of the Chief Scientist (OCS) in Israel (Lach, 2002), the low interest loans
expenditure on export promotion measured at the state level may be masking firm specific differences in terms of access to the information on foreign markets that these expenditures may provide. Secondly, information on foreign markets per se may not be sufficient to ensure that firms can successfully compete on the international markets. More important may be that firms are productive enough to do so. In this regard it may be other types of support specifically encouraging productivity related aspects that could prove more effective. However, to date there have been, as far as we are aware, no study that has explicitly studied this indirect channel of government subsidies.

In this paper we explicitly investigate whether firm specific subsidies of all types can play a role in encouraging export activity. More specifically, we take advantage of the case of Irish manufacturing where an extensive and diverse grant support system has been used in an attempt to make indigenous industry more internationally competitive. In this regard we have access to plant level data including, amongst many other things, the total amount of output export for the period 1983-1998 and to an exhaustive database containing information on all grants provided by Irish authorities.

A crucial issue in estimating how government support may affect firm exporting activity is how to deal with the problem of what exporting activity would have been without government support. Ideally, the researcher would want to observe what would have happened to exporting activity in the firm if it had not received a subsidy. Clearly, however, this is unobservable; one can only

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provided by the Japan Development Bank (Beason and Weinstein, 1996), or the regional policy subsidies administered by NUTEK in Sweden (Bergström, 2000).
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. Thus, properly identifying the effects of public funding on exporting activity requires generating the appropriate counterfactual in order to deal with the possible selection bias.

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 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**

Industrial policy has arguably been an important component of the evolution of Irish manufacturing. Originally a sector based on more traditional activities, Irish manufacturing has evolved to become a highly modernised, technologically intensive sector that is justifiably known to be an important part

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2 This problem was pointed out as early as by Lichtenberg (1984).
3 Moreover, awareness of these criteria may mean that plants will self select themselves into the application process.
4 See Meyler and Strobl (2000) for a more detailed discussion.
of what is justifiably known as the ‘Celtic Tiger’. More generally, the approach taken by industrial policy makers in trying to modernise Irish manufacturing has been two-pronged – on the one hand encouraging foreign multinationals to locate in Ireland, while at the same time encouraging indigenous industry to develop. While employment creation was perhaps the more short-term goal post towards which Irish policymakers were geared, it is without doubt that the ultimate goal in achieving this and economic growth in general was to make, what was in the seventies still a declining sector, Irish indigenous industry international competitive.

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.5 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

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

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 Irish Economy Expenditure survey, collected from 1983 until 1998. 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 20 employee cut-off point. 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, and total and domestically purchased inputs. 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 be 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). Since foreign multinationals in Irish manufacturing used Ireland primarily as an exporting base, we focus here exclusively on indigenous plants.

Importantly, Forfás also has an exhaustive annual database on all grant payments that have been made to plants in Irish manufacturing since 1972. 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 IEE 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 20 employees.

Preliminary Empirics

To be completed....

Section IV: Econometric Methodology

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⁶ All nominal variables are appropriately deflated by the consumer price index.
The major problem in evaluating the effect of government grants on exporting 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. Blundell and Costa Dias (2000) argue that a combination of matching and difference-in-differences analysis may be a particularly suitable approach in an evaluation study such as ours and we thus 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. Arguably in the case of the effect of grant provision on exporting activity, 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 exporting activity. In this regard let there be \( K+1 \) different states, where these consist of \( K \) pre-specified categories of mutually exclusive grant amounts and the case of no grant receipt (\( k=0 \)). If we denote exporting by \( Y \), then the number of potential outcomes associated with each state for each plant \( i \) is \( Y_i^0, Y_i^1, \ldots, Y_i^K \). 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:

\[
E(Y_k - Y_{k'} | T=k) = E(Y_{k'} | T=k) - E(Y_{k'} | T=k) \text{ for } k, k' \in \{0, 1, \ldots, K\}, k \neq k'
\]  

(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:

\[
E(Y_{k'} | T=k) = E_X[E(Y_{k'} | T=k', X) | T=k]
\]  

(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 one 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:

\[
P(T_{it}=k | T_{it}=k, k') = F(X) \tag{3}
\]

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.\(^7\) More formally, for each grant type \(k\) receiving plant \(i\), a grant type \(k'\) plant \(j\) is selected such that for the predicted probability, \(P_{i_k}\), of receiving a \(k\) type grant at time \(t\) of grant recipient plant \(i\) and the predicted probability, \(P_{j_{k'}}\), of receiving a \(k\) type grant at time \(t\) for \(k'\) type grant recipient plant \(j\):

\[
\lambda > \left| P_{i_k} - P_{j_{k'}} \right| = \min_{j \in [k']} \{ | P_{i_k} - P_{j_{k'}} | \} \tag{4}
\]

\(^7\) The matching is performed in STATA Version 8 using the software provided by Sianesi (2001).
where $\lambda$ is a pre-specified scalar which defines the boundary for the neighborhood where matching is allowed. If none of the $k'$ grant type recipients plants is within $\lambda$ 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 $\Delta^t Y$ be the difference in exporting before and after receiving a grant of amount $k$, and difference this with respect to the before and after differences for all comparison control groups, say $\Delta Y^{k'=k}$. One then obtains the difference-in-differences estimator $\delta = \Delta Y^k - \Delta Y^{k'=k}$. In terms of practical implementation this amounts to estimating:

$$\Delta Y_{it} = \alpha + \delta \sum_{k} \Delta G_{it}^{k} + \varepsilon_{it}$$

where $\Delta$ 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 exporting activity 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 exporting remain.

Finally, one must consider the appropriate nature of the dependent variable $Y$. Feasibly grant support may induce already exporting plants to export more. Additionally it may also be the case that the loosening of financial constraints via subsidies could induce non-exporters to commence selling some of their output on the world market. In order to deal with both of these aspects we use alternatively two dependent variables. The first one is the incidence of exporting – a zero-dummy variable that takes on the value of one if the plant is exporting and zero otherwise. The second is the log of total exports for exporting incumbents.

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 exporting. 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 exports 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 22,947 Euros as small, between 22,947 and 87,769 Euros as medium, and those above 87,769 Euros as large (all measured in 1998 prices).

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 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 grant in the previous year in case there are links in payments across years.

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 \( \lambda \) equal to 0.1. In doing so, from a total amount of 6728 non-recipients, 1636 small grant recipient, 1639 medium grant recipient, and 1727 large grant recipient observations were able to match 2463, 1549, 1521, and 1495 observations, respectively. We assess the matching quality of this procedure using a variety of indicators shown in Table 1. For instance, as can be seen the pseudo R-squared of running the same probits with only the matched sample is multiple time lower in all cases except where non-grant receipt is used as the

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8 In our case, \( \lambda \) is set equal to 0.1. We also experimented with lower and higher values. Marginal changes (for example reducing or increasing \( \lambda \) by 0.05) seemed to make relatively little difference in terms of the matched sample. However, increasing \( \lambda \) 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.

9 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
treatment group. We also, as suggested by Rosenbaum and Rosin (1985), calculated the standardized bias of the propensity scores for our individual matching pairs as:

\[
SB = 100 \times \frac{\text{abs}(\bar{P} - \bar{P}_0)}{\sqrt{0.5 \times (V_1(P) + V_0(P))}}
\]

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 20 to 60 per cent. Thus, the matching quality indicators are clearly supportive of our underlying matching procedure.

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:

\[
Y = \alpha + \beta_5 \text{SMALL}_u + \beta_6 \text{MEDIUM}_u + \beta_7 \text{LARGE}_u + \epsilon_u
\]

where \( \text{SMALL} \), \( \text{MEDIUM} \), and \( \text{LARGE} \) are zero-one type dummies indicating whether a plant received a small, medium, or large sized subsidy, \( Y \) measures the logged value of the subsidy, and \( \epsilon \) is a random error term. One should note that \( \beta_i > 0 \) indicates additionality effects, \( \beta_i < 0 \) suggests crowding out effects, while a \( \beta_i \) not significantly different from zero implies neither of these for exporting 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 exporting intensity of already exporting firms.\textsuperscript{11} The resultant statistically significant coefficients, shown in the first row of Table 2, are negative for small grants but positive for medium and large grants. This would, somewhat peculiarly, suggest that grants seem to discourage exporting if they are small, but are effective in promoting further exporting activity in firms.

Clearly, there are many other factors that affect both grant receipt and the intensity of exporting among exporters, 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 2. As can be seen, this dramatically changes any conclusions drawn from the coefficients. For the overall sample one finds that there are now only significant effects for large grants recipients, thus indicating that perhaps a grant needs to be large enough to further help a plant compete on the international market.

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 export more and are also more likely to receive a grant. Although our matching procedure is intended to create samples of ‘similar’ plants across all relevant characteristics, including size, and

\textsuperscript{10} 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.
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 included employment as an explanatory variable in our regression. As can be
seen, reassuringly the results remain the same.

We then proceeded to investigate how government support may affect the
incidence of exporting. Using a simple probit one finds that, regardless of size
category, government subsidies encourage plants to export in Irish
manufacturing. Comparing the size of the coefficients suggests, however, that
while all sizes of grants may have a positive effect on plants exporting, the larger
the grant the more likely a firm will export. Again we examined whether time
invariant effects may be biasing our estimates by first differencing our data and
running OLS on our data. As can be seen, we now find that only small grants
encourage firms to export more. Again, this result is robust to including an
indicator of size.

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).12 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

11 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.
conclusions drawn. More precisely, while still only large grants have a positive
effect on the export intensity of exporting plants, the coefficient has more than
tripled, suggesting that not ensuring common support will tend to underestimate
the effect. In terms of export incidence we now find no effect of government
support, regardless of the size of the grant.

Section VI: Concluding Remarks

We investigated the relationship between government support and
exporting activity. 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 if grants are large enough they can encourage already exporting
firms to compete more effectively on the international market. However, there is
little evidence that grants encourage non-exporters to start exporting, or that the
withdrawal of grants will result in the withdrawal from the international market.

12 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.
References


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http://fmwww.bc.edu/RePEc/usug2001/psmatch.pdf
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Table 2 – Regression Results of Effect of Subsidy on Private R&D Spending

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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.