REGIONAL SELECTIVE ASSISTANCE IN SCOTLAND: DOES IT MAKE A DIFFERENCE TO PLANT PRODUCTIVITY?

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Abstract

This paper examines whether receipt of an RSA grant has a causal impact on plant TFP. To tackle the problem of self-selection into the treatment group, propensity score matching is employed. In order to control for the endogeneity of other variables in the model, estimations are performed using the system GMM estimator. The results show that for low technology manufacturing, receipt of an RSA grant leads to a fall in TFP.

JEL classifications: D24, J24, L52, L60

Introduction

Regional Selective Assistance (RSA) is the largest and oldest business support scheme currently operating in Scotland. On average, almost £50 million (2003 prices) of RSA grants were offered and accepted in Scotland per annum between 1973 and 2003. This is far larger than expenditure on other schemes such as the Small Firm Merit Awards for Research and Technology (SMART) and Support for Products under Research (SPUR) schemes for which the average value of grants offered and accepted per annum during the period of operation was £568 thousand and £809 thousand respectively.

RSA provides grants to plants undertaking investment projects in economically deprived 'Assisted Areas'[1]. Eligible investment includes expenditure on land, buildings, plant, machinery and software. As a component of regional policy, the scheme is principally designed to safeguard and generate employment in the Assisted Areas. As such, many of the grants are given to help foreign firms establish plants in Scotland.[2] The amount that can be offered is determined by a number of factors including

[1] The map of assisted areas is developed by the UK and devolved governments in accordance with EU regional aid guidelines.

[2] According to the most recent annual summary, 26% of the accepted offers in 2010/11 were made to foreign-owned companies while 52% of the total value of accepted offers went to foreign-owned companies (Scottish Enterprise, 2011).

the location and size of the project and the number of jobs it will create or safeguard. In order to receive an RSA grant, an additionality criterion must be satisfied which requires that awards will only be made if the project could not have proceeded in the same form and time frame without the grant. A displacement criterion must also be met which demands that the jobs created by the project must not be offset by job losses in other Assisted Areas in Scotland.

This paper examines whether receipt of an RSA grant has a causal impact on plant total factor productivity (TFP) in Scotland using a dataset created by merging the Selective Assistance Management Information System (SAMIS), a register of RSA recipients dating from 1972 when the scheme began, into the longitudinal Annual Respondents Database (ARD). This is an important question given the importance of productivity in determining living standards.[3] If RSA grants merely support plants that would otherwise be forced to close, these subsidies may impede the Schumpeterian process of 'creative destruction' that creates growth in the economy by shifting resources from low to high productivity plants (Schumpeter, 1943). On the other hand, if the resources previously

[3] According to Krugman (1997), in the determination of living standards, 'productivity isn't everything but in the long run, it is almost everything'. Similarly, Baumol (1984) states that 'it can be said without exaggeration that in the long run probably nothing is as important for economic welfare as the rate of productivity growth'. Empirical evidence showing the importance of productivity is provided by the OECD (2003).

employed by the plant would be redundant after closure of the plant, the subsidy would make a positive contribution to growth in the economy.

TFP is used instead of labour productivity because it is a better measure of efficiency and technology and will therefore be a stronger determinant of plant performance. Furthermore, labour productivity, unlike TFP, is determined by factor input levels in addition to levels of efficiency and technology (Harris, 2005). Receipt of a grant will have a positive impact on the employment of capital and labour because, in the case of capital, grants are only provided after expenditure on capital has occurred and, in the case of labour, ‘clawback’ clauses dictate that grants must be returned if employment targets are not met. This is shown empirically by Criscuolo et al. (2009). The impact of RSA on labour productivity will therefore be determined jointly by its impact on employment, capital and TFP and will therefore be difficult to interpret.

The analysis is conducted separately for the high-tech, medium high-tech, medium low-tech and low-tech sectors of the economy. Such a disaggregation is necessary because different sectors will operate with different production technologies and the impact of RSA is therefore likely to differ across sector.

RSA may have both positive and negative impacts on TFP. Harris (1991) argues that there are two main channels through which an RSA grant may improve TFP. The first is by allowing the acquisition of modern capital which requires the reorganisation of the plant along more efficient lines. For example, movement to a new plant, the acquisition of new machinery or investment in information and communication technology may trigger a wholesale reorganisation of production processes which will have an impact on TFP. An RSA grant may also raise TFP by allowing the plant to create a new product that can be produced with greater efficiency than older product.

On the other hand, RSA may have a negative impact on TFP if firms can increase their profits by accepting the grant and increasing their use of capital and labour beyond the point at which they would operate if they did not receive the grant. In this situation, the grant can be regarded as compensation from the government to the firm for the loss of profits that the firm would incur from operating at a point with sub-optimally high employment.

Previous studies have generally failed to find a statistically significant impact of receipt of an RSA grant on productivity. One exception is Harris and Robinson (2004) who, using a control group consisting of all untreated plants in Great Britain (GB), find a positive and statistically significant impact on TFP for RSA recipients throughout GB for the period, 1990-1998. However, when the model is estimated using a control group drawn from untreated plants from the assisted areas, they find that it is only RSA recipients in Scotland that received a large TFP boost. Their results also confirm that plants assisted by RSA are a self-selected group of the population of plants which have lower than average productivity before receiving the grant. Criscuolo et al. (2009), using ARD data covering the period, 1988-2003, do not find a significant effect of RSA on either labour productivity or TFP in GB using an instrumental variables strategy. Finally, Hart et al. (2008), using the control functions approach on cross-sectional data taken from a telephone survey of Scottish firms, do not find a positive impact of receipt of an RSA grant on labour productivity. While the latter two papers use appropriate methods to tackle the consequences of self-selection into the treatment group, they fail to deal with the endogeneity of other explanatory variables in the model. Harris and Robinson (2004), by contrast, do not employ a sufficiently sophisticated method to control for self-selection but do control for the endogeneity of control variables. The strategy below addresses both sources of bias.

The paper is organised as follows: section 2 sets out the methodology; section 3 describes the data; section 4 provides the results and section 5 concludes.

Methodology

Consider the following Cobb-Douglas production function:

(1) $$Y_{it} = A_{it} E_{it}^{\beta_E} M_{it}^{\beta_M} K_{it}^{\beta_K},$$

where Y_{it} is gross output in plant i at time t, E_{it} represents employment, M_{it} is intermediate inputs, K_{it} represents the capital stock and A_{it} is TFP. Taking natural logs of equation (1) gives:

(2) $$y_{it} = \beta_E e_{it} + \beta_M m_{it} + \beta_K k_{it} + a_{it},$$

where the lower case is used to denote the natural logarithm of a variable.

It is postulated that the natural logarithm of TFP can be modelled as follows:

(3) $$a_{it} = \beta_X x_{it} + \beta_{ATT} D_{it} + (\eta_i + \upsilon_{it}),$$

where x_{it} is a vector of variables thought to influence TFP (in which continuous variables are logged) and D_{it} is a dummy taking the value of one if a plant receives an RSA grant in that period or has done so in the past. The error term is composed of η_i, an unobservable, plant-specific, time-invariant effect and v_{it}, a TFP shock. The RSA dummy is the key variable in the model as its coefficient, β_{ATT}, will provide the estimate of the impact of receiving an RSA grant on TFP.

The model is therefore:

(4) $$y_{it} = \beta_E e_{it} + \beta_M m_{it} + \beta_K k_{it} + \beta_X x_{it} + \beta_{ATT} D_{it} + (\eta_i + \upsilon_{it}).$$

The group of observations that receive 'treatment' are said to be self-selected when the decision of whether or not to receive 'treatment' is taken by the plant. In such a situation, the 'treatment' group is not a random sample of the population and will have characteristics that would lead to better or worse performance than observations in the 'untreated' group, in the event that neither group received treatment. A comparison of the mean of an outcome variable across the ‘treated’ and ‘untreated’ groups will then not provide an unbiased estimate of the average effect of ‘treatment’ on the ‘treated’ (ATT) (see, for example, Blundell and Costa Dias, 2009, for a more detailed exposition of self-selected bias).[4]

Assuming that all relevant characteristics are observed, differences in characteristics across ‘treated’ and ‘untreated’ groups can be controlled for using a correctly specified regression. However, in practice, finding the correct specification is difficult. This is a serious problem as estimating an incorrectly specified equation will generate biased estimates of the ‘treatment’ effect because the estimate of the dependent variable for ‘treated’ plants, in the event that they did not receive ‘treatment’, is entirely dependent on the specification of the model for values of the covariates for which only ‘treated’ plants are observed (see, for example, Blundell et al., 2005). One solution to this problem is to create a matched sample in which ‘treated’ and ‘untreated’ plants are observed for all values of the covariates. This is done here using propensity score matching (see Dehejia and Wahba, 2002) which creates a sample that includes plants that received a grant and a

[4] Note that the decision of whether or not a grant application is successful is taken by a governmental body. However, this does not alter the fact that the ‘treated’ and ‘untreated’ group will have different characteristics. Indeed, if the government tries to choose ‘winners’, it will increase the likelihood of ‘treated’ and ‘untreated’ groups having different characteristics.

sub-set of plants which did not receive a grant but which have characteristics that are similar to the treated plants. This is accomplished by estimating a probit model of ‘treatment’ status including variables that determine both output and whether a plant receives an RSA grant, and then matching on the estimated predicted values.[5] This approach will improve the match, or the balance, of the covariates across ‘treated’ and ‘untreated’ groups. The advantage of propensity score matching over other forms of matching is that it overcomes the difficulties of matching on a large number of variables (Zhao, 2004).[6]

The matching estimator, as commonly described (see, for example, Blundell et al., 2005), suggests that, once a matched sample has been constructed, a simple regression of the outcome variable on the ‘treatment’ dummy will provide an unbiased estimate of the ‘treatment’ effect. However, even within a matched sample, it is possible that large differences in the distribution of the covariates across ‘treated’ and ‘untreated’ observations may remain. This suggests that covariates ought to be included in the outcome regression to control for residual differences in the covariate

[5] Variables that determine output but not receipt of an RSA grant and variables that determine receipt of an RSA grant but not output are excluded because they do not cause differences in the value of the outcome variables across treated and untreated groups.

[6] Propensity score matching is performed in Stata 9.2 using the ‘psmatch2’ command developed by Leuven and Sianesi (2003).

distribution across ‘treated’ and ‘untreated’ groups. This approach is therefore a combination of matching and regression.[7]

Having constructed a matched sample, difficulties remain in the estimation of (4) due to the potential for simultaneity and attrition bias.[8] Simultaneity bias arises because plants may have some knowledge about the value of the productivity shock and use this knowledge to choose the level of inputs in the production function (Marschak and Andrews, 1944). Attrition bias is present if plants base their exit decisions on their productivity level. As plants with a larger capital stock will be able to withstand lower productivity levels, this will generate a negative correlation between the productivity shock and the capital stock variable. Although the main variable of interest is the RSA dummy, it is essential to deal with the endogeneity of other explanatory variables if an unbiased estimate of the ATT is to be obtained. This point is made forcefully by Frölich (2008) who shows that the asymptotic bias of the estimate of the treatment effect can be large if the endogeneity of other variables in the model is ignored.

Therefore, the coefficients in equation (4) will be estimated using the system GMM estimator developed by Blundell and Bond (1998) (see Bond,

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[7] Such an approach is recommended by Imbens and Wooldridge (2009) over the simple matching estimator in their survey of the literature.

[8] Van Beveren (2007) lists other potential sources of correlation between factor inputs and the error term.

2002 for an introduction). This estimates the equation as a system, using lagged levels and lagged first differences of the endogenous variables as instruments for the equations in first differences and levels respectively.[9] The endogenous variables in the model that will be dealt with in this way are employment, intermediate inputs and capital. It is assumed that the variables in x_{it} and D_{it} are exogenous[10].

Data

The ARD is a longitudinal dataset containing financial variables such as investment, intermediate inputs and gross output collected at the reporting unit (or establishment) level on the basis of a stratified sampling frame. Other variables such as employment are given for all reporting units and plants (or local units) (see Griffith, 1999, and Robjohns, 2006 for more information on the ARD). When a plant cannot provide the full range of financial information necessary for the survey, another plant within the firm will report on their behalf and the reporting unit then consists of more than

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[9] This estimator is implemented in Stata 9.2 using the ‘xtabond2’ command developed by Roodman (2005).

[10] The possibility that plants have unobserved characteristics that are correlated with the treatment dummy is not considered here. The existence of such characteristics would invalidate the conditional independence assumption (see e.g. Blundell et al, 2005), upon which this approach is based and cause biased estimates of the treatment effect.

one plant. When a plant can provide the required information and only reports on behalf of itself, the reporting unit consists of only one plant.

The nature of the ARD presents two issues that need to be addressed when estimating the impact of receiving an RSA grant. Firstly, the reporting unit is not an appropriate unit of analysis for estimating the impact of RSA grants because RSA is awarded to support investment in specific plants rather than throughout the enterprise. Secondly, the reporting unit is an accounting rather than an economic unit. As such, the number of plants covered by a reporting unit may change as enterprises open and close plants, buy and sell plants or simply because of changes in the way that an enterprise chooses to report to the ARD (Harris, 2005a). To permit analysis at the more appropriate plant level, it is therefore necessary to 'spread back' to the plant those financial variables that are only available in the ARD at the reporting unit. This is done using the plant level employment data available for all plants using the assumption of constant labour-investment ratios and labour productivity levels within reporting units.[11]

To estimate the impact of receiving an RSA grant, it is, of course, necessary to identify which plants received assistance in the ARD. The

[11] Because the variance of the data is lower using this method than if data were available for every plant, the standard errors on the estimated coefficients will be artificially reduced. However, using reporting unit data is not a solution to this problem as it also reduces the variance of the data through the aggregation of potentially disparate plants.

SAMIS database, which is maintained by the Department of Business, Innovation and Skills, has data on firms in Great Britain that applied for an RSA grant. This includes the postcode, standard industrial classification (SIC) code and employment level of the applicant firm and the date on which the application was made. For successful applications, the date when the payment was made and the value of the grant are also recorded.

Variables common to both SAMIS and the ARD can then be used to identify plants in the ARD that had received an RSA grant. The starting point for the linking process was the linkage achieved by Harris (2005b). Further links were added on the basis of work done by Criscuolo et al. (2009). If a plant in SAMIS had still not been linked, matching was done manually using postcodes, SIC codes, employment levels and application years. In the end, this process achieved a link from SAMIS to the ARD of 91.4% of the manufacturing plants that received an RSA grant in Scotland. This is higher than the level achieved in previous studies using datasets created by combining SAMIS with the ARD (Harris and Robinson, 2004; Harris, 2005b; Criscuolo et al., 2009) and therefore provides a firmer basis for empirical analysis.

Variables

The ARD contains information which allows the construction of a number of variables which can be included in x_{it} in equation (4).[12] The Herfindahl Index (Herfindahl, 1950) is a measure of the degree of concentration and, under certain assumptions (see, e.g., Cabral, 2000), competition within an industry. Intuitively, it would be expected that greater competition (which implies a lower Herfindahl index) will pressure firms into adopting new technologies and operating more efficiently. However, following Schumpeter (1943), it can also be argued that competition will be inversely related to productivity if monopoly rents are required for management to invest in the R&D which leads to innovations and improvements in TFP (see, for example, Aghion and Howitt, 1992).

Spatial spillovers or agglomeration economies are benefits that accrue to plants from being located in the vicinity of concentrations of other plants. According to Duranton and Puga (2004), the mechanisms which give rise to agglomeration economies are the sharing of common pools of assets, matching between firms and workers and the transfer of knowledge between firms, all of which are facilitated by their spatial concentration. Agglomeration economies take two main forms: localisation (or Marshallian) externalities, and urbanisation (or Jacobian) externalities. The

[12] Further discussion on why these variables would be expected to determine productivity is given in Harris and Moffat (2011).

former arise from the concentration of plants from the same industry in a given area (Marshall, 1890; Arrow, 1962; Romer, 1986). The latter arise from diversity in the activities of plants in a particular area (Jacobs, 1970). In the analysis below, localisation externalities are measured by a variable measuring the proportion of industry output located within the local authority. Urbanisation externalities are measured by a variable calculated as the number of different SIC codes within the local authority.

Also included in the model is a foreign ownership dummy. This is justified by the observation that, to make it worthwhile for a foreign firm to incur the costs of setting up or acquiring a plant in the domestic market, foreign firms must possess characteristics that give them a cost advantage over domestic firms (Hymer, 1976). These characteristics may include specialised knowledge about production or better management, both of which would lead to higher TFP. On the other hand, cultural differences may cause a lack of understanding between management and labour (Dunning, 1988) which could reduce TFP in foreign-owned plants. Furthermore, foreign-owned firms may undertake FDI to source technology from the host economy rather than to exploit superior technology from the home country (Driffield and Love, 2007). Plants owned by foreign owned firms that are motivated by technology sourcing are then likely to have lower TFP than domestically owned plants (Fosfuri and Motta, 1999; Cantwell et al., 2004). Foreign-owned plants would also be expected to have lower productivity if foreign-owned firms keep their high value production at home and leave lower value added operations to their foreign subsidiaries (Doms and Jensen, 1998).

A single-plant firm dummy, equal to one if that plant is the only plant owned by the firm, is also included in equation (4). Multi-plant enterprises which serve a large geographic market where transport costs are relatively high will benefit from being able to locate plants close to their markets (Harris, 1989). Furthermore, single plant firms will be at a productivity disadvantage compared to multi-plant firms if technology is shared within multi-plant enterprises (Jarmin, 1999). Conversely, multi-plant firms may be less efficient if principal-agent problems are more severe in multi-plant enterprises (Leibenstein, 1966). There may also be significant bureaucratic costs to organising production over a large number of plants (Chandler, 1962). Finally, single-plant firms may be more innovative and flexible because they have access to a higher level of localised knowledge than multi-plant firms (Kelley and Harrison, 1990).

An age variable is included among the covariates to measure whether younger plants use more modern vintages of capital embodying better technology than older plants or if through learning-by-doing productivity increases as the plant ages (e.g., Jovanovic and Nyarko, 1996). Note that the measure of the capital stock used here (see Harris and Drinkwater, 2000; Harris, 2005a) is in theory adjusted to take account of vintage effects. Thus the coefficient obtained on the plant age variable should be an estimate of only the learning-by-doing effect. In practice though, it is unlikely that the capital stock estimates are fully adjusted for obsolescence.

Finally, a time trend is included in equation (1) to account for (Hicks-neutral) technical change. This is done to capture the impact on TFP of exogenous improvements in technology common to all plants. Further detail on all the variables used in the analysis is given in Table 1.

Table 1 around here

Table A1 in the appendix shows the mean of these variables across plants that received an RSA grant and plants that did not receive an RSA grant. This table shows that RSA grant recipients are larger, in terms of output and employment, than plants that did not receive an RSA grant in all four sectors. They also have larger capital stocks and use more intermediate inputs. They operate in less concentrated industries (as shown by the lower value of the Herfindahl Index) and in less diversified areas which have a higher proportion of their industry's output. RSA grant recipients are also older, less likely to belong to a multi-plant enterprise and more likely to be foreign-owned. It is these differences in characteristics for which the combination of propensity score matching and regression is designed to control.[13]

Results

Rather than performing the analysis using the entire sample, the sample is split according to the sophistication of the technology employed in the production process. This is done to avoid the imposition of common coefficients across disparate industries. In particular, it is undesirable to impose common coefficients for labour, intermediate inputs and capital as different industries operate with different technologies. The sample is therefore split into high-tech, medium high-tech, medium low-tech and low-tech industries. Plants were organized into these industries according to the Eurostat classification of SIC codes (with some minor adjustments).[14]

Table 2 around here

The estimated parameters from the probit model used to generate the propensity scores are given in the appendix. Table 2 gives the difference in the mean of the variables which will be used in the empirical analysis between plants that received an RSA grant and plants that did not receive an RSA grant. This provides an indication of the extent to which the match, or

[13] Chapter 5.2 of Moffat (2010) provides information on the number and value of RSA grants over time and the distribution of these grants across sector within Scotland.

[14] See http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an3.pdf

balance, of the covariates is improved across ‘treated’ and ‘untreated’ groups by moving from the full to the matched sample. In the full sample, the differences in the mean of the covariates are statistically significant at the 99% level for each variable in each sector with the exception of the time variable in the medium low-tech sector. Differences in the mean of the covariates are considerably reduced in the matched sample compared to the full sample to the extent that they are not statistically significant in the medium high-tech and medium low-tech sectors. However, significant differences remain in the high-tech and low-tech sectors. This provides support for the strategy employed of including covariates in the outcome regression to control residual differences in the distribution of the covariates in the matched sample.

Table 3 gives the coefficients obtained from estimation of equation (4) using the matched sample. The instruments are lagged three times to allow for autocorrelation in the error term which would invalidate instruments which are lagged an insufficient number of times. This proved to be a sufficient number of lags to avoid rejection of the null of valid instruments in the Hansen test for each sector.

Table 3 around here

Because the creation of the matched sample involves the removal of untreated plants that are dissimilar from treated plants, covariates have a smaller variance in the matched sample which causes their coefficients to become less statistically significant.

The most important coefficient is that associated with the RSA dummy. This is negative but not statistically significant in the high-tech and medium high-tech manufacturing sectors. In the medium low-tech and low-tech manufacturing sectors, the coefficient on the RSA dummy is negative and statistically significant. The size of the coefficient indicates that, in medium low-tech manufacturing, receipt of an RSA grants leads to a fall in TFP of 3.3%[15] while, in low-tech manufacturing, receiving an RSA grant reduces TFP by 4.3%. Therefore, the estimated impact of receipt of an RSA grant is most negative in those sectors which employ the most basic technologies. This may be explained by different rates of obsolescence across sectors. If capital becomes obsolete faster in high-tech sectors, new capital will be needed to restore a plant to the technological frontier. However, in low-tech sectors, where obsolescence occurs at a slower rate, the need for new capital is not so pressing. There is therefore more scope for RSA-supported investments in capital which lead to an inefficiently high level of inputs.[16]

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[15] The following conversion is necessary to calculate the marginal effect: 100*(exp(-0.034)-1)=3.3

[16] Note that, as discussed above, an attempt has been made to adjust the estimates of the capital stock for obsolescence so that the capital stock variable should measure efficiency

Having obtained the results from the basic specification in equation (4), the specification of the 'treatment' dummy was modified in two ways to gain a better understanding of how receipt of an RSA grant determines productivity. Firstly, rather than assuming that an RSA grant has an impact on plant TFP for the duration of the plant's existence, as is implicit in the baseline specification in which the RSA dummy equals one from the year in which a grant is received, the RSA dummy was modified so that it only took the value of one for a given number of years after the grant was received. The marginal effects obtained using different numbers of years are shown in Figure 1. Using a dummy that takes the value of one only in the period in which the grant is received yields a positive and significant coefficient for high-tech plants. However, all other specifications of the RSA dummy give coefficients that are not statistically significant which shows that an RSA grant has no long-term impact on plant TFP in this sector.

Figure 1 around here

Regardless of the specification used, there is no significant impact of receipt of an RSA grant on TFP in medium high-tech while the impact is always negative and significant in low-tech manufacturing. The most important finding of Figure 1 is that the impact of an RSA grant on plants in the medium low-tech sector is not robust to different specifications of the

units of capital. However, it is doubtful whether the capital stock variable adequately takes account of obsolescence, given the problems inherent in estimating rates of obsolescence.

RSA dummy. Using a dummy that equals one for 18 years and more after a grant is received always gives a negative and statistically significant coefficient. However, the estimated coefficient is not significant when fewer years are used (the exceptions being four and fourteen years). As it would be expected that the impact of an RSA grant on TFP would become apparent well before 18 years after the grant is received if the coefficient is truly measuring a causal impact, it cannot be said that receipt of an RSA grant has a significant impact on TFP in this sector.

Table 4 around here

Secondly, differences in the impact of receipt of an RSA grant between UK and foreign-owned plants were tested for by including an interaction variable between the FDI dummy and the RSA dummy. The results are provided in Table 4. The RSA dummy was not statistically significant for any of the sectors used which suggests that domestically-owned and foreign-owned plants experience similar impacts on TFP from receiving an RSA grant.

Conclusion

This paper has sought to establish the existence of a causal impact of receipt of an RSA grant on plant TFP in Scotland using a dataset created by merging SAMIS with the ARD. Estimation was performed using a matched sample to deal with the consequences of self-selection into the ‘treatment’ group. For high-tech and medium high-tech manufacturing, the estimated coefficient on the RSA dummy was not statistically significant. This was also the case in Criscuolo et al. (2009) and Hart et al. (2008). However, for medium low-tech and low-tech manufacturing, receiving an RSA was found to reduce TFP although the result for medium low-tech manufacturing was found to be not robust to changes in the specification of the RSA dummy. This suggests that RSA grants lead plants in low-tech manufacturing, the sector which received the highest number of grants, to employ an inefficiently high level of inputs. Without such grants to compensate them for employing a sub-optimally high level of inputs, they would employ fewer inputs but have higher levels of TFP. The existence of such a productivity cost is not surprising as, according to the rules of the scheme, grants are provided to get firms to do something which they would not otherwise do: create or safeguard employment. Whether this negative contribution to aggregate productivity should be regarded as a necessary evil for the extra employment in the economy is a moot point which is worthy of future research.

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Appendix

Table A1 around here

Table A2 around here

Table 1. Variable Definitions

Variable	Definition	Source
RSA	Dummy variable indicating whether the plant received an RSA grant	SAMIS
Gross Value Added	Sales minus intermediate inputs (2000 prices)	ARD
Employment	Number of employees within the plant	ARD
Capital	Plant & machinery capital stock (Harris and Drinkwater, 2000, updated)	ARD
Age	Age of plant in years	ARD
Time	Time trend calculated from 1984 base year	ARD
Herfindahl Index	Herfindahl index of industry concentration (calculated at 4-digit SIC level)	ARD
Local authority industry share	Share of (4-digit) SIC industry output within local authority in which plant is located for industry in which plant operates	ARD
Local authority diversification	Number of (4-digit) SIC codes within local authority in which plant is located	ARD
FDI	Dummy variable indicating whether the plant is owned by a foreign enterprise	ARD
Single	Dummy variable indicating whether the plant is a single-plant enterprise	ARD

Table 2. Difference in variable means for RSA-assisted and non-RSA assisted plants for different sectors, Scottish manufacturing 1984-2005

Sector	High-tech		Medium high-tech		Medium low-tech		Low-tech	
Sample	Full	Matched	Full	Matched	Full	Matched	Full	Matched
ln(Employment)	2.09***	-0.12	1.68***	-0.09	1.90***	0.00	1.50***	-0.03
	(28.95)	(-1.58)	(33.69)	(-1.50)	(32.27)	(-0.05)	(44.62)	(-0.93)
ln(Intermediate Inputs)	2.61***	-0.38***	1.82***	-0.08	1.67***	0.05	1.58***	-0.05
	(30.37)	(-3.44)	(32.44)	(-1.07)	(28.20)	(0.70)	(36.70)	(-1.02)
ln(Capital)	3.51***	0.48***	2.77***	-0.06	2.30***	0.12	2.06***	-0.09
	(30.20)	(4.84)	(31.65)	(-0.67)	(26.29)	(1.28)	(33.35)	(-1.53)
ln(Herfindahl Index)	4.99***	4.83	-0.10***	-0.04	-0.30***	0.07	5.45***	5.58
	(3.25)	(-1.47)	(-4.02)	(-1.16)	(-10.49)	(1.70)	(-6.27)	(0.61)
ln(Local Authority	1.05***	0.34	0.27***	0.05	0.18***	0.02	1.55***	1.27
Industry Share)	(9.15)	(-1.50)	(6.30)	(1.08)	(5.29)	(0.52)	(9.73)	(-0.84)
ln(Local Authority	-0.33***	0.12***	-0.10***	0.02	-0.10***	0.04	-0.10***	0.01***
Diversification)	(-12.35)	(3.25)	(-4.19)	(0.82)	(-4.70)	(1.08)	(-3.05)	(0.34)
ln(Age)	0.66***	0.39***	0.67***	0.03	0.55***	0.02	0.50***	0.00
	(18.48)	(9.02)	(23.37)	(0.89)	(18.97)	(0.57)	(25.38)	(-0.15)
Single	0.21***	-0.10***	0.08***	0.02	0.16***	-0.03	0.11***	-0.01
	(11.12)	(-2.75)	(5.62)	(1.10)	(10.84)	(-1.14)	(11.69)	(-0.82)
FDI	0.31***	0.05**	0.16***	0.00	0.09***	0.01	0.08***	0.02*
	(16.48)	(2.03)	(11.55)	(-0.09)	(7.78)	(0.40)	(11.45)	(1.73)
Time	0.50***	-0.74*	0.87***	0.11	0.33	0.33	0.44***	0.47**
	(1.95)	(-2.42)	(4.40)	(0.41)	(1.56)	(1.16)	(3.17)	(2.55)
Number of RSA Grants	89		86		87		196	
‘Treated’ Observations	746		1,129		937		2,198	
‘Untreated’ Observations	2,799	388	8,198	825	9,964	758	24,494	1,844

*/**/*** denotes significance at the 90/95/99% levels
t-statistics are in parentheses

Table 3. Estimated parameters from estimation of an augmented production function using a matched sample, Scottish manufacturing 1984-2005

Sector	High-tech	Medium high-tech	Medium low-tech	Low-tech
ln(Employment)	0.401***	0.371***	0.412***	0.278***
	(0.102)	(0.116)	(0.111)	(0.068)
ln(Intermediate Inputs)	0.579***	0.565***	0.647***	0.743***
	(0.088)	(0.081)	(0.083)	(0.058)
ln(Capital)	0.005	0.055	-0.029	-0.029
	(0.079)	(0.062)	(0.033)	(0.036)
ln(Herfindahl Index)	-0.004	0.009	0.013	0.018*
	(0.036)	(0.021)	(0.015)	(0.010)
ln(Local Authority Industry Share)	0.011	0.010	0.018	0.009
	(0.029)	(0.021)	(0.019)	(0.009)
ln(Local Authority Diversification)	0.007	0.006	-0.037*	-0.003
	(0.046)	(0.035)	(0.019)	(0.011)
ln(Age)	0.012	-0.051	0.027	0.041
	(0.113)	(0.082)	(0.051)	(0.059)
Single	-0.026	-0.012	-0.011	-0.050
	(0.042)	(0.024)	(0.038)	(0.037)
FDI	0.112	0.071*	0.028	0.105***
	(0.075)	(0.040)	(0.039)	(0.034)
Time	0.034***	-0.001	0.003	-0.001
	(0.006)	(0.004)	(0.003)	(0.003)
RSA	-0.019	-0.029	-0.034*	-0.044***
	(0.045)	(0.023)	(0.018)	(0.015)
AR(1)	-2.175**	-4.289***	-3.526***	-4.123***
AR(2)	-0.241	-1.690*	-1.957*	-0.139
Hansen test	59.78	56.53	68.46	57.12
Observations	1,134	1,954	1,695	4,042

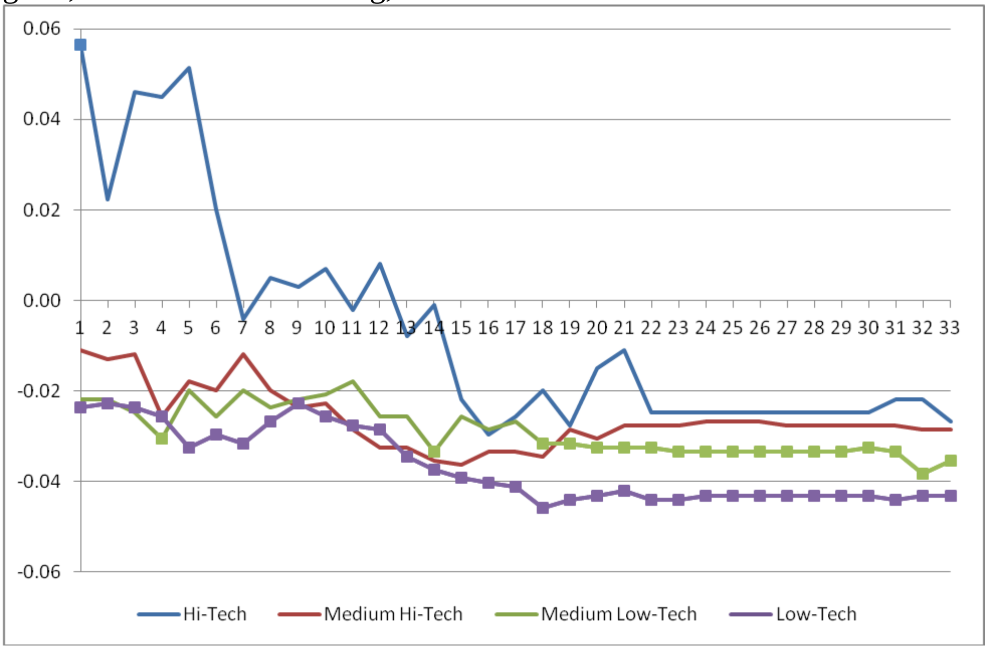
*/**/*** denotes significance at the 90%/95%/99% level
Standard errors are in parentheses

Table 4. Estimated parameters from estimation of an augmented production function using a matched sample including interaction between RSA and FDI, Scottish manufacturing, 1984-2005

Sector	High-Tech	Medium high-tech	Medium low-tech	Low-tech
ln(Employment)	0.393***	0.369***	0.412***	0.279***
	(0.105)	(0.119)	(0.112)	(0.069)
ln(Intermediate Inputs)	0.584***	0.567***	0.646***	0.743***
	(0.088)	(0.082)	(0.083)	(0.058)
ln(Capital)	-0.005	0.055	-0.031	-0.031
	(0.072)	(0.063)	(0.034)	(0.036)
ln(Herfindahl Index)	-0.001	0.009	0.014	0.018*
	(0.036)	(0.021)	(0.015)	(0.010)
ln(Local Authority Industry Share)	0.013	0.010	0.019	0.010
	(0.029)	(0.021)	(0.019)	(0.009)
ln(Local Authority Diversification)	0.002	0.006	-0.037*	-0.003
	(0.045)	(0.035)	(0.020)	(0.011)
ln(Age)	0.021	-0.050	0.031	0.045
	(0.099)	(0.082)	(0.054)	(0.059)
Single	-0.028	-0.012	-0.012	-0.052
	(0.042)	(0.024)	(0.038)	(0.037)
FDI	0.070	0.067*	0.041	0.121***
	(0.071)	(0.040)	(0.038)	(0.039)
Time	0.033***	-0.001	0.003	-0.001
	(0.006)	(0.004)	(0.003)	(0.003)
RSA	-0.044	-0.031	-0.030	-0.041***
	(0.047)	(0.025)	(0.019)	(0.015)
RSA x FDI	0.073	0.005	-0.016	-0.026
	(0.080)	(0.042)	(0.045)	(0.037)
AR(1)	-2.127**	-4.279***	-3.518***	-4.116***
AR(2)	-0.252	-1.691	-1.961	-0.160
Hansen Test	59.55	56.58	69.05	56.89
Observations	1,134	1,954	1,695	4,042

*/**/*** denotes significance at the 90%/95%/99% level
Standard errors are in parentheses

Figure 1. Estimated impact of receipt of an RSA grant on TFP using an RSA dummy that takes the value of one for 1 to 33 years after receipt of the grant, Scottish Manufacturing, 1984-2005



Squares denote that the coefficient is statistically significant at the 10% level
Note that the SAMIS database contains information on RSA recipients back to 1972.

Table A1. Mean of logged variables for non-RSA and RSA plants, Scottish manufacturing 1984-2005

	High-Tech			Medium High-Tech			Medium Low-Tech			Low-Tech		
	Non-RSA	RSA	Total	Non-RSA	RSA	Total	Non-RSA	RSA	Total	Non-RSA	RSA	Total
Ln(Gross Output)	7.56	9.98	8.07	7.40	9.18	7.62	7.14	8.84	7.28	7.39	8.91	7.51
Ln(Employment)	3.50	5.59	3.94	3.11	4.80	3.32	2.77	4.67	2.94	3.27	4.77	3.39
Ln(Intermediate Inputs)	6.98	9.59	7.53	6.77	8.59	6.99	6.55	8.22	6.70	6.75	8.33	6.88
Ln(Capital)	4.82	8.33	5.56	4.48	7.25	4.82	4.72	7.02	4.92	4.78	6.84	4.95
Ln(Herfindahl Index)	-2.54	-2.44	-2.52	-2.72	-2.84	-2.74	-2.51	-2.83	-2.54	-2.67	-2.78	-2.68
Ln(Local Authority Industry Share)	-0.82	-0.23	-0.70	-1.15	-0.88	-1.11	-1.32	-1.13	-1.30	-0.90	-0.65	-0.88
Ln(Local Authority Diversification)	2.73	2.40	2.66	2.75	2.66	2.73	2.54	2.43	2.53	2.53	2.48	2.53
Ln(Age)	2.27	2.93	2.41	2.31	2.98	2.39	2.43	2.97	2.48	2.50	3.00	2.54
Single	0.27	0.48	0.32	0.29	0.37	0.30	0.22	0.37	0.23	0.24	0.36	0.25
FDI	0.27	0.58	0.33	0.25	0.41	0.27	0.12	0.21	0.13	0.09	0.17	0.10
Time	11.53	12.03	11.64	11.50	12.37	11.61	11.45	11.78	11.47	11.17	11.61	11.20
Observations	2,799	746	3,545	8,198	1,129	9,327	9,964	937	10,901	24,494	2,198	26,692

Table A2. Estimated parameters from probit model used to calculate propensity scores, Scottish manufacturing 1984-2005

Sector	High-Tech	Medium high-tech	Medium low-tech	Low-tech
ln(Employment)	0.008 (0.047)	0.205*** (0.033)	0.368*** (0.032)	0.370*** (0.018)
ln(Intermediate Inputs)	0.072** (0.035)	0.035 (0.028)	-0.060** (0.029)	-0.013 (0.014)
ln(Capital)	0.256*** (0.031)	0.071*** (0.016)	0.019 (0.016)	0.005 (0.010)
ln(Herfindahl Index)	-0.006 (0.041)	-0.195*** (0.024)	-0.114*** (0.022)	-0.095*** (0.016)
ln(Local Authority Industry Share)	0.025 (0.024)	0.039* (0.020)	0.035 (0.024)	0.054*** (0.014)
ln(Local Authority Diversification)	-0.364*** (0.050)	-0.157*** (0.037)	-0.136*** (0.033)	-0.108*** (0.019)
ln(Age)	0.188*** (0.054)	0.397*** (0.038)	0.341*** (0.039)	0.224*** (0.024)
Single	0.700*** (0.062)	0.219*** (0.043)	0.222*** (0.044)	0.373*** (0.028)
FDI	0.411*** (0.065)	0.343*** (0.045)	0.104* (0.056)	0.223*** (0.038)
Time	0.031*** (0.006)	0.047*** (0.004)	0.041*** (0.004)	0.036*** (0.002)
Log-likelihood	-1163	-2617	-2510	-6247
Pseudo-R^2	0.362	0.240	0.214	0.177
Observations	3,545	9,327	10,901	26,692

*/**/*** denotes significance at the 90%/95%/99% level
Standard errors are in parentheses