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ARE FIRMS IN CLUSTERS REALLY MORE INNOVATIVE?

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This paper examines empirically whether firms located in strong industrial clusters are more innovative than firms located outside these regions. The study performs a firm-level analysis for two countries: Italy and the United Kingdom. European patent data for the period 1990–98 are used as indicator of firms' innovative activity, and are related to employment in the region where the firms are located, and other cluster-specific and firm-specific variables. The main result of the paper is that clustering alone is not conducive to higher innovative performance. Whereas location in a cluster densely populated by other innovative firms positively affects the likelihood of innovating, quite strong disadvantages seem to arise from the presence of non-innovative firms in a firm's own industrial sector. Regarding the impact of other industrial sectors, preliminary results seem to indicate, in the case of Italy, that a strong presence of firms in other related industries spurs innovative performance.

Keywords: Clusters; Innovation; Knowledge; Agglomeration economies

JEL classification: L10, O30, O40, R12

1 INTRODUCTION

This paper studies the spatial clustering of economic activities and its impact upon firms' innovative processes. A considerable amount of research effort has been devoted in recent times to examine the spatial distribution of innovative activities and the economic forces driving it. On the empirical side, a substantial body of recent research has convincingly shown that innovative activities tend to be more spatially clustered than manufacturing activities. On the theoretical side, it has been argued that the emergence of innovative clusters suggests the presence of agglomeration economies specific to innovation processes, although there seems to be less of a consensus on the most important sources of such economies (*i.e.* "knowledge spillovers" *vs.* "pecuniary externalities" or market-based effects). Although still in a fluid state, this literature has been already extensively surveyed by several authors (Baptista, 1998; Feldman, 1999; Breschi and Lissoni, 2001a,b).

Building upon this stream of literature, the purpose of this paper is to examine empirically in what sense and to what extent 'clustering' is really beneficial to firms' innovative activities.

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In this paper, we take a rather pragmatic approach and define a geographical cluster as a strong collection of related companies located in a relatively small geographical area (Porter, 1998). The paper follows the methodology developed by Baptista and Swann (1998), who have modelled firm innovation as a function of the strength of the cluster in which it is located, using a positive feedback negative binomial model. The paper combines data on innovation and economic characteristics at the firm level, with economic data at the geographical level for two countries: Italy and the United Kingdom. As such, it is able to overcome what are, in our view, two main limitations of most existing empirical tests, namely the fact that regions, and not firms, are usually assumed as the unit of analysis, and secondly the lack of a comparative perspective, especially among European countries.

The paper is organised as follows. The next section discusses the theoretical background of the empirical models estimated, and identifies a number of hypotheses to be tested. After discussing the data collection process, the paper then presents the regression results. A final section concludes and provides indications for further research.

2 BACKGROUND

2.1 Clustering and Firm Innovation: An Appreciative Model

Various conceptual arguments have been advanced to suggest that firms located in clusters should be more likely to innovate than firms outside these regions. In trying to distil a wide range of empirical observations and theoretical perspectives into a model of clustering, one can argue that the impact of clustering on firms' innovation is broadly defined by two features: agglomeration economies and congestion externalities. Table I, adapted from Swann (1998), summarises this model in a convenient and compact way.

Clustering effects can in principle be positive or negative, and can emanate from the demand or the supply side. Moreover, some externalities are in some measure sector-specific, notably the availability of labour with sector-specific skills, while others have a more generic nature, cutting across industries. In discussing these various effects, we start from the top right-hand cell of the table, as supply-side effects have attracted attention in the recent literature as the most relevant benefits from clustering.

Following seminal papers by Jaffe (1989) and Jaffe *et al.* (1993), it has been argued that the transmission of technological knowledge works better within spatial boundaries because this type of knowledge has a tacit and uncodified nature and thus flows through networks of interpersonal communication (Audretsch, 1998). Following this line of reasoning, one should then expect a firm located in a cluster that is strong in its own industry to be relatively more innovative than an isolated firm, because of the greater likelihood of sharing tacit knowledge

TABLE I Impact of Clustering on Firm Innovation.

Demand side	*Supply side*
Advantages	
Sophisticated users	Knowledge spillovers
User-supplier interaction	Skilled labour and specialised inputs
Informational externalities	Informational externalities
Disadvantages	
Competition in output markets	Competition in input markets
Strong relational ties	Inward orientation and lock-in

and accessing a larger pool of discoveries and ideas (Audretsch and Feldman, 1996; 1999).[1] In addition to localised knowledge spillovers, location in a densely populated and competitive environment provides further pressures and stimuli to innovate and experiment with new techniques, either because of technological bottlenecks arising in production or because of informational externalities arising from emulation, imitation and easier assessment of competitors' economic and innovative performance. A further important source of sector-specific pecuniary externalities relates to the fact that a localised industry attracts and creates a pool of specialised workers with relevant skills that may be harder to attract to an isolated location (David and Rosenbloom, 1990). Moreover, a localised industry can also support a greater number of specialised local suppliers of industry-specific intermediate inputs and services, thus obtaining a greater variety at a lower cost (Feldman, 1994).

On the negative side, location in a dense cluster may also imply some supply-side disadvantages. First of all, there are negative pecuniary externalities related to congestion and competition in input markets, whether it be the cost of real estates or the cost of labour. Many of these disadvantages are likely to be generic rather than sector-specific, *i.e.* imposed by the grand total of businesses located in the region. Furthermore, location in a cluster may also hinder technical change, especially where firms take an inward-oriented attitude leading to technological lock-ins and resistance to innovations generated elsewhere (Suarez-Villa and Walrod, 1997).

Regarding demand-side advantages from locating in a cluster, firms may cluster to take advantage of strong local demand, particularly that deriving from sophisticated users and related industries (Malerba, 2002). Moreover, consumer search costs and demonstration effects arising from the observation of successful firms at a particular location might also be important determinants of agglomeration. In the realm of innovation, it has also been pointed out that customers represent important sources of new ideas and that a continuous flow of incremental innovations is generated through the localised user-supplier interaction (von Hippel, 1988; Lundvall, 1988). Beside these advantages, some congestion effects or external diseconomies are also likely to arise on the demand side. Increased local competition in output markets may result in lower profit margins, thereby reducing the amount of resources devoted to R&D. More importantly, greater physical isolation from other producers also entails more limited obligations and weaker relational ties, which under certain circumstances may induce higher flexibility and responsiveness to technical and organisational changes.

2.2 Some Testable Clustering Propositions

On the basis of the appreciative model of clustering sketched above, one can derive some testable propositions concerning the expected relationship between location in a spatial agglomeration and a firm's innovative performance. In the models estimated below, the strength of a cluster in a specific industrial sector and in other sectors have been measured by the size of each cluster in terms of employment. To help the reader interpret parameter estimates, we will thus outline some scenarios, considering separately the impact of clustering in a firm's own industry and in other industries.

Starting from the effect that clustering in an industry has on the innovative performance of a firm active in the same industry, the arguments presented above suggest the following:

PROPOSITION 1 *To the extent that the sector-specific benefits from clustering outweigh the disadvantages, firms located in clusters that are strong in their own industry should be more likely to innovate than firms outside these regions.*

[1]Please note that while the greater part of technology spillovers are perhaps sector-specific, one can expect some of them to cut across sectoral boundaries.

Under the scenario outlined above, the coefficients for own-sector employment is expected to be positive. Previous works seem to support this prediction, by showing that a firm located in regions where the presence of firms in its own industry is strong tends to grow faster (Swann *et al.*, 1998), and to generate a greater number of innovations than more isolated firms (Baptista and Swann, 1998; Beaudry, 2001). It should be noted, however, that these works refer either to a restricted group of high technology industries or to single countries, notably the United States and the United Kingdom. Taking a broader perspective, Beaudry *et al.* (2001) find a positive impact of own sector clustering on firms' growth rate in most, even though not all, industrial sectors. This mixed record of results suggests that the aforementioned proposition perhaps needs a conceptual refinement. In our view, there are two major arguments, which suggest that clustering in itself may not be sufficient to explain all of a firm's propensity to innovate.

On the one hand, it is recognised that innovative activities have a highly cumulative nature for both firms and clusters (Thompson, 1962; Feldman, 1994). For this reason, inventive activity will tend to concentrate in locations where invention rates *had long been high* and where a *market for technology* has evolved more fully, irrespective of the share of industry production (Lamoreaux and Sokoloff, 1997). In this respect, the 'bridging' institutions that provide information about technological opportunities and mediate relations among inventors, suppliers, and those that commercially develop or exploit new technologies play an important role in the cluster. This also implies that industries may move across regional and even national borders without a corresponding relocation of inventive activity. Inventive activity tends to be more 'sticky' than production, possibly because the richness of *generic technological know-how* in some regions serves as an effective substitute for specific knowledge and allows finding of new applications across a wide range of industries. If this argument were true, one would then expect to observe higher innovation rates in clusters with a larger accumulated stock of knowledge, irrespective of the size in terms of employment.

On the other hand, most of the arguments advanced to support the claim that firms in strong clusters should innovate more are based on the importance of firm-specific competencies and skills embodied in human capital. In this perspective, it should be noted that firms are highly heterogeneous with respect to their innovative capabilities, and that workers differ in terms of embodied skills. This implies that not all the firms and not all the employees located in a cluster will generate equal spillovers. In general, one should expect high levels of spillovers to flow mainly or even exclusively from employees of innovative companies, whereas the presence of non-innovative companies is likely to be a source of congestion effects. Please note that, to the extent that the location of innovative firms in a cluster is the result of a historical cumulative process, the two arguments presented above are strictly related.

Based on the two arguments just discussed, one can therefore propose the following:

PROPOSITION la *Concentration of firms and production in a certain location is neither a necessary nor a sufficient condition to determine high rates of firms' innovative activity. Firms' propensity to innovate will be higher in clusters with a large accumulated stock of knowledge and with a strong presence of innovative firms and skilled human capital, while the co-location with other non-innovative firms from the same sector will result mainly in congestion effects.*

Considering now the impact that the co-location with firms in other industries has on a firm's innovative activity, the argument presented above suggests that, to the extent that the advantages from clustering originate mainly on the supply-side and concern knowledge spillovers, a positive effect should result from a strong presence of innovative firms in other industries, whereas the co-location with non-innovative firms in other sectors is likely to generate mainly congestion effects. At the same time, it has often been argued in the literature that the major benefits for a firm's innovative activity arising from the co-location with firms in other industries are mainly associated with the presence of related and complementary sectors, *i.e.* sectors sharing similar or complementary knowledge bases, inputs and distribution channels (Jacobs, 1969; Porter, 1998).[2] These arguments can thus be summarised in the following:

PROPOSITION 2 *Firms located in clusters with a strong presence of innovative companies in other industries and/or companies in technologically related sectors should exhibit a higher propensity to innovate than firms located in clusters not presenting these features.*

Before proceeding to empirical testing, we want to point out two final observations, which help delimiting the scope of the paper. In the first place, it is worth remarking that the strength of advantages and disadvantages from clustering, as well as the balance between these forces, is likely to vary across industrial sectors. Recent work in the field of the economics of innovation has pointed out that the specific features defining a technological regime in an industry are also likely to have a spatial dimension and thereby consequences for the geographical distribution of innovative activities (Cohen, 1995).[3] Although this issue seems to be relevant, it will not be pursued in the context of this paper. Secondly, the literature on national systems of innovation also suggests that the industrial structure, institutional system and history of industrial development of each country should affect in fundamental ways the spatial distribution of productive and innovative activities, and the actual working of agglomeration economies. In the case of Italy, for example, an important part of the current spatial distribution of production and innovation is rooted in the post-war history of industrialisation, in which a subsystem of industrial districts, based on highly specialised small firms located in the so-called Third Italy, gradually emerged beside the largest metropolitan areas dominated by large companies and public research centres (Malerba, 1993). Similarly, industrial policies adopted in the United Kingdom during the 1970s and the 1980s are largely responsible of the relocation of most innovative activities in the South-East (Walker, 1993). This stream of literature, however, has not yet produced any theoretical argument about how the specific characteristics associated with any specific national innovation system should

[2]This argument is only partly related to the recent dispute over the most relevant source of agglomeration economies. On the one hand, some of the advantages from clustering arise from industry specialisation. This happens whenever knowledge externalities exist, but are limited to firms within the same industry. This type of effect has been termed Marshall–Arrow–Romer (MAR) externalities or *localisation economies.* The implication of MAR externalities is that concentration of an industry in a location will induce higher levels of knowledge spillovers and therefore facilitate innovation. On the other hand, some external economies arise from diversity or variety between complementary industries. Firms in a certain industry can benefit from innovative ideas, skills, know-how and human capital originating from different, but somehow related industries. This type of effect has been termed Jacobs or *urbanisation economies* (Jacobs, 1969). The implication of this hypothesis is that regions that exhibit a broad and diversified industrial base will also promote firms' innovative activities. Empirical tests of the two hypotheses have so far yielded mixed results (Audretsch and Feldman, 1999; Paci and Usai, 2000). It is quite important to note that in this paper we are not testing the *specialisation vs. diversity* hypotheses, our focus being rather the impact of *clustering* on firms' innovative performance.

[3]First of all, if technological opportunities affect the rate of innovation, then the spatial location of innovative firms will be affected by where such opportunities are available (Universities, public research centres, users, suppliers) and by the nature of the relevant knowledge base. One can argue about the latter that the more the knowledge base is tacit and non-codifiable, the higher the spatial concentration of innovative firms one can expect. This type of knowledge is better transmitted through informal means and interpersonal contacts, whose effectiveness sharply decreases with the geographical distance between agents. Conversely, the more codified, simple and independent is the relevant knowledge base in a sector, the less important is the role of geographical distance in mediating knowledge flows. The fraction of knowledge base that is tacit and non-codifiable is especially high for industries and technologies that are in the early stages of their life-cycle, when knowledge is still highly complex and ever-changing. However, the importance of tacit know-how can be high also in relatively mature industries (*e.g.*, mechanical engineering), where the innovation process involves idiosyncratic capabilities to 'design' products that fit customers' specific requirements.

affect the strength of agglomeration economies at the regional level. In this respect, one of the aims of this paper is to provide some empirical evidence regarding possible similarities and differences in the impact of agglomeration economies between two European systems of innovation.

3 DATA AND METHODOLOGICAL ISSUES

This paper combines three sources of data: patent data, company data, and regional employment data. In this section, we discuss in detail the data collection process and the specific issues associated with their merger.

The first set of data used in this study is the EPO-CESPRI[4] database, which provides information on patent applications to the European Patent Office (EPO) of firms from Italy and the United Kingdom from 1978 to 1998.[5] For this study, the address of the patenting firm reported in the patent document has been used to locate each firm in a specific region. The level 3 regions of the *Nomenclature of Statistical Territorial Units* (NUTS) have been adopted here as the spatial unit. According to the definition provided by the European Office of Statistics (Eurostat), this level referred in 1991 to 65 *counties* for the UK and 95 *provinces* for Italy. A few remarks are needed in order to explain the choice of the applicant's address and the possible biases resulting from it. First, this paper focuses on firms' innovative performance and the choice of the inventors' address would not serve as well as the address of the applicant, *i.e.* the firm. Second, it is recognised that the use of the applicant's address to locate patents in space introduces a potential bias due to the widely diffused practice of firms' headquarters to patent inventions which have been originally developed by divisions and manufacturing establishments located in different regions.[6] Particularly, this approach can lead to an over-estimation of the volume of innovative activities carried out in large metropolitan areas within each country, where most headquarters are located. While this problem is not easy to solve, there are a number of reasons that can help mitigate the resulting bias.[7] First, misattributions of patents to the company headquarter cluster rather than another cluster are likely to be most serious only in the case of larger firms (which are a minority in this database) and in certain industries, where multi-plant firms are important. Second, Howells (1990) has shown that many large firms tend to locate their R&D facilities close to company headquarters and do not disperse them throughout the corporation. This implies that as long as a greater proportion of patents can be effectively considered as flowing from basic and applied research activities (*i.e.* from R&D laboratories), then the extent of the

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[5]The EPO-CESPRI database has been constructed at the level of individual firms and institutions. Firms that are part of business groups have been treated in the present analysis as individual companies. In case of co-patenting, each co-patentee has been credited the patent. Individual inventors have been excluded from the dataset. Overall, the EPO-CESPRI database includes 39,582 patents and 7,121 firms for Italy, and 25,058 patents and 6,265 firms for the UK.

[6]Only in few cases the applicant name reported in patent documents refers to manufacturing divisions or establishments where the invention has originated. An alternative approach, which has been followed in the empirical literature, is to use the inventors' address, instead of applicant's address. However, this criterion is not immune to problems, given that it is not clear whether the inventors' address really reflects the location where the inventive activity has been actually carried out. In the absence of serious empirical analyses, which allow discriminating between the two approaches, and for the reasons reported in the text, we believe that any possible bias arising from our choice should not invalidate the results.

[7]If headquarters tend to be located in stronger clusters than other divisions and establishments of the company, then any misattribution of patents to the company headquarter cluster can lead to an upward bias in the effect of cluster employment on the probability of patenting. However, for the reasons given in the text, it is probable that this bias is not particularly large.

distortion is likely to be further lessened. Third, it can also be argued that any potential innovation has to pass through the company headquarter before it is patented (*e.g.*, through internal mobility of researchers), so that some kind of knowledge spillover is likely to benefit the company headquarter even if the invention has been originally developed elsewhere.

The second type of data used in this paper refer to company economic information. Two commercial company databases were used to extract company economic data: Dun and Bradstreet's OneSource *UK vol. 1 and 2* for the UK and Bureau Van Dijk's *AIDA* for Italy.[8] Three categories of company information were considered for this study: firm size measured by the number of employees, primary sector of activity and NUTS 3 level region in which the headquarter is located.[9] Each company was assigned, according to its main activity, to one industrial sector, each corresponding to a two-digit *UK Standard Industry Classification* (SIC) (1980 Rev.) industry for the UK, and to a two-digit *Nomenclature of Economic Activities in the European Community* (NACE) (Rev. 1) industry for Italy. The present study considers 15 manufacturing sectors for the UK and 17 manufacturing sectors for Italy.[10] The list of industries considered in this study and a correspondence between the two industry classifications are reported in Appendix A.

The third type of data used in this paper is the level of employment by NUTS 3 level region for the United Kingdom and Italy. These data are provided by the *Central Statistical Office* (CSO) for the United Kingdom and by *Istituto Nazionale di Statistica* (ISTAT) for Italy, and refer to the year 1991. For the present study, regional employment data at the two--digit UK SIC (1980 Rev.) level for the United Kingdom and at the two-digit NACE (Rev. 1) level for Italy were used.[11]

In addition to the specific features of each database, some important issues appeared while merging the three databases. As a first step, we had to match the EPO-CESPRI database containing the names of patenting companies with the business databases OneSource *UK* and *AIDA*, containing economic information on companies. We successfully found economic data for 2,142 patenting firms for the United Kingdom, and 3,067 patenting firms for Italy.[12]

Our final sample includes 26,055 and 37,724 manufacturing firms for the United Kingdom and Italy, respectively. Two points need to be clarified regarding the sampling design used in this paper. First, the sources used for company data exclude very small companies (see note 8). This represents a potential source of sample bias, which makes drawing conclusions on the likelihood of innovating by small *vis-à-vis* larger firms difficult. Since the focus of this

[8]It is important to note that both databases include a sample of all manufacturing companies active in each country. *AIDA* provides balance sheet data of all Italian companies with an annual turnover higher than 2 million Euros, and of a significant proportion of companies with an annual turnover higher than 1.5 million Euros. Overall, the release of *AIDA* used for this study (28, June 1998) contained economic information for 48,216 manufacturing firms. OneSource *UK vol. 1 and 2* (release of January 1998) on the other hand, provides very detailed data on 360,000 UK companies, but applies a more complicated cut off point to choose which firms to include. In total, OneSource *UK vol. 1 and 2* provide information on 60,306 manufacturing firms.

[9]In addition to these, a fourth information, only available for the United Kingdom, refers to the type of company: parent, subsidiary, or independent.

[10]Note that it was necessary to aggregate up to the two-digit industry level since a large proportion of Italian companies in *AIDA* were classified at this level.

[11]Employment regional data are available up to the four-digit UK SIC level (1980 Rev.) for the UK, and up to the three-digit NACE (Rev. 1) level for Italy. However, it was necessary to aggregate up to the two-digit level in order to keep homogeneity with company data (see note 10).

[12]In percentage terms, we found economic data for 32.9% of all firms that applied for patents in the period 1990–98 for the United Kingdom, and 53.8% of all firms that applied for patents in the period 1990–98 for Italy. This corresponds to 49.2% of all patent applications for the United Kingdom and 68.5% for Italy, over the same period of time. The merger of the two databases was carried out manually and presented several difficulties that partly explain the relatively low matching ratio. First, there was no common pattern in naming companies across databases. Second, the number of firms included in company databases is limited and consequently many small innovative companies are simply not reported in these databases. Third, patenting firms that have ceased to exist are not reported either and therefore cannot be matched.

paper is not the relationship between size and innovation and the excluded firms are likely to be very small, however, we think possible to ignore the sampling bias. Second, observations are only available for the group of firms that existed in 1998. There is then a sample selection bias via the exclusion of firms that exited before that year. This bias may not be too important for two reasons: on the one hand, it is likely that unsuccessful firms are less innovative and, therefore, provide a lesser amount of externalities; on the other hand, exiters who did innovate are likely to have been bought by larger firms and, therefore, spillovers resulting from their innovative activities may still be accounted for by the data. In addition, we can safely ignore the sampling bias assuming that the probability of exit is uncorrelated with the explanatory variables included in the model. It is important to note that the vast majority of firms in our sample did not patent. For the period 1990–98, the proportion of firms with no patenting activity is slightly higher in the United Kingdom (94.2%) than in Italy (93.8%) (see Tab. II). Moreover, Italy also shows (in this sample) a higher proportion of firms with one or two patents compared with the United Kingdom.[13]

Another important issue concerns the technology classification of patents. Indeed, all patent documents are assigned by patent examiners of the EPO to one main classification code of the *International Patent Classification* (IPC).[14] It is important to note that these technology codes do not correspond directly to any UK SIC or NACE industry codes. For this reason, in this paper we sum up all patents of each company into a single value as a first approximation and ignore the distinction of patents into technological fields as well as the possible correspondence between technology fields and industry codes.[15]

TABLE II Number of Patents by Firm (1990–98), United Kingdom and Italy.

United Kingdom			*Italy*		
Patents per firm	*Number of firms*	*Proportion (%)*	*Patents per firm*	*Number of firms*	*Proportion (%)*
0	24541	94.189	0	35409	93.863
1	713	2.737	1	1372	3.637
2	270	1.036	2	356	0.944
3	155	0.595	3	152	0.403
4	81	0.311	4	103	0.273
5	47	0.180	5	70	0.186
6	38	0.146	6	39	0.103
7	28	0.107	7	41	0.109
8	22	0.084	8	18	0.048
9	14	0.054	9	18	0.048
10–19	66	0.253	10–19	79	0.209
20–29	25	0.096	20–29	22	0.058
30–39	9	0.035	30–39	15	0.040
40–49	10	0.038	40–49	5	0.013
50–99	20	0.077	50–99	15	0.040
100–499	12	0.046	100–499	9	0.024
500–782	4	0.015	500–832	1	0.003
Total	26055	100.000	Total	37724	100.000

[13]If we consider the entire period of time 1978–1998, the percentage and number of patenting firms in the sample increase, respectively, to 8.2% and 2142, for the United Kingdom, and to 8.3% and 3067, for Italy. So the countries display similar patenting behaviour in that respect.

[14]The IPC is an internationally agreed, non-overlapping and comprehensive patent classification system. Currently, the IPC (6th ed.) refers to almost 60,000 individual codes (12-digits) and it may be used at different hierarchical levels (WIPO, 1994).

[15]It is extremely difficult to evaluate the technological fields that should be counted as being related to the main sector of activity of a firm, to a secondary sector of activity or not related at all.

4 ECONOMETRIC APPROACH

4.1 Empirical Model and Variable Definitions

The dependent variable in the models estimated in this paper is the total number of patents produced by firm *n*, active in industry *i* and located in cluster *c*, over the period 1990–98 (INNOV). Because this is a limited dependent count variable, where the large majority of observations are zeros (see Tab. II), a simple ordinary least-squares regression analysis would yield biased results. In this study, we adopt a negative binomial regression model, which is more appropriate for count data (Hausman *et al.*, 1984; Crepon and Duguet, 1997; Greene, 1997).[16] The advantages and limitations of patent indicators are well known and there is no need to review them here. It suffices to say here that since the focus of the paper is not on the value of innovation and its effects on firm performance, the use of patents as an indicator of innovative activity is perfectly legitimate. Moreover, the inclusion of industry fixed effects in the model specification controls for any differences across industries in the propensity to patent.[17]

The specification of the model follows quite closely that used by Baptista and Swann (1998). The right-hand side of the model includes firm-specific and cluster-specific variables.

The principal firm-specific characteristic that could affect the propensity to innovate is firm size. Even tough the empirical evidence on the impact of firm size on innovation performance has so far been inconclusive (Cohen, 1995), we included this variable in the model in order to avoid possible misspecifications.[18] Firm size was measured by the average number of employees over the period 1989-96 (CIEEMP).[19]

We used pre-sample information about the firms' innovative record to control for unobservable fixed effects across firms. An important issue arising here is in fact the question of individual heterogeneity. Following Baptista and Swann (1998) and Blundell *et al.* (1995), who suggest that the 'permanent' capacity of individual firms to innovate should be reflected in their pre-sample innovation record, we dealt with the problem by including two firm-specific variables in the model. The first variable measures the knowledge stock of individual firms prior to the sample period. This is a depreciated sum of patents over the period 1978–1989,

[16]The negative binomial model introduces an individual unobserved effect into the conditional mean thus permitting to solve the major problem of the Poisson regression model. A major drawback of the Poisson model is in fact that the conditional mean is assumed to be equal to the conditional variance, so that any cross-sectional heterogeneity is ruled out. However, this restriction is normally violated in most economic phenomena, resulting in problems of over-dispersion, *i.e.* the variance exceeds the mean (conditional on covariates).

[17]Although not perfect, patents represent an extremely valuable source of data for the spatial analysis of innovative activities. First, by containing the address of the inventing firm, they permit to map the spatial structure of technological activities at a level of geographical detail that no other indicator to date has been able to provide. Second, patents represent a very homogeneous measure of technological novelty, are available for long time series, and provide very detailed data at the firm level, which make them suitable for comparing the innovative activities of firms located in clusters of different countries. For a recent discussion on the use of patents as economic indicator see Griliches (1991).

[18]A potential problem arises when companies file consolidated accounts. Indeed, when a holding company files consolidated accounts, and its subsidiaries appear in the database alongside the parent company, double counting of employees occurs. This problem was especially serious for the United Kingdom. For this country, dummy variables (not reported in the tables) for holding companies and consolidated accounts were therefore introduced to test the extent of the problem of double counting of employees.

[19]Since the number of patents is measured over the period 1990–98, the choice of taking the average employment over the period 1989–96 raises a problem of endogeneity between the dependent variable and the regressor for firm size. Data constraints forced us to adopt this choice. Information on the number of employees at the beginning of the sample period was only available for a very limited number of companies. Moreover, the sources of company information contain many missing values, which render impossible the reconstruction of the whole time series for firm employment. The decision of averaging the number of employees has thus been taken in order to minimise any problem arising from endogeneity. In any case, as the focus of this paper is on the impact of clustering on firm innovation, we think the solution adopted represents an acceptable compromise.

using a depreciation rate equal to 0.3 (KSTOCKFIRM).[20] The second is a dummy variable that is set to one if the firm has previously innovated, and to zero if it has not (PATPREV).[21] It should be noted that these variables are included in the model solely to control for the unobservable heterogeneity between firms, and it is not argued here that there are no problems with this measure of the knowledge stock. The negative binomial model with variables controlling for individual fixed effects thus accounts for both overdispersion and firm heterogeneity.[22]

The first of our cluster-specific variables represent regional strength in an industry and is measured by sector employment (OWNEMP) at the beginning of the sample period. Following Baptista and Swann (1998) once again, the rationale of relating innovative output to employment measures is that, if the arguments over cluster-specific supply-side agglomeration externalities are true, then the propensity to innovate would be a function of the number of employees in the cluster. Moreover, a relative measure, such as the share of sector employment in the region's total employment, would not serve as well, by neglecting the fact that a given region might represent a strong cluster in a certain industry, even if this industry account for a negligible share of the region's overall breadth of activities. Similarly, the regional strength in other industries is measured by the regional employment in all other industries (OTHEMP).[23]

Two cluster-specific control variables are also included throughout all specifications adopted. The first variable is simply the Herfindahl index for employment in all two-digit manufacturing sectors within each region (EMPHERF). It should be noted that this measure captures in a very imperfect way intra-regional industry variety or the notion of Jacob's externalities (Jacobs, 1969). On the one hand, it rules out any complementarity between industries, assuming that all sectors are equally close to each other. On the other hand, it is also likely that, at the level of industry aggregation considered in this study (two-digit), most agglomeration externalities take place within and not across these two-digit industries. The second variable represents the share of regional population located in the region's main town and aims to measure a cluster-specific effect associated with the extent of urbanisation (GCONC).

The benchmark model specification is:[24]

$$\begin{aligned} INNOV_{inc} = \beta_0 + \beta_1 CIEEMP_{inc} + \beta_2 OWNEMP_{ic} + \beta_3 OTHEMP_c \\ + \beta_4 EMPHERF_c + \beta_5 GCONC_c + \sum_{i=1}^{I-1} \gamma_1 D_i \end{aligned} \tag{1}$$

To verify the arguments discussed above that clustering in itself is not sufficient to explain firms' propensity to innovate, we proceeded in two steps. In a first instance, two cluster-specific variables were added to the basic specification of the model aiming to capture the stock of previously accumulated knowledge within a cluster. The first variable measures the cluster knowledge stock in a firm's own industry and it is the depreciated sum of patents

[20]Altering the value of the depreciation rate did not affect the results substantially.

[21]The correlation coefficient between the variables KSTOCKFIRM and PATPREV is 0.16 for the UK and 0.24 for Italy.

[22]It is worth noting that, once individual fixed effects are estimated, the models estimated also account for any specific effect of individual R&D expenditures on innovative output (which are likely to exist).

[23]In principle, this variable could be replaced by a sum of effects, one for each sector, but given the likely collinearities this was thought impractical.

[24]In the following estimates, all independent variables, except GCONC and EMPHERF, are expressed in logarithms in order to reduce the influence of outliers and overdispersion.

in an industry over the period 1978–1989 (KSTOCKOWN). The second variable measures the cluster knowledge stock in all other industries and it is defined in a similar way (KSTOCKOTH).

Then, the benchmark model was re-specified, by distinguishing between cluster employment of innovative and non-innovative companies in a firm's own industry.[25] Similarly, we distinguished between employment of innovative and non-innovative companies in all other industries.

Finally, in order to capture the argument that inter-industry spillovers are likely to occur mainly or exclusively between related industries, whereas employment in unrelated sectors is likely to be a source of congestion effects, cluster employment in all other industries was also separated into employment in related and unrelated sectors. For each industry considered in this paper, we considered the distribution of patent citations across all other industries. Specifically, for any industry i, employment in related industries was calculated by summing up employment in any other industry j ($\neq i$) proportionally to the share of patent citations received by firms active in industry i.[26] It should be noted that this approach is likely to capture mostly supply-side technology spillovers, rather than demand-side pecuniary externalities (Verspagen, 1997).[27] For this reason, estimation results in the following section have a rather exploratory nature.

Summary statistics for the variables used in the econometric estimates are reported in Appendix B.

4.2 Estimation Results

Pooled estimates of Eq. (1) are reported in Table III, column [1]. As expected, firm-specific variables have a highly significant explanatory power and their sign is strongly robust. Throughout all specifications, the coefficient of firm size (CIEEMP) is positive and statistically significant, thus indicating that (in our sample) large firms produce on average a larger number of patented innovations than small and medium sized enterprises. Similarly, the coefficient of the variable measuring firm knowledge stock (KSTOCKFIRM) is positive and statistically significant, both for the United Kingdom and Italy, thus providing evidence for the highly cumulative nature of innovative activities. Firms with a higher stock of knowledge tend to generate a higher number of innovations than firms with a lower past innovation record. The coefficient of the dummy variable that indicates whether a firm innovated in the pre-sample period or not (PATPREV), takes a negative sign, but is statistically significant only in the case of Italy. It is worth noting that this result does not contradict the previous finding that firms with a higher knowledge stock have a higher probability of innovating. Rather, it seems to indicate that innovative persistence features only in firms with a sufficiently high stock of previously accumulated knowledge (Geroski *et al.*, 1997). Moreover, the fact that the coefficient is statistically significant only in the case of Italy is coherent with other works showing that the degree of turbulence associated with entry and exit of innovative firms in this country is remarkably higher in this country than in other European countries (Breschi *et al.*, 2000).

[25]Specifically, we used employment in companies that innovated in the pre-sample period 1978–89 to weigh industry employment from census data.

[26]Self-citations and intra-industry citations have been excluded in the calculation.

[27]In addition, it should be also pointed out that patent citations are not the only indicator to assess the degree of relatedness and similarity in knowledge bases among industries. Jaffe (1986) proposes to use an index of similarity between firms (and industries) based on the distribution of patents across different technology fields. We applied this alternative way of measuring knowledge relatedness between industries obtaining fairly robust results.

TABLE III Impact of Clustering on Firms' Innovation (Negative Binomial Model[1], Pooled Analysis).

	United Kingdom		*Italy*	
	[1]	[2]	[1]	[2]
CIEEMP	0.563[a]	0.564[a]	0.873[a]	0.871[a]
	(0.022)	(0.022)	(0.021)	(0.020)
OWNEMP	−0.063	−0.107[b]	−0.014	−0.130[a]
	(0.047)	(0.051)	(0.035)	(0.039)
OTHEMP	0.066	−0.160[b]	0.086[c]	−0.164[b]
	(0.061)	(0.071)	(0.045)	(0.064)
PATPREV	−0.049	−0.050	−1.247[a]	−1.236[a]
	(0.323)	(0.322)	(0.356)	(0.354)
KSTOCKFIRM	0.379[a]	0.378[a]	0.476[a]	0.471[a]
	(0.045)	(0.046)	(0.052)	(0.052)
KSTOCKOWN		0.025[c]		0.057[a]
		(0.013)		(0.011)
KSTOCKOTH		0.055[b]		0.150[a]
		(0.025)		(0.032)
EMPHERF	−0.889	−0.810	1.182	1.446
	(1.977)	(1.989)	(0.937)	(0.941)
GCONC	−0.689[c]	−0.349	0.156	−0.103
	(0.276)	(0.297)	(0.177)	(0.185)
Constant	−1.100	−0.017	−3.958[a]	−0.593
	(0.697)	(0.769)	(0.539)	(0.720)
α^2	7.147[a]	7.097[a]	4.906[a]	4.815[a]
	(0.319)	(0.317)	(0.196)	(0.193)
Industry fixed effects[3]	yes	yes	yes	yes
Observations	26055	26055	37724	37724
Log-Likelihood	−7274.1	−7268.7	−10214.6	−10185.4
Likelihood ratio test of $\alpha = 0$[4]	11632.1	11525.5	10057.3	10059.4
Pseudo R^2	0.214	0.216	0.219	0.221
Likelihood ratio test[5, 6]	3982.4	3993.1	5710.5	5768.8
	$\chi^2_{0.99}[23] = 41.63$	$\chi^2_{0.99}[25] = 44.31$	$\chi^2_{0.99}[23] = 41.63$	$\chi^2_{0.99}[25] = 44.31$

Note:

[1]Estimations obtained using Stata 7. Standard errors in brackets. Symbols a, b and c beside parameter estimates indicate, respectively, statistical significance at the 1%, 5% and 10% levels.

[2]Estimate and Standard deviation of the overdispersion parameter produce by the model.

[3]A likelihood ratio test for the inclusion of industry fixed effects showed that these are significant at the 1% confidence level for both countries.

[4]Chi-squared test of the overdispersion parameter is minus two times the difference between the log-likehood for the comparison Poisson model and for the negative binomial model fitting all parameters ($\chi^2_{0.99}[1] = 6.64$).

[5]The likelihood ratio test and the pseudo R^2 compare the values of likelihood functions for the full model (including the dummy variables for industry sectors) with a model comprising only the constant term.

[6]For the UK, dummy variables for company status (holding *vs.* subsidiary) and the type of accounts (consolidated *vs.* unconsolidated) it files are also included but not shown here.

Regarding the cluster-specific variables, which represent the focus of this paper, our results apparently seem to contradict previous findings by Baptista and Swann (1998), who found moderately large positive effect of own sector employment on the probability of a firm to innovate. For both Italy and the United Kingdom, the coefficient on the variable referring to cluster employment in a firm's own industry (OWNEMP) has a negative sign, even though it is statistically not significant. On the contrary, the variable related to cluster employment in other industries (OTHEMP) has a positive sign, even though it is (weakly) significant only in the case of Italy. All in all, these results suggest the absence of any significant effect of clustering on firms' propensity to innovate.

As argued above, however, these results might actually originate from a problem of mis-specification of cluster effects. In order to ascertain the problem, we included into our bench-mark specification the two variables accounting for the cluster stock of knowledge in a firm's own sector (KSTOCKOWN) and in other sectors (KSTOCKOTH) (see Tab. III, column [2]). Both the coefficients of these variables have a positive sign and are statistically significant, indicating that, all else equal, firms located in clusters providing a larger pool of intra and inter-sectoral potential spillovers, deriving from a larger stock of accumulated knowledge, tend to produce a higher number of innovations than firms located elsewhere. Even more interestingly, while firm-specific variables retain their sign and statistical significance, once we control for these effects, the coefficient on the variables referring to own industry and other industries employment take both a negative sign and become statistically significant. Moreover, the magnitude of both coefficients increases.

The fact that both employment variables become statistically significant, take a negative sign and increase their magnitude, after controlling for the cluster knowledge stock, means that in the benchmark specification these variables may capture both positive and negative effects arising from clustering. These results thus indicate quite clearly that clustering in itself is not a source of benefits for firms' innovative activities, and it may even be a source of negative externalities. If clustering matters at all, its impact is likely to differ from cluster to cluster, depending on the type of firms and employees located in a region. In other terms, it is not the size of the cluster in terms of own sector employment, but the importance of innovations by peers within the cluster that matters.

TABLE IV Clustering of Innovative Companies and Firms' Innovation (Negative Binomial Model[1], Pooled Analysis).

	United Kingdom		*Italy*	
	[1]	[2]	[1]	[2]
CIEEMP	0.746[a]	0.529[a]	1.080[a]	0.821[a]
	(0.022)	(0.022)	(0.021)	(0.020)
OWNINN	0.263[a]	0.213[a]	0.267[a]	0.241[a]
	(0.020)	(0.018)	(0.035)	(0.016)
OWNOINN	−0.350[a]	−0.252[a]	−0.386[a]	−0.305[a]
	(0.044)	(0.038)	(0.040)	(0.036)
OTHINN	0.081	0.068	0.016	0.009
	(0.054)	(0.043)	(0.031)	(0.028)
OTHNOINN	−0.201[b]	−0.299[b]	0.057	−0.017
	(0.084)	(0.071)	(0.065)	(0.062)
PATPREV		−0.088		−1.338[a]
		(0.316)		(0.341)
KSTOCKFIRM		0.371[a]		0.474[a]
		(0.044)		(0.050)
EMPHERF		−0.314		0.339
		(2.138)		(0.992)
GCONC		0.096		−0.047
		(0.285)		(0.180)
Constant	−2.636[a]	1.149	−5.889[a]	−1.550[a]
	(0.617)	(0.704)	(0.438)	(0.615)
α^2	11.889[a]	6.532[a]	6.621[a]	4.443[a]
	(0.459)	(0.293)	(0.238)	(0.179)
Industry fixed effects[3]	yes	yes	yes	yes
Observations	26055	26055	37724	37724
Log-Likelihood	−7633.7	−7152.2	−10414.2	−9986.4
Likelihood ratio test of $\alpha = 0$[4]	25759.2	11392.4	20706.0	10097.2
Pseudo R^2	0.176	0.228	0.203	0.236
Likelihood ratio test[5, 6]	3263.0	4226.1	5311.2	6166.8
	$\chi^2_{0.99}[21] = 38.93$	$\chi^2_{0.99}[25] = 44.31$	$\chi^2_{0.99}[21] = 38.93$	$\chi^2_{0.99}[25] = 44.31$

Note: see Table III.

In order to investigate further this issue, we re-estimated our benchmark model distinguishing between cluster employment of innovative companies and cluster employment of non-innovative companies in a firm's own industry and in other industries[28]. Results are reported in Table IV, and show that in both countries examined here, cluster employment of innovative firms in a firm's own industry (OWNINN) affects in a positive and statistically significant way a firm's innovative performance, while a negative and statistically significant effect is associated with a strong presence of non-innovative firms (OWNNOINN). In this respect, the lack of evidence of any significant impact of own-sector employment (OWNEMP) in the benchmark model can thus be interpreted as a consequence of a potential misspecification problem. Imposing the restriction that the coefficients of OWNINN matches that of OWNNOINN is clearly wrong. This result thus suggests that intra-sectoral positive externalities are likely to flow locally only from innovative firms, whereas the presence in a cluster of non-innovative firms is associated with negative (congestion) effects. In other words, the benefits from clustering with other firms in the same industry are not generic, instead they arise only in clusters that are already densely populated by innovative firms and have a large accumulated stock of knowledge.

TABLE V Clustering of Related Industries and Firms' Innovative (Negative Binomial Model[1], Pooled Analysis).

	United Kingdom		*Italy*	
	[1]	[2]	[1]	[2]
CIEEMP	0.745[a]	0.528[a]	1.080[a]	0.822[a]
	(0.023)	(0.022)	(0.021)	(0.021)
OWNINN	0.250[a]	0.192[a]	0.265[a]	0.242[a]
	(0.019)	(0.017)	(0.017)	(0.016)
OWNOINN	−0.394[a]	−0.323[a]	−0.400[a]	−0.304[a]
	(0.039)	(0.033)	(0.040)	(0.036)
OTHREL	−0.006	0.111	0.299[a]	0.173[b]
	(0.095)	(0.087)	(0.082)	(0.079)
OTHUNREL	0.011	−0.108	−0.221[a]	−0.191[b]
	(0.088)	(0.082)	(0.083)	(0.080)
PATPREV		−0.079		−1.324[a]
		(0.316)		(0.340)
KSTOCKFIRM		0.369[a]		0.471[a]
		(0.045)		(0.050)
EMPHERF		−0.123		0.145
		(2.181)		(0.980)
GCONC		0.098		−0.010
		(0.276)		(0.177)
Constant	−3.795[a]	−0.855	−5.520[a]	−1.321[a]
	(0.347)	(0.496)	(0.314)	(0.512)
α^2	11.916[a]	6.551[a]	6.595[a]	4.428[a]
	(0.460)	(0.294)	(0.237)	(0.179)
Industry fixed effects[3]	yes	yes	yes	yes
Observations	26055	26055	37724	37724
Log-Likelihood	−7636.7	−7160.5	−10408.7	−9983.6
Likelihood ratio test of $\alpha = 0$[4]	26061.0	11442.4	20701.6	10115.7
Pseudo R^2	0.176	0.227	0.203	0.236
Likelihood ratio test[5, 6]	3257.9	4209.4	5322.7	6172.4
	$\chi^2_{0.99}[21] = 38.93$	$\chi^2_{0.99}[25] = 44.31$	$\chi^2_{0.99}[21] = 38.93$	$\chi^2_{0.99}[25] = 44.31$

Note: see Table III.

[28]Please note that we did not include into the estimation the cluster knowledge stock. The reason for doing this is that the stock of knowledge accumulated in a cluster and the pre-existence in a cluster of a large population of innovative companies point essentially to the same phenomenon: the history dependent accumulation of innovation related skills and knowledge in a region.

Results are less clear regarding employment in other industries. On the one hand, a negative impact is associated with the location in a cluster of non-innovative companies in other industries (OTHNOINN), but the coefficient is statistically significant only for the United Kingdom, thus implying at least for this country quite significant congestion effects associated with the presence of non-innovative firms in other sectors. On the other hand, although the sign of the coefficient of employment in innovative firms in other industries (OTHINN) has a positive sign, it is not statistically significant in both countries. Thus, a strong presence in a cluster of innovative companies in other industries does not seem to affect in a significant way a firm's innovative activities.

The lack of significance of this variable may of course reflect the rather crude way in which employment in other sectors was aggregated. In a more positive fashion, however, it may also indicate that what is really important for firms' innovative activities is to be co-located with firms in related and complementary other industries, no matter whether they are highly innovative or not.

In order to test this hypothesis, we re-estimated the model distinguishing between employment in other related (OTHREL) and unrelated industries (OTHUNREL). Results reported in Table V indicate that a larger number of employees in other related industries encourage firms' innovative performance, although the coefficient on this variable is only significant for Italy. On the contrary, clustering of firms in unrelated industries seems to be a source of negative externalities, even though the coefficient on this variable is once again statistically significant only in the case of Italy.

5 CONCLUSIONS

The main concern of this paper was to test some of the arguments recently proposed in the literature to support the view that companies located in strong industrial clusters should be more innovative. The main result emerging from a firm level analysis of patent counts for two countries is that clustering in itself is not a source of benefits for firms' innovative activities, and it may even be a source of negative externalities. More specifically, we found that a firm is more likely to innovate if located in a region where the presence of innovative firms in its own industry is strong and where there is a large pool of potential spillovers associated with a large accumulated stock of knowledge. On the contrary, quite strong disadvantages arise from a strong presence of non-innovative companies in a firm's own industry. We interpret these results as evidence that positive agglomeration externalities are likely to flow only from innovative firms. Moreover, these results seem to be coherent with a careful reading of the theoretical literature and suggest the existence of an important regional dimension in the cumulativeness of technical advances.

Regarding the effects of the proximity of firms in other industries, the empirical evidence is less robust. On the one hand, some evidence of the existence of possible congestion effects related to the presence of non-innovative companies in other industries emerges only for the United Kingdom, but no effect seems to derive from the co-location with innovative companies in other sectors and that, for both countries. On the other hand, our results also seem to indicate that, in the case of Italy but not for the United Kingdom, firms' innovative performance is enhanced by the presence of firms in related industries, while clustering in unrelated sectors is mainly a source of congestion effects. These results are certainly affected by the level of industry aggregation used in this study and need further empirical research.

One possible line of future research is to investigate the impact of clustering at the level of individual industries, using if possible a lower level of industry aggregation. Our estimates indicate that industry effects are significant and there are theoretical reasons to expect that the workings of agglomeration economies differ across industrial sectors. Besides, research efforts should be also devoted to investigate in a more accurate way the technological and market linkages across sectors and their relations in a spatial context. An interaction between the technological space and the geographical space is needed here with the degree of proximity of these two dimensions taken into account.

As a final remark, this study offers an analysis of the statistical correlation between a firm's propensity to innovate and the strength of the region in which it is located, finding that positive effects arise only from the co-location within an existing population of innovative companies. This finding adds an important qualification to previous studies on this issue. Yet, the paper raises perhaps more questions than it is able to answer. In our view, the most fundamental question left to us is related to understanding the mechanisms underlying these observations. In particular, the kinds of tests proposed so far are unable to discriminate between the sources of pecuniary externalities, which are rooted in the workings of local markets for labour and specialised services and inputs, and the sources of knowledge spillovers, which originate in the localised flow of skills and ideas and which has so frequently referred to using the Marshallian metaphor that 'knowledge is in the air'. This is in our view the most challenging task ahead in this field of study.

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