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Do firms in clusters innovate more?

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Abstract

This paper analyses whether firms located in strong industrial clusters or regions are more likely to innovate than firms outside these regions. The study examines innovative activity using a database of innovations in the UK. The innovative record of 248 manufacturing firms during 8 years (1975–1982) is examined and related to employment in the region where they are located, and other variables. The results show that a firm is considerably more likely to innovate if own-sector employment in its home region is strong. On the other hand, the effect of strong employment in other industries does not appear to be significant. This may indicate that congestion effects outweigh any benefits that may come from diversification within clusters. The limitations of the data, however, do not allow for any definitive conclusion.

Keywords: Innovation; Clusters; Spillovers; Regional patterns

1. Background

In the last decade, there has been a widespread resurgence of interest in the economics of industrial location and, particularly, in the issue of industrial clusters. This field has been researched by economic geographers and through detailed case studies, such as Dorfman (1988), Hall and Markusen (1985) and Saxenian (1985, 1994). Regional and urban economists have provided theoretical analyses of industrial location choice (see Beckman and Thisse, 1986 and Stahl, 1987 for reviews). Following work by Porter (1990) and Krugman (1991), there has emerged a different strand of literature concerning industrial clusters both in industrial organisation and international trade.

A geographical cluster is defined here as a strong collection of related companies located in a small geographical area, sometimes centred on a strong part of a country's science base. Krugman (1991) develops a theory of regional specialisation of industrial activities based on the advantage of specialised labour pools and intermediate goods, and the presence of knowledge externalities. Porter (1990) points out that, underlying the phenomenon of clustering, are mechanisms that facilitate the interchange and flow of information between firms while rivalry is still maintained.

Some of the work on clustering focuses on the dynamic process generating clusters. More specifically, this examines how entry, growth rates and innovative activity can vary with the strength of the cluster in which they are located and indeed how innovative activity can, in itself, foster clustering. In a comparative study of clustering in the US and UK computer industries, Baptista and Swann (1996)

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found that strong clusters are more likely to attract new entrants, and also that firms in strong clusters tend to grow faster.

Innovative activity and output are closely associated with firm entry and productivity growth, as reported by Acs and Audretsch (1990), Baldwin and Gorecki (1991) and Geroski (1991, 1995). If the transfer of technological knowledge works best with geographical proximity, then any supply-side spillovers that might be gained from a strong core of manufacturing and R&D activities will be easiest to exploit if the receiver of such spillovers locates near this core.

Central to this argument is the concept of knowledge externalities or spillovers. The existence and effects of knowledge spillovers as sources of innovative output and productivity growth have been an important research issue in the economics of technology (see Griliches, 1991 and Nadiri, 1993 for reviews). Jaffe (1986, 1989) and Jaffe et al. (1993) have explored to what extent spillovers associated with R&D activity are geographically localised, thereby playing an important role in the clustering process.

The literature on *new growth* economics has also emphasised the importance of technological spillovers. If resources and knowledge can be combined to produce new knowledge, some of which spills over to the research community, then the creation of still more knowledge is facilitated, leading to a cumulative process (Grossman and Helpman, 1992). The fact that these increasing returns may somehow be geographically bounded would explain spatial differences in growth rates and the distribution of economic growth (Romer, 1986, 1990; Lucas, 1988).

Pavitt (1987) suggests that, due to its informal, uncodified nature, new technological knowledge should flow locally more easily than over great distances. This way, industrial centres would generate more knowledge spillovers and, therefore, more innovative output. Feldman (1994) and Audretsch and Feldman (1996) found strong evidence in favour of the geographical concentration of innovative activity and output for the US industry.

The importance of knowledge spillovers and innovative inputs suggests that firms' R&D activities do not proceed in isolation, but are supported, in each stage, by external sources (Nelson, 1993). If geographical proximity to these sources is important, one should observe significant differences in innovative output between firms located in different areas. Moreover, given the cumulative nature of knowledge, firms located in strong innovative areas should benefit from self-reinforcing advantages in order to innovate more. Innovating firms will tend to enjoy permanent advantages in profit margins over non-innovators (as found by Geroski et al., 1993) and, consequently, should grow relatively faster. This would lead to the growth of innovative regions.

The objective of this paper is then to determine if firms located in strong clusters (using regional employment as a measure of the strength of the cluster) are more likely to innovate than other firms. The rest of the paper is arranged as follows: Section 2 reviews four strands of the literature which provide a theoretical rationale for why firms located inside clusters may be more innovative. Section 3 describes the data and methodology used in this study, and Section 4 summarises the econometric approach used. Section 5 shows the results and Section 6 presents some concluding remarks.

2. Theory underlying the paper

Clusters are generated and reinforced by a positive feedback process based on a set of advantages that arise from the geographical agglomeration of industrial activities. If benefits from locating in an industrial centre increase as more new firms locate there, then a process of positive feedback and *lock-in* (Arthur, 1990) will result. Regions do not, however, enjoy this kind of increasing returns indefinitely. If the attractiveness exerted by the presence of others was permanent, some region should always dominate and shut out the others. In fact, what is usually observed is that attractiveness levels off, leading to solutions in which a few regions share the industry.

The sub-sections that follow approach the relationship between clusters and innovative activity from four different perspectives, concerning the nature of the clustering process, the nature of technology, the nature of innovative process, and the nature of economic growth.

2.1. Sources and limits of the clustering process

The benefits that lead to clustering can be divided into demand and supply side (Swann, 1993). On the demand side, firms may cluster to take advantage of strong local demand, particularly that deriving from related industries. Furthermore, under certain conditions, firms stand to gain market share if they move closer to their rivals (as originally suggested by Hotelling, 1929); this gain may admittedly be short-lived as other firms enter, or if the incumbents in the cluster react to this unwanted competition. Consumer search costs might also be an important determinant: certain small businesses selling differentiated goods might choose to locate in a cluster because they are more likely to be 'found' by customers. Moreover, customers are a good source of ideas for innovation (Von Hippel, 1988), and firms can readily exploit these flows of information by locating near key-users and establishing customer services.

On the supply side, the main sources of location externalities can be traced as far back as Marshall (1920) and were restated by urban and regional economists (see Henderson, 1986 and Fujita and Thisse, 1996 for reviews of the arguments) and also by Krugman's (1991) widely known work on geography and trade. The most frequently mentioned is labour market pooling. Geographical concentration of firms in the same industry (or in closely related ones) creates a pooled market for workers with the same skills, helping to cope with the uncertainty related to business cycles and unemployment. A second advantage has to do with the provision of related inputs. Location in an industrial centre allows for the provision of traded and non-traded inputs specific to an industry in a greater variety and at a lower cost. The third supply-side externality is one concerning knowledge spillovers: an industrial centre generates positive externalities related to the transmission of knowledge between nearby firms. Easy access to physical infrastructure, such as major motorways, can also be considered as an attractive feature for some locations.

The limits to the positive feedback process by which clusters are self-reinforced are related to congestion and competition effects that arise from input and output markets. One would expect that, as the cluster grows, congestion effects eventually overcome the benefits. Ultimately, as leading technologies are overtaken by new ones, new centres tend to emerge, while old clusters decline (Brezis and Krugman, 1993).

The importance of knowledge spillovers can make geographical proximity vital for innovative activity. A cluster provides a set of knowledge inputs that make for a technological infrastructure that supports innovative activity (Feldman, 1994). These inputs can come from competitors, firms in related industries, suppliers, customers and other entities carrying out research, such as universities and public-funded institutions. The argument is that innovative activity will tend to geographically concentrate close to agglomerations of this infrastructure, which is relatively immobile and place-specific (Tassey, 1991) in order to benefit from spillovers.

2.2. Technological regimes

Another approach to analysing different patterns of innovation is the concept of *technological regimes*. This notion can originally be found in Nelson and Winter (1982) and has been further developed by Malerba and Orsenigo (1990). A combination of four factors influencing the rate of innovation is used to provide a characterisation of the technological environment faced by a firm.

Opportunity conditions reflect a firm's likelihood to innovate, given the amount of investment in R&D. *Appropriability conditions* reflect the possibility of protecting innovations from imitation, and therefore gaining a larger share of the profits. The *degree of cumulativeness* represents the probability of innovating in a period, given the amount of innovations produced in previous periods. Finally, the *knowledge base* characterises the type of knowledge upon which the firm's activities are based.

It seems reasonable to claim that there is a spatial dimension to technological regimes, and that the basic features defining a firm's technological regime will have consequences for its geographical location and for the spatial distribution of innovative activity (Cohen, 1992; Breschi, 1995).

If technological opportunity affects the rate of innovation, then the spatial location of innovators will be affected by where such opportunity is available and effectively accessible to firms. This is determined by the kind of knowledge base associated with each firm's activity. The knowledge base determines how information about technologies is transmitted between agents and the spatial boundaries in which this transmission can effectively take place.

So long as much technological knowledge has a tacit nature and cannot be codified through plans, instructions or scientific articles, it seems reasonable to expect a greater geographic concentration of innovators. This type of knowledge can only be learned through everyday practice and use of a technology (Nelson and Winter, 1982) and its transmission relies, for the most part, in informal personal contact (Pavitt, 1987). This is specially relevant when a technology is on the early stages of its life-cycle, being still highly complex and ever-changing. In these conditions, the use and transfer of new, non-codified knowledge is the key to successful development (Lundvall, 1988). The more an industry's knowledge base is simple and well codified, the less important is geographical concentration for innovators but, since this probably means that the technology has reached its maturity, a smaller number of significant innovations will also be expected.

Industries with a higher level of appropriability and cumulativeness at the firm level will be associated with stronger selective pressures and allow for successful innovators to acquire and maintain high levels of market power. Technological leaders will be more likely to innovate further, keeping their competitive advantage (Breschi, 1995). This means that a high level of sectoral concentration will be expected and, with a lower number of innovators, geographical concentration of innovative activity is more likely to happen.

2.3. Stylised facts about innovation

Another line of argument concerning the location of innovative activity stems from the fundamental nature of the innovative process. Feldman (1994) develops this argument drawing on five *stylised facts* about the industrial innovation process presented by Dosi (1988). These are: *uncertainty, complexity, reliance upon basic research, importance of learning-by-doing* and *cumulativeness*.

By definition, what is searched cannot be known in advance, so that the technical and commercial outcomes of innovative efforts are, by nature, uncertain and complex. The formation of channels for exchange of information, such as networks of innovators, can be thought of as an approach to reduce this uncertainty. Being part of a network enables a firm to exploit developments in a technology in a timely manner and facilitating problem-solving tasks through the sharing of experience obtained dealing with similar technologies. Networks of innovators tend frequently to be localised (Freeman, 1991). Debresson and Amesse (1991) argue that localised networks appear to be more durable than formal, international strategic alliances. This would happen because regional networks are reinforced by social, cultural and symbolic bonds that result in a kind of 'social solidarity' made possible by geographical proximity and frequent contact.

Industrial innovation relies heavily upon sources of basic scientific knowledge such as universities and government-funded R&D. Most major new technological opportunities come from advances in scientific knowledge. Geographical proximity to universities gives direct access to individuals that can turn information into usable knowledge in a timely manner, making commercial control over a technology easier and faster. The pervasiveness of academic research spillovers and its geographic concentration has been confirmed empirically by Jaffe (1989) and Acs et al. (1992).

One other stylised fact about innovation is the importance of learning-by-doing and learning-by-using. This means that people can learn about how to produce, use, or improve things by carrying out their activities of solving production problems, meeting customers' requirements and overcoming various types of bottlenecks. Expertise of this kind comes from direct contact with a variety of sources, such as competitors, suppliers, customers and providers of different kinds of business services (Von Hippel, 1988).

Finally, technological innovation is able to draw from novel opportunities stemming from previous scientific advances. The direction of technical change is often defined by the latest technologies already in use. This means that regions that accumulate high levels of innovative success have assembled information that facilitates the next round of innovation, since the ability to innovate successfully would be a function of the technological levels already achieved.

2.4. New growth externalities

The literature on new growth economics has considered the effects of two kinds of knowledge externalities on growth (Glaeser et al., 1992), resulting from the geographical agglomeration of industries.

The first kind, where knowledge spillovers arise from industry specialisation, originates in the work of Marshall (1920) and Arrow (1962) and was restated by Romer (1986, 1990), being usually referred to in the literature as MAR (Marshall–Arrow–Romer) externalities. This kind of effect considers that spillovers occur *within industry*. This would happen because knowledge accumulated by one firm tends to help the development of technologically close firms. Industries that are regionally specialised benefit most from transmission of knowledge *within industry* and should, therefore, grow faster. This is not dissimilar to the argument presented by Porter (1990), although this stresses the importance of rivalry between competitors.

The second type of externalities arises from diversity or variety between complementary industries. Following work by Jacobs (1969, 1984) on cities and urban industrial development, Lucas (1988) argued that cities play the role of *external human capital* for economic activity and the growth of knowledge. Positive externalities would then arise from the variety of related economic activities that can be found in a city (or, to be more comprising, a cluster). Knowledge spillovers would occur primarily between different but complementary industries. Bairoch (1988) supports this argument by considering that the diversity of urban activities encourages attempts to apply in one sector technological solutions adopted in others. Moreover, Scherer (1984) has confirmed the significance of *inter-industry* technology flows.

A similar form of distinction between these two kinds of externalities can be traced further back in the urban economics literature to Lösch (1954) and Isard (1956). Benefits derived by firms in a particular industry from locating close to each other are termed *localisation economies*, while the gains obtained by firms from many industries by locating in the same area or city would be *urbanisation economies*.

These forms of external effects have been tested on firm growth (Glaeser et al., 1992; Henderson, 1994) and on innovative performance (Feldman and Audretsch, 1995) in cities and metropolitan areas. It seems preferable to test the effects of external factors on innovative performance rather than firm growth. If externalities related to knowledge are viewed as the ‘the engine of growth’ (Romer, 1986; Lucas, 1988), then they should manifest themselves primarily on innovative output. Besides, if industries that are spatially agglomerated innovate more and grow faster, then regions where these industries locate should account for the larger part of the innovative output.

The arguments discussed here stress the importance of knowledge spillovers and information sharing on innovative activity. This leads to a localised networking of firms engaged in related research and to proximity to the sources of novel scientific knowledge (universities and public research laboratories), in a process where interaction with suppliers and clients also assumes an important role. The cumulative nature of innovative activity manifests itself not just at the firm and industry levels, but also at the geographical level, creating an advantage for firms locating in areas that are abundant in the innovative resources, leading innovation to exhibit pronounced geographical clustering.

3. Data and empirical approach

This study combines two sources of data. The first is a subset of the SPRU innovation database: [1] the sample is a balanced panel including data on the

[1] The Database on Innovations in the UK: 1945–1983 collected by the Science Policy Research Unit (SPRU) at the University of Sussex identifies over 4300 technologically significant and commercially successful innovations introduced in Britain, as judged by a panel of over 400 experts from science, trade and industry. The data set is described at length in Robson and Townsend (1984).

count of significant innovations for 248 companies over the period 1975–1982. There is also data on each firm's market share and on the degree of concentration in their main domestic market. This is very similar to the data used in Blundell et al. (1993, 1995). Since the SPRU database spans the period 1945–1982, data on the firms' innovation records before the sample period was also available.

The use of direct innovation counts as a measure of innovative output presents several advantages over other measures such as R&D expenditures, which is really a measure of innovative input (or part of it), or even patents. The fact is that not all new inventions are patented and patents differ greatly in terms of economic impact—patents can be a measure of inventive output but hardly of innovative success (Freeman, 1982). Scherer (1983) found that the 'propensity to patent' is highly variable across industries and also across firm sizes.

Each of the companies was assigned, according to its main activity, to one of ten industry groupings, each corresponding to a two-digit Standard Industry Classification (SIC) industry: 22, 23, 25, 32, 33, 35, 43, 46 and 47; or a collection of two: 41 + 42 (see Table 1A). It was necessary to aggregate up to the two-digit level since the matching regional employment data was only available at this level. Further aggregation is due to the need to bridge the different industry classification codes used before and after 1980. For each firm, the standardised Central Statistical Office (CSO) region in which its headquarters are located was also identified.

It is recognised that, in the case of larger firms (the majority in this database), activities could be widely dispersed, though often this dispersion will be confined to one or possibly two CSO regions, and a specific innovation may well have its origin in a different region from the firm's headquarters, particularly if it comes directly from the manufacturing site and not from a research laboratory. In such cases, it is still assumed that the decisive location for innovative activity is the region where the firm's headquarters are located.

It has been shown (Howells, 1984, 1990) that a very high proportion of British corporate R&D facilities are located close to company headquarters. Furthermore, it has been argued (Leigh and North, 1978) that many large firms in England centre their R&D activities in the South East, near their headquarters, and do not disperse them throughout the corporation. This is particularly evident for the period of the sample. Similarly, a study carried out for the US industry ranked 'staying near home base' as the main factor influencing corporate R&D location decisions (Lund, 1986). This means that, if the greater proportion of innovations effectively comes out originally from research laboratories, then the assumption taken here is not as strong as it may seem. [2] It can also be argued that any prospective innovation has to pass through headquarters before introduction, so it is likely that some kind of spillovers are enjoyed by headquarters, even if the actual innovation comes from elsewhere. Yet, this somewhat at odds with the general arguments on knowledge spillovers being geographically bounded.

The second set of data is the employment by region for the 11 CSO standard regions of Great Britain and Northern Ireland over the sample period, as collected by the Central Statistical Office. Regional industrial strength is measured by the absolute value of sector employment. A relative measure, such as the proportion of sector employment in the region's total employment, would ignore the fact that a region might make for a strong cluster in a certain industry, even if this industry is not important in the region's overall breadth of activities. The rationale of relating innovative output to employment measures is that, if the argument over cluster-specific supply-side spillovers and technological infrastructure is true, then the propensity to innovate would be a function of the number of employees in the cluster or region. [3]

It seems clear that most clusters, being larger than a single city, will be smaller than a CSO standard

[2] If headquarters tend to be located in stronger clusters than other parts of the company, then any misattribution of the innovation to the company headquarters cluster rather than another cluster could lead to an upward bias in the effect of employment on the probability of innovation. Conversely, if R&D labs are located in the South East while company headquarters are placed in another region, there would be a downward bias. It is probable that these biases are not especially large, for the reasons given.

[3] Not, of course, that all employees generate equal spillovers, but a spillover-weighted measure of employment is not an easy thing to construct.

Table 1
Data and variables

A: Two-digit SIC sectors

SIC code	Description
22	Metal manufacturing
23	Extraction of minerals not elsewhere specified
25	Chemical industry
32	Mechanical engineering
33	Manufacturing of office machinery and data processing equipment
35	Manufacture of motor vehicles and parts thereof
41/42	Food, drink and tobacco manufacturing industries
43	Textile industry
46	Timber and wooden furniture industries
47	Manufacture of paper and paper products, printing and publishing

B: Variable definitions and descriptive statistics

Variable	Definition	Descriptive statistics[a]	Data source
Innovations (INNOV)	total number of innovations produced by all innovating units owned by the firm	0.156 (0.826)	SPRU innovations database
Own-Employment (OWNEMP)	regional employment in a firm's own industry	117.77 (75.925)	Computed from CSO Business Monitor
Other-Employment (OTHEMP)	regional employment in all other industries	985.63 (444.09)	Computed from CSO's Business Monitor
Market Share (MS)	total firm sales divided by three-digit industry total sales and work done	0.0496 (0.10195)	Datastream and ACOP
Concentration (CONCT)	five firm three-digit industry concentration ratio by sales	0.42188 (0.16629)	Datastream and ACOP
Industry Fixed Effects (*Ds*; *s* = 22, 23, 25, 32, 33, 35, 41/42, 43, 47)	dummy variables set for each of the 10 two-digit manufacturing industries (except-sector 46)	–	–
Employment Dispersion (DISPER)	two-digit industry Herfindhal index for employment in each firm's region	0.11424 (0.001)	Computed from CSO's Business Monitor
Region Population (POP)	total population in each firm's region averaged over ten years (1971–81)	10696 (6076)	Computed from CSO's Regional Trends
Dummy for entry knowledge stock (DKNST)	Dummy set to 1 (one) if the firm had innovated previously to the sample period	–	–
Entry Knowledge stock (EKNST)	Depreciated sum of past innovations prior to the sample period	0.47498 (2.1403)	Computed from SPRU Innovations Database

[a] The numbers presented are the mean and standard deviation (in brackets) over the 1984 observations.

region. Unfortunately, as in most other studies, the data constrains us to examine cluster-related effects at the region/state level. Evidence shows that spillovers and other agglomeration externalities become stronger when the geographical level of analysis is reduced (Glaeser et al., 1992; Jaffe et al., 1993), so it is expected that any bias coming from the use of CSO regional data would be against the relevance of spillovers. Data on total regional population was also collected to account for regional dimension.

Together, this data set is a balanced panel of 248 firms by eight years (1984 observations), each company allocated to an industry and a region. Table 1B presents information on all the variables used. For each company, employment data is organised in two variables: employment in industry i in region j, and employment in all other industries bar i in region j.

4. Econometric approach

The dependent variable in the model is the number of innovations introduced by each company in each time period (INNOVit). This is clearly a limited dependent count variable where the large majority of observations is zero (see Table 2A–C for a more detailed description).

Although a simple OLS estimate is carried out, this work concentrates on linear exponential models that are appropriate for count data, such as the Poisson and the negative binomial models, following Hausman et al. (1984) and Blundell et al. (1993, 1995).

Given the limited time span of the data (8 years), it proved unrealistic to estimate separate models for each sector. It was therefore necessary to pool the data and introduce constant fixed effects for each sector through industry dummies. Tests for the significance of these fixed effects (F-test for the OLS model and likelihood ratio tests for the count data models) found, not surprisingly, that they were very significant. [4]

[4] For the Poisson and negative binomial models, for instance, the likelihood ratio statistics are 88.62 and 33.01, respectively, for a chi-squared value (9, 0.05) of 16.92.

Table 2
Innovation data

A: Innovations by observation

Innovations per observation	Number of observations	Proportion
0	1831	92.28%
1	92	4.64%
2	30	1.52%
3	18	0.91%
4	3	0.15%
5	3	0.15%
6	1	0.05%
10	3	0.15%
12	1	0.05%
13	1	0.05%
16	1	0.05%
Total	1984	100%

B: Innovations by firm

Innovations per firm	Number of firms	Proportion
0	188	75.81%
1	27	10.89%
2	7	2.82%
3	7	2.82%
4	2	0.81%
5	2	0.81%
6	2	0.81%
7	3	1.21%
8	1	0.4%
10	2	0.81%
11	1	0.4%
13	1	0.4%
14	1	0.4%
16	2	0.81%
21	1	0.4%
78	1	0.4%
Total	248	100%

C: Innovations by region

Region	Number of innovations	Proportion
North	0	–
Yorkshire and Humberside	6	1.94%
East Midlands	1	0.32%
West Midlands	18	5.81%
East Anglia	13	4.19%
Southeast	245	79.03%
Southwest	9	2.9%
Northwest	16	5.16%
Scotland	2	0.65%
Wales	0	–
Northern Ireland	0	–
Total	310	100%

Blundell et al. (1995) found that variables related to market structure and firm size (market share and concentration) were significant for the explanation of innovative results. Evidence on the effects of firm size and market power on innovative performance is numerous, but somewhat inconclusive (see Scherer, 1967; Acs and Audretsch, 1987; and Geroski, 1990), but these two variables usually appear to be significant. It was decided, therefore, to include them in the model in order to avoid misspecification.

The simplest model to be estimated is, therefore:

$$\begin{aligned}\mathrm{INNOV}_{it} = \beta_1 \cdot \mathrm{OWNEMP}_{it} \\ + \beta_2 \cdot \mathrm{OTHEMP}_{it} + \beta_3 \cdot \mathrm{MS}_{it} \\ + \beta_4 \cdot \mathrm{CONCT}_{it} + \sum_s \gamma_5 \cdot \mathrm{D}_s\end{aligned} \tag{1}$$

where OWNEMP_{it} is regional employment in the firm's own industry and OTHEMP_{it} is regional employment in all the other industries; MS_{it} is the firm's market share, CONCT_{it} is industry concentration and D_i are industry fixed effects.

Two other variables are, each in turn, subsequently included in the model. Total region population (POP_{it}) aims to measure a region-specific effect associated with regional dimension. A firm might innovate more for being in a certain region because of a regional demand effect that results from region size. This is particularly relevant if one recognises the importance assumed by the South East region on the distribution of population, manufacturing and innovative activities in the UK. A measure of employment dispersion (or concentration) across industries within each region was also included. This is a simple Herfindhal index computed for employment in all manufacturing SIC sectors (following Henderson, 1994) and is intended to measure industry variety in the region. This is, of course, a very rough approach to the concept of externalities by Jacobs (1969, 1984) originating in regional industry diversity, since it does not consider any measure of complementarity between sectors, therefore assuming that all industries considered are equally close. It is indeed likely that at this high level of aggregation, Jacobs' externalities will act within and not across industries, and this should be taken into account when analysing results.

The simplest form of a count data model is the one where the dependent variable follows a Poisson distribution, so its variance is set equal to the mean and unobservable heterogeneity, such as the one resulting from individual fixed effects, is ruled out. However, count data does not usually respect the mean–variance equality restriction. This results in an overdispersion problem that is not dissimilar to the one of heteroscedasticity in the linear model. The negative binomial model provides a useful generalisation allowing for heterogeneity on the mean (see Hausman et al., 1984). The model demands a specific parametric assumption about the way in which the variance differs from the mean. Two types of specifications can be found on the literature: a linear relationship (Hausman et al., 1984) and a quadratic one (Gouriroux et al., 1984 and Blundell et al., 1995). This second specification was chosen for the estimation procedure to be carried out here:

$$V(Y) = E(Y) + \alpha \cdot E(Y)^2 \tag{2}$$

A simple regression test for the original Poisson model estimates (as suggested by Cameron and Trivedi, 1986, 1990) confirmed a significant quadratic relationship between mean and variance, although a linear specification for the mean–variance relationship was also significant. A consistent estimation of the quadratic parameter α is provided by the model, and the problem of overdispersion is effectively dealt with.

If individual fixed effects exist and are correlated with the regressors, the Poisson and negative binomial models will not be consistent, since the residuals will be serially correlated. If there is cumulativeness in the innovative process at the individual firm level, it seems natural to expect that innovative output will not be independent over time. This means that the probability of innovating today will depend on the previous innovation record of each firm, and that there will be an effect on innovation which is specific to each firm. Moreover, Blundell et al. (1993, 1995) suggest that there is a permanent feedback effect between innovation performance and market share, which would be reflected in the model. Individual fixed effects should therefore be considered or otherwise their presence can induce persistent serial correlation.

Hausman et al. (1984) suggest testing for serial correlation using a generalised residual-based test. This uses a covariance matrix of standardised residuals:

$$\Sigma = \frac{1}{N}\sum_{t=1}^{N}\left(\varepsilon_i \cdot \varepsilon_i'\right) \text{ with: } \varepsilon_{it} = \frac{y_{it} - \lambda_{it}}{\sqrt{\lambda_{it}}} \quad (3)$$

where y is the observed dependent count variable and λ_{it} are the Poisson model estimates. For the data in the present model, this is a symmetric (8×8) matrix, where each row or column refers to a year between 1975 and 1982. Non-zero off-diagonal elements will indicate serial correlation of the residuals.

Computation of this matrix for the Poisson model residuals presents results that are somewhat inconclusive (see Table 3A). The off-diagonal elements are very close to zero and no specific pattern of serial correlation seems to be present. However, some of these elements might not be small enough to rule out the existence of some serial correlation between residuals. Besides, since market share is the only firm-specific variable present in the model, it may be picking up some of the individual heterogeneity.

If fixed effects are present but are uncorrelated with the regressors, then the Poisson and negative binomial models used will still be consistent. However, it seems unreasonable to exclude the existence of some kind of feedback between a firm's innovative record and its market share, since any successful innovation is likely to lead to an increase in a firm's market power. This means that at least one of the regressors will be correlated with the fixed effects, since market share will be correlated with past innovations, and therefore the residual in any period t will also be correlated with past residuals.

An estimator that allows for individual fixed effects is then needed. Hausman et al. (1984) developed models allowing for random and fixed effects based on a conditional maximum likelihood approach that is contingent on the sum over time of the dependent variable. These models rely, however, on the assumption of strict exogeneity of the residuals. This assumption does not hold when there are dynamic feedback mechanisms such as the one that most likely exists between past innovative output and market share. This means that the regressors will be correlated with past residuals.

Although a fixed effects panel data estimator could have been developed for this specific case of

Table 3
Testing for serial correlation. Standardised residuals covariance matrix

A: Poisson model without individual heterogeneity							
1.0127							
−0.0619	1.6528						
−0.0323	−0.0279	0.8476					
0.3373	−0.1812	0.0774	2.254				
0.3578	−0.2203	−0.003	0.223	2.7078			
−0.1075	0.0952	−0.0248	0.1188	−0.0533	3.1185		
−0.0026	−0.0023	0.1782	−0.0664	−0.0507	−0.0325	0.3651	
0.1906	−0.0299	−0.0351	0.1058	0.1283	−0.1127	−0.0059	2.0226
B: Model controlling for individual heterogeneity							
1.069							
0.1317	1.1526						
−0.0559	−0.0415	2.8609					
−0.0014	0.0837	−0.0028	2.0949				
−0.0017	−0.0596	0.0112	−0.0063	1.4014			
−0.0413	0.0045	−0.033	−0.0149	−0.0172	1.8399		
−0.0004	−0.0059	0.0614	−0.0036	0.0282	−0.032	0.1547	
0.0472	−0.0426	−0.1361	0.2354	−0.0087	0.1004	−0.0102	9.1161

Matrices are symmetric (8×8).

count data, the existence of pre-sample information about the firms' innovative record allows for an indirect way to control for unobservable fixed effects across firms. This can be done since the SPRU database spans from 1945 to 1983, providing a long pre-sample history of the endogenous variable. Blundell et al. (1995) suggest that the 'permanent' capacity of individual firms to innovate should be reflected in their pre-sample innovative record. They argue that this pre-sample innovative activity provides a good approximation to the unobservable heterogeneity.

Using a data set which is very similar to ours, Blundell et al. (1995) use the information on the pre-sample innovative records of firms to account for individual heterogeneity. Although we realise that estimating an actual linear exponential model with fixed effects would be the most accurate econometric procedure, we believe that the solution presented by Blundell et al. (1995) deals with the problem of individual heterogeneity adequately enough for our purpose. Following their models, two firm-specific variables are included in the Poisson and negative binomial regressions. The first variable measures entry knowledge stock, that is the existence of innovative output prior to the sample period. This is a depreciated sum of past innovations:

$$\mathrm{KNST}_{it} = \mathrm{INNOV}_{it} + (1-\delta)\cdot \mathrm{KNST}_{it-1} \tag{4}$$

where, as in Blundell et al. (1995), a value of $\delta = 0.3$ is assumed. The second is a dummy variable (DKNST) that is set to one if the firm has previously innovated, and to zero if it has not.

It should be noted that, in including these variables, it is not suggested that there are no problems with this measure of the knowledge stock or with its theoretical relevance to the explanation of innovative success (although cumulativeness at firm level should manifest itself through knowledge stock). They are included solely to control for the unobservable heterogeneity between firms.

Blundell et al. (1995) found that making the model conditional on the two knowledge stock variables, serial correlation was considerably reduced, leading to a better performance of the models. Running them with our data improves the general performance of the models and the absolute values of the off-diagonal elements of the standardised correlation matrix are, with few exceptions, considerably reduced (see Table 3B). The negative binomial model with variables controlling for individual fixed effects accounts for both overdispersion and firm heterogeneity. Moreover, once individual fixed effects are estimated, regional fixed effects are also accounted for, since it is assumed that firms do not change location through the sample period, and so are any specific effects of absolute firm size and individual R&D expenditure on innovative output (which are likely to exist).

5. Results

The results obtained (see Table 4A–D) are similar for all the models estimated. This suggests that they are reasonably robust. OLS estimates were included as a benchmark, [5] although least squares estimations require a slightly different interpretation from the linear exponential models.

All models yielded a significant and moderately large positive effect of own sector employment on the probability that a firm would innovate. Roughly speaking, the models say that, if region *A* has about 100 000 more employees in a certain industry than region *B*, then a firm belonging to that industry and located in *A* will, on average, produce one more innovation per year than a similar firm located in region *B*. Firms located in clusters that are strong in their own industry are, therefore, considerably more likely to innovate.

The effects of regional employment in other sectors are negative and not significant. This could be interpreted as a weak congestion effect, but the two-digit level of aggregation is probably inadequate to draw any conclusions concerning cross-sectoral effects. It is likely that the presence of certain industries should actually favour innovative activity while the presence of others only leads to congestion. These effects probably depend on technological distance and complementarity, as suggested by the Jacobs-type externalities. At the two-digit level of

[5] We also considered a Tobit model as a possible benchmark. The estimated results were very similar to the ones for the OLS model, so we decided to keep the latter, since they are less sensitive to instability problems.

aggregation, positive spillovers and congestion effects seem to offset each other, with the congestion effect dominating (though not significantly).

Market share is always very significant, confirming the suggested feedback effect between innovative success and market power. In the models that do not account for individual heterogeneity, it probably absorbs some individual fixed effects—being the only firm specific variable. That could explain why the absolute value of its coefficient falls sharply when the knowledge stock variables are introduced, while significance remains high.

Table 4
Estimation results

A: OLS model[a]

Innovation	(1)	(2)	(3)
Years	1975–1982	1975–1982	1975–1982
Observations	1984	1984	1984
Log-Likelihood	−2322.933	−2322.269	−2322.353
OWNEMP	0.00169 (0.000452)	0.00185 (0.000475)	0.00168 (0.000452)
OTHEMP	−0.000116 (0.0000645)	−0.00000708 (0.000125)	−0.000118 (0.0000645)
MS	2.3093 (0.1857)	2.3375 (0.1873)	2.3272 (0.1864)
CONCT	−0.23215 (0.2293)	−0.2909 (0.2349)	−0.27901 (0.2334)
D22	0.061 (0.1552)	0.0738 (0.1556)	0.084 (0.1567)
D23	−0.0697 (0.1202)	−0.0719 (0.1202)	−0.0563 (0.1209)
D25	0.0886 (0.121)	0.0987 (0.1213)	0.10252 (0.1217)
D32	0.0234 (0.1016)	0.0201 (0.1017)	0.0318 (0.1019)
D33	0.21534 (0.1443)	0.22881 (0.1448)	0.24173 (0.1464)
D35	0.0958 (0.1715)	0.10378 (0.1716)	0.12502 (0.1736)
D41	−0.0828 (0.1319)	−0.07 (0.1323)	−0.0679 (0.1326)
D43	−0.033 (0.1168)	−0.0341 (0.1168)	−0.045 (0.1173)
D47	−0.12677 (0.1163)	−0.12773 (0.1163)	−0.12368 (0.1163)
POP	–	−0.0000111 (0.00000966)	–
DISPER	–	–	−2.026 (1.887)
Constant	0.0348 (0.1014)	0.0313 (0.1014)	0.27473 (0.2454)

B: Poisson model[a]

Innovation	(1)	(2)	(3)
Years	1975–1982	1975–1982	1975–1982
Observations	1984	1984	1984
Log-Likelihood	−808.284	−806.953	−808.253
OWNEMP	0.0106 (0.0022)	0.0113 (0.00223)	0.0107 (0.00221)
OTHEMP	−0.0000985 (0.000302)	−0.000506 (0.000481)	0.000112 (0.000307)
MS	5.1841 (0.2918)	5.295 (0.3024)	5.193 (0.2942)
CONCT	−0.33522 (0.7624)	−0.63066 (0.7856)	−0.37145 (0.7762)
D22	1.3409 (1.162)	1.367 (1.162)	1.3611 (1.165)
D23	1.8318 (1.047)	1.7964 (1.047)	1.8474 (1.044)
D25	1.8583 (1.045)	1.9195 (1.045)	1.8707 (1.046)
D32	1.5895 (1.047)	1.5999 (1.046)	1.5904 (1.047)
D33	1.3868 (1.12)	1.4878 (1.121)	1.3955 (1.121)
D35	1.8515 (1.151)	1.8603 (1.153)	1.8766 (1.155)
D41	0.0778 (1.106)	0.18585 (1.108)	0.09 (1.107)
D43	1.3269 (1.091)	1.316 (1.092)	1.3062 (1.094)
D47	−0.0907 (1.107)	−0.0704 (1.106)	−0.0905 (1.107)
POP	–	−0.0000551 (0.0000340)	–
DISPER	–	–	−2.2694 (9.172)
Constant	−5.0848 (1.035)	−5.0949 (1.035)	−4.088 (1.152)

Table 4 (*continued*)

C: Negative binomial model[a]

Innovation	(1)	(2)	(3)
Years	1975–1982	1975–1982	1975–1982
Observations	1984	1984	1984
Log-Likelihood	−635.39	−635.326	−635.207
OWNEMP	0.0112 (0.00358)	0.0114 (0.00361)	0.0111 (0.00361)
OTHEMP	−0.000269 (0.000443)	−0.000372 (0.00111)	−0.000238 (0.000467)
MS	8.9337 (1.312)	8.9524 (1.313)	8.8989 (1.328)
CONCT	−3.258 (1.736)	−3.3511 (1.742)	−3.1364 (1.724)
D22	2.1292 (1.509)	2.1409 (1.508)	2.0565 (1.511)
D23	1.6645 (1.179)	1.6435 (1.217)	1.687 (1.216)
D25	2.2745 (1.163)	2.2974 (1.162)	2.2109 (1.167)
D32	1.8021 (1.133)	1.8071 (1.131)	1.7846 (1.136)
D33	1.7554 (1.359)	1.7946 (1.359)	1.7001 (1.358)
D35	3.0204 (1.478)	3.0168 (1.489)	2.91006 (1.476)
D41	1.3602 (1.214)	1.3877 (1.213)	1.326 (1.216)
D43	1.4694 (1.258)	1.4676 (1.262)	1.5172 (1.279)
D47	−0.18107 (1.304)	−0.16644 (1.303)	−0.19698 (1.314)
POP	−	−0.0000206 (0.0000911)	−
DISPER	–	–	7.4172 (17.53)
Constant	−4.5411 (1.075)	−4.5495 (1.075)	−5.4414 (2.505)
α[b]	5.0416 (0.8851)	5.0177 (0.8899)	5.0619 (0.8883)

D: Model controlling for fixed effects[a]

Innovation	Poisson	Negative binomial
Years	1975–1982	1975–1982
Observations	1984	1984
Log-Likelihood	−637.409	−554.758
OWNEMP	0.00977 (0.00231)	0.0098 (0.00329)
OTHEMP	−0.000351 (0.000285)	−0.000382 (0.000409)
MS	2.4387 (0.3365)	2.4387 (1.012)
CONCT	−0.4848 (0.7665)	−0.4848 (1.482)
D22	0.7112 (1.1771)	0.7112 (1.329)
D23	1.1771 (1.052)	1.1771 (1.178)
D25	0.7206 (1.048)	0.7206 (1.131)
D32	0.283 (1.057)	0.383 (1.071)
D33	0.9218 (1.13)	0.9218 (1.267)
D35	0.2621 (1.157)	0.2621 (1.33)
D41	−0.2911 (1.095)	−0.2911 (1.156)
D43	0.7701 (1.092)	0.7701 (1.237)
D47	−1.18 (1.114)	−1.18 (1.179)
DKNST	3.6523 (0.312)	3.6523 (0.3197)
EKNST	0.0913 (0.0153)	0.0912 (0.0385)
Constant	−6.1799 (1.071)	−6.1799 (1.007)
α	−	1.8164 (0.4022)

[a]Estimations obtained using Limdep. Numbers in brackets are standard deviations.
[b]This is an estimate and standard deviation of the dispersion parameter produced by the model.

Market concentration has a negative coefficient, although this is never significant in these results. This negative effect suggests that, while it is true that firms with higher market share innovate more, firms in industries where competition is more intense have a greater probability of innovating. This seems to support the argument of Porter (1990) that rivalry fosters innovation and the result given by Geroski

(1990) that concentration hinders innovation. It has been suggested, however, that other measures (such as, for instance, the number of workers per firm in the region for each industry), might make for a better measure of local rivalry for new ideas and competition for new innovations (see Feldman and Audretsch, 1995).

Although industry fixed effects are clearly significant when taken as a whole, the sector dummies are not significant when taken individually. A smaller level of industry aggregation should allow for clearer results on industry specific cumulativeness.

A model including regional population as an explanatory variable was also estimated. This was done in order to control for effects of regional dimension, where innovation is more frequent in more populated regions because demand pressures are stronger. This new variable is clearly insignificant and does not affect estimated coefficients on the other variables, so dimension effects seem to be unimportant. One could argue that cumulativeness at the regional level appears to be primarily related to supply side, rather than demand side effects.

The inclusion of the variable measuring diversity across sectors also does not change the results much. It is never significant, and it has different signs for Poisson and negative binomial models. However, this does not necessarily indicate lack of evidence for industry variety effects, or ‘Jacobs externalities’ on innovation, since most of the complementary or technologically close industries that are likely to provide positive effects on innovative performance will be bounded within two-digit sectors.

The negative binomial model including knowledge stock variables, and controlling for fixed effects, seems to be the best specification, dealing conveniently with the overdispersion and individual heterogeneity problems. However, the basic results obtained are not very sensitive to the precise choice of model.

6. Concluding remarks

This paper presents a study of whether firms located in strong clusters are more likely to innovate, and some evidence was found that they are. Part of the reason for this may be the effects of location externalities on innovative performance. These location externalities are associated with the phenomenon of industrial clustering.

One of the main reasons behind the existence and success of clusters is the pervasiveness of knowledge externalities or spillovers. It seems likely that spillovers, particularly those associated with new technological knowledge, tend to be geographically localised. Certain regions accumulate sources of spillovers, which in turn attract and support innovators. This adds a regional dimension to the cumulative nature of the innovation process, and this has implications for the balance between regional and national industrial R&D policy.

Using regional employment as a measure of a cluster’s strength, it was found that a firm is more likely to innovate if located in a region where the presence of firms in its own industry is strong. The effects of the proximity of firms in other industries do not appear to be significant, perhaps suggesting the presence of congestion effects, but this is highly conditioned by the level of industry aggregation.

This study offers an analysis of the statistical association between the probability of innovation and cluster strength. As such, it is obviously an indirect way of measuring the effect of clusters on innovative activity, but it does find that it is the strength of the cluster (as measured by own-sector employment) rather than the strength of demand (as measured by population) which is correlated with a firm’s innovative activity. This, combined with earlier results in the literature, suggests that innovation, entry and growth tend to be stronger in clusters. An important next step is for research to develop our understanding of the mechanisms underlying these observations.

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