ASSESSING THE IMPACT OF UNIVERSITY SCIENCE PARKS ON RESEARCH PRODUCTIVITY: EXPLORATORY FIRM-LEVEL EVIDENCE FROM THE UNITED KINGDOM

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Abstract

University science parks are alleged to stimulate technological spillovers. However, there is no virtually empirical evidence on the impact of these facilities on research productivity. We begin to fill this gap by examining whether companies located on university science parks in the United Kingdom have higher research productivity than observationally equivalent firms not located on a university science park. The preliminary results appear to be consistent with this hypothesis and are robust to the use of alternative econometric procedures to assess relative productivity.

Keywords: Science Parks, R&D, Productivity, University Technology Transfer
JEL Codes: O32, O33, O38, L31

I. INTRODUCTION

In recent years, there has been substantial growth in university technology transfer. A burgeoning academic literature has emerged that seeks to assess the antecedents and consequences of the rapid rise in patenting, licensing, and the formation of entrepreneurial startups at universities. An aspect of university technology transfer that has not attracted as much scholarly attention is the science park.

According to the United Kingdom Science Park Association (UKSPA (1996)), science parks have three fundamental features. They are designed to foster the creation and growth of R&D-intensive firms, provide an environment that enables large companies to develop relationships with small, high-tech companies, and promote formal and operational links between firms, universities, and other research institutions (e.g., federal research labs). Thus, science parks are expected to provide access to critical human and physical capital for innovative companies. Furthermore, the clustering of high-tech firms should serve to stimulate technology transfer and the acquisition of key business skills, such as the ability to develop new products.

All U.K. science parks are located on or near universities. The university environment could be especially conducive to enhancing the ability of firms to conduct R&D.[1] In OECD nations, two policy initiatives are alleged to have accelerated the rate of knowledge transfer from universities to firms: targeted legislation designed to stimulate research joint ventures between universities and firms (e.g., the European Union Framework Programmes) and a major shift in the intellectual property regime in favor of universities (e.g., enactment of the Bayh-Dole Act of 1980

[1] Link and Scott (2002) attempt to show that there is a reverse flow of knowledge and influence from the park to the university.

in the U.S.). It appears that these trends have resulted in a rapid rise in all forms of university-industry research relationships (e.g., licensing, co-authoring of academic articles by university and industry scientists, and sponsored research). This includes property-based institutions that foster university technology transfer, such as engineering research centers, industry-university cooperative research centers (see Adams et al. (2001)), and science parks.[2]

Despite the potential importance of university science parks as a mechanism for stimulating technological spillovers, there is no direct empirical evidence on the impact of these facilities on the research productivity of firms. The purpose of this paper is to fill this gap. This analysis could have important policy implications, since university science parks are typically supported by public funds. One measure of the "success" of such facilities, from a public policy perspective, is whether they stimulate higher research productivity. This can be viewed as one dimension of the social return to public investment in R&D. Our empirical analysis of these returns is based on a rich, firm-level U.K. dataset. These data allow us to assess the difference between the average research performance of firms that are located on university science parks and observationally equivalent firms that are not located on these facilities.

The remainder of this paper is organized as follows. Section II provides background information on university science parks and reviews the limited empirical evidence on other aspects of the performance of science park firms. Section III outlines the econometric models used to assess research productivity. Data and empirical findings are presented in Section IV.

[2] Mowery, Nelson, Sampat, and Ziedonis (2001) provide a cautionary note on a causal interpretation of the effects of Bayh-Dole on university technology transfer. See Poyago-Theotoky, Beath, and Siegel (2002), for a broader consideration of the economic and managerial implications of the rise of university-industry research relationships.

The final section consists of preliminary conclusions, caveats, and suggestions for additional research.

II. BACKGROUND INFORMATION AND BRIEF LITERATURE REVIEW

We begin with some stylized facts. In 1972, the first U.K. science parks were established in Cambridge and Heriot-Watt. By 1992 (the year our survey was conducted), there were 32 parks in operation, as most of the older U.K. universities had adopted this organizational innovation. Over time, more "polytechnics" or "new" universities also established such a facility, so that by 1999, there were 46 fully operational university science parks in the U.K.

As noted earlier, in contrast to the U.S. (see Link and Scott (2002)), all science parks in the U.K. are university science parks, located at the institution or within close proximity. The UKSPA (1999) also reports that 80% of the science park firms have fewer than 15 employees and that over half of the firms located on these facilities are engaged in R&D and/or new product development. Some of these companies are attempting to commercialize leading-edge technologies, most notably, biotechnology, materials, computers/ telecommunications, and technologies with environmental, energy, and industrial applications.

There is limited empirical evidence on some dimensions of the relative performance of firms on U.K. science parks.[3] A major breakthrough in this literature was the creation of a longitudinal dataset containing performance indicators for firms located on parks and a control group of firms not located on parks. These data were originally collected by Monck et al. (1988) and updated and extended by Westhead and Storey (1994). Our empirical analysis will also be based on this file. In Section IV, we will describe the construction of this dataset in great detail.

In a series of studies, Westhead and Storey (1994) and Westhead (1997) used this file to compute differences in the mean values of several performance indicators for science park and non-science parks firms. The authors reported statistically insignificant differences in the probability of survival, job creation, R&D expenditures, the number of scientists and engineers, the number of patents and copyrights, and the creation of new products[4]

Although these findings are useful, they do not allow us to make inferences regarding relative research productivity, i.e., whether firms located on science parks are more efficient in conducting R&D. In the following section, we outline several variants of an econometric model that enables us to address this issue.

III. ECONOMETRIC MODELS

Three econometric strategies are used to test whether science park firms have higher research productivity than observationally equivalent non-science park firms. We specify an R&D production function (Griliches (1998)) with three possible R&D "outputs" and two R&D "inputs":

(1) NEWPRODS, PATENTS, or COPYRIGHTS
= f (RDEXP, RDSCI, SCIPARK)

where NEWPRODS = number of new products/services
PATENTS = number of patents applied for or awarded
COPYRIGHTS = number of copyrights
RDEXP = R&D expenditures
RDSCI = number of scientists and engineers
SCIPARK = a dummy variable=1 if a firm is located on a science park; 0 otherwise

A key parameter in equation (1) is the coefficient on SCIPARK, which will have a positive sign if location on a science park is associated with better research performance. However, the

[3] See Siegel, Westhead, and Wright (2003b) for a more comprehensive review of this evidence.

inclusion of SCIPARK in equation (1) raises concerns regarding endogeneity, since it is conceivable that the location decision and R&D output could be jointly determined.[5]

The existence of an endogeneity bias could cloud the accuracy of estimates of the impact of university science parks on the research productivity of firms. To address this concern, we estimate a variant of the model that includes an additional equation:

(2) $SCIPARK = g(RADICAL, TECH, \Sigma_m Z_m)$

where RADICAL is a dummy variable denoting whether the firm is engaged in research on a "radical" innovation; TECH is a categorical variable classifying the nature of the firm's existing technology (i.e., whether it is "leading edge," advanced, or established); and Z is a vector of m control variables. We conjecture that firms engaged in "radical" innovation (i.e., firms developing a major technological breakthrough) could be more likely to locate on a science park.[6] That is because establishing a physical presence on (or near) campus could enable them to benefit more directly from knowledge spillovers arising from cutting-edge university research. The location decision could also be related to the extent to which a firm's existing technology is state-of-the-art.

In each variant of the regression model, we will report the coefficient on SCIPARK, with and without controlling for the possibility of an endogeneity bias. In the latter case, we will use a two-stage estimation procedure for a count variable. An alternative to the use of a dummy variable as a regressor involves splitting the sample into science park and non-science park firms

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[4] See Westhead and Storey (1994) and Westhead (1997).
[5] Another econometric concern, which often arises in production function studies, is simultaneity. As shown in Olley and Pakes (1996), there are ways of dealing with this problem with panel data. The cross sectional nature of our data limits our ability to address this problem.
[6] Hall, Link, and Scott (2000) report that firms often invite universities to join an RJV in order to help them

and estimating separate R&D production function regressions. This approach yields separate estimates of the marginal product of R&D, which could be higher for firms located on university science parks if such facilities do indeed foster technological spillovers.

The final method we use to assess relative research performance is stochastic frontier estimation (henceforth, SFE), which generates a production frontier with a stochastic error term consisting of two components: a conventional random error ("white noise") and a term that represents deviations from the frontier, or relative inefficiency.[7] Siegel, Waldman, and Link (2003a) used SFE to assess the relative efficiency of university technology transfer offices.[8]

In SFE, a production function of the following form is estimated:

(3) $y_i = \mathbf{X}_i \beta + \epsilon_i$

where the subscript i refers to the i^{th} firm, y denotes an R&D output (e.g. the number of new products), $\mathbf{X}$ is a vector of R&D inputs, β is the unknown parameter vector, and ϵ is an error term with two components, $\epsilon_i = V_i - U_i$, where U_i represents a non-negative error term to account for technical inefficiency, or failure to produce maximal output, given the set of inputs used. V_i is a symmetric error term that accounts for random effects. A standard assumption in SFE (see Aigner, Lovell, and Schmidt (1977)) is that the U_i and V_i have the following distributions:

$$U_i \sim \text{i.i.d. } N^+(0, \sigma^2_u), \quad U_i \geq 0$$
$$V_i \sim \text{i.i.d. } N(0, \sigma^2_v)$$

understand basic research results.

[7] See Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977). SFE can be contrasted with data envelopment analysis (DEA), a non-parametric estimation technique that has been used extensively to compute relative productivity in service industries. See Charnes et al. (1994).

[8] Thursby and Kemp (2002) use DEA to study the same phenomenon.

That is, the inefficiency term (U_i) is assumed to have a half-normal distribution; i.e., firms are either "on the frontier" or below it.[9]

SFE models have been developed that allow the technical inefficiency or relative productivity term to be expressed as a function of a vector of additional variables (e.g., organizational and environmental characteristics). Consistent with Reifschneider and Stevenson (1991), we assume that the U_i are independently distributed as truncations at zero of the $N(m_i, \sigma^2_u)$ distribution with

$$(4)\ m_i = \mathbf{Z}_i \delta$$

where **Z** is a vector of additional variables that are hypothesized to influence relative productivity and δ is a parameter vector.[10]

Following Battese and Coelli (1995), we derive maximum likelihood estimates of the parameter vectors β and δ from simultaneous estimation of the production function and relative inefficiency equations, using the FRONTIER statistical package (See Coelli (1994)). The first equation is the following (single output) translog production function:

$$(5)\ \ln(NEWPRODS_i) = \beta_0 + \beta_1 \ln(RDEXP_i) + \beta_2 \ln(RDSCI_i) + \gamma_{11} \ln(RDEXP_i)^2 + \gamma_{22} \ln(RDSCI_i)^2 + \gamma_{12} \ln(RDEXP_i)\ln(RDSCI_i) + V_i - U_i$$

The second equation describes the determinants of relative productivity:

$$(6)\ U_i = RELPROD = \delta_0 + \delta_S\, SCIPARK + \delta_T\, TOTEMP_i + \delta_R\, REVENUE_i + \delta_P\, PROFIT + \mu_i$$

where SCIPARK is a dummy variable denoting whether a firm is located on a university science park; TOTEMP refers to total firm employment; REVENUE is annual revenue; and PROFIT is a dummy variable denoting whether a firm generated a profit in the previous fiscal year.[11]

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[9] An important parameter in this model is $\gamma = \sigma^2_u / (\sigma^2_v + \sigma^2_u)$, the ratio of the standard error of technical inefficiency to the standard error of statistical noise, which is bounded between 0 and 1. Note that $\gamma = 0$ under the null hypothesis of an absence of inefficiency, signifying that all of the variance can be attributed to statistical noise.

[10] Battese and Coelli (1995) extend this model to incorporate panel data, although we only have cross sectional data.

[11] Unfortunately, we don't have a continuous measure of profitability.

IV. DATA AND EMPIRICAL RESULTS

As noted earlier, our primary data source is a U.K. firm-level survey constructed by researchers at the Centre for Small and Medium Size Enterprises at the University of Warwick in the late 1980s. The file was then updated and extended by Paul Westhead and David Storey, who analyzed the data in several papers in the late 1990s. The first objective in constructing the dataset was to generate a random sample of science park firms. This was not too difficult, since the UKSPA provided the Warwick researchers with information on the universe (population) of companies located on such facilities. A more onerous task was to generate a random sample of "comparable" non-science park companies.

To facilitate generalization, interviews were conducted with representative firms in many science parks. Also, structured questionnaires were implemented in 1986 and 1992 to gather information from owner-managers of science park firms. In-person interviews with the owner-managers of science park firms were conducted (in 1986 and 1992), to ensure a high response rate and more accurate information. In order to control (albeit, imperfectly) for sample selection bias, data were collected in both years from observationally equivalent firms (a control group of similar firms not located on a science park). Samples of science park and off-park firms were matched, in 1986, along the following dimensions: age of firm, industry, ownership status, and region.

This matching process is highly dependent on the ability to identify privately-held companies, since many firms on a university science park are in emerging industries. Many companies in such sectors have not yet gone public. Fortunately, it is easier to collect information on the characteristics of privately-held firms in the U.K. than in the U.S., due to the existence of the Inter-corporate (ICC) and Financial Analysis Made Easy (FAME) databases. However, it is difficult to know whether we have a random sample of science park firms, since there are no population statistics to compare our final sample with.

A notable feature of the Westhead and Storey sample design is that the authors decided to survey only "independent" science park firms. This precludes an assessment of large firms with smaller R&D units on such facilities. Thus, we cannot examine intra-firm spillovers that might arise when a firm located on a science park benefits from R&D conducted by its parent company (perhaps at a corporate R&D facility) at other locations. On the other hand, it does allow for a cleaner analysis of the impact of the science park on research productivity. The bottom line is that it was obviously much easier to construct a "matched pairs" sample using this criterion.

Our final sample contains 177 firms, consisting of 89 science park firms and 88 non-science park firms, reporting information for 1992. Descriptive statistics for the inputs and outputs of the R&D production function are presented in Table 1. The average firm in our sample generated approximately 5 new products or services, at least one patent and copyright, spends about £345K on R&D, and employs over 7 scientists or engineers. Although it appears as though science park firms generate slightly more patents and new products, t-tests of differences in means for all three R&D output measures were insignificant. It is important to note, however, that such comparisons do not simultaneously take account of input usage, as we will do in our econometric analysis of research productivity equations.

Note that our three R&D output measures are count variables and there are some zero values. Therefore, we considered Poisson and negative binomial (generalized Poisson) specifications, which were estimated using LIMDEP.[12] Given that the Poisson specification was decisively rejected, based on values of the χ^2 statistic, we present only the negative binomial results.[13]

Table 2 contains the first set of econometric findings. Recall that we have three R&D output measures: the number of new products and services, patents, and copyrights. We present two sets of results for each of the three R&D outputs. Columns (1), (3), and (5) contain negative binomial parameter estimates with no controls for endogeneity bias, while columns (2), (4), and (6) contain "two-step" negative binomial estimates (see Greene (1995)), which control for possible endogeneity bias associated with the science park dummy variable (SCIPARK).

Several interesting patterns emerge from this table. First, for two out of three output measures, the model appears to be fit fairly well. Most of the coefficients on the R&D inputs have the expected (positive) signs, and some are statistically significant. To assess whether firms on university science parks are more "productive" in research, we focus our attention on the coefficients on SCIPARK. These parameter estimates are positive and statistically significant for new products and services and patents. Note, however, that the magnitudes of these coefficients are fairly small. It appears that these findings hold even when we control for the possibility of endogeneity bias, although the "two-step" estimates are considerably lower.

Table 3 presents estimates of the output elasticity or marginal product of R&D for the entire sample of 177 firms (row 1), the 89 science park firms (row 2), and the 88 non-science park firms (row 3). We also report test statistics for differences in these elasticity estimates between

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[12] Since the seminal paper by Hausman, Hall, and Griliches (1984), Poisson models are quite commonly employed in empirical studies of count variables (especially, patents).

[13] The Poisson results, which do not differ much from the negative binomial estimates, are available upon request

science park and non-science park firms. Our findings are similar to those contained in the previous table, in the sense that for two of the three R&D output measures (new products and patents), the output elasticities of R&D are positive and statistically significant. More importantly, the significant F statistics in the first two columns imply that the marginal product of R&D is higher for firms located on university science parks.

Table 4 contains maximum-likelihood estimates of the determinants of relative productivity (equation (6), based on stochastic frontier analysis for those firms with non-zero research outputs.[14] The results imply that these variables have some explanatory power. The negative and significant coefficient on TOTEMP indicates that larger firms may be more productive in research (less inefficient, in the stochastic frontier framework). On the other hand, the coefficient on REVENUE, which is also sometimes used as a proxy for firm size in empirical studies of the Schumpeterian hypothesis, is insignificantly different from zero. We also find that firms generating a profit tend to be closer to the frontier. More importantly, the estimated coefficients on SCIPARK (for new products/services and patents) appear to confirm our previous results indicating that science parks firms are more productive in research.

V. CONCLUSIONS, CAVEATS, AND EXTENSIONS

Our preliminary results suggest that firms located on university science parks have slightly higher research productivity than observationally equivalent firms not located on university science parks. These impacts are not as strong when we control for endogeneity bias, or the possibility that location on a university science park and the generation of research output are

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from the authors.

[14] The full set of parameter estimates of the translog production frontier is available upon request from the authors.

jointly determined. However, they do appear to be robust to alternative econometric specifications, including testing for a shift factor (the use of a dummy variable), an examination of differences in the marginal product of R&D, and stochastic frontier analysis.

The notion that location on a university science park is associated with higher research productivity presents an opportunity for analysis of the factors underlying this difference in research performance. Aside from some vague notion of technological/knowledge spillovers from universities to firms, it would be interesting to examine the connection between the productivity differential and the "closeness" of the relationship between the science park firm and the university. For this, we need a direct measure of contact between these companies and academics and graduate students. The role of distance also needs to be explored.

Several caveats should be noted. One concern, which is common to studies of patents, is that we have count measures, as opposed to estimates of the values of these technology flows. A more accurate measure of research performance ("true" research productivity) would be based on properly deflated R&D outputs, where for example, patents would be weighted by citations (Hall, Jaffe, and Trajtenberg (2001)). Another limitation of our empirical analysis is that is based on data that is a decade old. This is problematic, since it is conceivable that the returns to being located on a science park may have shifted over time.

We also hope to pursue several extensions of this research. Further exploration of the heterogeneity across different types of science parks might also be useful. That is, it is conceivable that our results could be masking important differences in the returns to different types of science parks. For instance, the UKSPA (1999) distinguishes between "managed" and "non-managed" science parks. A managed science park has a full time, on-site manager, who may prove useful in terms of facilitating knowledge spillovers from universities to firms and among companies located on the same science park. It might also be useful to conduct international comparisons of the returns to location on university science parks.

REFERENCES

Adams, J.D., E.P. Chiang, and K. Starkey. (2001). Industry-University Cooperative Research Centers. Journal of Technology Transfer, Vol. 26, Nos. 1-2, pp. 73-86.

Aigner, Dennis J., C.A.K. Lovell, and P. Schmidt. (1977). Formulation and Estimation of Stochastic Frontier Production Functions. Journal of Econometrics, Vol. 6, pp. 21-37.

Battese, G. and T. Coelli. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. Empirical Economics, Vol. 20, pp. 325-332.

Bercovitz, J., M. Feldman, I. Feller, and R. Burton. (2001).Organizational Structure as Determinants of Academic Patent and Licensing Behavior: An Exploratory Study of Duke, Johns Hopkins, and Pennsylvania State Universities. Journal of Technology Transfer, Vol. 26, Nos. 1-2, pp. 21-35.

Charnes, A. W. W. Cooper, A. Lewin, and L. M. Seiford, eds. (1994). Data Envelopment Analysis: Theory, Method, and Applications, Boston, MA: Kluwer Academic Publishers.

Coelli, T. (1994). A Guide to FRONTIER Version 4.1: A Computer Program for Frontier Production and Cost Function Estimation. mimeo, Department of Econometrics, University of New England, Armidale.

Greene, W.(1995). LIMDEP-Version 7.0 Users Manual Econometric Software, Inc: Bellport, N.Y.

Griliches, Z.. (1998). R&D and Productivity: The Econometric Evidence, National Bureau of Economic Research for the University of Chicago Press, Chicago: University of Chicago Press.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg. (2001). The NBER Patent Citations Data File: Lessons, Insights, and Methodological Tools. NBER Working Paper #8498.

Hall, Bronwyn H., Albert N. Link, and John T. Scott. (2000). Universities as Research Partners. NBER Working Paper No. 7643 and forthcoming, Review of Economics and Statistics.

Hausman, J., B.H. Hall, and Z. Griliches. (1984). Econometric Models for Count Data with an Application to the Patents-R&D Relationship. Econometrica, Vol. 52, pp. 909-938.

Link, A.N. and J.T. Scott, (2002). Science Parks and the Generation of University-Based Knowledge: An Exploratory Study. International Journal of Industrial Organization, forthcoming.

Meeusen, W. and J. Van den Broeck. 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Errors. International Economic Review, Vol. 18, pp. 435-444.

Monck, C. S. P., Porter, R. B., Quintas, P., David J. Storey, and P. Wynarczyk. (1988). Science Parks and the Growth of High Technology Firms. London: Croom Helm.

Mowery, D.C., R.R. Nelson, B. Sampat, and A.A. Ziedonis. (2001). The Growth of Patenting and Licensing by U.S. Universities: An Assessment of the Effects of the Bayh-Dole Act of 1980. Research Policy, Vol. 30, pp. 99-119.

Olley, S.G. and A. Pakes. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica, Vol. 64, No. 6, pp. 1263-1297.

Poyago-Theotoky, J., J. Beath, and D.S. Siegel. (2002). Universities and Fundamental Research: Reflections on the Growth of University-Industry Partnerships," Oxford Review of Economic Policy, Vol. 18, No. 1, pp. 10-21.

Reifschneider, D. and R. Stevenson. (1991). Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency. International Economic Review, Vol. 32, No. 3, pp. 715-723.

Siegel, D.S., D. Waldman, and A.N. Link. (2003a). Assessing the Impact of Organizational Practices on the Productivity of University Technology Transfer Offices: An Exploratory Study. Research Policy, Vol. 32, No. 1, pp. 27-48.

Siegel, D.S., P. Westhead, and M. Wright (2003b). Science Parks and the Performance of New Technology-Based Firms: A Review of Recent U.K. Evidence and An Agenda for Future Research. Small Business Economics, Vol. 20, No. 2, March 2003, pp. 177-184.

Thursby, J.G., and S. Kemp. (2002). Growth and Productive Efficiency of University Intellectual Property Licensing. Research Policy, Vol. 31, No. 1, pp. 109-124.

UKSPA. (1996). UKSPA 96: The United Kingdom Science park Association Annual Report 1996. Birmingham: The United Kingdom Science Park Association.

UKSPA. (1999). 15th Anniversary 1984-1999. Birmingham: The United Kingdom Science Park Association.

Westhead, P. (1997). R & D 'Inputs' and 'Outputs' of Technology-Based Firms Located On and Off Science Parks. R&D Management, Vol. 27, pp.45-62.

Westhead, P. and D. J. Storey (1994). An Assessment of Firms Located On and Off Science Parks in the United Kingdom. London: HMSO.

Table 1
Descriptive Statistics for the Inputs and Outputs of the R&D Production Function
(n=177 firms, 1992)

		All Firms		Science Park Firms		Firms Not Located on Science Parks	
Variable Name	Description	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
NEWPRODS	Number of New Products or Services	5.2	9.1	5.6	10.3	4.9	8.9
PATENTS	Number of Patents Applied for or Awarded	1.4	2.3	1.7	2.5	1.5	2.2
COPYRIGHTS	Number of Copyrights	1.2	1.5	1.1	1.6	1.3	1.4
RDEXP	R&D Expenditures (£000)	345.2	874.8	338.9	855.9	353.4	888.6
RDSCI	Number of Scientists and Engineers	7.2	11.4	7.5	10.3	7.1	12.8

Source: Westhead and Storey (1994) Survey of Independent Science Park and Non-Science Park Firms in the U.K.

Table 2

Maximum Likelihood Estimates of Negative Binomial (NB) and "Two Step" Negative Binomial (TSNB) Regressions of the Determinants of R&D Outputs (Equation (1))

	Dependent Variables: Proxies for R&D Output					
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficients on	New Products/Services		Patents		Copyrights	
Independent Variables	NB	TSNB	NB	TSNB	NB	TSNB
INTERCEPT	-1.028***	-1.214***	-1.236***	-1.215***	-1.623***	-1.424***
	(.389)	(.368)	(.508)	(.567)	(.780)	(.568)
RDEXP	.362**	.320**	.276**	.201**	.069	.058
	(.184)	(.159)	(.130)	(.093)	(.058)	(.046)
RDSCI	.111	.108	.190**	.093	.123**	.078
	(.066)	(.070)	(.094)	(.058)	(.061)	(.061)
SCIPARK	.150**	.122**	.140**	.110**	.074	.081
	(.072)	(.060)	(.067)	(.052)	(.048)	(.060)
Log Likelihood	-144.24	-146.21	-143.99	-147.02	-157.51	-159.23
Chi-Squared	20.20	18.38	19.87	17.96	17.43	14.05

Notes:
Heteroskedastic-consistent standard errors are reported in parentheses.
*** Significant at the 1% level, ** Significant at the 5% level
Columns (1), (3), and (5)-NB-Negative Binomial Estimation
Columns (2), (4), and (6)-TSNB-"Two-Step" Negative Binomial Estimation (see Greene (1995) p. 581)

Table 3

Estimates of the Elasticity of R&D Output With Respect to R&D Expenditure

	Proxies for R&D Output:		
	New Products/ Services (1)	Patents (2)	Copyrights (3)
ALL FIRMS (N=177)	.429*** (.185)	.318** (.159)	.069 (.048)
FIRMS LOCATED ON UNIVERSITY SCIENCE PARKS (N=89)	.569*** (.154)	.453*** (.212)	.051 (.042)
FIRMS NOT LOCATED ON UNIVERSITY SCIENCE PARKS (N=88)	.263** (.131)	.223** (.108)	.123 (.079)
F Statistic for Difference in Elasticity Estimates Between Firms Located on University Science Parks and Firms Not Located on University Science Parks	5.78**	5.03**	1.58

Notes: Heteroskedastic-consistent standard errors are reported in parentheses.
*** Significant at the 1% level, ** Significant at the 5% level

Table 4

Maximum Likelihood Estimates of the Determinants of Relative Inefficiency (Equation (6))

Determinants of Relative Productivity	Dependent Variables: Proxies for R&D Output New Products/Services	Patents	Copyrights
SCIPARK	-.072**	-.062**	.028
	(.034)	(.029)	(.033)
TOTEMP	-.121**	-.103*	-.036
	(.058)	(.044)	(.024)
REVENUE	-042	-.037	-.073
	(.025)	(.023)	(.071)
PROFIT	.020	-128**	-.055**
	(.057)	(.062)	(.027)
Log Likelihood	-31.67	-29.64	-33.02

Notes: Maximum likelihood estimates of the parameter vector δ from simultaneous estimation of the production function and relative inefficiency equations, using the FRONTIER statistical package (See Coelli (1994)).

Standard errors in parentheses

*** Significant at the 1% level, ** Significant at the 5% level