The Impact of University Research on Corporate Patenting*

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ABSTRACT

This paper analyses the association between the number of patenting manufacturing firms and the quantity and quality of relevant university research across UK postcode areas. We show that different measures of research 'power' and 'excellence' positively affect the patenting of small firms within the same postcode area. Patenting by large firms, in contrast, is unaffected by research undertaken in nearby universities. This confirms the commonly held view that location matters more for small firms than large firms. We also investigate specific channels of technology transfer, finding that university-industry knowledge transfer occurs through both formal and informal channels. From a methodological point of view, we contibute to the existing literature by accounting for potential simultaneity between university research and patenting of local firms by adopting an instrumental variable approach. Moreover, we also allow for the effects of the presence of universities in neighbouring postcode areas to influence firms' patenting activity by incorporating spatial neighborhood effects.

KEYWORDS: Patents, universities, knowledge transfer, spillover, UK

JEL Classification: L22, L26, O34

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1 Introduction

The capacity of university research to act as a catalyst for business sector innovations is of critical importance. Universities have a potential impact on firms' innovation in a variety of ways including: publication of fundamental research; university patenting and licensing; spin-offs and university incubators; joint research with firms; targeted knowledge transfer to firms; consultancy projects; training of students including continuous professional development and executive training programmes; and informal knowledge networks. From a policy perspective, there are a number of key issues. Perhaps of paramount importance is how should money for university research be allocated? This involves choices over both how many universities should be funded and also the distribution of funding within the chosen universities. For example, is it important to ensure university research is spread across a wide range of regions? Equally, to what extent should research be focused on the 'best' universities and, of course, how should one determine the 'best'? In addition, there are a range of other issues surrounding university-business links including the incentives facing a university to patent and license, engage in formal joint research agreements with business, promote university spin-offs, or rather to pursue informal knowledge transfer programs.

Our central research question is: does a university's research affect the innovative activity of manufacturing firms located close to the university? We are particularly interested in whether the quality of the research undertaken at universities impacts on the effectiveness of localised university-industry knowledge transfer. Understanding whether knowledge transfer is geographically localised is essential to provide an answer to the question of whether university research should be spread across regions or whether individual clusters of excellence are more conducive to university-industry knowledge transfer.

The UK has developed an elaborate methodology to assess the quality of research called the Research Assessment Exercise (RAE), which is used as a metric to allocate research funds. We use data from the 2001 RAE in this paper to measure university research quality. Innovative activity is notoriously difficult to measure but patents and R&D are frequently used proxies.[1] Since in the UK, as in other countries, data on the R&D activity of smaller firms is limited, this paper uses patenting as the proxy for innovation. Using patent data does direct the focus to specific types of innovations, but this may be appropriate when considering certain types of university research. For this reason, we focus on research by engineering and biological sciences departments. Our data allow us to analyse separately large and small companies.[2] Small firms might be thought to rely on local universities more than larger firms, hence the impact of geographically nearby universities might differ between the two types of firms. The ability to look at the innovative activity of smaller firms in isolation drives an important contribution of our paper: we only find a positive association between university research and patenting of small firms at the postcode area level. Large firm patenting, in contrast, is unaffected by the quantity and quality of research undertaken at

[1] For a discussion see Greenhalgh and Rogers (2009).

[2] Our small firm category contains both micro firms and small & medium enterprises (SMEs).

nearby universities. This does not imply that large firms are not benefitting from relevant university research. Rather, it means that only small firms benefit from localised university-industry knowledge transfer. In addition, we find that research quality matters: there is a positive association between the RAE grade obtained by the relevant university departments and small firm patenting.

In order to establish our main result, we address a critical issue in the assessment of the association between patenting and university research within a narrowly defined geographical area: endogeneity of university research due to unobservable agglomeration externalities as well as simultaneity between university research and firms' innovative activity. We instrument the RAE research quality measure, our main variable of interest, by a university's age. Universities in the UK are well suited for this identification strategy as there is large variation in university age across universities and postcode areas which we find to be strongly correlated with research quality. At the same time, we argue that a university's age is not associated with patenting of local companies other than through its effect on the quality of research undertaken at the corresponding university.

A final contribution is to investigate the channels of knowledge transfer between universities and firms. Information on universities' knowledge transfer activities, including licensing of university intellectual property, consultancy services and the presence of science parks and incubators is used to test for specific channels through which knowledge transfer to smaller companies occurs. Our findings suggest that both formal and informal channels are effective in promoting small firm patenting, although their effectiveness differs for knowledge generated by engineering and biological sciences departments.

The paper is organised as follows. The next section reviews the existing empirical results on the role of universities in business innovation. Section 3 discusses some of the difficulties of analysing the link between university research and corporate patenting, together with outlining our approach. Section 4 discusses the data used. Section 5 explains the estimation method adopted. Section 6 describes our results and Section 7 offers some concluding thoughts.

2 Literature

This section reviews the existing empirical work on the broader impact of university research on corporate innovative activity. The literature essentially originates in Jaffe's (1989) seminal work in which he analyses spillovers from university research to corporate patent activity using the Griliches (1979) type knowledge production function framework. Corporate patenting in 29 US states is the basic dependent variable although this is broken down into different technology areas for the period 1972-77, 1979, and 1981.[3] The determinants of patenting are: the number of universities; university R&D (again

[3]The technology areas are drugs/medical, chemical, electronics/optics/nuclear, mechanical arts and 'other'.

broken down by technology area), total R&D performed by industry, a geographical coincidence indicator (an index that captures concentration of universities and firms) and a number of control variables such as population and public research laboratories. Jaffe allows for a simultaneous relationship between private sector R&D and university research by estimating a system of simultaneous equations. The results suggest that there are spillovers from universities to corporate patenting, most strongly in drugs but also in chemicals, electronics and mechanical arts. Acs et al. (1992) complement Jaffe's study by using innovations as the dependent variable (from the 1982 US Small Business Administration innovation database). They also find positive associations between university research and innovation at the state level, although this is not the case for electronics-based industries.

More recently, Harhoff (1999) looks at the formation of new firms in 328 West-German counties over the period 1989 to 1993 and, specifically, how the existing industry structure and presence of publicly-funded research measured in 1987 and 1989 respectively affect rates of firm creation between 1989 and 1993.[4] Harhoff focuses his analysis on two 2-digit industries, the electrical machinery and mechanical engineering sectors. These industries are further divided into high-technology and low-technology on the basis of R&D intensity at the 4- and 5-digit industry level. A Poisson Pseudo Maximum Likelihood model is then used, with number of new entrants as the dependent variable where the data is treated as a pooled cross-section. To model the effect of research on firm formation, Harhoff uses county-specific employment shares of R&D personnel, scientific personnel at universities as well as at extra-university research laboratories and institutes. Industry structure is captured by the share of the industry's employment in the county's total manufacturing employment, as well as through a Herfindahl concentration measure for the manufacturing industry.[5] In addition, a wide range of other explanatory variables are included, which are similar to above studies. The results indicate that the employment share of scientists and engineers in universities and extra-university research institutions are positively associated with high-tech firm formation. Moreover, Harhoff finds new firm formation within the sectors studied to be persistent in highly specialised regions. Yet, high-tech start-ups are found to be much less persistent, i.e., high-tech start-ups are more likely to be found in counties with heterogeneous industry structures. The results also suggest a positive association between high-tech start-ups and the presence of business-oriented service providers.

Another study using West-German data is by Fritsch and Slavtchev (2007). The authors use West-German data for NUTS-3 regions with the dependent variable being counts of patent applications between 1995 and 2000.[6] Fritsch and Slavtchev estimate

[4]The conditioning variables refer to the pre-reunification period, while start-ups are investigated also during the period directly after Germany's reunification. Harhoff does not account for re-unification effects and it is not clear to what degree the important structural shock induced by reunification has influenced start-up activity.

[5]This measure excludes the specific industry studied and captures a county's degree of diversification in the manufacturing sector.

[6]Note that patents are allocated to regions using the address of the inventor, rather than the address of the firm. So an important assumption Fritsch and Slavtchev make is that firms' location and place of residence of inventors coincide within the same NUTS-3 region. Also, it is unclear whether only

a Griliches-type knowledge production function. The inputs are R&D (equal to the number of private sector employees in R&D),[7] and universities' regular as well as additional external funds. Inter-regional spillovers are captured by allowing private R&D and university funds to affect patent counts in neighbouring regions (where the distance between regional centres is within 0-50km and 50-75km). Similar to the other studies, Fritsch and Slavtchev also include an industrial concentration index (in the form of a Gini coefficient). To account for the higher propensity to patent in the manufacturing sector compared to services, the authors also include a manufacturing specialisation index, which is the share of manufacturing employment relative to the national average. The authors estimate a negative binomial model for their panel that constrains any research impact on patenting to be after three years. The results suggest that there is no evidence of universities' regular budget having any positive association with patenting. However, external funds are associated with increased patent counts. External funds also affect patenting within a 50km radius (the authors do not allow for spillover effects for regular funds).

For the UK, Abramovsky et al. (2007) analyse the relation between university research on the location pattern of business R&D in six specific product groups at the establishment level. The data on R&D active firms comes from the ONS Business Entreprise Research and Development (BERD) data. The analysis uses 2-letter UK postcode areas as the unit of analysis. University research in a postcode area is proxied by the number of research departments that get 2001 RAE rankings of 5 or 5*, and those that get (lower) 1 to 4 rankings.[8] In addition, the log of the number of research students (also divided between universities ranked 4 and below and 5 and 5*) is included. Location of business R&D is the average number of establishments in a postcode area (i.e., no data on R&D spending is used) during the 2000-2003 period. Moreover, they also look at the number of new R&D performing entrants within postcode areas between 2000-2003 as compared to differences in RAE rankings between 1996 and 2001 (in an attempt to account for unobserved heterogeneity of spatial units that is correlated with the level of research quality). Cross sectional regressions are run separately for the number of R&D establishments in the different product groups,[9] as well as domestic/foreign establishments. In all cases it is assumed that the dependent variables follow a negative binomial distribution.

The different product group regressions include explanatory variables based on different university research departments (biology, chemistry medical, materials science, computer science, and electrical as well as mechanical engineering). A range of other control variables at the postcode area level are used including total manufacturing employment, diversification of manufacturing employment, skill levels in the population, and a dummy for science parks. The results indicate nearly no statistically significant

national patent applications are included or whether the data set contains also EPO patents.

[7]Fritsch and Slavtchev assume that every employee with a tertiary degree in engineering or natural sciences works in R&D.

[8]The 2001 RAE grade scale is 5* (highest), 5, 4, 3a, 3b, 2 or 1.

[9]The product groups are pharmaceuticals, chemicals, machinery, electrical, TV and radio, and motor vehicles.

correlation between the average number of R&D performing firms and the presence of universities, their number, or their overall research quality. Using the RAE rankings for specific university departments, there are some statistically significant associations between university research and the count of R&D performers, although the overall correlation pattern is weak. Nevertheless, the results suggest that 5 or 5* rankings have an influence in pharmaceuticals and chemicals, while RAE rankings 1 to 4 also have an effect in pharmaceuticals and additionally in machinery and communications equipment when the sample is restricted to foreign R&D active firms. With respect to the effect of the change in RAE rankings on the number of R&D entrants, the results confirm a statistically significantly positive association between the quality of chemistry research departments and entry of R&D performing firms in the pharmaceutical industry, as well as of material science research departments on the chemical sector. All other coefficients capturing the change in research quality across research departments for the different sectors are not statistically significant, with the exception of the TV and radio equipment industry, in which entry is correlated with research quality of electrical and mechanical engineering departments.

Laursen et al. (2008) also explore the importance of geographical distance as a channel for knowledge transfer between firms and universities in the UK. The authors combine data from the UK innovation survey covering the period 2002-2004 with the 2001 RAE and other firm-level and regional variables. Using the RAE, they categorise universities into three quality groups. The top group contains the ten highest ranking universities in the UK. The second group contains all universities ranked between 11 and 40; the third tier contains the remaining 59 universities included in the sample. The information contained in the innovation survey allows Laursen et al. to construct a binary dependent variable indicating whether a firm reports to have collaborated with a university at the local level. They then estimate a logit model analysing the correlation between a firm's propensity to collaborate and its distance to the nearest university.[10] Alternatively, they use three distance measures: the distance to the nearest top tier university, to the nearest second tier university and the nearest third tier university. Their findings suggest that the closer firms are to universities the more likely they are to report collaboration.[11] Distinguishing between the different university quality categories, Laursen et al. find that firms are more likely to collaborate if they are geographically close to third-tier universities. The propensity of a firm to collaborate with a first-tier university is a decreasing function of geographical distance between firm and university. While the findings by Laursen et al. suggest the importance of geographical proximity for university-industry collaboration to occur, it is not clear how they disentangle the proximity effect from unobserved heterogeneity or agglomeration externalities. Universities and innovative firms are likely to co-locate in urban areas for reasons other than university-industry transfer. Also, given the nature of their analysis, it is likely to find spatial autocorrelation in the residuals of their regression which could invalidate inference.

[10]Note that they only have information on the postcode area in which a firm is located which is the same level of geographical detail as used in Abramovsky et al. (2007).

[11]Note however, that their data does not allow to infer which firm has collaborated with which university in the sample.

Abramovsky and Simpson (2008) extend the analysis of Abramovsky et al. (2007) by analysing the determinants of the number of R&D conducting firms within postcode districts located in proximity to university research departments. In addition, they investigate whether firms that are located close to universities are more likely to engage in collaborative research. The dependent variable for the analysis of firms' location choice is a count of the average number of establishments reporting non-zero own R&D expenditure during 2000-2003 for a product group within postcode districts in the UK.[12] In order to carry out this research, Abramovsky and Simpson combine Business Entreprise Research and Development (BERD) data for 2000-2003 together with Community Innovation Survey data for the UK.[13] While the BERD data provides information on which firms conduct R&D, the CIS data are used to construct a measure for the existence of university-business links. As in Abramovsky et al. (2007), RAE 2001 data is used to construct measures for university presence and quality of research conducted at universities' research departments. In addition, the authors also consider the count of universities within a radius of 10km as well as a radius of 10 to 50km from the centre of each postcode district. As in all the studies discussed above, Abramovsky and Simpson use a large range of additional controls at the postcode district and area level, such as the number of employees, the percentage of employees with a tertiary degree in science or engineering, R&D intensity, and public funding for R&D, a density measure (count of postcodes at the district level), a measure of skill composition of the work force at the postcode area level, the percentage of economically active population in the postcode area, total manufacturing employment in the postcode area, the percentage of total manufacturing employment in the relevant industry, and a measure indicating the presence of science parks. Similar to Harhoff (1999), the estimation of firms' location choice is carried out by a negative binomial model treating the data as a cross-section and running separate regressions for each product group. To estimate firms' propensity to conduct collaborative research with universities, the authors estimate a probit model. The results suggest that pharmaceutical firms tend to locate close to world-class chemistry research departments. There is also some evidence for firms located close to universities to be more likely to engage in collaborative research in the fields of chemicals (with materials science departments) and vehicles (with mechanical engineering departments). At the same time, the authors also find that chemicals, vehicles and machinery industries tend to locate in areas with higher manufacturing employment and which are specialised in the respective industry.

While the paper offers additional insight with respect to business-university collaboration, the paper does not address the endogeneity problem inherent in this kind of analysis of firms' location choice. Moreover, the evidence for co-location may be confounded with more general unobserved agglomeration externalities. This problem

[12]The product groups considered are pharmaceuticals, chemicals, machinery, electrical machinery, TV and radio equipment, vehicles, precision instruments and aerospace. Note also that they restrict their sample to firms that report in the CIS to have introduced a product or process innovation or have ongoing or abandoned innovative activities or that have innovation-related expenditures over the past three years.

[13]They use both the CIS3 (1998-2000) and CIS4 (2002-2004) data.

becomes evident when considering the location of firms in London, where also the largest number of universities is found. Hence, what may be interpreted as co-location of firms and universities may equally well be due to more general unobserved agglomeration effects than specific university-business spillovers. Note also that Abramovsky and Simpson do not consider the possibility for spatial autocorrelation in their analysis.

An example of attempting to address the endogeneity problem arising from agglomeration is Kantor and Whalley (2009). In order to assess the effect of university spending on local private sector labour income, the authors take advantage of the fact that in the US a university's spending is a function of the market value of its endowment. This allows Kantor and Whalley to instrument university expenditures by the interaction of a university's initial endowment and time-varying stock market shocks. The results indicate that university expenditures have a minor albeit positive effect on labour income in large urban US counties. A 10 percent increase in university spending results in 0.5 percent higher private sector labour income. This effect intensifies for firms that are found to be technologically close to the research conducted at universities within the same county.

Overall, the empirical literature finds some evidence that university research may have a positive association on surrounding firms' R&D and patenting activity, as well as local labor income. At the same time, the literature focusing on R&D and patenting is rather descriptive in investigating the co-location of university research and innovative activity of private companies and remains largely silent on specific channels for university-industry knowledge transfer. The evidence by Kantor and Whalley (2009) suggests that the relationship between firms' innovative activity and the presence/quality of university research is simultaneous since both universities and firms are likely to benefit from collaboration. Also the issue of confounding university-business links with unobserved agglomeration externalities, most evident in the case of London, demands attention. Finally, while Harhoff (1999) and Fritsch and Slavtchev (2007) consider the issue of spatial autocorrelation, the potential implications of spatial spillovers across spatial units deserve more in-depth analysis. Spatial units, fixed either at the postcode or county level, draw their boundaries in rather arbitrary ways, making it likely for innovation as well university research to spill over to neighbouring spatial units.

3 Identification issues

As has been indicated above, there remain a series of challenges in analysing the relationship between university research and business innovation. In this paper we take corporate patenting as a proxy for innovation, something that is commonly done, but nevertheless an assumption we should openly discuss. It is well known that patents are a noisy measure of innovation due to different propensities to patent across firms and industries.[14] These differences can be due to differences in firm-level strategies, as well as large heterogeneity in underlying innovations. Moreover, not all innovations are

[14] For relevant survey evidence see Graham et al. (2010).

patentable in the UK, such as innovations in managerial practices or in the creative industries. Patent data do, however, have certain advantages. A major advantage of our data is that we can identify the patenting activity of all UK micro firms and SMEs. Complete R&D data are almost always only available for the largest firms.[15] Hence, it is only by using patent data that we can test the hypothesis that the impact of universities varies across firm size. It is clear, however, the propensity to patent is much higher in some industries; we therefore restrict our attention to university research that tends to generate patentable innovations, namely engineering related departments and medicine/biology/chemistry related departments and limit the analysis to manufacturing firms.

A second challenge is that there are no direct measures of the links between universities and firms. While we use information on knowledge transfer activities undertaken by universities to test for specific channels of knowledge transmission, the precise mechanisms of knowledge transmission between pairs of individual universities *and* firms remain unobserved and unspecified. As put by Jaffe (1989: 957) 'If the mechanism is primarily journal publications, then geographic location is probably unimportant in capturing the benefits of spillovers. If [...] the mechanism is informal conversations, then geographic proximity to the spillover source may be helpful or even necessary in capturing the spillover benefits.' Many argue that knowledge transfer between universities and private firms occurs through channels that operate within a certain geographical distance, such as frequent (informal) face-to-face interaction or are directly influenced by geographical proximity, such as personal networks, seminars and workshops etc. Another important factor may be the location choice of recent university graduates. If graduates tend to choose a location to work or establish their own business in proximity to their university, geographical distance plays a role. Our initial assumption is that university knowledge transmission is restricted to a postcode area (and, implicitly, is uniform within that postcode area). This type of assumption is widespread in the literature, but is clearly criticisable. We do relax this assumption by allowing universities in neighbouring postcodes to generate knowledge flows. However, this 'local' assumption is still unappealing in a global world with rapid travel and communication. In fact, we hypothesise that geographical location should not matter, especially for large, sophisticated firms with access to wide networks, both nationally and internationally. Hence the hypothesis is that the impact of universities on smaller firms within a postcode region should be greater than the impact on larger firms. The view that local universities can have important impacts on smaller firms is familiar, but statistical tests of this are rare. We therefore choose to split the sample into patenting micro firms & SMEs and patenting large firms.

A further concern, which is rarely discussed, concerns simultaneity. The presence and quality of university research and the patenting outcomes of private firms is likely to be simultaneous. This means that not only firms gain from knowledge transfer from

[15]In particular, in the UK even the Office for National Statistics (ONS) does not have comprehensive data on smaller firms hence, for example, they cannot produce statistics on the geographical spread of micro and SME R&D activity.

universities, but that also university research benefits from private firms' innovative activity. For example, successful local private firms may support the university with research grants or consultancy contracts, or the successful innovation of private firms may stimulate and direct new (basic) research. This problem is closely linked with endogeneity arising from agglomeration of economic activity. If universities and innovative firms co-locate in economically dense areas where unobserved agglomeration externalities exist, a positive correlation between university presence and patenting by firms may be observed without there being an actual link. Even including variables accounting for agglomeration will not suffice to avoid endogeneity if these externalities remain unobserved. In order to control for such simultaneity and agglomeration, we adopt an instrumental variable (IV) approach. We argue that universities' age is an informative and valid instrument for the quality of university research. It is informative as it correlates highly with our measures of research quality. It is a valid instrument since we argue that the age of a university should have no effect on current patenting other than through research quality accounting also for a range of control variables such as economic activity within postcode areas.

Modeling firms' patenting decisions

How should one attempt to model any relationship between university research and its impact on firm-level patenting? The previous literature, including those papers that use R&D rather than patents, has considered both quantity and quality. There has also been recognition that different types of research will have differential impacts across industries and technical areas. For example Jaffe (1989) found the effect of university research on patenting to be more visible within technical areas. In addition, there has been an inability to differentiate between impacts on small and large firms, since most databases do not have firm-level patent data. However, Acs et al. (1994) and Audretsch (1998) suggest that universities are particularly important as a source of innovative knowledge for small firms. Also, previous research points to the importance of location in the relationship between innovative firms and university research. Fritsch and Slavtchev (2007), for example, find substantial clustering of patent applications in regions, particularly in urban agglomeration areas.

We assume the following relationship. Patenting P_i by companies in postcode area i is some function of university research U_i within area i and a vector $\mathbf{X}$ of k covariates with dimension $k \times 1$.

$$P_i = f(U_i, \mathbf{X}_i) \tag{1}$$

Patenting by companies is broken down by large firm versus small firm (which is micro firm and SME combined) where we estimate separate regressions by size category. We employ different measures for university research including (i) the number of universities within a postcode area, (ii) the presence of engineering or biological sciences research departments, (iii) the number of researchers active at these departments at universities located within a given postcode area, and (iv) 'quality' of research conducted at these departments as assessed by the RAE 2001.[16] Measures (i) and (iii) aim to capture the amount of research undertaken within a postcode area. The intuition is that the larger the amount of research conducted within a postcode area, the greater the potential for knowledge transfer is and hence the higher the level of patenting should be. To measure quality, we differentiate between departments that received grades 1-4 versus those that received top grades 5 or 5* in the RAE 2001. Moreover, we also use the single overall RAE grade received by a university, which can be regarded as a global measure for the quality of research conducted at a university.[17] Specification (1) remains agnostic about the precise channels of knowledge transfer from universities to companies; it only assumes that knowledge transfer is localised as it is confined to postcode areas. We test for more specific channels of knowledge transmission in Section 6.2.

Covariates included in $\mathbf{X}$ are (i) the population density (i.e., the number of people per hectare as indicated in the Census, 2001) within postcode area i, (ii) the log of the total number of people employed in the manufacturing sector (Census, 2001), (iii) the total number of small or large firms within a postcode area to account for scale effects, (iv) the diversification of the industrial production within a postcode area where the measure varies between 0, indicating no diversification, and 1 indicating complete diversification,[18] (v) the ratio of unskilled to skilled labour where the information comes from the labour Census 2001, and (vi) log R&D by region as reported by the ONS.

Covariates (i)-(iii) are included to control for agglomeration of economic activity in order to avoid endogeneity caused by co-location as discussed above. The inclusion of (iv) above relates to the debate about so-called Marshall-Arrow-Romer (MAR) and Jacob externalities (Glaeser et al., 1992). MAR externalities arise when industries are concentrated within a location. In contrast, Jacobs externalities (Jacobs, 1969) emerge as a result of the diversity of industries within a location. Hence, MAR externalities can be regarded as intra-industry spillovers while Jacobs externalities are inter-industry spillovers.[19] Covariates (v) and (vi) capture the level of technology and research within postcode areas.

4 Data

The data for the analysis comes from two main sources. Data on firm-level patenting comes from the Oxford Firm Level Intellectual Property (OFLIP) database. The database draws on the Financial Analysis Made Easy (FAME) data that covers the entire population of registered UK firms (FAME downloads data from Companies House

[16] For more information on the RAE 2001 see www.rae.ac.uk/2001.

[17] We use the maximum grade received by all universities within a postcode area.

[18] The manufacturing diversification measure is constructed as the sum of squares of the share of 4-digit SIC within postcode areas using the entire population of UK firms which is available in FAME (for more information on FAME see Section 4). It takes a value of 0 if a single 4-digit SIC produces all the output in the postcode, and tends to 1 as diversification increases.

[19] The question of whether diversity or concentration promotes innovation has been analysed by Feldman and Audretsch (1999). They find, for their cross-sectional data, that innovative activity in complementary industries that share a common fundamental science base cluster, both in terms of production activity and innovation.

records). OFLIP contains additional information on the IP activity of firms in the form of patents and trade marks. In this paper we use publications of both UK and EPO patents (in 2001) as our measure of patenting. OFLIP has been constructed by matching the FAME database and a number of firm-level IP datasets.[20]

The second source of data is the RAE for 2001, which is collated by the Higher Education Funding Council of England and Wales (HEFCE). The HEFCE data provide a range of indicators from which those listed in Table 1 are selected.[21] Note that even though the RAE is collated in 2001 it relates to research activity over the period 1996 to 2001.[22] This allows for a considerable time lag in the effect of university research on patenting even bearing in mind the usual 18 month lag between a patent's application and publication date.[23] In order to test for specific university-industry knowledge transfer channels, we use data collected by HEFCE in its Higher Education-Business Interaction surveys (HE-BCI). We use data by institution from the 2000-01 HE-BCI survey (which was made available by HEFCE), and then averaged by 2-digit postcode, to construct a number of technology transfer variables (for a description see Section 6.2).

Population density and skills data come from the England and Wales Census 2001 (and also Scottish Census 2001). The R&D data is downloaded from the ONS website (database rdbd7) and is at the regional level since more disaggregated data is not collected. The age of universities used as an instrument for research quality has been collected directly from universities' websites. Table 1 shows the summary statistics for the variables. The statistics are for 2-digit postcodes, of which there are 117 in the UK. Table 2 shows correlation coefficients between patenting and university variables.

Figure 1 shows histograms for two of the dependent variables: the count of patenting large and small (both micro firms and SMEs) firms by postcode. Large firms are defined as those with more than £39 million in total assets (the EU definition).[24] For large firms, in 42 of the 117 postcodes there are no patentees at all, and the postcode area (Birmingham) with the largest number of large-firm patentees has 17 large firms that patented in 2001. Restricting attention to smaller firms, there are only four postcodes that have no patenting firms. The postcode with the greatest number of smaller patentees is, again, Birmingham with 68.[25]

[20]For details on the matching process and further details on the database see Helmers and Rogers (2009).

[21]Our definition of 'engineering' department includes General Engineering, Chemical Engineering, Electrical and Electronic Engineering, Mechanical, Aeronautical and Manufacturing Engineering and Mineral and Mining Engineering. Our definition of 'biological sciences' department includes Clinical Laboratory Sciences, Pre-Clinical Studies, Anatomy, Physiology, Pharmacology, Pharmacy, Biological Sciences, and Chemistry.

[22]For humanities the period is 1994-2000 but we do not use RAE data on humanities in this paper.

[23]Note that the correlation between patenting in 2001 and subsequent years is very high (when aggregated to the postcode level). The correlation coefficient between 2001 and 2002 is 0.95 and only falls to 0.9 for between 2001 and 2005. This implies that an analysis of the lag structure of any impacts from university research is problematic.

[24]Total assets are used since this variable has the best coverage in FAME. This is due to the fact that in the UK all firms have a legal requirement to report total assets, but not total revenue or employment.

[25]The influence of Birmingham for the regressions on smaller firms has been checked and it does not

Figures 2 and 3 plot departments' RAE grade, i.e., our measure for research quality within postcode areas, against the number of patenting firms distinguishing between small and large firms.[26] The plots show some evidence of a weak positive association between the number of patentees and a university's RAE score by postcode area. This applies to both engineering and biological sciences departments, although the positive relationship appears to be more visible for engineering departments. Similarly, the possible relationship between quality of research and patenting appears to be stronger for smaller than for larger firms.

5 Estimation

Our outcome variable, the number of patentees, is a count variable, i.e., it assumes non-negative discrete values and has no natural ceiling. We begin with estimating the model ignoring the fact that the dependent variable is not normally distributed. The problems with applying OLS in a setting with a discrete outcome variable are well known from the binary response case. Most importantly, $E(y|\mathbf{x})$ should be non-negative while OLS will usually still result in $\mathbf{x}\beta' < 0$ (i.e. predicted values can be negative). Non-linearity of $E(y|\mathbf{x})$ is another characteristic of count data ignored by OLS. An obvious alternative is to estimate the model assuming a Poisson distribution. The problem with the assumption of a Possion distribution is its equidispersion property, i.e., it assumes that the mean and variance are the same. However, in our data, we find overdispersion to be present, which means the mean is not equal to the variance. To account for overdispersion, we use the negative binomial model as proposed by Cameron and Trivedi (1986).

Assume a conditional mean function

$$E(y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i\beta) \tag{2}$$

The corresponding variance is

$$Var(y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i\beta)[1 + \alpha_i^2 \exp(\mathbf{x}_i\beta)] \tag{3}$$

where α_i^2 denotes the variance of α_i which can be interpreted as a measure of unobserved heterogeneity. Parameters β and α are jointly obtained from maximizing the following log-likelihood function

$$l_i(\beta, \alpha^2) = \alpha^2 \log[\frac{\alpha^{-2}}{\alpha^{-2} + \exp(\mathbf{x}_i\beta)}] + y_i \log[\frac{\exp(\mathbf{x}_i\beta)}{\alpha^{-2} + \exp(\mathbf{x}_i\beta)}] + \tag{4}$$

$$+ \log[\Gamma(y_i + \alpha^{-2})/\Gamma(\alpha^{-2})] \tag{5}$$

where $\Gamma(\cdot)$ is the gamma function defined for $r > 0$ by $\Gamma(r) = \int_0^\infty z^{r-1} \exp(-z)dz$.

affect the qualitative results, although the magnitude of coefficients does change.

[26] The fact that we observe a postcode that has a score of 5.333 for biological sciences is due to the fact that a single university submitted several reports which we averaged.

IV Approach

The relationship between the quality of research undertaken at a university and patenting activity of private firms may be characterized by a simultaneous relationship. This means that (x denoting university research) is, in part, determined by y (the number of patentees) and hence x is correlated with the error term ϵ. This means that in the data generating process, the outcome variable and the regressor are simultaneously generated. The simultaneous relationship may also be generated by other unobservables, such as agglomeration externalities. In order to address the simultaneity concern, we employ an IV approach. The instrument has to be informative and valid. An instrumental variable is informative if it is correlated with the endogenous variable, which can easily be verified. In our case, the correlation coefficient between university age and the RAE grade of the engineering and biological sciences departments is 0.51 and 0.58 respectively. Validity requires that the variable is uncorrelated with the disturbance term. This is achieved if the instrument affects the outcome variable exclusively through the endogenous variable conditional on all other exogenous covariates.

As before, we first estimate a linear probability model assuming normality using a standard IV estimator. Denoting the instrumental variable as z, we assume that $E(z, \epsilon) = 0$. Hence, the IV estimator is

$$\beta_{IV} = (z'x)^{-1}z'y \tag{6}$$

with $\hat{Var}(\beta_{IV}) = \hat{\sigma}^2(z'x)^{-1}(z'z)(x'z)^{-1}$. Since the linear model has the drawbacks discussed above, we employ a control function approach to account for endogeneity assuming a negative binomial distribution. As suggested in Wooldridge (2001), we assume that our structural model is

$$E(y_{1i}|y_{2i}, \mathbf{x}_i, e_i) = \exp(\beta_1 y_{2i} + \mathbf{x}_i'\beta_2 + e_i) \tag{7}$$

where y_2 denotes endogenous research quality, $\mathbf{x}$ is a vector of covariates, and e is an unobserved latent variable. If research quality is endogenous, we have $E(y_2, e) \neq 0$ while we still assume that $E(\mathbf{x}, e) = 0$. We assume that y_2 is given by a linear reduced form

$$y_{2i} = \mathbf{x}_{1i}'\phi_1 + \phi_2 z_i + \varepsilon_i \tag{8}$$

Crucially, z_i is a variable that is correlated with endogenous research quality while it does not affect y_1 other than through y_2 conditional on $\mathbf{x}$. We assume that $E(z, \varepsilon) = 0$. Since we only have a single exclusion restriction, the model is exactly identified. While this does not pose any problem for identification, it limits our ability to test for the validity of the instrument. In order to estimate Equation (7) using the structure imposed on the endogenous variable in Equation (8), we have to make a rather restrictive assumption on the error terms. We assume that

$$e_i = \gamma_i \varepsilon_i + \xi_i \tag{9}$$

where ξ is white noise and independent of ε. The assumption made in Equation (9) that e and ε are linearly related always holds if e and ε are jointly normally distributed. Clearly, if $\gamma \neq 0$, y_{2i} is endogenous. Using (8) and (9), we can rewrite (7) as

$$E(y_{1i}|y_{2i}, \mathbf{x}_i, \varepsilon_i) = \exp(\beta_1 y_{2i} + \mathbf{x}_i' \beta_2 + \gamma_i \varepsilon_i) \tag{10}$$

in order to obtain unbiased and consistent estimates for β_1, β_2, and γ_i. In practice, we estimate Equation (10) using a two-step procedure, estimating first (8) which allows recovering an estimate for $\hat{\varepsilon}_i$ which is plugged into (10) where inference is based on bootstrapping over the entire two-step procedure.

Spatial Approach

Some of the previous studies discussed in Section 2 tested (e.g., Harhoff, 1999) and accounted for spatial autocorrelation (Fritsch and Slavtchev, 2007). Spatial dependence may arise in our setting because borders of postcode areas do not necessarily coincide with geographical coverage of economic activity. To capture geographic proximity, we construct a spatial weight matrix which assumes the value of one if postcode areas are adjacent and otherwise zero. Hence, weights are binary. In order to capture spatial spillovers of university research, we construct the weighted sum of our university research measures in adjacent postcode areas, i.e., $\sum_{j=1}^{N} w_{ij} x_j$ where $w_{ij} = 1$ if postcode areas i and j are adjacent and $w_{ij} = 0$ otherwise. If there is no spatial dependence in the error term and no spatially lagged dependent variable is added to the basic specification, OLS and ML still yield consistent estimates. From a theoretical point of view there is no reason to include a spatially lagged dependent variable and we therefore concentrate on testing for the absence of spatial autocorrelation in the residuals using a Lagrange Multiplier test.[27]

6 Results

6.1 Main Results

Table 3 shows a set of OLS regressions as a baseline. The first two columns, which use a simple count measure of universities located in a postcode area, indicate support for the basic hypothesis that smaller firms benefit from close proximity to universities, but large firms do not. The other variables that are significant for both large and smaller firms are the population density, the ratio of skilled/unskilled labour and the number of firms in the postcode area. The coefficient associated with the latter variable indicates that the more firms there are within a postcode, the higher the number of patenting firms, which represents strong evidence for the presence of scale effects. The last four columns use the number of engineering and biological sciences departments, instead of number of universities. A similar pattern of results is found. While a larger number of engineering and biological sciences departments is associated with larger numbers of patenting small firms within postcode areas, no such statistically significant association is found for larger firms. As discussed above, OLS is not well suited for count data.

[27] For a detailed description of the test in the context of spatial econometrics, see Anselin (1988).

Table 4 repeats the specifications in Table 3 using a negative binomial model and reporting marginal effects. The qualitative results are unchanged when using the number of engineering and biological sciences departments. Only when using a simple count of the number of universities, marginal effects for small firms are no longer statistically significant in Column 2. For the small firm regressions using the number of university departments, all covariates are statistically significant with the exception of the industry diversification measure. The statistically significant covariates measure the availability of resources relevant to innovation and density of economic activity. Hence, these resource variables appear to matter more for patenting than the composition of industries within postcode areas. In summary, when considering associations between the presence of local universities and patenting, in general, only smaller firms are found to exhibit positive associations.

As an alternative measure of research power, Table 5 looks at associations between the number of researchers in engineering departments and also the number in biological sciences and the number of patentees using both OLS (Columns (1)-(4)) and the negative binomial model (Columns (5)-(8)). Again, only the number of patenting small firms is positively associated in a statistically significant way with the number of researchers located at universities within postcode areas where this result is strongest for engineering.

Table 6 investigates this further by considering the quality of research conducted at the different departments (as assessed by the RAE in 2001). The RAE grades departments from 1 (lowest) to 5* (highest), but in these regressions we use a count measure based on those with grades 1-4 versus those 5 or 5*, which means we allow for different effects for research judged to be nationally and internationally recognised. For example, the central Birmingham postcode has five engineering departments, with two of these graded 1-4 and three with grades 5 or 5*. The regression results reported in Table 6 indicate that quality does matter. When using OLS in Columns (1)-(4), in both engineering and the biological sciences only the number of 5 or 5* ranked departments has a significant, positive association with the number of small firms patenting. When using the negative binomial model in Columns (5)-(8), both small and large firm patenting is positively associated with the number of 5 or 5* ranked engineering and biological sciences departments. In the case of large firms, a higher number of departments graded 1-4 within the same postcode is even associated with a lower number of large firm patentees in a statistically significant way. Since we do not explicitly account for unobservables driving co-location of firms in these regressions, this finding may simply suggest that less innovative large firms and weaker research universities are located in the same geographical area, whereas more innovative large firms and world-class research universities co-locate.

Table 7 uses the maximum RAE grade achieved by engineering departments within a postcode area. Similarly, Table 8 shows the results for the maximum RAE grade achieved by biological sciences departments within postcode areas. The first four columns in both tables show again results using OLS and a negative binomial model. It is clear that in both cases the coefficients associated with research quality as assessed by the RAE are statistically significant only in the regressions for smaller firms (except for Table 7 Column (4)). This means that there is a positive correlation between the number of small firm patentees within postcode areas and better RAE grades both in engineering and biological sciences. The following four columns (Columns (5)-(8)) report results when using university age as an instrument for overall research quality. Columns (5) and (6) report standard IV OLS results whereas Columns (7) and (8) report the results from using a control function approach. Since the control function approach attempts to account for endogeneity using a negative binomial model, it is our preferred specification. The negative and statistically significant coefficient of the control term in Column (8) of Table 7 indicates that the latent factor captured by university age, which is positively correlated with research quality, is negatively correlated with the number of patentees within postcode areas. Hence, simultaneity appears to cause a downward bias in the coefficients associated with research quality. Also, we find the magnitude of the bias to be considerable for engineering as the coefficient more than doubles and becomes statistically significant when using the control function approach. As before, we only find coefficients of instrumented research quality to be statistically significant for small firms. Since we only have a single instrument, we are unable to repeat the analysis of Table 6 accounting for endogeneity of university research quality and thus to investigate further the reason for the negative association between the number of grade 1-4 departments and large firm patenting. Although not shown in Table 7, but when we restrict the large firm sample to postcode areas with grade 1-4 departments, we do not find any statistically significant association between patenting and research quality even when using the control function approach accounting for endogeneity. This suggests that departments graded 1-4 do not have any effect on large firm patenting within the same postcode area.

Table 9 shows results when a spatially lagged university variable is included in the specification to account for neighbourhood effects. The variable represents the average of adjacent postcode areas' university variables. Column (2) therefore suggests that not only the number of universities within a postcode area but also the number of universities in adjacent postcode areas is positively correlated with the number of small firm patentees. When we look at the number of engineering and biological sciences departments in Columns (3)-(6), we only find this positive neighbourhood effect for the number of engineering departments. Note that we also test for spatial autocorrelation in the error term using a Lagrange Multiplier test. We find that the null hypothesis of absence of spatial autocorrelation is never rejected for both the samples of small and large firms at the 1-percent level.

6.2 Technology Transfer Channels

In this section, we investigate specific channels through which technology transfer takes place. In light of our preceding findings, we limit the analysis to small companies.[28]

[28]Also note that because interaction terms are easier to interpret in linear models, we estimate the model only using OLS.

There is a broad distinction between formal and informal transfer mechanisms. The term informal may appear somewhat misleading as such mechanisms often do involve formal agreements between the involved parties. Examples of such informal mechanisms are: informal social and professional networks, public university lectures and workshops (including continuing education), consulting, commissioned research by firms, academic-scientist exchanges and recruitment of university graduates by firms (Yusuf, 2008). Such mechanisms are likely to transfer certain types of knowledge (in particular tacit knowledge) continuously and often without record. More advanced and codifiable knowledge, for example related to inventions or break through discoveries, is likely to be formalised into an intellectual property right (IPR). In such cases there may be the need for on-going formal technology transfer and also the creation of IPRs. Hence, the formal mechanisms include patents and other IPRs, licensing and royalty agreements, formation of spin-outs and venture capital. The formation of spin-outs is also closely related to the formation of university incubators and university science parks.

The data collected by HEFCE in its 2000-01 HE-BCI survey (for summary statistics see Table 1) allow us to investigate in more detail the channels of technology transfer and thus to explore the positive correlation between university research and corporate patenting uncovered in Section 6.1. The survey responses by universities we use, relate to the following formal and informal technology transfer channels:

- **Licensing and assignment of patents and other IPRs (industrial designs, database rights, copyright, trademarks):** Under this transfer channel, a university as the owner of the IPR gives an outside firm the (non)exclusive right to use and modify the patented invention or sells directly the IPR to the third party (assignment). Thursby et al. (2001) provide evidence collected from 62 major US universities providing evidence for the early stage character of university IP at the moment of licensing. Only 12 percent of inventions were ready for practical or commercial use and for only 15 percent manufacturing feasibility was known. Hence, knowledge licensed out by universities is of an early-stage type and commonly remote from commercial application. Hence, the commercial exploitation of a university invention may require substantial additional research and development which may give rise to opportunities for licensees to patent. We use two measures to capture this important transfer channel. First, we use information on the number of inventions disclosed by researchers to the university in 2000-01. This captures a broad range of inventions and is therefore including the larger set of commercialisable knowledge. Second, we use the number of UK patents filed by the university to measure the more narrow types of inventions that are commercialised either through licensing or assignment of the patent right. The results are reported in Columns (1)-(4) of Table 10 and suggest that both broader disclosed inventions and UK patent applications serve as a channel for technology transfer for engineering research. Interestingly, we do not find any statistically significant evidence in the case of biological science related research. Moreover, none of the coefficients associated with the technology transfer channel variables is on its own statistically significantly different from zero.

- **Consultancy:** Universities provide expert advice to address and solve specific questions and (technical) problems which requires knowledge possessed by academic researchers. It may involve the temporary physical presence of academics in client companies. Link et al. (2007) present an analysis of survey data collected among 1,514 university scientists and engineers at 150 research intensive US universities in 2004/05 for which they find that 18 percent worked as consultants for the private sector during the past 12 months. Thursby et al. (2009) look at a sample of 5,811 US patents where one or more of the listed inventors is a faculty member in one of 87 US research universities. They find that only 62 percent of patents are exclusively owned by universities. Thursby et al. (2009) explain the relatively large number of patents not held by universities as being due to academics engaging in consultancy contracts which lead to patenting of the resulting invention. Hence, it appears that consultancy contracts lead to patentable inventions, where the ownership of these IPRs remains with companies and scientists. We measure the channel of consultancy by the total income generated by a university from its consultancy activities between 2000 and 2001. Columns (5) and (6) of Table 10 show the corresponding results. The interaction term is only statistically significant for biological sciences, while no such evidence is found for engineering. The consultancy variable on its own, however, is statistically significantly negative for engineering, implying a negative correlation between the number of patenting small firms and the amount of consultancy provided by universities.

- **Science Parks and Incubators:** The UK Business Incubation defines business Incubation as 'a unique and highly flexible combination of business development processes, infrastructure and people, designed to support entrepreneurs and grow new and small businesses, products and innovations through the early stages of development and/or change' (UKBI, 2007). University incubators are a rather recent phenomenon in the UK; Helmers (2010) finds 75 percent of the 125 university business incubators existing in 2009 were established after 2000. Incubators can differ substantially in terms of type of start-ups hosted (high-tech firms or student ventures) and in terms of their organisation ranging from virtual incubators to incubators physically integrated into large science parks. A science park, in contrast, is defined as 'a cluster of technology-based organizations that locate on or near a university campus in order to benefit from the universitys knowledge base and ongoing research. The university not only transfers knowledge but expects to develop knowledge more effectively given the association with the tenants in the research park' (Link and Scott, 2006). The HE-BCI survey allows us to construct a variable that indicates whether a university offers a science park and/or incubator facilities. We aggregate both channels of technology transfer as the ultimate mechanism is very similar. The results are reported in Columns (7) and (8) of Table 10. We only find a statistically significant coefficient for the specification using the RAE grade in engineering, suggesting that in this area, science parks and incubators facilitate technology transfer that leads to increased patenting by private companies close to the university. While the incubator/science park term on its own is negative in Column (7), the combined effect of the interaction term (evaluating the incubator/science park variable at its mean) and the variable on its own is 1.389, i.e., positive and large in magnitude.

There are advantages and drawbacks associated with formal and informal mechanisms which have substantial bearing on their relative effectiveness in transferring knowledge. The advantages of informal collaboration are mostly access to industry funding of basic and applied research, exposure to applied problems allowing the application of basic research results, and the possibility of obtaining new ideas for basic research. The salient drawback of informal agreements is the time needed by academic researchers to develop the relationship and to deliver the agreed product. It may also distract university researchers from undertaking fundamental research, which may even negatively impact on university-industry technology transfer as suggested by our results. Licensing, in contrast, does not require the involvement of the academic inventor. Although empirical work shows that this may also be its main drawback (both theoretical and empirical studies have shown that the involvement of the academic inventor is crucial for the success of the licensing agreement, or the spin-off, resulting from IPRs). Other transfer channels that involve physical facilities to host companies in university proximity, i.e., science parks and incubators, may also play an important role in knowledge transfer. Our results suggest that both informal and formal channels of technology transfer are at work although formal channels apply to engineering sciences whereas informal channels serve to transfer knowledge generated in biological science departments.

7 Conclusion

This paper analyses the link between university research and the patenting activity of firms located close to universities. There are a number of major challenges in such an analysis. First, university research has many different dimensions, including subject area, quantity and quality. Second, the channels through which this research may impact on firms are unclear, as are the lag times involved. Following from this is the uncertainty of how to define 'local' and why it may be that 'local' firms benefit more from university research. Third, there are important and difficult issues surrounding simultaneity and endogenous location choices. This paper has approached these challenges in the following way. The analysis is based upon the 117 two-digit postcode areas in the UK. For each of these postcodes we construct the following measures of university research activity (i) the number of universities in the same postcode area, (ii) the presence of engineering or biological sciences research departments, (iii) the number of researchers active in these departments, (iv) the 'quality' of research (as assessed by the RAE 2001). Similarly, for each postcode we construct a count of the number of patentees, importantly our new data allow this to be broken down by large firm patentees and small firm patentees. Our hypothesis is that any impact of university research is more likely to occur for small firms. In contrast, large firms are likely to have access to many universities' research from around the UK, if not globally, hence it is less likely to find a specific impact from local universities.

We do not claim that even when instrumenting university research quality, we uncover causal effects between university research and corporate patenting. The analysis merely shows that, in almost all specifications, it is only the number of small firm patentees that show a significant, positive correlation with university research. This is not to say that university research has no impact on large firms, only that any such effects cannot be detected with the two-digit postcode specification used here (or even when allowing for neighbouring postcodes as in Table 9).

The analysis uncovers a number of other findings. First, when considering research from engineering and biological sciences departments separately, the regression analysis indicates that the number and scale of engineering departments has a stronger association with the number of small firm patentees. Second, using the RAE 2001 grading of engineering and biological sciences research departments, the analysis finds that research quality matters: only the departments with the highest RAE grades exhibit positive and significant associations with the number of small and large firm patentees. Third, in order to try to remove potential simultaneity, we use the age of the university as an instrument for RAE grade. The results indicate that the main findings are supported, in fact the magnitude of the coefficients rises. The paper also relaxes the assumption that university research can only impact on firms within a two-digit postcode by incorporating neighbourhood effects (from adjacent postcode areas). This specification still indicates no impact on large firms, but does indicate that small firms benefit from neighbourhood effects. Lastly, we provide an initial analysis of different forms of technology transfer finding, for example, that both formal and informal channels serve as a way of knowledge transfer, although the significance of specific channels differs for engineering and biological research.

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Figure 1: Histograms of large and small patentees, by postcode area

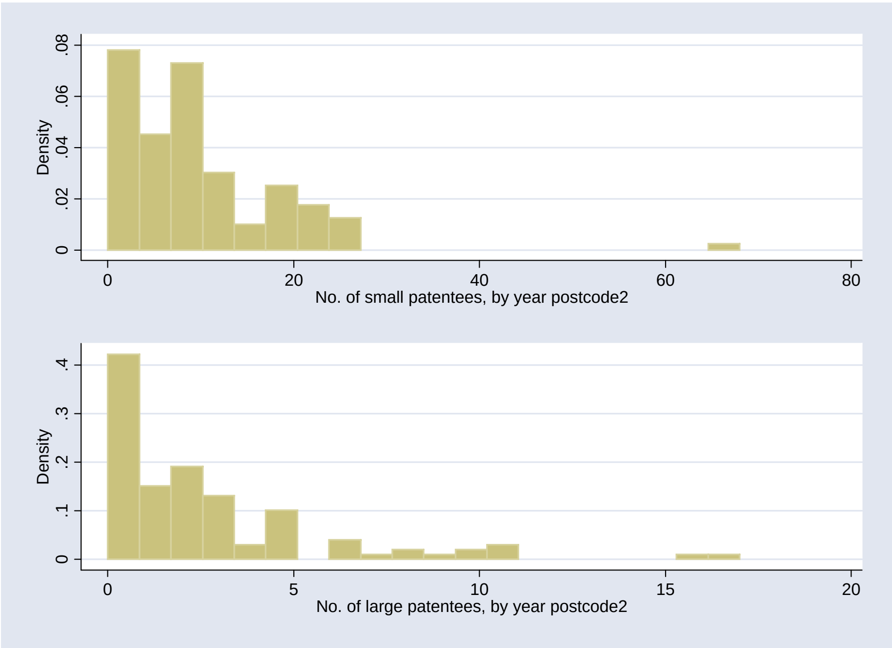

Figure 2: Scatter plot of large and small patentees and RAE grade in biological sciences, by postcode area

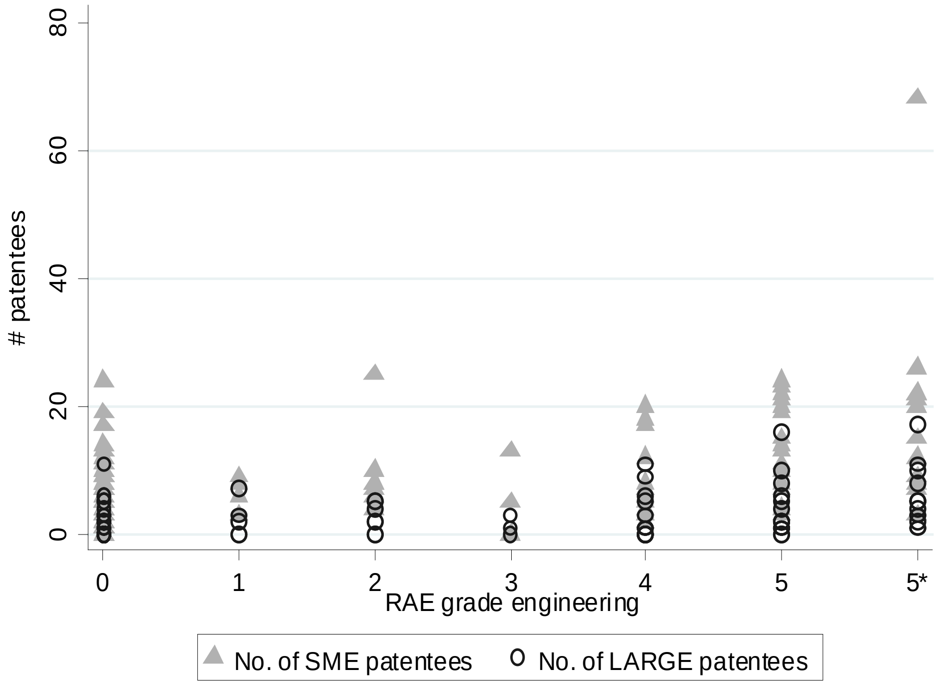

Figure 3: Scatter plot of large and small patentees and RAE grade in engineering, by postcode area

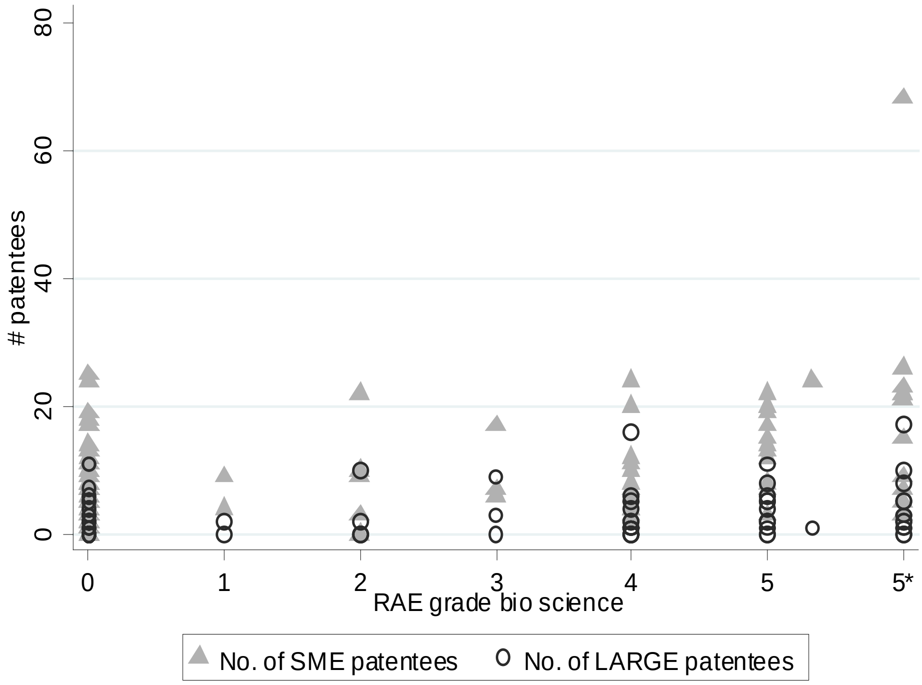

Table 1: Summary statistics, 2001

	Mean	Std. Dev.	Min	Max
Count of patentees	12.10	11.34	0	85
Count of large patentees	2.53	3.31	0	17
Count of small patentees	9.57	8.75	0	68
Number of universities	0.95	1.09	0	6
Number of engineering departments	1.27	1.83	0	9
Number of biological science dept.	1.45	2.42	0	14
Number of engineering dept. $\leq$ grade 4	0.81	1.21	0	7
Number of engineering dept. grade 5 or 5*	0.50	1.10	0	5
Number of bio. science dept. $\leq$ grade 4	0.68	1.12	0	6
Number of bio. science dept. grade 5 or 5*	0.79	1.75	0	10
University age	70.58	143.94	0	834
Continuing Education	3.70	5.49	0	31
# Invention Disclosures	8.72	16.24	0	77.5
# UK Patents	6.52	13.66	0	80.66
Consulting	0.42	0.84	0	6.92
Science Park/Incubator	0.37	0.48	0	1
Population density	10.97	18.06	0.12	93.77
Log manufacturing employment	10.15	0.84	6.58	11.87
Log Number of large firms	2.468	1.097	0	4.691
Log Number of small firms	6.378	0.741	3.784	8.366
Diversification of industry	84.69	13.61	19.46	97.14
Ratio of skilled to unskilled	0.58	0.37	0.26	2.31
Log R&D	6.75	0.89	4.83	8.07

Note: There are 117 observations for all variables.

Table 2: Correlation Matrices

Engineering Sciences	Patenting	# University	# Engineering Department	# Researchers	Quality	# Departments 5 or 5*	# Departments 1 – 4
Patenting	1.000						
# University	0.398	1.000					
# Engineering	0.479	0.809	1.000				
# Researchers	0.549	0.668	0.862	1.000			
Quality	0.473	0.780	0.826	0.762	1.000		
# Departments 5 or 5*	0.503	0.662	0.809	0.812	0.682	1.000	
# Departments 1 – 4	0.310	0.674	0.859	0.648	0.677	0.414	1.000

Biological Sciences	Patenting	# University	# Biology Department	# Researchers	Quality	# Departments 5 or 5*	# Departments 1 – 4
Patenting	1.000						
# University	0.398	1.000					
# Biological	0.424	0.778	1.000				
# Researchers	0.389	0.683	0.937	1.000			
Quality	0.387	0.732	0.799	0.696	1.000		
# Departments 5 or 5*	0.453	0.651	0.909	0.927	0.704	1.000	
# Departments 1 – 4	0.225	0.689	0.769	0.614	0.653	0.437	1.000

Note: All correlations statistically significant at least at 5% level.

Table 3: Regressions: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Large firms	Small firms	Large firms	Large firms	Small firms	Small firms
No. of universities	-0.066	0.911*				
	(0.248)	(0.549)				
No. engineering dept.			0.062		0.948**	
			(0.139)		(0.370)	
No. bio science dept.				-0.007		0.841***
				(0.118)		(0.309)
Population per hectare	-0.042*	-0.208***	-0.042*	-0.041*	-0.201***	-0.206***
	(0.023)	(0.039)	(0.023)	(0.023)	(0.037)	(0.039)
Log manufacturing employment	-0.096	0.874	-0.150	-0.106	0.653	0.483
	(0.281)	(1.316)	(0.424)	(0.287)	(1.158)	(1.225)
Log No. of firms♭	2.171***	7.265***	2.123***	2.153***	6.851***	7.288***
	(0.294)	(2.259)	(0.307)	(0.307)	(2.205)	(2.143)
Ind. diversification	0.008	0.003	0.007	0.007	0.005	0.008
	(0.016)	(0.026)	(0.016)	(0.016)	(0.025)	(0.027)
Skilled/unskilled labour	2.134*	8.945**	2.004	2.101	8.565**	7.294*
	(1.219)	(3.884)	(1.215)	(1.292)	(3.579)	(3.782)
Log R&D	0.377	0.163	0.413*	0.389*	0.337	0.201
	(0.235)	(0.663)	(0.218)	(0.224)	(0.637)	(0.613)
Constant	-5.781	-50.779	-5.387	-5.733	-47.452	-47.099
	(3.047)	(10.821)	(3.109)	(3.087)	(9.758)	(9.949)
R-squared	0.582	0.583	0.583	0.582	0.602	0.614
Observations	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.

♭ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Table 4: Regressions: Negative Binomial (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
	Large firms	Small firms	Large firms	Large firms	Small firms	Small firms
No. of universities	-0.073	0.375				
	(0.066)	(0.253)				
No. engineering dept.			-0.021		0.261**	
			(0.030)		(0.133)	
No. bio science dept.				0.001		0.289***
				(0.022)		(0.085)
Population per hectare	-0.010	-0.173***	-0.011	-0.011*	-0.170***	-0.170***
	(0.007)	(0.024)	(0.007)	(0.007)	(0.024)	(0.023)
Log manufacturing employment	0.096	1.865***	0.112	0.097	5.448***	1.445***
	(0.100)	(0.578)	(0.101)	(0.097)	(0.681)	(0.438)
Log No. of firms$^\flat$	1.505***	5.432	1.480***	1.464	0.049	5.651***
	(0.114)	(0.694)	(0.113)	(0.108)	(0.033)	(0.571)
Ind. diversification	0.002	0.015	0.002	0.002	0.014	0.016
	(0.005)	(0.018)	(0.005)	(0.005)	(0.018)	(0.019)
Skilled/unskilled labour	0.122	9.447***	0.178	0.180	9.183***	8.492***
	(0.394)	(1.367)	(0.402)	(0.383)	(1.317)	(1.195)
Log R&D	0.118	0.541*	0.126	0.141*	0.579**	0.519**
	(0.086)	(0.286)	(0.087)	(0.082)	(0.278)	(0.249)
Observations	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.
$\flat$ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Table 5: Regressions: OLS and Negative Binomial (Marginal Effects)

	OLS				Negative Binomial			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large firms	Large firms	Small firms	Small firms	Large firms	Large firms	Small firms	Small firms
No. engineering researchers	0.004		0.051***		-0.001		0.013***	
	(0.006)		(0.015)		(0.001)		(0.004)	
No. bio science researchers		-0.001		0.017***		0.0002		0.006***
		(0.002)		(0.005)		(0.0004)		(0.001)
Population per hectare	-0.040	-0.042*	-0.181***	-0.198***	-0.011	-0.011*	-0.163***	-0.165***
	(0.024)	(0.023)	(0.036)	(0.039)	(0.007)	(0.006)	(0.024)	(0.023)
Log manufacturing empl.	-0.172	-0.093	0.140	0.498	0.116	0.088	1.429***	1.421***
	(0.288)	(0.281)	(1.060)	(1.228)	(0.104)	(0.096)	(0.549)	(0.455)
Log No. of firms[♭]	2.106***	2.161***	7.056***	7.594***	1.473***	1.464***	5.589***	5.853***
	(0.311)	(0.314)	(2.050)	(2.287)	(0.112)	(0.105)	(0.622)	(0.599)
Ind. diversification	0.008	0.007	0.009	0.007	0.002	0.002	0.014	0.014
	(0.016)	(0.016)	(0.025)	(0.026)	(0.005)	(0.005)	(0.019)	(0.018)
Skilled/unskilled labour	1.897	2.209*	6.699*	6.801*	0.195	0.159	8.461***	8.172***
	(1.266)	(1.295)	(3.609)	(3.779)	(0.407)	(0.376)	(1.309)	(1.314)
Log R&D	0.396*	0.388*	0.020	0.003	0.138*	0.143*	0.444	0.424
	(0.227)	(0.226)	(0.646)	(0.674)	(0.082)	(0.082)	(0.273)	(0.273)
Constant	-5.011	-5.896	-41.066	-47.162				
	(3.110)	(3.073)	(8.827)	(10.121)				
R-squared	0.584	0.582	0.635	0.607				
Observations	117	117	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.
♭ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Table 6: Regressions: OLS and Negative Binomial (Marginal Effects)

	OLS				Negative Binomial			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large firms	Large firms	Small firms	Small firms	Large firms	Large firms	Small firms	Small firms
No. engineering dept: <4	-0.267		-0.264		-0.102*		0.285	
	(0.174)		(0.485)		(0.054)		(0.363)	
No. engineering dept:5 or 5*	0.491		2.215***		0.071*		1.035**	
	(0.315)		(0.767)		(0.038)		(0.447)	
No. bio science dept: <4		-0.352		-0.278		-0.123*		-0.048
		(0.223)		(0.611)		(0.066)		(0.266)
No. bio science dept:5 or 5*		0.173		1.426**		0.052**		0.434***
		(0.214)		(0.639)		(0.021)		(0.113)
Population per hectare	-0.047**	-0.039	-0.218***	-0.197***	-0.013**	-0.010	-0.179***	-0.169***
	(0.021)	(0.024)	(0.037)	(0.041)	(0.006)	(0.007)	(0.025)	(0.023)
Log manufacturing empl.	-0.109	-0.071	0.739	0.487	0.069	0.071	1.542***	1.401***
	(0.343)	(0.299)	(1.139)	(1.245)	(0.076)	(0.087)	(0.463)	(0.023)
Log No. of firms$^\flat$	2.086***	2.159***	6.921***	7.432***	1.482***	1.473***	5.557***	5.726***
	(0.293)	(0.306)	(2.159)	(2.133)	(0.098)	(0.102)	(0.622)	(0.521)
Ind. diversification	0.005	0.002	-0.001	-0.009	0.003	-0.002	0.014	0.009
	(0.015)	(0.014)	(0.023)	(0.026)	(0.005)	(0.004)	(0.018)	(0.018)
Skilled/unskilled labour	1.925*	1.928	8.243**	6.533***	0.168	0.084	9.017***	8.269***
	(1.159)	(1.346)	(3.463)	(4.047)	(0.318)	(0.373)	(1.212)	(1.224)
Log R&D	0.378*	0.359	0.152	0.087	0.118	0.159**	0.482	0.475*
	(0.220)	(0.241)	(0.672)	(0.655)	(0.085)	(0.079)	(0.297)	(0.263)
Constant	-5.139	-5.292	-46.251	-45.113				
	(3.512)	(3.152)	(9.795)	(10.135)				
R-squared	0.602	0.594	0.629	0.632				
Observations	117	117	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.
$\flat$ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Table 7: Regressions: OLS and Negative Binomial (Marginal Effects)

	OLS		Negative Binomial		IV OLS		Control Function	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large firms	Small firms	Large firms	Small firms	Large firms	Small firms	Large firms	Small firms
RAE grade engineering	0.077	0.576**	-0.018	0.159	-0.284	1.201***	-0.049	0.431**
	(0.097)	(0.232)	(0.027)	(0.116)	(0.206)	(0.385)	(0.074)	(0.183)
Population per hectare	-0.040*	-0.190***	-0.012	-0.164***	-0.048*	-0.169***	-0.012	-0.150***
	(0.024)	(0.038)	(0.007)	(0.027)	(0.025)	(0.039)	(0.008)	(0.031)
Log manufacturing employment	-0.177	0.539	0.116	1.669***	0.129	0.301	0.151	1.483*
	(0.291)	(1.236)	(0.106)	(0.616)	(0.349)	(1.587)	(0.181)	(0.896)
Log No. of firms[♭]	2.113***	7.317***	1.477***	5.632***	2.290***	0.035	1.484***	5.420***
	(0.300)	(2.306)	(0.109)	(0.693)	(0.363)	(0.029)	(0.211)	(0.959)
Ind. diversification	0.008	0.006	0.001	0.015	0.007	0.035	0.002	0.016
	(0.016)	(0.026)	(0.005)	(0.018)	(0.016)	(0.029)	(0.007)	(0.023)
Skilled/unskilled labour	1.851	7.862**	0.223	8.832***	2.923**	16.691***	0.339	7.727***
	(1.221)	(3.810)	(0.414)	(1.505)	(1.459)	(2.856)	(0.629)	(2.089)
Log R&D	0.415*	0.124	0.132	0.482*	0.307	1.287**	0.123	0.581*
	(0.226)	(0.680)	(0.082)	(0.274)	(0.243)	(0.525)	(0.093)	(0.317)
Constant	-5.144	-47.588			-7.702	-43.292		
	(3.138)	(10.079)			(3.744)	(10.342)		
Control Term							0.038	-0.356*
							(0.080)	(0.196)
1st Stage Partial R^2					0.165	0.187		
F-Test					13.615	18.121		
					(0.000)	(0.000)		
R-squared	0.584	0.591			0.393	0.419		
Observations	117	117	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.

♭ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Bootstrap standard errors for control function approach in Columns (7) and (8) (399 replications).

Table 8: Regressions: OLS and Negative Binomial (Marginal Effects)

	OLS		Negative Binomial		IV OLS		Control Function	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large firms	Small firms	Large firms	Small firms	Large firms	Small firms	Large firms	Small firms
RAE grade bio science	-0.005	0.615**	-0.016	0.223*	-0.218	0.970***	-0.037	0.366**
	(0.095)	(0.264)	(0.031)	(0.120)	(0.142)	(0.346)	(0.042)	(0.149)
Population per hectare	-0.042*	-0.191***	-0.011	-0.164***	-0.048*	-0.179***	-0.012	-0.156***
	(0.024)	(0.040)	(0.007)	(0.025)	(0.026)	(0.039)	(0.011)	(0.032)
Log manufacturing employment	-0.105	0.090	0.123	1.428**	0.130	-0.296	0.153	1.226
	(0.287)	(1.314)	(0.112)	(0.631)	(0.323)	(1.217)	(0.170)	(0.926)
Log No. of firms$^\flat$	2.152***	7.891	1.467***	5.795***	2.182***	7.823***	1.464***	5.844***
	(0.313)	(2.355)	(0.110)	(0.653)	(0.331)	(2.347)	(0.208)	(0.979)
Ind. diversification	0.007	-0.001	0.002	0.011	0.009	-0.002	0.002	0.010
	(0.016)	(0.025)	(0.005)	(0.018)	(0.016)	(0.027)	(0.007)	(0.023)
Skilled/unskilled labour	2.099*	7.269*	0.210	8.538***	2.841**	5.995	0.321	7.748***
	(1.261)	(4.067)	(0.409)	(1.492)	(1.373)	(3.652)	(0.618)	(2.084)
Log R&D	0.389*	0.146	0.131	0.524**	0.297	0.304	0.123	0.569*
	(0.228)	(0.647)	(0.080)	(0.263)	(0.231)	(0.709)	(0.090)	(0.302)
Constant	-5.739	-45.839			-7.624	-42.548		
	(3.085)	(9.910)			(3.433)	(10.366)		
Control Term							0.031	-0.203
							(0.049)	(0.158)
1st Stage Partial R^2					0.252	0.256		
F-Test					34.451	36.295		
					(0.000)	(0.000)		
R-squared	0.582	0.596			0.563	0.588		
Observations	117	117	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.

$\flat$ The number of large firms is included when the dependent variable is ‘Large firms’ and the number of small firms is included when the dependent variable is ‘Small firms’.

Bootstrap standard errors for control function approach in Columns (7) and (8) (399 replications).

Table 9: Regressions: Negative Binomial Spatial Lag of University Research (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
	Large firms	Small firms	Large firms	Small firms	Large firms	Small firms
No. of universities	-0.064	1.293**				
	(0.227)	(0.588)				
Spatial Lag No. of universities	0.011	0.484**				
	(0.081)	(0.214)				
No. engineer dept.			0.055	1.155***		
			(0.133)	(0.345)		
Spatial Lag No. engineer dept.			-0.007	0.220*		
			(0.047)	(0.122)		
No. biological sciences dept.					-0.002	1.115***
					(0.105)	(0.349)
Spatial Lag No. bio science dept.					0.006	0.130
					(0.040)	(0.103)
Population per hectare	-0.040**	-0.203***	-0.041**	-0.193***	-0.041**	-0.193***
	(0.020)	(0.052)	(0.020)	(0.054)	(0.020)	(0.054)
Log manufacturing employment	-0.068	0.649	0.119	0.460	-0.082	0.315
	(0.356)	(1.248)	(0.360)	(1.219)	(0.360)	(1.231)
Log No. of firms$^\flat$	2.106***	7.007***	2.067***	6.503***	2.087***	6.677***
	(0.291)	(1.453)	(0.293)	(1.436)	(0.287)	(1.442)
Ind. diversification	0.007	0.006	0.006	0.002	0.006	0.004
	(0.015)	(0.039)	(0.015)	(0.039)	(0.015)	(0.039)
Skilled/unskilled labour	2.183*	6.515**	2.117*	7.535**	2.148*	7.070**
	(1.242)	(3.167)	(1.195)	(3.033)	(1.254)	(3.112)
Log R&D	0.365	0.363	0.391	0.562	0.378	0.476
	(0.250)	(0.646)	(0.249)	(0.670)	(0.245)	(0.672)
LM test spatial autocorr	0.256	0.022	0.264	0.216	0.256	0.161
	(0.613)	(0.883)	(0.608)	(0.642)	(0.613)	(0.688)
Observations	117	117	117	117	117	117

Notes: * indicates significance at 10%; ** at 5%; *** at 1%.
$\flat$ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.

Table 10: Regressions: Technology Transfer Channels - Small Firms (OLS)

	# Invention Disclosures		# UK Patents		Consulting		Science Park/ Incubator	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RAE grade engineering	-0.415		0.207		0.314		0.094	
	(0.342)		(0.304)		(0.268)		(0.347)	
RAE grade bio science		-0.356		0.327		0.201		0.273
		(0.307)		(0.339)		(0.254)		(0.310)
RAE grade × TT† Channel	0.070*	0.048	0.061**	0.868	0.786	1.101*	1.464**	0.692
	(0.036)	(0.031)	(0.027)	(0.544)	(0.539)	(0.699)	(0.750)	(0.611)
TT† Channel	-0.170	-0.056	-0.226	-0.001	-3.813*	-4.277	-4.392*	-1.414
	(0.135)	(0.118)	(0.153)	(0.111)	(2.272)	(2.592)	(2.560)	(1.995)
Population per hectare	-0.167**	-0.172***	-0.176***	-0.181***	-0.186***	-0.184***	-0.202***	-0.197***
	(0.041)	(0.039)	(0.036)	(0.038)	(0.038)	(0.043)	(0.036)	(0.040)
Log manufacturing employment	-0.182	-0.149	0.348	-0.019	0.624	0.339	1.161	0.408
	(1.117)	(1.103)	(1.079)	(1.257)	(1.175)	(1.185)	(1.236)	(1.300)
Log No. of firms♭	7.730***	7.708***	7.524***	7.991***	7.475***	8.006***	6.611***	7.566***
	(1.948)	(1.878)	(2.190)	(2.414)	(2.277)	(2.275)	(2.090)	(2.256)
Ind. diversification	-0.012	-0.012	0.002	-0.003	0.006	-0.004	-0.001	-0.004
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)
Skilled/unskilled labour	5.098	5.501	6.767*	6.625*	7.672**	15.065***	9.215**	8.356**
	(3.855)	(3.793)	(3.600)	(3.908)	(3.758)	(3.358)	(3.529)	(3.722)
Log R&D	-0.176	-0.066	-0.071	0.083	-0.027	0.147	0.192	0.232
	(0.686)	(0.651)	(0.667)	(0.613)	(0.725)	(0.647)	(0.655)	(0.641)
Constant	-59.917	-38.812	-44.576	-44.487	-47.854	-48.043	-49.490	-47.610
	(11.485)	(8.940)	(14.873)	(9.760)	(9.929)	(10.287)	(10.708)	(10.578)
R-squared	0.689	0.681	0.609	0.607	0.610	0.622	0.608	0.602
Observations	117	117	117	117	117	117	117	117

Note: * indicates significance at 10%; ** at 5%; *** at 1%.

† TT: Technology Transfer; this variable refers to the specific channels listed in the header of the table.

♭ The number of large firms is included when the dependent variable is 'Large firms' and the number of small firms is included when the dependent variable is 'Small firms'.