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Published on: 01 Feb 2008 - The Review of Economics and Statistics (MIT Press Journals)

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GRANT SUPPORT AND EXPORTING ACTIVITY

Holger Görg, Michael Henry, and Eric Strobl*

Abstract—This paper investigates whether government support can act to increase exporting activity. We use a uniquely rich data set on Irish manufacturing plants and employ an empirical strategy that combines a nonparametric 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 nonexporters to start exporting.

I. Introduction

MOST governments seem to take a positive view on exporting, so that the more firms in the economy that export, the better. In this regard it is not surprising that many governments have taken some initiative in encouraging firms to export. Despite the potential importance of using explicit policies to promote exporting activity, there are, however, few empirical studies that have investigated this issue. One exception is the recent study by Bernard and Jensen (2004) on the determinants of exporting activity in the United States which, among other things, investigates whether export promotion expenditures at the state level influence the decision of U.S. plants to export. Their findings suggest little evidence that such policies encourage participation in the global market by U.S. manufacturers.

Arguably, export promotion expenditures on their own may not have a significant effect on exporting. Firstly, expenditure on export promotion measured at the state level may be masking firm-specific differences in their ability to access information on foreign markets and, hence, heterogeneity in the ability to export. Secondly, information on foreign markets per se may not be sufficient to ensure that firms can successfully compete on the international markets. Even more important may be that firms are productive enough to do so. As the recent theoretical and empirical literature on firm-level export activity argues, selling abroad involves sunk costs, and it is only the "better" firms, that is, those that are more efficient or productive, that are able to overcome these entry barriers and export successfully (Clerides, Lach, & Tybout, 1998; Bernard & Jensen, 1999; Melitz, 2003). These findings perhaps highlight the fact that other types of government support specifically targeted at improving productivity-related aspects of the firms' operations, to assist them in overcoming barriers to exporting, could prove more effective. Examples of such relevant support programs arguably include subsidies, such as for R&D and training, among others.[1] However, to date there has been, as far as we are aware, no study that has explicitly investigated 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 manufacturing industries in the Republic of Ireland 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, among many other things, the total amount of output exported and an exhaustive database containing information on all grants provided by Irish authorities. It is important to note that these grants are not specifically designed to promote exporting but are related to encouraging investment in technology, training, or physical capital.

A crucial issue in estimating how government support may affect firm exporting activity is how to deal with the problem of what it 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 witness a funded firm's actual exports and not what it would have sold abroad without a subsidy. This leaves as a control group only those firms that were not subsidized. The use of nonrecipients 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

Received for publication November 30, 2005. Revision accepted for publication November 29, 2006.

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The authors are grateful to Forfás for the provision of the data and to an anonymous referee and participants at ETSG 2005 in Dublin for helpful comments. Financial support through the Leverhulme Trust (grant no. F114/BF) and the ESRC (grant no. RES-000-22-0468) is gratefully acknowledged.

[1] Well-known examples include the Small Business Innovation Program in the United States (Wallsten, 2000) or R&D support available from the Office of the Chief Scientist (OCS) in Israel (Lach, 2002).

will select recipients among the pool of candidates according to some selection criteria.[2]

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. A number of econometric approaches have been applied to deal with this issue, including instrumental variables techniques, selection models, difference-in-differences estimators, or propensity-score matching. In their survey of the various estimation methods that can be used for this type of evaluation in nonexperimental data, Blundell and Costa Dias (2000) conclude that a combination of the nonparametric propensity-score matching with the difference-in-differences estimator is likely to considerably improve the accuracy of an evaluation study. This is the technique we employ in this paper to investigate the impact of subsidies on plants' export performance.

The remainder of the paper is organized 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.

II. Grant Provision in Ireland[3]

Industrial policy has arguably been an important component of the evolution of Irish manufacturing. Originally based on more traditional activities, Irish manufacturing has evolved to become a highly modernized, technologically intensive sector that is an important part of the Irish economy. More generally, the approach taken by industrial policymakers in trying to modernize 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 toward which Irish policymakers were geared, the ultimate goal was to make indigenous Irish industry internationally competitive and to contribute to enhanced economic growth.

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.[4] The types of grants that have been available to firms include capital grants, training grants, R&D grants, rent subsidies, employment grants, feasibility study grants, technology acquisition grants, loan guarantees and interest subsidies.

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 summarized 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. To be eligible, the applicant generally has to show that the project requires 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 favorable view of projects that are more technology intensive and of a more entrepreneurial nature. The actual grant level is generally very project specific and subjected to a cost-benefit analysis. Moreover, total grant levels can generally not exceed certain capital cost thresholds, usually between 45% and 60%. Grants are usually paid in prespecified installments such that further payment is often subject to periodic reviews.

III. Data and Preliminary Empirics

A. Data

We utilize information from a number of data sources collected by Forfás, the policy and advisory board with responsibility for enterprise, trade, science, and technology in Ireland. Our first data source is the Irish Economy Expenditure (IEE) survey, collected from 1983 until 1998, which then became the Annual Business Survey (ABS) and to which we have access until 2002. This is an annual survey of Irish manufacturing plants with at least twenty employees, although a plant, once included, is generally still surveyed even if its employment level falls below this cutoff point.[5] The data available from this source that are relevant to the current paper are the level of output and exports, employment, wages, both total and domestically purchased inputs, nationality of ownership, and sector of production.[6]

One should note that Forfás defines foreign plants as plants that are majority owned by foreign shareholders, that is, where there is at least 50% foreign ownership. While, arguably, plants with a lower percentage of foreign ownership should still possibly be considered 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 & Bradley, 1997). Since foreign multinationals in Irish manufacturing used Ireland primarily as an export base, we only use data on indigenous plants in our subsequent analysis.

We also used data from the Forfás's R&D surveys undertaken in 1986, 1988, 1990, 1991, 1993, 1995, and 1997, and the innovation surveys 1990/1992 and 1994/1996, which provide information with regard to plants' R&D activity. These surveys are largely considered to be close to exhaustive of R&D undertaken by large plants in Irish manufacturing, such as those covered by the IEE, during the surveyed years. This information can be linked to the IEE via a unique plant identifier maintained by Forfás. Additionally, the ABS collected information on whether a plant incurred any R&D expenditures, which provides us with information on R&D activity of plants after 1998. We use these data sources to create a zero-one indicator of whether a plant

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

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

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

[5] To be precise, in the ABS (since 1999) the official threshold cutoff point was plants with at least ten employees. However, by 1998 there were a considerable number of plants in the IEE with fewer than twenty employees, and we thus did not drop these from either of the two sources. One should note that we did experiment with excluding observations from both that fell below twenty, but this made essentially no qualitative and quantitative difference in our results.

[6] All nominal variables are appropriately deflated by the consumer price index as there are no official sector-level price deflators available to us.

has any R&D expenditure in the years for which the information on R&D activity was available.[7]

We use the R&D variable as a proxy for whether a plant developed any new products. Bernard and Jensen (2004) show that U.S. plants switching into new products are significantly more likely to export than others. Their definition of a new product is based on firms' switching from one four-digit industry to another. Our argument is that R&D activity is a reasonable proxy for new products as it allows plants to diversify their goods. In this way, R&D activity could capture the introduction of new products both that involved industry changes and that did not. In contrast, using industry changes as a proxy for new products only captures the introduction of new goods that involved changes in industry of the main product of the firm.[8]

It is important of course to verify that R&D activity is indeed correlated with new product generation. In this regard some of the R&D surveys asked whether the R&D expenditure was used to develop new products.[9] The surveys indicate that nearly 93% of plants spent at least some of their R&D expenditure to develop new products. Of those that spent some positive money on R&D, on average 54% of the expenditure was for the development of new products. It thus seems reasonable to assume that R&D activity is at least strongly correlated with the introduction of new products.

Importantly for the question to be addressed in this paper, Forfás also has an exhaustive annual database on all grant payments that have been made to plants in Irish manufacturing since 1972. Again a unique numerical identifier allows us to link the grant information with the variables derived from the IEE, ABS, R&D, and innovation surveys. One should note that by linking information across data sources, our sample consists of plants of generally at least twenty employees for the years 1986–2002.[10]

B. *Preliminary Empirics*

In figure 1, we graph total exports and grant payments received by the plants in our sample for the years 1983–2002. As can be seen, both variables have on average increased substantially over the time period considered. Moreover, they seem to move in conjunction with each other. In fact, the raw correlation coefficient is 0.82 and statistically significant.

We also provide some summary statistics in table 1. In line with previous evidence for Ireland (for example, Ruane & Sutherland, 2005), we find that exporters are, on average, larger (in terms of employment) than plants that produce only for the domestic market. They also pay higher wages, import a larger share of their inputs from abroad, and have greater R&D incidence. Most importantly, the summary statistics show that exporters receive per unit of output nearly twice as much grant support.

FIGURE 1.—TRENDS IN EXPORTS AND GRANT PAYMENTS

Notes: Both series are in 2002 prices and millions of euros.

IV. Econometric Methodology

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. As stated earlier, 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.

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 utilize 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 prespecified 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 the "effect of treatment on the treated." More precisely, for $(K + 1)\ K$ pairwise 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

$$\begin{aligned} E(Y^k - Y^{k'} | T = k) &= E(Y^k | T = k) \\ &\quad - E(Y^{k'} | T = k) \text{ for } k, k' \in \{0, 1, \ldots K\}, k \neq k'. \end{aligned} \tag{1}$$

One should note that 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

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

[7] Unfortunately not all surveys have information on the actual expenditure figures.

[8] Unfortunately Forfás does not keep track of industry changes of plants; rather, plants remain classified by industry as they are first tracked in the data. However, the view of Forfás is that in Ireland very few plants would change industries in terms of their main products. Part of the reason for this may be that because of the structural changes in Irish manufacturing since E.U. entry in 1973, most new plants were entering industries relatively new to Ireland.

[9] This question was posed in the 1986, 1990, 1991, 1995, and 1997 surveys.

[10] Obviously years during this sample period where there was missing information from the R&D and innovation surveys had to be dropped. Since we used this information as lagged controls in our matching, this meant dropping observations for the years 1986, 1988, 1990, and 1999.

TABLE 1.—SUMMARY STATISTICS BY EXPORTING STATUS

TYPE:	EXPORTER		NONEXPORTER	
	Mean	*St. Dev.*	Mean	*St. Dev.*
WAGE	23.52	*16.77*	22.72	*13.52*
DOM. INPUTS	0.55	*0.29*	0.60	*0.32*
GRANT/SALES	18.34	*383.77*	6.76	*52.24*
RD INCIDENCE	0.379	—	0.341	—
EMPLOYMENT	95.00	*208.51*	60.46	*133.76*

for some set of observable characteristics X. There are two important aspects to note with regard to equation (2). First, in order for the inner expectation of equation (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 (PSM) estimator 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 nontreated 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 pairwise 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 with grant amount type k' receipt (or propensity score) conditional on a set of observables $\boldsymbol{X}$ 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.[11] 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 grant at time t of grant recipient plant i and the predicted probability, P_{jt}, of receiving a k type grant at time t for k' type grant recipient plant j:

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

[11] The matching is performed in Stata version 8 using the software provided by Sianesi (2001).

where λ is a prespecified scalar that defines the boundary for the neighborhood 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 (DID) estimator, which compares the change in the outcome variable for the k treated groups with the change in the outcome variable for all non-k type grant amount recipients, and thus can purge further time-invariant effects from the specification. Accordingly, let ΔY^k 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 $\Delta Y^{k' \neq k}$. 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

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

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 if these are time varying. 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 nonsuccessful 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 are 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. First, 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 nonexporters to commence selling some of their output on the world market (for example, Du & Girma, 2007, Greenaway, Guariglia, & Kneller, 2005). To deal with both of these aspects, we use alternatively two dependent variables. The first one is the incidence of exporting—a zero-one dummy variable that takes on the value of 1 if the plant is exporting and 0 otherwise. The second is the log of total exports for exporting incumbents.

V. Empirical Results

A. *Propensity-Score Matching Results*

Importantly, our information on grant receipt provides us with the actual amount of each grant and thus allows us to examine the impact

TABLE 2.—INDICATORS OF MATCHING QUALITY

Treat.	Control	Sample	Treat. Obs.	Control Obs.	Pseudo R^2 Before	Pseudo R^2 After	BiasRed. (%)
SMALL	*No Grant*	Total	1,229	997	0.146	0.013	0.914
MEDIUM	*No Grant*	Total	1,209	997	0.208	0.019	0.908
LARGE	*No Grant*	Total	1,247	997	0.267	0.028	0.896
SMALL	*MEDIUM*	Total	1,229	1,209	0.040	0.018	0.546
SMALL	*LARGE*	Total	1,229	1,247	0.111	0.042	0.622
MEDIUM	*LARGE*	Total	1,209	1,247	0.059	0.019	0.683
No Grant	*SMALL*	Total	997	1,229	0.146	0.096	0.341
No Grant	*MEDIUM*	Total	997	1,209	0.208	0.133	0.362
No Grant	*LARGE*	Total	997	1,247	0.267	0.162	0.394
MEDIUM	*SMALL*	Total	1,209	1,229	0.040	0.013	0.668
LARGE	*SMALL*	Total	1,247	1,229	0.111	0.027	0.759
LARGE	*MEDIUM*	Total	1,247	1,209	0.059	0.020	0.658

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 predefined 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 infeasible 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 clearly grounded a priori expectations of what "threshold amounts" would be reasonable.

With these aspects in mind and after considerable experimentation, we proceeded with using three different grant size categories, which for the sake of convenience we termed small, medium, and large, and defined respectively as the amounts that fall below the 33.3 percentile, within the 33.3 to 66.6 percentile, and above the 66.6 percentile of the entire distribution of subsidies over the full sample period. Therefore, we are slicing the entire distribution of grants into three equally probable groups. In terms of actual amounts, this corresponds 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 authorities may take into account when deciding on handouts of grants as discussed above in section II. As noted, Irish policymakers were 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 provide, we identified the following plant-level characteristics that may be important in this regard: size (employment), domestic input use (domestically purchased intermediates over total intermediates), new product development (dummy equals 1 if positive R&D expenditure), average wage, domestic ownership, age, and a dummy for previous export activity. We use lagged values of these variables to ensure that 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.[12] In doing so, from a total amount of 6,728 nonrecipient, 1,636 small-grant recipient, 1,639 medium-grant recipient, and 1,727 large-grant recipient observations we were able to match 2,463, 1,549, 1,521, and 1,495 observations, respectively. We assess the matching quality of this procedure using a variety of indicators shown in table 2. For instance, as can be seen, the pseudo R-squared of running the same probits with only the matched sample is multiple times lower in all cases except where nongrant receipt is used as the treatment group. We also, as suggested by Rosenbaum and Rubin (1985), calculated the standardized bias of the propensity scores for our individual matching pairs as

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

where P is the propensity score, $\bar{P}$ represents its average, and V its variance. One finds from the resulting figures in table 2 that the bias reduction is considerable, ranging anywhere from 35% to 90%. Thus, the matching quality indicators are clearly supportive of our underlying matching procedure.

B. *Econometric Results on the Treatment Effect*

To estimate the effect of grant provision on exporting, we started with the benchmark specification:

$$Y_{it} = \alpha + \beta_S SMALL_{it} + \beta_M MEDIUM_{it} + \beta_L LARGE_{it} + \varepsilon_{it}, \tag{7}$$

where *SMALL, MEDIUM,* and *LARGE* are zero-one type dummies indicating whether a plant received a small, medium, or large subsidy, and ε is a random-error term. The dependent variable is defined alternatively as the log of total exports or incidence of exporting (dummy = 1 if plant exports).[13]

We first estimate equation (7) with the log level of exports as dependent variable using the total sample (unmatched) with simple OLS. This is thus the benchmark case of the effect of government subsidies on exporting intensity of already exporting firms.[14] The

[12] We use a value of λ equal to 0.1.

[13] We use the logged value in order to take account of outliers. To avoid the dropping of observations where exporting was zero, we set expenditure in levels equal to one euro for these.

[14] 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 equation (7) in order to keep our sample size consistent across unmatched estimation types.

TABLE 3.—REGRESSION RESULTS OF EFFECT OF SUBSIDY ON EXPORTING ACTIVITY

Matched	Dep. Var.	First-Diff.	*SMALL*	*MEDIUM*	*LARGE*	EMPLOYMENT	Obs.
			−0.246**	0.154*	1.118**		
No	*Level*	*No*	(0.073)	(0.070)	(0.066)		5,931
			0.006	0.001	0.046*		
No	*Level*	*Yes*	(0.017)	(0.017)	(0.018)		5,931
			0.418**	0.641**	1.032**		
No	*Incidence*	*No*	(0.049)	(0.052)	(0.063)		8,749
			0.005	0.005	−0.003		
No	*Incidence*	*Yes*	(0.006)	(0.007)	(0.007)		8,749
			−0.002	−0.009	0.054**		
Yes	*Level*	*Yes*	(0.019)	(0.019)	(0.017)		3,757
			−0.001	−0.010	0.048**	0.084**	
Yes	*Level*	*Yes*	(0.018)	(0.018)	(0.017)	(0.009)	3,757
			0.007	0.010	0.002		
Yes	*Incidence*	*Yes*	(0.006)	(0.006)	(0.006)		4,329
			0.007	0.009	0.002	0.0001**	
Yes	*Incidence*	*Yes*	(0.006)	(0.006)	(0.006)	(0.0000)	4,329

Notes: (1) Standard errors are in parentheses. (2) For the matched sample, standard errors are generated via bootstrapping (500 replications). (3) ** and * represent 1% and 5% significance levels, respectively.

resultant statistically significant coefficients, shown in the first row of table 3, 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 if they are medium or large.

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 second row of table 3. As can be seen, this dramatically changes any conclusions drawn from the coefficients obtained from our initial estimation. For the overall sample one finds that there are now only significant effects for large-grant recipients, thus indicating that perhaps a grant needs to be large enough to further help a plant compete on the international market.

We then proceed to investigating how government support may affect the incidence of exporting (rows 3–4). Using a simple probit model 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' incidence of 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 then running OLS. However, we now find no statistically significant evidence that grants encourage firms to become exporters.

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 to estimate a first-differenced version of equation (7).[15] 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 still only large grants have a positive effect on the export intensity of exporting plants, the magnitude of the coefficient is substantially lower than in the OLS estimation in row 1, suggesting that not ensuring common support tends to overestimate the effect in our case. In terms of export incidence we now find no effect of government support, regardless of the size of the grant. Clearly, thus, our results suggest that a multiple-treatment matching framework can potentially avoid considerable bias due to sample selection.

One possible concern with the matching estimator may be, given that it is based on a multidimensionality of firm characteristics, that our results are driven by the possibility that larger plants export more and are also more likely to receive a grant. As a matter of fact, Bernard and Jensen (2004) show that employment is an important determinant of the propensity to export, while Barrios, Görg, and Strobl (2003) find a similar result in terms of the impact on export intensity. Although our matching procedure is intended to create samples of "similar" plants across all relevant characteristics—including size, which we measure by employment—the use of the summary score in the face of multidimensionality of characteristics may feasibly result in less than perfect matching in this regard. To investigate this, we therefore also include employment as an explanatory variable in our regression. As can be seen, reassuringly the results remain the same.

[15] 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 procedure further complicates the calculation of the actual estimation variance.

VI. Concluding Remarks

We investigated the relationship between government support and exporting activity. To this end, we used a uniquely rich data set on Irish manufacturing plants and employed an empirical strategy that combined a nonparametric matching procedure with a difference-in-differences estimator in order to deal with the potential selection problem inherent in such an 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 nonexporters to start exporting.

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DECOMPOSING PRODUCTIVITY GROWTH IN THE U.S. COMPUTER INDUSTRY

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Abstract—In this paper, we examine the sources of the productivity growth in the U.S. computer industry from 1978 to 1999. We estimate a joint production model of output quantity and quality that distinguishes two types of technological changes: process and product innovations. Based on the estimation results, we decompose total factor productivity (TFP) growth rate into the contributions of process and product innovations and scale economies. We find that product innovation associated with better quality accounts for about 30% of the TFP growth in the computer industry. Furthermore, the TFP acceleration in the computer industry in the late 1990s is mainly derived from a rapid increase in product innovation.

I. Introduction

DURING the last few decades, there has been a remarkable productivity growth in the production of information technology (IT) products such as computers, communications equipment, and semiconductors. A typical measure of productivity is total factor productivity (TFP), defined as the amount of output produced from a given amount of input. Hence, the traditional TFP approach mainly focuses on how much productivity growth is caused by the improvement in the technological efficiency of production process (process innovation).

In contrast to process innovation, productivity growth can take place in the improvement of output quality (product innovation). In particular, improvement in output quality, such as in microprocessor speed and the capacity of storage devices and memory, is one of the most prevailing characteristics in IT production. This suggests that technological innovation associated with better quality can be an important source of the TFP growth in the IT-producing industry. As Hulten (2001) pointed out, however, the TFP approach is silent about product innovation.[1] Therefore, the identification of both process and product innovations is crucial to the exploration of the sources of productivity growth in the IT-producing industry.

In this paper, we examine the sources of the productivity growth in the U.S. computer industry from 1978 to 1999. The novelty of this paper is that we separate two different technical changes in TFP growth: product innovation associated with better quality and process innovation associated with more quantity. Using both the hedonic (quality-adjusted) and list (quality-unadjusted) prices, we construct the variables of output quantity and quality. Then, we formulate the

Received for publication March 7, 2003. Revision accepted for publication November 29, 2006.

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We are especially grateful to Daron Acemoglu (the editor) and two anonymous referees for very helpful comments and insights. We also thank Diego Comin, Boyan Jovanovic, and Edward Wolff for their suggestions and Steve Rosenthal for providing the data used in this paper. The financial support of the C.V. Starr Center for Applied Economics at New York University and the PSC-CUNY at the City University of New York is also gratefully acknowledged.

[1] Although some recent studies by Jorgenson and Stiroh (2000), Oliner and Sichel (2000), and Whelan (2002) have attempted to measure the TFP growth in the IT-producing industry, there have been few studies that distinguish the contributions of process and product innovations in the productivity growth in this industry.

The Review of Economics and Statistics, February 2008, 90(1): 174–180