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The effect of grant receipt on start-up size: Evidence from plant level data*

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Abstract:
In this paper we use plant level data on the start-up size of new plant entries and detailed information on the grants received by such plants in order to investigate whether grant receipt encourages plants to start-up with more employment than without support. The data relate to manufacturing plants in the Republic of Ireland, where industrial policy has a long history of using discretionary grants to encourage employment growth. We use a matching procedure to deal with the issue of selectivity into grant receipt, and a quantile regression estimator to allow for different effects of grants on plants depending on their position in the start-up size distribution. Our results provide evidence that grants do indeed encourage plants to start-up larger. We also find that this effect is generally higher for foreign than for domestic plants, and that it differs for plants at different quantiles of the start-up size distribution.

Keywords: grants, subsidies, entry, start-up size

JEL classification: H2, L2

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Section I: Introduction

The entrepreneurship literature has long recognized two stylized facts: Firstly, start-up firms have an unequal chance of getting adequate finance at their inception due to imperfections in the capital markets favouring large established firms which are viewed as generally financially transparent (Stiglitz and Weiss, 1981; Greenwald et al., 1984). Secondly, it is widely seen that the employment growth rates of young firms is higher than that of mature firms (Dunne et al., 1989; Evans, 1987). Coupled with the higher employment rates evidenced for small firms spawned by start-ups, is the fact that small firms account for the vast majority of employment, not necessarily output, in an economy i.e. around 77 percent in Germany, nearly 90 percent in the UK (Grahl and Teague, 2004; CBI, 2000) And if start-ups do manage to surmount initial financing obstacles and survive, the employment generated by start-ups is often in areas of industry of interest to policy makers (industries deploying new and advanced technologies)

Herein is the dilemma: One the hand the recognition that capital markets frequently fail start-ups and on the other hand the recognition that supporting start-ups is important for employment generation and the skilling/output composition of industry. This dilemma strongly underpins Government intervention in the capitalization of start-ups. Analogously, the intuition of market failure in the capital markets coupled with the need to promote firms which generate high externalities (employment creation, worker skilling, strong innovation potential) underpins the intuition behind much Government support for industry in general. Subsidizing manufacturing firms is a commonly used policy tool in the OECD; see OECD (1998). Prominent examples are the low interest loans of the *Japan Development Bank* (Beason and Weinstein, 1996), the *Small Business Innovation Program* in the US (Wallsten, 2000), and the *Enterprise Initiative* or *Regional Selective Assistance* in the UK (Wren and Storey, 2002, Harris and Robinson, 2004).

But does Government subsidization of start-ups result in genuine employment growth? This is a notoriously tricky question because in answering this, researchers have to set up an appropriate counter-factual: What would have happened employment in the start-up had it not been subsidized by Government? In sum, grants must offer additionality (and not result in deadweight) if policy makers are to justify subsidizing small firms. In relation to deadweight, Storey (1994) points out that grants are justifiable if they "induce changes which would not have occurred otherwise" (p.286).

Given the complexity for researchers in constructing an appropriate counter-factual, this question remains largely unanswered in the entrepreneurship literature. Certain studies evaluate policy programmes but do not systematically apply matching (Maung and Erens, 1991; Cowling and Clay, 1995). More recently, efforts have been made to address this question through matching. Lerner (1999) in his evaluation of the SBIR (Small Business Innovation Research) programme manually matches firms receiving a grant with non-recipients on industry and size characteristics. He concludes that the subsidy performs an important signalling effect to external providers of venture capital, allowing recipients to leverage funding from external investors in subsequent financing rounds. Importantly, recipients demonstrate higher growth rates than non-recipients. Almus and Czarnitzki (2003) apply a non-parametric matching approach to evaluate whether a Government programme to stimulate R&D in East German firms generated real innovation growth. The reveal that the recipients increased their innovation activities by circa 4 percent compared to firms in the control group.

Neither Lerner (1999) nor Almus and Czarnitzki (2003) look at employment growth in start-ups however. Both studies evaluate subsidies aimed at stimulating innovation, not employment growth. However, employment growth is a key aspiration of most policy makers, the entrepreneurship literature being replete with reference to how small, young firms represent an important driver of employment growth. Indeed, neither existing study focuses specifically on firm start-ups and yet firms are arguably most vulnerable at their inception. This is when information asymmetry is highest, transparency lowest and capital constraints bite most. Lack of funding may then ultimately result in such plants beginning to operate at less than efficient scale, hence justifying government intervention.[1] For example, examining the evolution of size of firms over their life cycle, Cabral and Mata (2003) provide evidence that financial constraints keep firms from reaching their optimal size in the earlier part of their life cycle. Specifically, in relation to small and young firms, the extent to which they are handicapped by capital constraints is largely sector specific (Agarwal and Audretsch, 2001). This is the gap in the literature that our paper sets out to fill: what is the real effect of a Government employment subsidy to start-ups on employment growth? In evaluating the employment generating efficacy of the firms start up grant programme, similar to Almus and Czarnitzki (2003), we exploit advances in statistical methodology and computing software which have made it easier to evaluate Government programmes with a higher degree of validity, i.e., to avoid the possibility of attributing employment growth to grants that would have incurred regardless of the grant receipt.

In this paper we address this issue by examining the effect of public funding provided to start-ups in the Republic of Ireland. Specifically, we use exhaustive data for Irish manufacturing plants covering all start-ups and the financial assistance they received since the early 1970s to examine whether government support has affected their scale of operation over and above the size they would have chosen if they had not received assistance.[2] Ireland is arguably a particularly suited case study for this task, as Irish industrial policy has had a long history of using

[1] Another important effect of such financial constraints may be that potentially viable businesses do not start up at all. Since the data used in this paper only covers plants that began to operate, addressing this issue is beyond the scope of the current paper.

[2] Previous analyses of similar government assistance scheme generally focus on effects of assistance on plant survival, growth and productivity. See, for example, Girma et al. (2007a,b) for the Irish case as well as Harris and Robinson (2004) and Wren and Storey (2002) for evaluations of the British Regional Selective Assistance scheme.

discretionary grants to encourage employment creation, growth and productivity of firms. For example, since the early 1970s the Irish government has spent nearly 200,000 Euros on average for each new business locating in Ireland.[3]

There are a number of important features of our analysis. Firstly, we measure the scale of production of a start-up by its level of employment. While this is in part dictated by our data, one should note that an important goal of Irish policy makers in terms of handing out grants has been job generation; see Meyler and Strobl (2000). Secondly, given the importance of FDI in the Irish economy, we make a point of examining the difference in the effect of subsidization of domestic compared to foreign plants. Arguably, the effect of grants on foreign multinationals locating in Ireland is different than indigenous entrepreneurs starting up a new business. For one, foreign plants, being part of a greater multinational operation, are less likely to be financially constrained. Also, they are less likely to be completely new start ups but rather affiliates of already established multinationals. Nevertheless, grants may still provide incentives for multinationals to operate at a larger scale, ceteris paribus, if it encourages them to locate some of their operation that could be undertaken elsewhere, in the host economy of the grant provider. Thirdly, we examine the effect of subsidization on the scale of operation across different points along the distribution of plants using quantile regression techniques. The intuition here is that one might expect funding to affect larger plants differently than smaller ones. Finally, our analysis addresses the fundamental question in such studies as ours in terms of the missing 'counterfactual'. By this we mean what would have happened to a plant if it had not received the grant. However, we cannot observe in the data what would have happened grant recipients had they not received the grant. We tackle this problem using a matching approach, where we

[3] Authors' own calculation from the data set described in the paper in 1998 prices. Note that this includes payments made to firms before and inclusive of their year of start-up, i.e., their first year of positive employment.

construct a control group based on non-grant receiving firms that are very similar in terms of observable characteristics to grant recipients.

The paper is organized as follows. In the following section we outline the mechanics of grant provision in Ireland. Section III describes our data and provides some summary statistics. The empirical specification and the econometric approaches used to estimate this are outlined in Section IV. We provide the results of employing these on our data set in Section V. Concluding remarks are provided in the final section.

Section II: Grant Provision in Ireland

Grants for industrial development were first offered in Ireland under the Underdeveloped Areas Act of 1952, which was enacted to assist the provision of an alternative source of employment to replace declining agricultural employment in rural sectors. Specifically, this involved providing cash grants of up to 50 per cent of the cost of machinery and equipment and up to 100 per cent of the cost of land and buildings and for the training of workers in certain underdeveloped areas.[4] In the late 1950s, however, there was an erosion of the regional emphasis in favour of a more nationally oriented approach based on export-led growth. Subsequently the Anglo-Irish Free Trade Agreement was signed in 1965, which paved way for Ireland's eventual membership of the EEC in 1973. This, in conjunction with the already existent export tax relief, made Ireland an attractive location for multinationals. At the same time the industrial grant system was expanded, increasingly trying to develop the virtually non-existent

[4] See Meyler and Strobl (2000) for details.

technology intensive sectors.[5] The essence of this industrial strategy has remained an integral part of Irish industrial policy until today.

The agency primarily responsible for the provision of grant assistance in manufacturing in the modern era was the Industrial Development Agency (IDA) until 1994,[6] 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 resides over assisting indigenous plants.[7] The conditions under which projects should be eligible for grants are set forth under Section 21 of the 1986 Industrial Development Act. Specifically projects are eligible in manufacturing industries if they

1. will produce products for sale primarily on world markets, in particular those products which will result in the development or utilisation of local materials, agricultural products or other natural resources; or
2. will produce products of an advanced technological nature for supply to internationally trading or skilled sub-supply firms within the State; or
3. will produce products for sectors of the Irish market which are subject to international competition

The project applicant must, however, show that:

1. financial assistance is necessary to ensure the establishment or development of the undertaking;
2. the investment proposed is commercially viable;
3. it has an adequate equity base;

[5] While regional concerns still dominated in the 1970s, by the early 1980s a strategic industry approach, encouraging the attraction of multinationals and the development of an indigenous sector in technology intensive sectors became the primary concern. Nevertheless regions always remained of at least some concern.
[6] In the very early years, grant provision was under the authority of the Underdeveloped Areas Board before this responsibility was taken over by the IDA.
[7] After 1998 Forbairt become Enterprise Ireland as a consequence of a merger with the Irish Trade board.

4. it has prepared a suitable company development plan; and
5. it will provide new employment or maintain employment in the State that would not be maintained without assistance given under this Act and increase output and value added within the economy

This last point emphasizes that an important aspect of financial assistance in Ireland has been and continues to be employment generation. In the earlier days of financial assistance, i.e., until about the mid 1980s, this resulted in some cases in setting explicit job creation targets for certain regions and putting pressure by organizational officials to meet these. While the emphasis in terms of job creation has shifted from regional location of jobs to a more "strategic" sectoral location of jobs it is important to stress that job creation has always been a major policy goal (see Meyler and Strobl, 2000). Additionally, until today large proposed job gains due to projects are generally widely publicized in the Irish media. Moreover, at the project level in practice grant levels were often determined at least in part with view to how many jobs the proposed project would create. As a matter of fact, in many cases specific job creation targets were attached to a specific project and agreed upon by both the grant provider and the applicant. However, even when employment creation targets were not explicitly stated as a condition for grant receipt, they are likely to have been a consideration in the formulation of the grants package. For example, Honohan (1998) notes that "…even when the statutory ceiling on grants is expressed in terms of a fraction of fixed capital investment, it is clear that this ceiling tends to be reached only for job rich projects".

The actual grant level is generally very project specific and subjected to a rudimentary 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. The range of grants that have been available to firms include capital grants, research and development grants, rent subsidies, employment maintenance grants, feasibility study grants, technology acquisition grants, loan guarantees and interest subsidies, and training grants. One should note that in its rudimentary features, i.e., providing subsidies to start-ups conditional on creating jobs, this grant program remained consistent over the sample period of our analysis, namely from the early 1970s until the turn of the century.

Section III: Data

For the empirical analysis in this paper we utilise information from two data sources collected by Forfás, the Irish policy and advisory board with responsibility for industrial policy development, and co-ordination for state bodies including IDA Ireland. The first is the Forfás employment survey which is an annual plant level survey, conducted since 1972, with information on the nationality of ownership, sector of production, the start-up year, and the level of full time employment each year. The response rate to this survey is reported by Forfás to be essentially 100 per cent so that the data can be seen to cover the entire population of manufacturing plants. One should also 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.[8]

Each plant is identified with a unique plant level number by Forfás. A plant is considered to be a `start up' in the first year of a new plant identifier showing up in the data with positive employment.[9] Given the exhaustive nature of our data we are confident that start ups are indeed

[8] 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).

[9] For plants where the first year of employment does not fall within our sample period frame we use information on the start-up year to determine the length of its existence.

new plants. Relocations of a plant within Ireland can be identified as such within the data and are not considered start ups. The same goes for a simple change in ownership of an already existing plant. Entry by foreign firms during the study period has been mainly by means of greenfield investment rather than acquisition of local firms (see Barry and Bradley, 1997).

Forfás also has an exhaustive annual database on all grant payments made to plants in Irish manufacturing since 1972. Specifically, there is information on the level of and the year of payment. In terms of using this data set with the employment data, the unique numerical plant identifier, allows one to link information across plants and years. Both data sets together allow us to examine a sample period stretching from 1972 to 2000. When considering grants received for start-up, we use all actual payments received up until and including the year of start-up.[10]

Some discussion is appropriate regarding the accuracy of our measure of start-up size, which is just full-time employment in the year of start-up. In this regard one may want to note that the survey is carried out for all plants at the same point in time. Thus, for some plants employment may refer to employment on the first day of start-up, while for others it may capture employment size for up to 364 days after start-up. Unfortunately our data set does not allow us to take account of this and we must thus assume that any measurement error with regard to the actual size at start-up is uncorrelated with respect to the effect of grant receipt.[11]

All in all our data set covers 11,475 start-ups from 1972 to 2000, with average employment at start-up of 10 employees. Of these (34 per cent) received financial assistance prior and during the first year of start-up. Payments to recipients were on average 553,286 Euros

[10] Grants are generally given before start-up and not afterwards as we were assured in discussions with Forfás.

[11] We did also experiment with using employment in the second year as an indicator of size and results were not always similar to the results for first year employment in the sense that many previously significant coefficients on our grant measures were no longer significant. However, two aspects speak against this alternative measure. Firstly, nearly ten per cent of total start-ups had already closed down by the second year and thus needed to be dropped from the sample. Secondly, also many of our other explanatory variables were also no longer significant, suggesting that employment in the second year was not related to determinants of the actual start-up year.

(in 1998 prices), which, if readjusted by recipients' average size (10 employees), translates into 55,329 Euros spent per new job. A total of 1,383 (12 per cent) of all start-ups were foreign.

We graph kernel density estimates of the distribution of start-up size of grant-recipient and non-recipient plants for indigenous and foreign plants in Figure 1. As can be seen, the size distribution of non-recipients is slightly more skewed to the right. As a matter of fact, average size of grant recipients is 11. This compares with, on average, 9 employees hired by non-recipient start-ups. Nevertheless, these differences are marginal, and a Kolmogorov-Smirnov test for equality of the distribution functions can reject equality of these groups only at the ten per cent level.

[Figure 1 here]

Section IV: Econometric Methodology

Empirical Specification

In order to examine whether the receipt of government grants had any impact on the choice of start-up size we estimate an empirical model of the determinants of plants' start up size. Following Mata and Machado (1996) and Görg and Strobl (2001), we postulate the following relationship between the start-up size (measured in terms of log employment) of entrant *i*, E_{it}, that enters over the period *t* to *t*+1, and a set of covariates,

$$Eit = \beta_0 + \beta_1 GRANT_{it} + \beta_1 FOR_{it} + \beta_1 MES_{it} + \beta_1 SUBOPT_{it} + \beta_1 INDS_{it} + \beta_1 TUR_{it} + \beta_1 INDGR_{it} + \beta_1 HERF_{it} + \beta_1 FSH_{it} + \beta_1 D_t + \varepsilon_i$$

where *GRANT* is a measure of plant *i*'s grant receipts prior to setting up. It is our main variable of interest and we alternatively define it as a zero / one dummy as an indicator of whether or not a plant received a grant, or in log level to examine whether there are differential effects of grant amounts.[12] *FOR* is an indicator variable equal to one if the plant is owned by a foreign multinational. We control for the nationality of the plant as it is well established that foreign-owned plants are generally larger than their domestic counterparts, see for example, Girma et al. (2001) for the UK and Ruane and Görg (1996) for Ireland.

The other explanatory includes a number of industry characteristics that Mata and Machado (1996) and Görg and Strobl (2001) postulate to be important for a plant's choice of start-up size:[13] MES_{jt} represents the minimum efficient scale in industry *j*, $SUBOPT_{jt}$ is the percentage of employment in plants with less than MES (i.e., operating at suboptimal scale), $INDS_{jt}$ is the industry size, TUR_{jt} denotes turbulence in industry *j*, $INDGR_{jt}$ denotes the growth rate of industry *j*, $HERF_{jt}$ is a proxy for local industry concentration measured as the Herfindahl index and FSH_{jt}, measures the presence of foreign direct investment within a sector. The definition of these variables and the justification for their inclusion is as follows:

- MES_{jt} is measured as the log of median employment size as suggested by Sutton (1991). It seems reasonable to assume that, the higher MES in an industry, the larger, on average, will be new start-ups in order to be able to compete effectively in the market. We would, hence, expect a positive relationship between the size of entrants and the MES.
- $SUBOPT_{jt}$ is a measure of the proportion of employment in plants operating at less than minimum efficient scale, i.e., at less than median employment size. These are plants operating at suboptimal scale. This variable provides an indirect measure of the cost disadvantage in the industry. All other things equal, the larger the proportion of plants

[12] More accurately, the level variable is defined as the natural log of the amount plus one in order to allow for zero grant receipts.
[13] The manufacturing sector is broken down into twelve sub-sectors: Non-Metallic Minerals; Chemicals; Metals & Engineering; Food; Drink & Tobacco; Clothing & Footwear; Textiles; Wood Products; Paper Products & Printing; Peat and other Mineral Extraction; and Other Manufacturing.

operating at suboptimal scale, the lower seems to be the cost disadvantage to such plants and, hence, the lower may be the start-up size a new entrant will choose.

- The size of the industry, $INDS_{jt}$, is measured as the log of total employment in the industry. The rationale for including this variable is that, the larger the industry (for a given MES), the larger will be the size of new entrants, as the probability of retaliation from incumbents is lower in a large than in a small market.
- TUR_{jt} is measured as the product of employment shares in plants that enter or exit industry j from t-1 to t.[14] Turbulence provides us with an indirect measure of sunk costs, as a large extent of simultaneous entry and exit in an industry can be taken as evidence of low sunk costs. Assuming that entrants are risk averse, one may expect that, the lower are sunk costs, the higher will be the start-up size of new entrants as the losses associated with a possible failure are lower.
- The growth rate of the industry, $INDGR_{jt}$ is calculated as the difference, in natural logs, between industry size in subsequent years. In a fast growing industry, the probability of a plant surviving is higher than in a slow growing (or declining) industry as incumbents may be less likely to retaliate in a fast growing market. This implies that entrants may choose to enter at a larger size in fast growing markets, due to the higher probability of survival.
- The Herfindahl index, *HERF*, calculated in terms of employment at the county level, is included to control for the effect of local industry concentration on start-up size choice. More specifically, it is defined as the within sector sum of the squared value of the share of employment of all plants within an industry. In particular, Holmes and Stevens (2002)

[14] Even though Beesley and Hamilton (1984) originally proposed to measure turbulence as the sum of entry and exit in an industry, Mata and Machado (1996) suggest to measure turbulence as the product of entry and exit as the product will only take on high values if entry and exit are both important.

show that a positive relationship exists between local industry concentration and establishment scale.

- Finally, FSH_{jt}, is defined the proportion of industry employment in foreign multinational companies. Görg and Strobl (2001) argue and provide evidence that a high presence of multinationals in an industry leads to a reduction in plant start-up size, due to competition effects.

Finally, D_t is a set of time dummies intended to control for year specific effects that take on a value of one in the specific year and zero otherwise. ε_{it} is a white noise error term that captures the unexplained components firm start up size.

Summary statistics of all our variables calculated from our data set are given for the total sample, the grant recipients, and the non-recipients in Table 1. One may want to notice from these that grant recipients tend on average to be larger than non-recipients, although the standard deviations indicate there is considerable variation even within these groups.

[Table 1 here]

Estimation Issues

The estimation of equation (1) inherently raises the problem of sample selection bias. More specifically, financial assistance is likely to be endogenous to the employment decision. First, certain firms may be more likely to receive a grant or a greater grant amount. For example, governments may be more likely to pick 'winners', i.e., firms that are likely to create a lot of jobs, in order to be seen to have spent funds 'well'. Secondly, without perfect information on potential job additionality, policymakers may use other criteria to select recipients, such as their nationality or the products they intend to produce. In other words, there may be certain plant specific characteristics important in the grant selection and amount determination process. Such factors, if unaccounted for, could result in a biased estimate of β_1. Moreover, sample selection across such features could result in grant recipients and non-recipients that are on average very different across these characteristics. An important feature in the analysis is therefore the construction of a valid counterfactual, i.e., the selection of a valid control group of non-grant-recipients that avoids the problem of selectivity. It is only if we have constructed such a valid control group that we can have some confidence that the additional employment growth was due to the subsidy.

One way of doing so is by employing matching techniques as familiar from the microeconometric evaluation literature (e.g. Dehejia and Wahba, 2002, Heckman et al, 1997). The purpose of matching is to pair each grant-receiving new entrant plant with a non-grant plant in such a way that the latter's start-up size can be used as the counterfactual for the grant-receiving plants, thus ensuring what is known as 'common support'. Under the matching assumptions, the only difference between the treated and control group is grant receipt and, hence, one can evaluate the effect of grants on start-up size by estimating the difference in size between the treated group and the matched control group. One crucial assumption of this approach is that of conditional independence, i.e., once one controls for observables, the outcomes of the non-treated control group are independent of grant receipt.

Since matching involves comparing grants and non-grants plants across a number of observable characteristics (such as sector of production, region of location, nationality, etc.), it would be difficult to determine along which dimension to match the plants, or what type of weighting scheme to use. It is therefore desirable to perform the matching on the basis of a single index that captures all the information from those variables. We adopt the method of propensity score matching due to Rosenbaum and Rubin (1983) which suggests the use of the probability of receiving grants conditional on plant specific characteristics, to reduce the dimensionality problem.

Accordingly, we first identify the probability of receiving grants (or 'propensity score') using a probit model, where the choice of covariates attempts to capture, or be correlated with, some of the factors that policy makers may take into account when deciding on handouts of grants as discussed above. Then let P_{it} denote the predicted probability of receiving grants at time *t* for plant *i* (which is an actual grant receiver) as estimated from this probit model, named the propensity score. A non-grants plant *m*, which is 'closest' in terms of its 'propensity score' to a grants plant, is then selected as a match for the latter using the 'caliper' matching method.[15] This involves nearest neighbour matching without replacement, where 'nearest' is defined in terms of the difference in propensity scores across the potential treatment and control groups using a caliper of 0.01. The calliper essentially the choice of maximum difference in estimated propensity scores between any two possible observations beign considered as a 'match'. If the difference in propensity scores between is larger than this value they cannot be matched. Thus our choice of 0.01 assumes that if the estimated probability of being a grant recipient between any two firm start-ups is more than one percentage point then these are not a good match. We refer to the resulting sub-sample of matched firms as the matched sample.

In terms of estimating (1) on our matched sample we employ the regression quantiles estimator as introduced by Koenker and Bassett (1978) rather than OLS. Quantile regression allows to quantify the effects of the independent variables specified in (1) at different points in the conditional distribution of the dependent variable *E* rather than just at its mean. As a matter of fact, both Mata and Machado (1996) and Görg and Strobl (2001) show that it is important to allow for the effects of the determinants on start-up size to differ across different points of the distribution.[16] Since the data set contains a finite number of observations, only a finite number

[15] The matching is performed in Stata Version 7 using the software provided by Sianesi (2001).
[16] Additionally quantile methods provide a more robust and efficient alternative to least squares estimators when the error term is non-normal. As can be seen from Figure 1, this may be an important feature of our data as (logged)

of quantiles are distinct. In our estimation we thus consider regression estimates at five different quantiles, namely, the 20th, 25th, 50th (median), 75th and 90th percentiles of the start up size distribution. [17]

One should note that normally propensity score matching is used to calculate average treatment effects. However, matching can be extended to calculate quantile treatment effects by using, for example as we do, quantile regression estimation in the second stage; see, for example, Diamond (2005). Furthermore, one cannot use normal standard errors to evaluate the statistical significance of explanatory variables when combining matching with other regressions techniques and we thus calculate bootstrapped standard errors using 500 replications in all regressions where we used the matched sample, as suggested by Lechner (2002).

Section V: Empirical Results

Propensity Score Matching Results

To create our treatment and control groups one would ideally like to use a set of covariates in the probit model that capture, or are correlated with, the factors that policy makers may take into account when deciding on handouts of grants as discussed above in Section II. In terms of the information that our data sets provide us with, we identified the following factors that may be important and created appropriate sets of dummy variables to capture these: nationality of ownerwship (dummy indicating whether foreign), industry (23 dummies), region (9 dummies), and whether it is located in a designated area (dummy indicating designated area location). These were then used to calculate propensity scores of grant receipt, which were then

plant level start-up size does not appear to be (log)normally distributed. This is further confirmed for both groups using the Shapiro-Wilk test which decisively rejected normality of the data.

used to generate matched samples of recipients and non-recipients with the method outlined in the previous section. Using the matching procedure on our total sample we were able to match 3,409 grant recipients with 1,444 non-recipients.[18] In order to graphically assess the accuracy of our matching procedure we display the kernel estimates of the distribution of the propensity scores of our unmatched and matched samples in Figures 2 and 3, respectively. More specifically, we plot the kernel density estimate of each point of the distribution as calculated by:

$$\hat{f}_k = \frac{i}{nh}\sum_{i=1}^{n} K[\frac{x = X_i}{h}]$$

where f_k are probability estimates of firm sizes falling at or near different values, X_i, and the range of the data is broken into overlapping bands of width h (which is chosen to minimise the mean squared error). The Kernel function thus attaches weight to each of the n observations in the bandwidth, with less weight going to points further from the midpoint of the bandwidth.

As can be seen, the distributions of the recipients and non-recipients in the unmatched sample is distinctly different. In contrast, there is substantially less difference between these distributions for our matched sample, thus providing some support for our matching procedure.

[Figures 2 and 3 here]

Regression Results

The results of estimating the basic version of equation (1) on the matched data are presented in Table 2. Column (1) shows results obtained from OLS while columns (2) to (6) show quantile regression results for the 20th, 25th, 50th, 75th and 90th quantile. One may want to

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[17] Our choice of the lowest quantile, i.e., 0.20, was dictated by the nature of our data set. For quantiles lower than this the lack of variation in start-up size meant that adequate convergence using maximum likelihood methods could not be reached.

note in this regard that the OLS specification, i.e., that estimated at the mean, explains around 22 per cent of the variation in start-up size, while the corresponding figures for the other points along the distribution of start-up size are much less successful in explaining why some firms start up in different sizes than others. Thus, at least in terms of our empirical model, much variation across start-up size remains random.

Focusing on OLS coefficient estimates as a starting point shows that not all the results on the industry control variables are as expected considering the findings in Mata and Machado (1996) and Görg and Strobl (2001). For instance, in accordance with the previous literature, a high share of plants causes plants to operate below optimal scale, while high rates of minimum efficient scale, turbulence and industry growth are positively associated with plants' start-up size. However, start up size is, contrary to a priori expectations, found to be lower the more concentrated is the industry.

We also find that foreign owned plants tend to start-off at a higher scale than domestic establishments, which concurs with the literature that generally finds that affiliates of foreign-owned multinationals are larger than their domestic counterparts. This can be interpreted following the theoretical model by Helpman, Melitz and Yeaple (2004), who argue that multinationals face larger sunk investment costs than purely domestic firms and therefore only the most productive firms tend to locate abroad. This implies that these firms are less affected by selection issues as discussed by Jovanovic (1982) and therefore may start up at a larger size than domestic firms.

In terms of the effect of government grants on start-up size, our result indicates that a grant receiving plant, ceteris paribus, sets up at a larger size than a non-grant receiving plant. In particular, the point estimate from the OLS regression indicates that a supported plant employs

[18] One should note that matching does not necessarily have to be restricted to one to one type matching.

on average (exp(0.189) =) 1.21 employees more at start up. Given an average size of about 10 employees at entry, this is a non-negligible impact of grants on employment generation. Examining the coefficient on the grant dummy from the quantile regressions we find that the effect of grants appears to be stronger for plants at the medium to high end of the size distribution, i.e., between the 50th and 75th quantile. Plants at the very low or high ends of the distribution appear to be less influenced by grants, although the sign for these quantiles is still positive and statistically significant.

[Table 2 here]

In order to assess the importance of taking account of selection bias using the matching estimator we also re-estimated Table 2 using our entire sample in Table 3. As can be seen, the explanatory power our specification in terms of both OLS and the quartiles is roughly similar to before. Moreover, the results with regard to the impact of grant incidence on plant size are qualitatively similar to those using the matched sample. However, there are clear differences in terms of the size of the coefficients. More specifically, for all except the 90th quantile the matched estimates are larger, suggesting that not taking account of the sample selection bias in terms of common support, induces a downward bias except for the largest start-ups.

[Table 3 here]

Turning back to the results from Table 2, one should note that while we find that foreign-owned plants choose a larger start-up size, ceteris paribus, one could also conjecture that the effect of grants on start-up size may be different for multinationals than for domestic plants. One rationale is that foreign multinationals may be expected to be less financially constrained than domestic firms. Hence, they can choose to set up at (or close to) optimal size, compared to domestic firms which are likely to enter an industry at less than optimal size due to greater financial constraints. As a result, foreign plants may be less reliant on grants for their choice of start-up size.[19] On the other hand, if grants are used to attract foreign multinationals and are specifically targeted at promoting employment creation in multinationals, larger grant receipts may lead to larger start-up sizes and higher employment generation.

In Table 4 we present results which take this issue into account by including an interaction term of the grant dummy with the foreign ownership indicator. While the results on the control variables remain essentially unchanged, the inclusion of the interaction term reveals that the positive effect of grants on start-up size is substantially higher for foreign-owned than for domestic plants. This effect is, however, strongest at the lower end of the size distribution as the quantile regression results indicate. Nevertheless the explanatory power across specifications remains similar to before.

[Table 4 here]

One potential criticism one could address at our analysis thus far is that we only consider the incidence of grant receipt, but not the magnitude. Arguably, if there is a positive effect of grants on start-up size then plants that receive higher levels of grants may be able to further increase their entry size compared to others. In this regard the dataset we have also provides detailed information on the amount of subsidy received and we can thus use grant size rather than our grant dummy variable to measure the effect of grants. Before proceeding to the results of this exercise, several caveats must be highlighted however. Firstly, the matching procedure above accounts only for sample selection bias in terms of grant incidence and does not take account of similar sample selection bias across grant levels. In using grant size to estimate the treatment effect we must thus additionally assume that there is no selection bias in this regard. Even apart from this qualification, one should note that the inclusion of such a grant size variable

[19] Harrison and McMillan (2003) have recently provided evidence that in Cote d'Ivoire only domestic firms face financial constraints. This is intuitively plausible, as foreign firms have many means of financing their operations,

in the second stage estimation assumes that the marginal effect is constant across grant amounts. Thus, with regard to the latter aspect, the interpretation on the coefficient on grant size will be different, measuring the marginal impact of the increase in one unit of grant, rather than just grant receipt per se.

Our results using the logged value of grant size instead of grant incidence are depicted in Table 5.[20] As with grant incidence one finds that grant payments have a significant effect along all points of the firm size distribution. This effect is lowest for those in the lowest quantiles and highest for those in the 50th and in the 75th quantiles. In Table 6 we also show results of allowing for an interaction effect between our grant size variable and foreign ownership. Accordingly, one finds that the effect of a marginal increase of grant size tends to be larger for foreign-owned plants (at least at the low to median end of the size distribution). Assuming that foreign owned plants are less financially constrained than domestic plants, this suggests that subsidising foreign plants is not aimed at reducing financial constraints but at providing incentives to operate at larger scale than would have been chosen without grant support.

[Tables 5 and 6 here]

Section VI: Conclusions

An important aspect of Ireland's industrial policy has been the use of government subsidies to plants to foster employment creation. In this paper we use plant level data on the start-up size of new plant entries and detailed information on the grants received by such plants

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not least foreign direct investment, i.e., capital transfers from the parent company. Hence, they are less likely to be reliant on the domestic capital market.

[20] We set grant amounts of zero equal to one in order to ensure their inclusion once we transformed the variable into its natural logarithm.

in order to investigate whether, indeed, grant receipt encourages plants to start-up with more employment than otherwise. We use a matching procedure in conjunction with a quantile regression estimator to deal with the issue of selectivity into grant receipt and to allow for different effects of grants on plants depending on their position in the start-up size distribution. Our results provide evidence that grants do indeed encourage plants to adopt a larger start-up size than otherwise would be the case. Hence the government policy tool in Ireland was not simply subsidising jobs that would have been created anyway.

We also find that this effect is generally higher for foreign than for domestic-owned plants, and that it differs for plants at different quantiles of the start-up size distribution. This latter finding suggests foreign firms are more responsive to employment creating grants. One possible reason may be that increasing grant assistance to a foreign firm may not necessarily translate into increased local employment at the Irish site or more labour intensive production. It could simply be that as a multinational operation with several actual and potential branches, the prospect of grant assistance induces the multinational would opt to locate more of its activity in Ireland. For domestic start-ups in contrast, greater employment actually does mean a greater size and/or higher labour intensity.

It is important to close with a caveat, however. Specifically, we must emphasize that our paper does not provide a cost-benefit analysis of the efficacy of government policy. In other words, we cannot rule out that grant recipients are creating genuine jobs and not as suggested above involved in an elaborate exercise to 'make up the numbers' in response to grant aid.

What we can show is ability of a particular policy tool to stimulate employment creation among new business start-ups, quite aside from the quality or additionality of these new jobs. Finally, one should note that we have simply investigated the effect of grant provision on start-up size. Of course, grant provision may also directly affect the decision of whether to start up a business at all for the case of domestic plants, or whether to locate an operation in Ireland rather than elsewhere in terms of foreign multinationals. In this regard it would be interesting to examine how subsidies have affected entry rates in Ireland. This represents an avenue of future research.

Most importantly, as we have shown, policy makers can now apply novel econometric techniques (i.e. matching techniques) to gauge the responsiveness of grant recipients to desired outcomes such as job creation. The possession of such a powerful metric represents a major addition to the policy toolkit. We would suggest however, that this metric represents only one, albeit important, dimension of grant effectiveness. Conscientious policy makers would be advised to shore up the main study findings, as estimated for the full population of firms in receipt of grants, by conducting an in-depth survey on a smaller subsample of the firms. This dual approach to grant evaluation (econometric approach plus qualitative interviewing) allows policy makers to investigate the *quality* and *permanence* of the grant created jobs.

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Table 1: Summary Statistics

	ALL		**GRANT**		NON-GRANT	
	Mean	*St. Dev.*	*Mean*	*St. Dev.*	*Mean*	*St. Dev.*
log(SIZE)	1.470	1.168	1.241	1.522	1.127	1.444
GRANT	0.340	0.474	----	----	----	----
FOREIGN	0.121	0.326	0.336	0.130	0.320	0.116
FSH	0.363	0.226	0.230	0.381	0.224	0.355
SUB	0.228	0.035	0.035	0.222	0.034	0.232
MES	3.362	0.621	0.620	3.333	0.620	3.376
INDS	9.378	0.733	0.759	9.365	0.719	9.385
TURB	0.001	0.001	0.001	0.001	0.001	0.001
INDGR	0.008	0.064	0.061	0.001	0.065	0.011
HERF	0.215	0.213	0.212	0.201	0.213	0.222

Table 2: Results using Grant Dummy – Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**quant(0.2)**	**Quant(0.25)**	**quant(0.5)**	**quant(0.75)**	**quant(0.9)**
GRANT(dummy)	0.189**	0.106**	0.130**	0.178**	0.243**	0.148*
	(0.037)	(0.038)	(0.040)	(0.045)	(0.056)	(0.075)
FOREIGN	1.010**	0.741**	0.810**	1.085**	1.222**	1.195**
	(0.056)	(0.089)	(0.084)	(0.085)	(0.079)	(0.109)
FSH	-0.286**	0.250	-0.069	-0.354*	-0.490*	-0.490*
	(0.116)	(0.148)	(0.155)	(0.177)	(0.190)	(0.220)
SUB	4.612**	3.676**	5.246**	6.043**	4.315**	4.025**
	(0.570)	(0.994)	(0.802)	(0.890)	(1.046)	(1.499)
MES	0.678**	0.319**	0.600**	0.765**	0.885**	0.780**
	(0.051)	(0.087)	(0.064)	(0.079)	(0.086)	(0.109)
INDS	-0.039	-0.117**	-0.050	-0.104**	0.001	0.077
	(0.029)	(0.044)	(0.046)	(0.039)	(0.054)	(0.056)
TURB	116.789**	3.807	53.444	104.977**	199.345**	200.909**
	(16.377)	(24.696)	(31.584)	(24.060)	(29.714)	(36.666)
INDGR	0.527	0.695	0.979*	1.082*	0.396	0.311
	(0.332)	(0.377)	(0.437)	(0.508)	(0.541)	(0.471)
HERF	-0.229**	-0.300*	-0.226*	-0.111	-0.202	-0.068
	(0.102)	(0.124)	(0.106)	(0.116)	(0.157)	(0.195)
Constant	-1.379**	-0.219	-2.118**	-1.751*	-1.501**	-1.538
	(0.437)	(0.606)	(0.645)	(0.821)	(0.544)	(0.844)
Observations	4853	4853	4853	4853	4853	4853
R-squared	0.21	0.11	0.11	0.12	0.14	0.15

Notes: (1) Standard errors in parantheses; (2) ** and * depict one and five per cent statistical significance levels; (3) R-squared is pseudo r-squared for quantile regression estimates.

Table 3: Results using Grant Dummy – Total Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**quant(0.2)**	**Quant(0.25)**	**quant(0.5)**	**quant(0.75)**	**quant(0.9)**
GRANT(dummy)	0.199**	0.063**	0.113**	0.166**	0.227**	0.237**
	(0.022)	(0.012)	(0.015)	(0.026)	(0.034)	(0.043)
FOREIGN	0.913**	0.753**	0.710**	0.938**	1.115**	1.153**
	(0.032)	(0.018)	(0.023)	(0.037)	(0.048)	(0.058)
FSH	-0.347**	0.139**	-0.035	-0.216*	-0.710**	-0.927**
	(0.074)	(0.041)	(0.053)	(0.086)	(0.111)	(0.130)
SUB	4.103**	2.742**	5.226**	5.712**	3.946**	2.348**
	(0.406)	(0.218)	(0.284)	(0.473)	(0.611)	(0.784)
MES	0.640**	0.244**	0.557**	0.671**	0.883**	0.849**
	(0.032)	(0.017)	(0.022)	(0.037)	(0.047)	(0.058)
INDS	-0.038	-0.047**	-0.029*	-0.073**	-0.074**	-0.013
	(0.017)	(0.009)	(0.012)	(0.020)	(0.027)	(0.033)
TURB	85.440**	1.211	37.195**	54.325**	135.739**	156.507**
	(9.744)	(5.225)	(6.841)	(11.356)	(14.828)	(18.040)
INDGR	0.307	0.144	0.299*	0.258	0.479	0.690
	(0.204)	(0.109)	(0.143)	(0.238)	(0.311)	(0.408)
HERF	-0.380**	-0.329**	-0.359**	-0.403**	-0.606**	-0.419**
	(0.056)	(0.030)	(0.039)	(0.065)	(0.084)	(0.104)
Constant	-1.285**	-0.942**	-2.366**	-1.471**	-0.716*	-0.023
	(0.208)	(0.109)	(0.142)	(0.242)	(0.324)	(0.423)
Observations	11474	11474	11474	11474	11474	11474
R-squared	0.20	0.12	0.09	0.11	0.13	0.14

Notes: (1) Standard errors in parantheses; (2) ** and * depict one and five per cent statistical significance levels; (3) R-squared is pseudo r-squared for quantile regression estimates.

Table 4: Results using Grant Dummy and allowing for differential effect across Ownership Type – Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**quant(0.2)**	**quant(0.25)**	**quant(0.5)**	**quant(0.75)**	**quant(0.9)**
GRANT(dummy)	0.099**	0.048*	0.055	0.086*	0.174**	0.064
	(0.034)	(0.029)	(0.038)	(0.052)	(0.059)	(0.074)
GRANT*FOREIGN	0.671**	0.788**	0.808**	0.711**	0.588**	0.530*
	(0.116)	(0.169)	(0.152)	(0.162)	(0.158)	(0.221)
FOREIGN	0.574**	0.253	0.315**	0.595**	0.792**	0.739**
	(0.097)	(0.143)	(0.117)	(0.116)	(0.142)	(0.192)
FSH	-0.284**	0.261	-0.116	-0.305	-0.554**	-0.525*
	(0.105)	(0.152)	(0.179)	(0.188)	(0.206)	(0.225)
SUB	4.623**	3.438**	5.385**	6.263**	4.350**	4.142**
	(0.611)	(0.871)	(0.868)	(0.739)	(1.139)	(1.407)
MES	0.679**	0.301**	0.604**	0.760**	0.904**	0.805**
	(0.050)	(0.087)	(0.079)	(0.072)	(0.096)	(0.105)
INDS	-0.045	-0.128**	-0.063	-0.104*	-0.002	0.068
	(0.029)	(0.042)	(0.041)	(0.042)	(0.053)	(0.063)
TURB	115.443**	3.726	51.699	108.396**	194.741**	191.799**
	(15.013)	(23.267)	(32.461)	(22.936)	(27.395)	(31.341)
INDGR	0.600	0.878*	1.231*	1.055*	0.370	0.137
	(0.344)	(0.386)	(0.533)	(0.474)	(0.566)	(0.560)
HERF	-0.252	-0.314**	-0.252*	-0.193	-0.212	-0.086
	(0.098)	(0.109)	(0.126)	(0.121)	(0.158)	(0.250)
Constant	-1.243**	0.030	-1.993**	-1.709*	-1.547**	-1.568
	(0.385)	(0.588)	(0.621)	(0.868)	(0.527)	(0.958)
Observations	4853	4853	4853	4853	4853	4853
R-squared	0.22	0.11	0.11	0.12	0.14	0.15

Notes: (1) Standard errors in parantheses; (2) ** and * depict one and five per cent statistical significance levels; (3) R-squared is pseudo r-squared for quantile regression estimates.

Table 5: Results using Grant Level – Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**quant(0.2)**	**quant(0.25)**	**quant(0.5)**	**quant(0.75)**	**quant(0.9)**
GRANT(level)	0.050**	0.036**	0.045**	0.055**	0.055**	0.047**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
FOREIGN	0.945**	0.693**	0.737**	0.957**	1.125**	1.103**
	(0.057)	(0.070)	(0.085)	(0.074)	(0.081)	(0.099)
FSH	-0.290**	0.122	0.168	-0.323	-0.600**	-0.592**
	(0.110)	(0.139)	(0.127)	(0.185)	(0.189)	(0.224)
SUB	4.528**	4.338**	5.018**	6.175**	4.411**	3.119*
	(0.554)	(0.684)	(0.683)	(0.844)	(0.968)	(1.320)
MES	0.663**	0.436**	0.517**	0.768**	0.921**	0.783**
	(0.046)	(0.062)	(0.065)	(0.079)	(0.084)	(0.101)
INDS	-0.047	-0.087*	-0.082*	-0.096*	-0.035	0.042
	(0.027)	(0.040)	(0.040)	(0.039)	(0.044)	(0.061)
TURB	111.226**	23.315	48.364	104.069**	162.389**	185.065**
	(15.60)	(21.641)	(24.711)	(20.776)	(26.938)	(31.242)
INDGR	0.533	0.715	0.606	0.764	0.225	0.120
	(0.379)	(0.380)	(0.451)	(0.452)	(0.587)	(0.583)
HERF	-0.233	-0.252*	-0.355**	-0.178	-0.289	-0.032
	(0.094)	(0.115)	(0.118)	(0.131)	(0.149)	(0.197)
Constant	-1.454**	-1.072*	-1.567**	-1.719*	-1.544*	-1.345
	(0.382)	(0.488)	(0.462)	(0.807)	(0.677)	(0.784)
Observations	4853	4853	4853	4853	4853	4853
R-squared	0.25	0.12	0.12	0.14	0.17	0.17

Notes: (1) Standard errors in parantheses; (2) ** and * depict one and five per cent statistical significance levels; (3) R-squared is pseudo r-squared for quantile regression estimates.

Table 6: Results using Grant Level and allowing for differential effect across Ownership Type – Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**quant(0.2)**	**quant(0.25)**	**quant(0.5)**	**quant(0.75)**	**quant(0.9)**
GRANT(level)	0.043**	0.027**	0.035**	0.049**	0.051**	0.043**
	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
GRANT*FOREIGN	0.032**	0.059**	0.058**	0.028*	0.019	0.016
	(0.008)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)
FOREIGN	0.688**	0.269**	0.278**	0.753**	0.957**	0.975**
	(0.086)	(0.103)	(0.105)	(0.141)	(0.144)	(0.156)
FSH	-0.289**	0.169	0.095	-0.370*	-0.574**	-0.699**
	(0.115)	(0.127)	(0.157)	(0.170)	(0.166)	(0.226)
SUB	4.562**	3.995**	5.005**	6.215**	4.423**	2.889*
	(0.533)	(0.791)	(0.738)	(0.788)	(0.904)	(1.280)
MES	0.665**	0.390**	0.542**	0.788**	0.904**	0.812**
	(0.048)	(0.070)	(0.070)	(0.067)	(0.084)	(0.096)
INDS	-0.049	-0.101*	-0.078	-0.111**	-0.039	0.051
	(0.029)	(0.041)	(0.045)	(0.039)	(0.050)	(0.058)
TURB	110.489**	12.713	50.946*	98.347**	161.011**	189.137**
	(16.013)	(21.038)	(24.517)	(20.406)	(25.480)	(40.013)
INDGR	0.579*	0.888*	0.914*	0.859	0.350	0.233
	(0.382)	(0.351)	(0.430)	(0.447)	(0.529)	(0.693)
HERF	-0.249	-0.319**	-0.338**	-0.179	-0.318	-0.014
	(0.091)	(0.122)	(0.102)	(0.102)	(0.169)	(0.193)
Constant	-1.390**	-0.275	-1.181*	-1.556**	-1.718**	-0.519
	(0.445)	(0.505)	(0.532)	(0.500)	(0.595)	(0.939)
Observations	4853	4853	4853	4853	4853	4853
R-squared	0.25	0.13	0.13	0.15	0.17	0.17

Notes: (1) Standard errors in parantheses; (2) ** and * depict one and five per cent statistical significance levels; (3) R-squared is pseudo r-squared for quantile regression estimates.

Figure 1: Size Distribution

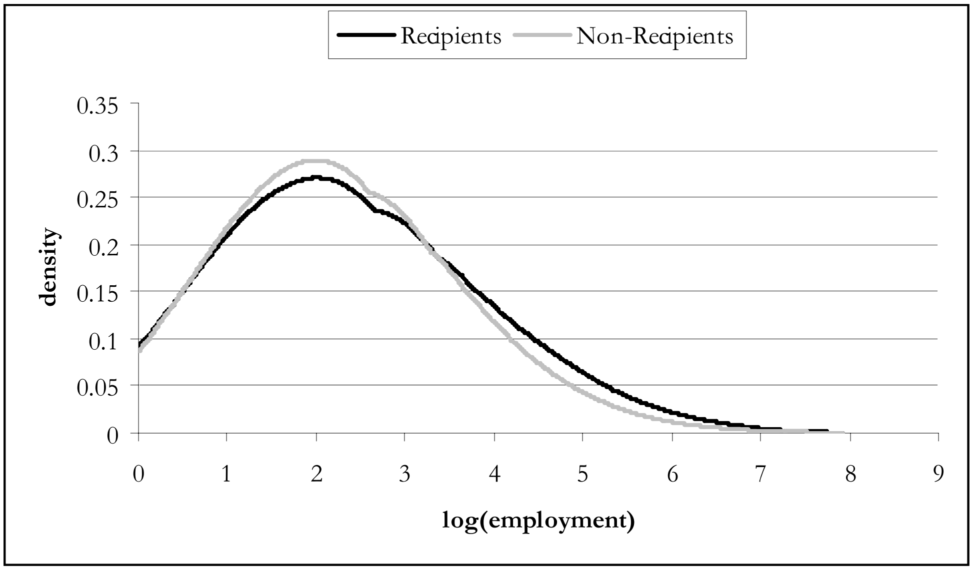

Figure 2: Unmatched Sample

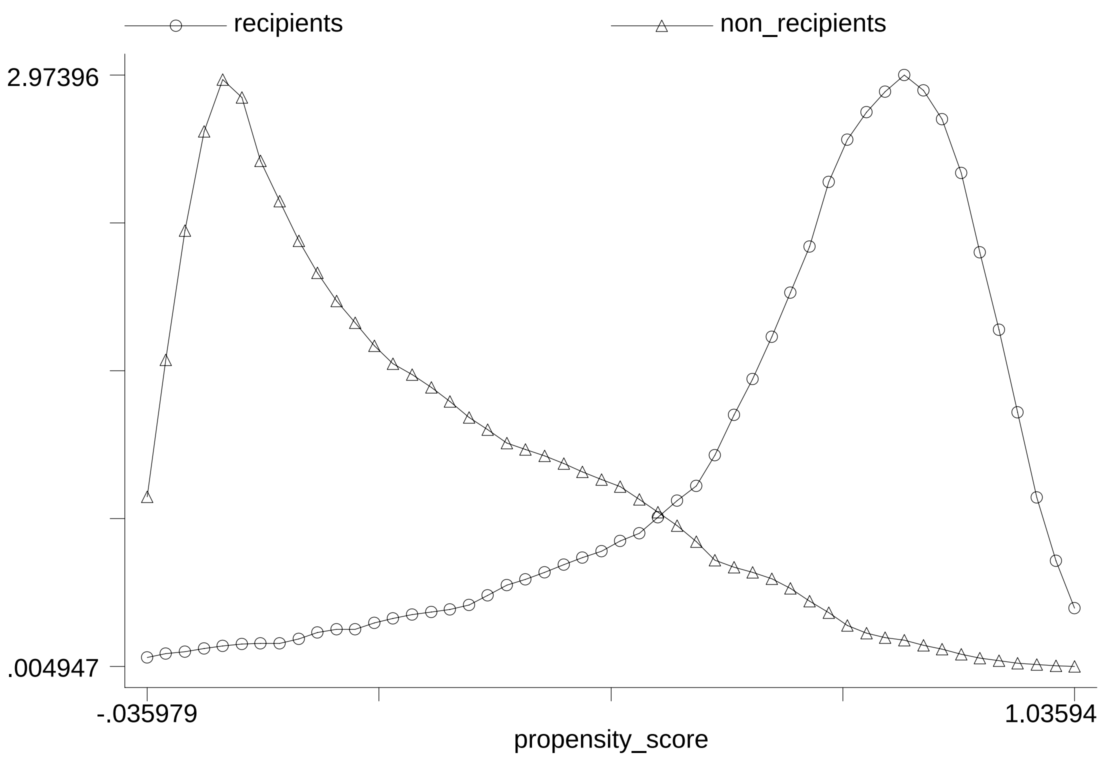

Figure 3: Matched Sample