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ORIGINAL PAPER

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How does accessibility to knowledge sources affect the innovativeness of corporations?—evidence from Sweden

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Abstract This paper studies the innovative performance of 130 Swedish corporations during 1993–1994. The number of patents per corporation is explained as a function of the accessibility to internal and external knowledge sources of each corporation. A coherent way of handling accessibility measures, within and between corporations located across regions, is introduced. We examine the relative importance of intra- and interregional knowledge sources from 1) the own corporation, 2) other corporations, and 3) universities. The results show that there is a positive relationship between the innovativeness of a corporation and its accessibility to university researchers within regions where own research groups are located. Good accessibility among the corporation's research units does not have any significant effects on the likelihood of generation of patents. Instead the size of the R&D staff of the corporation seems to be the most important internal factor. There is no indication that intraregional accessibility to other corporations' research is important for a corporation's innovativeness. However, there is some

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indication of reduced likelihood for own corporate patenting when other corporate R&D is located in nearby regions. This may reflect a negative effect from competition for R&D labor.

Keywords Accessibility · Private and university R&D · Patents · Spillovers · Sweden

JEL Classification O33 · H41 · R11

1 Introduction

One of the most important and challenging questions in economics concerns the determinants of innovation among firms. A study of the literature reveals that knowledge is maintained to be the most important as well as the most generic input into innovation processes [see, inter alia, Lundvall, 1992]. Consequently, much research has focused on how firms gain and generate new knowledge and how such processes relate to innovation performance. The lack of confidence in the linear model of innovation (Kline and Rosenberg, 1986; Fischer et al., 1999; Fischer, 1999) has indeed made this a complex task. It is increasingly being recognized that firms should not be studied in isolation. Interdependent relations with the surrounding environment are also important factors to be incorporated in the analysis (see e.g. Cohen and Levinthal, 1990). Accordingly, a firm's knowledge is not only dependent on its internal learning activities, but also on the learning activities of various actors around the firm.

A mixture of externalities based upon localization economies can be used to explain how and why the performance of an individual firm is affected by factors external to the firm. From the seminal works of Marshall (1920), Arrow (1962) and Romer (1986), the idea of so-called MAR-externalities has been advanced. In principle, it tells us that the size and the intensity of (positive) industry-specific externalities increase with the size of the industry. MAR-externalities are sometimes referred to as static externalities (see e.g. Echeverri-Carroll and Brennan, 1999), since it is the current scale/size of the industry that generates the externalities. Despite the recognition of the MAR-externalities, some authors claim that dynamic externalities play a greater role than static ones. For example, Krugman and Obstfeld (2000) maintain that externalities stemming from the accumulation of knowledge are probably more important for innovation performance. Notwithstanding the distinction between different types of externalities, it is clear that the economic milieu in which a firm operates has an effect on its performance. The impact of external knowledge on the innovation performance of the firm is most often explained by knowledge spillovers, a particular type of MAR-externalities.

What are then knowledge spillovers? In the literature, Griliches (1992) makes a distinction between 1) pure knowledge spillovers (or idea spillovers) and 2) rent spillovers.[1] Pure knowledge spillovers are pure externalities, in the sense that they are uncharged, unintended and not mediated by any market mechanism. Rent spillovers are those externalities that are at least partially paid for. For instance,

[1] The latter term seems equivalent to what some call pecuniary externalities (Scitovsky, 1954).

they may be embedded in goods or they may be the result of explicit transactions of patent rights, etc.

A precise distinction between the two categories is difficult to draw in practice, especially as spillovers become more complex and there is a 'club element' to knowledge. For instance, suppose that being a member of a network of skilled knowledge workers involves the sharing of useful information with other members of the network. If a member expects some information in return in the future, is this a pure knowledge spillover or a rent spillover? Clearly there is some important middle ground for which the literature has yet to come up with precise definitions. Johansson (2004) fills this gap by *parsing the menagerie of agglomeration and network externalities*.

Much attention in the literature has been given to spatial aspects of knowledge flows (among others Jaffe, 1989; Acs et al., 1992, 1994; Audretsch and Feldman, 1996; Anselin et al., 1997, 2000; Autant-Bernard, 2001). Such flows are seen as being most effectively mediated through face-to-face (FTF) contacts. Thus, proximity between knowledge exchangers is deemed critical. Recalling the well-established axiom in regional economics that "interaction decreases with distance," (Beckmann, 2000, p. 129), it is clear that proximity has a role to play. Some confusion can easily emerge around such a reasoning. On the one hand, flows of knowledge need not be bounded by space. Geroski (1995), for instance, refers to knowledge as the classic example of a public good, i.e. it is non-rival and non-excludable. On the other hand, all kinds of knowledge are not distance-insensitive. Different forms of knowledge certainly require different amounts of efforts to be transmitted. The concept of tacit knowledge is repeatedly employed by many authors to explain why FTF-contacts are necessary for efficient transmission of knowledge (e.g. Audretsch and Feldman, 1996). In fact, it seems to be a consensus among researchers that much relevant knowledge is tacit in nature (see e.g. Maillat and Kebir, 2001; Lorenzen, 1996). In contrast to knowledge that can relatively easily be transformed into information and, hence, is possible to transmit via existing communication channels, tacit knowledge has been defined as semi-and unconscious knowledge that does not exist in printed explicit forms (Leonard and Sensiper, 1998). For example, learning to ride a bicycle is something most easily done by practice, and is difficult (if possible) to communicate in written form.

The unit of observation in this paper is a corporate group, which is defined as being either an individual corporation or two or more corporations with ownership relations. A company is a parent company of another (subsidiary) company if it owns more than 50% of the latter's total stock.[2] It has long been recognized that R&D may be placed in special departments, or companies. For example, Whitehead (1926, p. 98) wrote that "The greatest invention of the nineteenth century was the invention of the method of invention." Mowery and Rosenberg (1998) describe the importance of the development of formalized R&D institutions in the U.S. in the 20th century. Thus, R&D decisions may be taken centrally at group headquarters, rather than in the individual companies belonging to the group. This gives credit to the use of the whole group as the observational unit when studying R&D. Also, knowledge flows between research departments *within* the

[2] Details about the requirements for being defined as a corporation can be found in the Swedish joint-stock company law (Svensk Författningssamling, 1975).

same groups can be expected to be higher than knowledge flows emanating from other groups' R&D departments.

The purpose of the present paper is to study how accessibility to knowledge sources affects the production of new knowledge in Swedish groups. In this process we check for effects arising from being close to other knowledge handlers, including those within the group. We use groups as our unit of analysis, because many of the research-intensive firms are part of large groups (multinationals) in Sweden (see Braunerhjelm, 1998) that are connected via "parent and daughter" relationships. For instance, Fors and Svensson (1994) report that 83% of total Swedish industrial R&D is conducted in multinational enterprises. In addition, the effects of (mainly product) R&D in Swedish multinational enterprises seem to have a causal bidirectional relationship to foreign sales, indicating that the benefits of Swedish R&D mainly occurs abroad (Fors and Svensson, 2002). No previous analyses have, to the authors' knowledge, been made in this setting using groups as the unit of analysis.

The analysis is conducted by investigating the relationship between a group's innovativeness and its accessibility to R&D resources. Innovativeness is measured as the number of patents granted to a group. The patent data used in the analysis come from the European Patent Office (EPO, 2002). It should be mentioned that patents are not the only way to signify innovations. In addition, R&D, innovation expenditures, sales of imitative and innovative products and new product announcements have been used. R&D is in our approach seen as an innovation input rather than an output.[3] Although patent data are not without their problems (most importantly, we do not know the commercial value of a patent), they are common and useful indicators of innovation and can be assigned to specific firms. We note that no indicator can match patents in terms of the availability of data on fine geographical levels, and over longer time periods. A potential problem of using EPO patent data is that European Patents are more costly to apply for than national patents. These costs are higher because the search for earlier priority (technical knowledge) becomes more pronounced and because more monetary value can be extracted from the monopoly right awarded the patentee. Thus, smaller firms with less far-reaching ambitions with regard to their patenting are likely to be excluded from the data. We believe that this is a minor problem with respect to the sources of data, since the R&D data mainly spring from large firms anyway. However, it implies that the material is somewhat more likely to reflect larger firms, in comparison with the use of national patent data. An advantage, in comparison with using national patent data is, however, that EPO data should more likely reflect a higher value to the group, since its investment is larger.

The R&D resources upon which a group's innovativeness is expected to depend, can be divided into internal and external sources: (1) the total input of R&D personnel (man-years) in the group; this represents deliberate efforts to influence innovative output and should be the most fundamental factor, (2) the average accessibility among the group's R&D staff; the accessibility within the

[3] Sales of imitative and innovative products refer to indicators from the community innovation survey (CIS). Sweden has been part of the second (1996–1998) and third (1998–2000) CIS. Because of sample problems, including low respondency problems in the Swedish CIS data, we chose patents granted as our preferred measure. See Kleinknecht et al. (2002) for a recent discussion of different innovation indicators. In addition, Griliches (1990) and Desrochers (1998) provide discussions of patents as innovation indicators.

group's units (companies) could have an effect on the outcome, (3) the average accessibility to other groups' R&D staff; this represents the possibility to access other groups' R&D efforts, and (4) the average accessibility to university R&D[4]; this factor represents the accessibility to public R&D.[5] Inspired by the work by Johansson and Klaesson (2001), a distinction is made between intra- and extra-regional accessibility. This gives us the opportunity to evaluate the relative benefits of accessibility to different R&D resources. The logic for including a company's accessibility to its own R&D comes from the fact that the total R&D staff of a group are often scattered over separate locations.

The paper proceeds as follows. In Section 2, a review of a selection of the studies on "knowledge spillovers" is presented. In Section 3, the dataset and the construction of variables are explained (part of the algebra has been put in an appendix). Thereafter, in Section 4, the model used for empirical estimation is presented, followed by empirical results and comments. Section 5 concludes the paper and outlines some directions for future research.

2 Space in knowledge flow models

2.1 The geography of "knowledge spillovers" in recent studies

Using the analytical distinction of Feldman and Audretsch (1999), it is possible to categorize studies of knowledge effects in regions into four tracks: (1) geographic knowledge production functions, (2) paper trails left in patent citations, (3) ideas in people or (4) ideas in goods. The following section discusses these approaches in turn.

Geographic knowledge production functions (KPF) are used extensively in the literature. The aim of a KPF is to study the effects of knowledge inputs on a variable of interest, such as a proxy for knowledge output, e.g. patents, or productivity. The origin of this literature and the setup of the main estimated equation, comes from Griliches (1979), who provides a thorough discussion of pros and cons of relating productivity to research input and R&D spillovers. A modified version was presented by Jaffe (1989):

$$\log(P_{ikt}) = \beta_{1k}\log(I_{ikt}) + \beta_{2k}\log(U_{ikt}) + \beta_{3k}[\log(U_{ikt})\log(C_{ikt})] + \varepsilon_{ikt},$$

with P_{ikt} in this case being corporate lab patenting in state i, technology area k in period t, I_{ikt} is industry R&D and U_{ikt} university research. C_{ikt} is *geographical coincidence* of university research with industry research and $\log(U_{ikt})\log(C_{ikt})$ is an interaction variable. The data material came from 29 US states for 1972–1977, 1979 and 1984. Jaffe (1989) found a strong relationship between corporate lab patenting and university research in the areas drugs, chemicals and electronics. Furthermore, it seemed that industrial R&D was stimulated by the presence of university research. Similar studies applying the KPF approach include Acs et al. (1992, 1994), Anselin et al. (1997, 2000), and Autant-Bernard (2001). Acs et al.

[4] Swedish higher education institutions are divided into universities and university colleges.

[5] The reader may ask why research institutes are not included as possible sources of information. The reason is that research institutes play a relatively small role in Sweden, especially compared with other countries.

(1992) examine how different industries respond to the R&D–innovation relationship using the U.S. small business administration innovation database for 1982, compared with Jaffe's (1989) patent exercise. Using the same database, Acs et al. (1994) find that small businesses innovate more relative to their (negligible) R&D efforts, seemingly through their greater ability to assimilate knowledge from research institutions and larger corporations than larger firms. Anselin et al. (1997) study the degree of spatial spillovers between university research and high technology innovations, by applying the KPF approach at the level of both the state and the metropolitan statistical areas (MSA) in the U.S. They find evidence of local externalities between university research and high-technology innovations. The same authors, Anselin et al. (2000), extend their previous work Anselin et al. (1997) by means of a sectoral disaggregation. Their main conclusion is that local university spillovers seem to be specific to certain industries.

In a critical paper, Breschi and Lissoni (2001) argue that many empirical studies employing the popular "knowledge production function" to test for the existence of knowledge spillovers are not capable of explaining the underlying mechanisms that generate them. They maintain that the standard line of argument[6] used to explain the results of such studies would imply that knowledge that diffuses is a pure externality. The authors go on to conclude that a more careful scrutiny might reveal that it is actually pecuniary (rent) externalities, i.e. involuntary knowledge flows mediated by market mechanisms, or even managed knowledge flows with intentional appropriation purposes that matter.[7]

Paper trail studies start off by noting that knowledge sometimes does leave a paper trail. Patent documents show an offprint of new technical knowledge (Jaffe et al., 1993). In addition, technical knowledge of existing patents on which the patent is based has to be recorded when a patent application is filed. Such a record is referred to as a patent citation. Patent citations, it is reasoned, show information on the direction of knowledge flows. Most authors conclude that citations are constrained geographically. Furthermore, citations spread over larger distances over time. The conclusion is usually that new knowledge diffuses locally at first, but knowledge becomes more publicly available, and hence less bounded by space, over time. A potential pitfall, however, of patent citations is that self-citations, i.e. citation of own work, should be disregarded if we want to study the direction of "spillovers". These self-citations do not reflect spillovers but rather knowledge flows from own work, that is own previous experience. The problem is therefore one of interpretation; what is actually under study. Jaffe et al. (1993) examined localization of citation patterns by constructing a *control sample* with similar properties as the original patents. It was found that patents were more likely to be domestic to the US if the cited patents were from within the country. Furthermore, citations were more likely to come from the same state or Standard Metropolitan Statistical Area as the original patent. Some evidence was also found that citations tended to become more dispersed over time,

[6] Namely that knowledge that spills over is a pure public good (non-excludable and non-rival) but that it is essentially local since transmission demands spatial proximity.

[7] In the first case the seller may be unaware of embedded opportunities which the buyer may realize; knowing this, the seller may want a higher return on his sale. In the second case embedded opportunities may yield long-lasting supplier–customer relations to realize the good's full potential.

which was also found to be true for specific technology areas. The work by Jaffe et al. (1993) spurred similar research efforts. In a study across European regions, Maurseth and Verspagen (2000) also found compelling evidence of a localization pattern of patent citations. However, national barriers were important; a patent was cited more often if the cited patent was registered in the same country as the citing patent. Fischer and Varga (2003) examined spillovers of knowledge from universities on patent application activity in 1993. Their sample consisted of firms belonging to one of six technology classes in 99 political units in Austria. Employing a spatial econometric approach, the authors found evidence of spillovers across regions, which is linked to a spatial decay effect.

The Jaffe et al. (1993) method has recently been challenged in two working papers. Thompson and Fox-Kean (2003) redid the control sample exercise of Jaffe et al. (1993), on a higher level of disaggregation, but were unable to replicate their results. Breschi and Lissoni (2005) constructed a database of all patenting inventors 1987–1989 in the Italian innovation system, to see how *social networks* and measurement of their strength influence the result of Jaffe et al. (1993). Their results suggest that the strength of these networks alone is able to explain all the localization effects of citations, thus casting doubt on the pure knowledge spillover hypothesis.

The third tradition of studying knowledge flows is more recent and builds on the idea that knowledge is mainly embedded in people. Therefore, mobility of labor, and in particular scientists, is studied. In this manner, Zucker et al. (1998b study the California biotechnology sector. They find that market mechanisms, facilitated by contracting of star scientists, induce transfer of knowledge if those star scientists retain their connections to universities while being affiliated to biotechnology firms. In an accompanying paper, Zucker et al. (1998a find that the localization of biotechnology star scientists over the US is an important factor in determining both the location and timing of entry of new biotechnology firms. Similarly, Almeida and Kogut (1999) study how the mobility of engineers in the semiconductor industry affects the pattern of citation of patents. Indeed, they find that there are strong effects of relocation of people on these, suggesting that movement of core individuals shape the evolution of industry.

If knowledge is embedded in labor, Møen (2000) suggests that we should be able to observe how wages reflect the accumulation of knowledge. He tests this with a large and informative dataset on technicians, using wages, mobility and the R&D intensity of firms in the Norwegian machinery and equipment industry. It is found that R&D investment is at least partially incorporated into the labor market through the mechanism outlined above.

Flow of goods refers to the literature on inter-industry spillovers. This literature assumes that the relationship between how much R&D spills over between industries can be proxied for by different weight matrices.[8] The *input–output* approach assumes that the amount of inter-industry spillovers can be proxied for by summing the R&D expenditures of the "emitting" industry and multiplying the number by the relationship between two industries as given by input–output tables, i.e. sales divided by sales value of either recipient industry or emitting industry

[8] See the discussion in Ejermo (2004). The way of classifying the weight matrices into three classes is adopted from van Pottelsberghe de la Potterie (1997).

(Terleckyj, 1974, 1980; Wolff and Nadiri, 1993; Wolff, 1997; Vuori, 1997; Ejermo, 2004). Also, the capital investments amounts from one type of industry to another have been used to proxy their relationship. *Technology flow matrices* use patent data to infer industry of use (Scherer, 1982), or user–producer relationships (Putnam and Evenson, 1994). *Technological proximity matrices* use patent citation information instead (cf. Verspagen et al., 1994; Verspagen, 1997). The literature has shown that estimates of spillovers are sensitive to the choice of weighing scheme. Many studies show social effects of R&D ranging from 0% to 60%. In the study by Ejermo (2004) only modest spillover effects of R&D on productivity between Swedish industries and firms were found.

To sum up, there is a vast amount of empirical literature using different approaches examining the nature of knowledge spillovers. Many more recent contributions cast doubt on whether spillovers are really pure knowledge spillovers, i.e. spillovers for which no compensations are given. Whether working through the labor market or through explicit knowledge-transfer contracts, knowledge flows seem more often to be pecuniary. Our paper clearly belongs to the KPF tradition. We think the approach may yield important insight into the procedures surrounding the workings of knowledge flows in a system of regions. In the next subsection, we present a simple framework, showing the role of proximity for knowledge flows.

2.2 A framework for analyzing spillovers within and across regions

This paper builds on the assumption that knowledge flows between two actors are more intense the higher the accessibility between the two. Using a slightly modified version of a set-up introduced by Beckmann (2000, p. 134), the importance of distance for the potential of assimilating knowledge flows can be illustrated in a relatively simple way. We assume that the knowledge of a corporation k, denoted K_k, depends on three sources: own research R_k, other corporations' research, $\overline{R}_k \equiv \sum R_l$, $l \neq k$, where R_l denotes research in one such other corporation l, and university research $U_k \equiv \sum U_i$, where U_i denotes university research at university i.[9] Thus, we can write:

$$K_k = f\left(R_k, \overline{R}_k, U_k\right) \tag{1}$$

We assume a Cobb–Douglas production for knowledge. Moreover, we assume that there are opportunity costs (in terms of time spent) associated with each knowledge resource: c_R for R_k, $c_{\overline{R}}$ for $\overline{R}_k$ and c_U for U_k. Therefore in the pursuit of new knowledge each corporation k wishes to maximize[10]:

$$\max_{R_k, \overline{R}_k, U_k} R_k^{\alpha} \overline{R}_k^{\beta} U_k^{\gamma} - c_R R_k - c_{\overline{R}} \overline{R}_k - c_U U_k \tag{2}$$

[9] This is a stylized simplification because it implies that all research, whether in other corporations or in universities, is treated equally for all corporations. In the applied empirical analysis we distinguish between own and other corporate research, as well as make a distinction between intra- and interregional accessibility to knowledge.

[10] Of course, as Beckmann (2000) notes, it is possible to replace the opportunity costs by a time budget constraint.

where α, β and γ are elasticities with respect to R_k, $\overline{R}_k$ and U_k. The first-order conditions for $\overline{R}_k$ and U_k imply:

$$\beta R_k^{\alpha} \overline{R}_k^{\beta-1} U_k^{\gamma} - c_{\overline{R}} = 0 \tag{3}$$

$$\gamma R_k^{\alpha} \overline{R}_k^{\beta} U_k^{\gamma-1} - c_U = 0 \tag{4}$$

and:

$$\frac{\beta R_k^{\alpha} \overline{R}_k^{\beta-1} U_k^{\gamma}}{\gamma R_k^{\alpha} \overline{R}_k^{\beta} U_k^{\gamma-1}} = \frac{c_{\overline{R}}}{c_U} \Leftrightarrow \frac{U_k}{\overline{R}_k} = \frac{\gamma}{\beta} \frac{c_{\overline{R}}}{c_U} \tag{5}$$

which shows that the utilization of university research relative to other corporation research depends on the ratio of the opportunity costs and the elasticities for $\overline{R}_k$ and U_k. It can safely be assumed that each opportunity cost is an increasing function of distance. Hence, if the distance to university researchers is significantly lower than the distance to other corporations' research, then we may expect that the exchange and collaboration with university researchers is larger.

3 Data description and computation of variables

This section describes the model and the variables used in the empirical analysis. Further, the model presented in Section 2 will be extended by expounding on the accessibility concept. A coherent way of handling accessibility measures within and between groups located across space is introduced.

3.1 Data

We use a cross-sectional dataset with the two main indicators of inventive activity being R&D inputs and patents granted. The geographic distribution of these has been shown to be highly concentrated to the three population dense regions Stockholm (mid-east Sweden), Gothenburg (west–south–west) and Malmö (south). This concentration is considerably higher than what is motivated by population size. For a more detailed description including maps see Andersson and Ejermo (2004).

Data for patents were taken from the EPO (2002) database of granted patents. Time distances between Swedish local labor market regions, used to calculate accessibilities, have been computed from raw data from the Swedish National Road Administration's database in Sweden.[11] Time distances for 1994 has been approximated with the average of time distances between functional regions (LA

[11] A paper by Ejermo and Karlsson (2004), although in a different context, experiments by comparing the minimum of flight time and road travel time with that of road travel time, with negligible difference for the result.

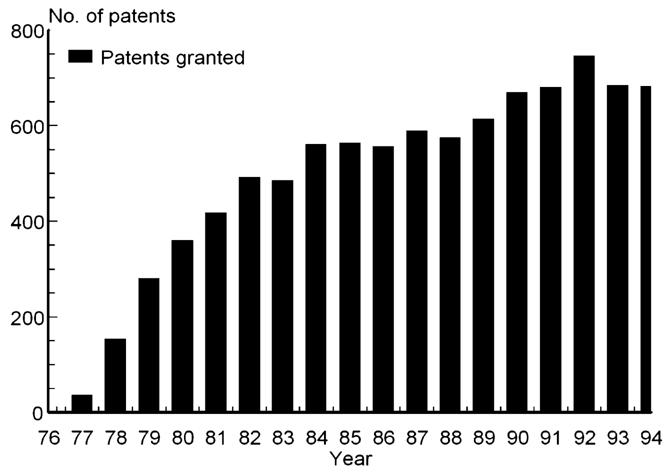

Fig. 1 Number of patents granted by the EPO with at least one Swedish inventor. Year shows the year priority. Patent data with priority date 1994 was used in the present paper

regions) in 1990 and 1998. The definition of local labor market regions follows the one given by NUTEK (1998). In essence, regions are identified by the intensity of commuting flows between Swedish municipalities.[12] The latest year for which we could be reasonably sure that most patent applications had been processed and granted is 1994, based on the priority date.[13] Swedish patents from this year were taken from the database, on a company-by-company basis (the names of the companies were also available). For each group the number of patents from 1994 were added together for all companies belonging to it. Figure 1 illustrates the number of Swedish granted patents with priority date from a specific year.

The second dataset contains information about the input in terms of man-years in research and development on the county level for 1993, which is the later year before 1994 for which such data are available. R&D data were taken from Statistic Sweden's microdata: "Business expenditure on R&D" (BERD). These data are collected biennially by Statistics Sweden, and form the basis for the statistics on research and development compiled for the OECD.[14] Companies were aggregated into groups as described in the Introduction, both for the patent and BERD datasets. Sources for this work were the corporate registers of Statistics Sweden (Statistiska Centralbyrån, 1997). The county data information from BERD was used to distribute R&D among local labor market regions. A third dataset contains data about university and higher education R&D measured in man-years. These data were also provided by Statistics Sweden.

[12] NUTEK aggregated the Swedish municipalities into 81 local labor market regions.
[13] The priority date is the first date of filing. From the priority date to the application date it takes on average almost a year (source: own calculations of Swedish applications to EPO).
[14] Although it would be desirable to incorporate earlier data, consistent time series were not available.

3.2 Computation of variables

As mentioned earlier, the analysis considers three knowledge sources available for a group. These are (1) own R&D, (2) other groups' R&D and (3) university R&D. As stated in the introduction, accessibility is used to operationalize geographical proximity. Measuring accessibility is an appropriate method to handle proximity since it is related to concepts such as ease of spatial interaction and potential of opportunities of interaction, etc (see, inter alia, Weibull, 1980). This implies that accessibility is by definition strongly connected to the potential of FTF interactions and thus knowledge exchange as discussed in Andersson and Karlsson (2004). The measure of accessibility used here is employed to represent the potential of opportunities and takes the following form with an exponential distance decay (see e.g. Johansson et al., 2002)

$$ACC_r = \sum_{s=1}^{n} D_s e^{-\lambda t_{rs}}. \tag{6}$$

In the formulation above, ACC_r denotes accessibility for region r to relevant opportunities D of regions $s = 1, \ldots, n$ discounted by $e^{-\lambda t_{rs}}$ where λ is a sensitivity parameter with respect to distance t. This variable can represent either geographical distance or time distance. The time distance of traveling between two regions r and s is denoted by t_{rs}. The internal time distances are calculated as the mean time distances between municipalities within the local labor market regions.[15] The use of time distances brings many advantages (see e.g. Andersson and Karlsson, 2004). Clearly, what is relevant in the context of FTF interaction is not merely geographical distance. It is rather the time (and cost) needed in order to overcome a certain distance. Moreover, geographical distances do not reveal important differences across regions. Two regions may have the same geographical distance to some relevant opportunity but unequal time distance due to, say, differences in the quality of the interregional transport infrastructure. It is important to take such difference into account when dealing with the potential for FTF interactions.

The value of the time sensitivity parameter, λ, is set to 0.1 for intraregional time distances, i.e. within the local labor market region. Interregionally (between local labor market regions) the time distance sensitivity λ is set to 0.017. These parameters represent the best information available. The intraregional parameter value was taken from Åberg (2000). The interregional value was taken from Hugosson (2001). Åberg (2000) sets up a model estimating local daily commuting as a function of data on work and living opportunities and commuting times. In the second case, the value is derived from the distance sensitivity of Swedish interregional business trips. Formulating accessibility as in Eq. (7) provides an easy way of separating intra-and interregional accessibility. If we let $W = \{1, \ldots, n\}$ be a

[15] If a local labor market region only consists of one municipality, the internal time distance is calculated as the mean of time distances between the SAMS (small area market statistics, roughly: living areas) of that municipality.

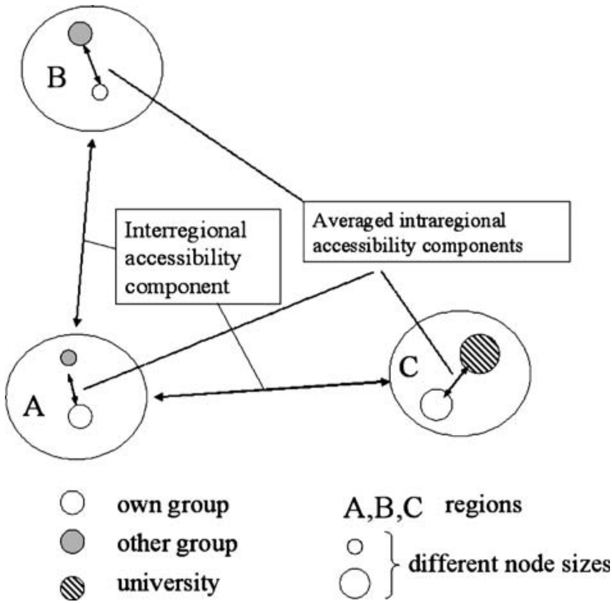

Fig. 2 An outline of our model

set of all regions in the economy and let $W_{-r} = W \backslash r$ denote a set of all regions in the economy except region r, the separation can be made in the following manner:

$$ACC_r = D_r e^{-\lambda_{ir} t_{rr}} + \sum_s D_s e^{-\lambda_{er} t_{rs}}, \quad r \in W \text{ and } s \in W_{-r} \tag{7}$$

where λ_{er} denotes the intraregional distance sensitivity parameter, and λ_{er} the distance sensitivity parameter for opportunities outside region r. Hence, the total accessibility to an opportunity for a region is a weighted sum of accessibility to opportunities within the region and accessibility to opportunities in other regions. In particular, we model accessibility to R&D resources internally and externally in the region where each group has research. Appendix B explains the algebraic details of how our variables were constructed. Figure 2 shows an outline of our model.

The method described above should be an effective way of assessing the role of closeness to knowledge resources. Since the distinction between intra- and interregional accessibility provides two parameters to be studied, it allows for a clear-cut evaluation of the relative importance of R&D resources within and outside regions. Concurrently, it may also give a hint of the nature of the crucial knowledge externalities. Of course, our approach will not be able to reveal the exact mechanisms through which knowledge is transferred. However, if we believe that FTF contacts are required for fruitful knowledge exchange and interregional accessibility turns out to be important one may question whether the process of knowledge exchange can be characterized as a pure externality. Unplanned and involuntary FTF contacts between researchers in different regions can be assumed to be less frequent since the time distances are sufficiently large to demand

Table 1 Variables, their meaning and definition with respect to intra- and interregional accessibility

Variable	Denotes
pat_k	Number of patents granted
R_k	Number of research personnel employed by the own group
$A_{\text{int},k}$	Average total accessibility to own research
$A_{\text{ext1},k}$	Average intraregional accessibility to other groups' research
$A_{\text{ext2},k}$	Average interregional accessibility to other groups' research
$AU_{1,k}$	Average intraregional accessibility to university
$AU_{2,k}$	Average interregional accessibility to university research

planning of meetings in advance. In this case one would expect that knowledge spillovers would occur through, for example, business meetings and networks across regions. On the other hand, if it is intraregional accessibility that is important we can at least conclude that the processes that generate knowledge exchange do indeed have a local character. It is in this case not possible to rule out the role of neither pure nor pecuniary externalities.

4 Empirical analysis

4.1 Estimation Issues

The number of patents pat_k of a group k is modeled as dependent on the variables presented in Table 1.

Since the number of patents is a discrete variable, count data techniques are appropriate. Normally, this type of regressions is handled by a Poisson regression model. However, only 39 of 130 groups (30%) in our dataset have patents granted and registered at the EPO. In the econometrics literature, another type of model, the Zero-Inflated Poisson (ZIP) model, has been advanced to take into account that decision units may be subject to one of two types of regimes: (1) whether to engage in patenting at all, (2) how many patents to "produce" (where 0 patents is still an option). Another potential limitation of the standard Poisson model is the implicit assumption that variance and mean are equal (Greene, 2003). This may of course not be true, but can be tested.

Another type of model, the Negative Binomial, relaxes this assumption by letting the variance differ from the mean. However, in this case the regime setup is dropped. A final possibility is the Zero-Inflated Negative Binomial (ZINB) model, which is a mixture of the two approaches. We briefly review the stated models below.[16]

The Poisson model is written

$$\Pr[PAT_k = pat_k] = \frac{e^{-\theta_k}\theta^{pat_k}}{pat_k!}, \quad pat_k = 0, 1, 2, 3, \ldots. \tag{8}$$

[16] The following text draws on the expositions in Cameron (1998) and Greene (2003).

where θ_k is in turn related to the set of regressors $\mathbf{x}_k$ (the explanatory variables in Table 1):

$$\ln \theta_k = \beta' x_k \tag{9}$$

and β is a vector of unknown parameters. As stated, a possibly erroneous assumption of the Poisson model is that variance and expected value are the same:

$$E[pat_k|x_k] = Var[pat_k|x_k] = \theta_k = \exp(\beta' x_k) \tag{10}$$

A more general form is given by the Negative Binomial regression model. θ_k is respecified as

$$\ln \theta_k = \beta' x_k + \varepsilon \Leftrightarrow \theta_k = e^{\beta' x_k} e^{\varepsilon}$$

where e^{ε} is here assumed to have a gamma distribution with mean 1 and variance α. The probability distribution of the Negative Binomial model is

$$\Pr[PAT_k = pat_k|\varepsilon] = \frac{e^{-e^{\beta' x_k} e^{\varepsilon}} \left(e^{\beta' x_k} e^{\varepsilon}\right)^{pat_k!}}{pat_k!}, \quad pat_k = 0, 1, 2, 3, \ldots. \tag{11}$$

In the Zero-Inflated Poisson model, we have two regimes at work. The probability of a zero outcome is the probability of regime 1 (no patents), plus the probability of zero patents, given regime 2 (patenting activity). The different outcomes may be stated as:

$$\Pr\left[pat_k = 0\right] = \Pr\left[\text{regime 1}\right] + \Pr\left[pat_k = 0|\text{regime 2}\right] \tag{12}$$

$$\Pr[pat_k = n] = \Pr[pat_k = n|\text{regime 2}] \Pr[\text{regime 2}], \quad n > 0 \tag{13}$$

An underlying variable, z_k, is a dummy, taking the value 1 if regime 2 holds and the value 0 if regime 1 is applicable, for each group k. Compared with the standard Poisson model, the probability of attaining a zero value has been "inflated". The process determining z_k is $z_k^* = \gamma' \mathbf{x}_k + \eta_k$, where η_k is i.i.d. with cumulative density function $\Phi(.)$. If $z_k^* > 0$ then $z_k = 1$ and if $z_k^* \leq 0$ then $z_k = 0$. Then Eqs. 12 and 13 may be reformulated as

$$\Pr\left[pat_k = 0\right] = 1 - \Phi(\gamma' x_k) + \Phi(\gamma' x_k) \cdot \Psi(0|\beta' x_k) \tag{14}$$

$$\Pr[pat_k = n] = \Phi(\gamma' x_k) \cdot (n|\beta' x_k), \quad n > 0 \tag{15}$$

The distribution of $\Psi\ (n\,|\,\boldsymbol{\beta}'\mathbf{x}_k)$ can be estimated either using a Poisson or a Negative Binomial model. The next section reports the results of the estimations.

4.2 Empirical results

4.2.1 Model specification issues

Table 2 presents the results from the Poisson and the Zero-Inflated Poisson model. Coefficients and significance levels are sensitive to model specification. Greene (2003) and the STATA website (2003) emphasize that the processes are very different. "Either unobserved heterogeneity or a process that has separate mechanisms for generating zero and nonzero counts can produce both over-dispersion and 'excess zeros' in the raw data". (STATA website, 2003). This makes it important to evaluate the models, preferably by formal test procedures. Thus, if we start out with a Poisson model, and if a test of overdispersion rejects the Poisson model, we must still test for zero inflation. The overdispersion test is done using a likelihood-ratio test as indicated by Eq. 16.

$$\begin{aligned} H_0 &: \mathrm{Var}[pat_k] = E[pat_k] \\ H_1 &: \mathrm{Var}[pat_k] = E[pat_k] + \alpha g(E[pat_k]) \end{aligned} \tag{16}$$

The LR test assesses whether α is different from zero. This test rejects the Poisson model in favor of the Negative Binomial model ($\chi^2 = 722.77$). In addition, a nonnested test by Vuong (1989) is used to test (a) the Zero-Inflated Negative Binomial model vs. the Negative Binomial model and (b) the Zero-Inflated Poisson model vs. the Poisson model. This test is specified as follows by Greene (2003, p. 751):

> Let $f_j(y_i\,|\,\mathbf{x}_i)$ denote the predicted probability that the random variable Y equals y_i under the assumption that the distribution is $f_j(y_i\,|\,\mathbf{x}_i)$, for j=1,2, and let

$$m_i = \log\left(\frac{f_1(y_i|x_i)}{f_2(y_i|x_i)}\right)$$

Table 2 Estimates of the Poisson and the zero inflated Poisson model

Dependent variable: pat_k		
Variable	Poisson	ZIP
Constant	0.4262 (0.1569)***	2.0615 (0.1703)***
R_k	0.0004 (2.68E−05)***	0.0002 (2.78E−05)***
$A_{\mathrm{int},k}$	0.0020 (0.0006)***	0.0007 (0.0006)
$A_{\mathrm{ext1},k}$	−5.60E−06 (0.0011)	0.0014 (0.0012)
$A_{\mathrm{ext2},k}$	−0.0001 (0.0001)	−0.0004 (0.0001)***
$AU_{1,k}$	0.0046 (0.0010)***	0.0042 (0.0011)***
$AU_{2,k}$	0.0009 (0.0004)**	0.0005 (0.0005)
Log-likelihood	−544.1548	−300.3189
LR-test	296.48	143.53
No. obs	130	130

Standard errors are in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level respectively

Then Vuong's statistic for testing the nonnested hypothesis of Model 1 versus Model 2 is

$$v = \frac{\sqrt{n}\left[\frac{1}{n}\sum_{i=1}^{n} m_i\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(m_i - \overline{m}\right)^2}}.$$

A large test statistic favors the Zero-Inflated Negative Binomial model for case (a) and the Zero-Inflated Poisson model for case (b). A low negative number favors the Negative Binomial model for case (a) and the Poisson model for case (b). We find that the Negative Binomial model is strongly rejected (1% level, test statistic 3.34) in favor of the Zero-Inflated Negative Binomial model and the Poisson model is rejected in favor of the Zero-Inflated Poisson model (5% level, test statistic 1.83). These results suggest either the Zero-Inflated Poisson model or the Zero-Inflated Negative Binomial model to be appropriate.

Unfortunately, there is no applicable test of Zero-Inflated Negative Binomial model vs. the Zero-Inflated Poisson model, but the likelihood ratio test that the model improves on a model with a constant only shows that the Zero-Inflated Poisson model is the better model.[17] This can also be seen from examination of the models' within sample prediction accuracy. In Appendix C, Fig. A and B show the predicted (within sample) values of pat_k compared with actual values for the Poisson, Zero-Inflated Poisson model and the Zero-Inflated Negative Binomial model (Fig. A) and the Negative Binomial model (Fig B). As can be seen, the Negative Binomial model performed remarkably poorly, with three extreme outliers (see Appendix C for details). Hence, the Zero-Inflated Poisson model gives the most reliable estimates. The estimates of the Negative Binomial and the Zero-Inflated Negative Binomial model are shown in Appendix B.

4.2.2 Interpretation of the results

The ZIP model suggests that research in the own group (R_k) has a highly significant effect on the likelihood to produce patents. Furthermore, internal accessibility is positive but not significant. This means that it is the size of the R&D staff that is important, while the accessibility to FTF contacts between the research units within the group is of minor importance. No significant intraregional effects have been found between groups. Thus Swedish groups formally engaged in R&D activities do not benefit from having high accessibility to other groups' research units in the same region. Patenting is also found to be somewhat less likely when there is higher accessibility to other groups' research in other regions than where the own group has its R&D. This could be due to a business-stealing effect. It could be that high accessibility to other groups' research staff indicates a competition for R&D personnel. Whereas this effect may contribute to labor pooling if it occurs *within* a region, it may be negative for the own group if competitors do R&D in nearby regions. An example of this would be that groups conducting R&D in a region *close* to the R&D-intensive Stockholm region would experience a negative effect

[17] The LR test value is 143.53 for the latter and only 13.26 for the Zero-Inflated Negative Binomial model.

from locating close to Stockholm, but not *inside* the Stockholm region. Our results are consistent with those of Ejermo (2004) who found that R&D spilled over only to a modest extent among Swedish industries.

We find that the likelihood of patenting is positive and stronger when the group has high intraregional accessibility to university research than the likelihood obtained from own research. This may be the result of established local networks to universities. Interestingly, it seems as if university contacts should be maintained close to where universities are located, since their effects are highly localized.

5 Conclusions

R&D effects on patenting in Swedish groups, i.e. parent and subsidiary companies tied together through ownership, have been examined in an accessibility framework. The R&D activities of our sample of groups have not been found to affect patent production of other groups intraregionally (variable $A_{\mathrm{ext1},k}$). However, interregionally the likelihood is negatively affected. A possible explanation for this relates to competition for R&D staff of groups located in different regions. This may be due to competition for researchers between groups across regions. Within a region, it is *possible* that such negative competition effects are balanced out by positive labor market effects; hence the total effect becomes non-significant. It must be stressed however, that not all learning in companies is the result of R&D. That is, small companies without formal R&D activities are not captured by our sample. Thus, it would be wrong to conjecture that no intraregional knowledge effects take place across companies. A future research issue could be to analyze local effects, investigating companies not included in the sample, perhaps using the community innovation survey (CIS) indicators (see the Introduction). It should in this context also be of particular importance to distinguish between large and small Swedish innovators, to see whether there are size-related differences in the ability to assimilate university research or research of other groups. The presence of high accessibility to university research in the same region seems to increase the likelihood of patenting in groups. Interregionally, no effects of this kind were found. Thus, the effects of university research on patenting in groups seem to be mainly local in nature.

The paper has stressed that any spillover effects involved may be of both pecuniary and pure externality type, i.e. it is not possible to separate between rent and idea spillovers, hence both market and non-market effects are estimated jointly. Thus, this research could be complemented along a number of lines. One such line would be to study the role of labor markets. For instance, one fruitful line of research would be to study inventors' role in forming new companies and their mobility between employers.

1 Appendix A: details on the construction of accessibility variables

These sections describe the construction of the accessibility variables used in the empirical estimations.

1.1 Internal corporate group knowledge accessibility

Internal accessibility to R&D plants within each group can be calculated by matrix algebra in the following way. First, we define an 81 × 81 symmetrical matrix, **T**, displaying mean time distance from one local labor market region to another. Since we did not have actual values for 1994, we took the average of time distances from 1990 and 1998.

$$\mathbf{T} = \begin{bmatrix} \tau_{1,1} & \cdots & \tau_{1,81} \\ \vdots & \ddots & \vdots \\ \tau_{81,1} & \cdots & \tau_{81,81} \end{bmatrix}, \text{ where } \tau_{i,j} = e^{-\lambda t_{i,j}} \tag{A.17}$$

We define a matrix **R** describing the distribution of each group's R&D personnel across space. This matrix is 81×130 so that:

$$\mathbf{R} = \begin{bmatrix} R_{1,1} & \cdots & R_{1,130} \\ \vdots & \ddots & \vdots \\ R_{81,1} & \cdots & R_{81,130} \end{bmatrix} \tag{A.18}$$

where for example $R_{39,53}$ denotes the research activity of group 53 in region 39. **R** denotes the number of research personnel. Also, a dummy matrix is defined so that

$$\mathbf{D} = \begin{bmatrix} D_{1,1} & \cdots & D_{1,130} \\ \vdots & \ddots & \vdots \\ D_{81,1} & \cdots & D_{81,130} \end{bmatrix} \tag{A.19}$$

Each value $D_{r,k}$ has a value of *1* if group *k* has research activity in region *r* and *0* otherwise. This matrix is constructed to ensure that if a group is not present in a region, it will not have access to other research within the group from that region. Then we define

$$\mathbf{TRD} = (\mathbf{TR}).*\mathbf{D} \tag{A.20}$$

where .* denotes the Hadamard (elementwise) matrix multiplication (./ will later denote Hadamard, elementwise, matrix division). To sum over the columns in the matrix **TRD** and account for the number of regions in which a group is present we form an 1 × 81 row vector i_{81} of ones and premultiply **TRD** by this. The result is a 1 × 130 row vector, showing the sum of a group's accessibility of all locations in which it is present.

$$\mathbf{TRD}_{sum} = i_{81}\mathbf{TRD} \tag{A.21}$$

Next, we premultiply the **D** matrix by the same row vector *i*. The resulting 1 × 130 row vector, *N*, shows for each element the number of locations in which a group has research activities.

$$\mathbf{N} = i_{81}\mathbf{D} \tag{A.22}$$

Finally, we divide each element of $\mathbf{TRD}_{\mathrm{sum}}$ by the corresponding element of $\mathbf{N}$ and take the transpose, so that internal accessibility shows up as a 130 × 1 column vector:

$$\mathbf{A}_{int} = (\mathbf{TRD}_{sum}./\mathbf{N})' \qquad \text{(A.23)}$$

1.2 Knowledge accessibility between groups

We want to separate external accessibility to other groups' knowledge into knowledge access within a region where the group has own research, and access to research staff outside regions of own research personnel. We wish to obtain a matrix 81×130 showing first total external accessibility to other groups' R&D. To accomplish this, we must first remove own research. We sum a region's research amount by post multiplying $\mathbf{R}$ with an identity column vector i_{130}. The result is an 81×1 column vector where each element shows the total amount of research in region r. Then we multiply the result with i_{130}. The end result is a 81×130 matrix, $\widetilde{\mathbf{R}}$, where an element from row r shows the sum of research within region r so that $\widetilde{R}_{r,1} = \widetilde{R}_{r,k}$. Then we deduct research from the own company so that only external research is left.

$$\mathbf{R}^e = \widetilde{\mathbf{R}} - \mathbf{R} = \begin{bmatrix} R^e_{1,1} & \cdots & R^e_{1,130} \\ \vdots & \ddots & \vdots \\ R^e_{81,1} & \cdots & R^e_{81,130} \end{bmatrix}$$

An element ${R_{r,k}}^e$ shows the potential amount of external knowledge available for group k coming from region r. Finally, we have to adjust for time distance to external knowledge and for a company's own research in the region, in a fashion similar to the above.

$$\mathbf{TRD}^e = (\mathbf{TR}^e).*\mathbf{D} \qquad \text{(A.24)}$$

We use the same procedure as outlined above to arrive at the column vector A_{ext}:

$$\mathbf{A}_{ext} = (i_{81}\mathbf{TRD}^e./\mathbf{N})' \qquad \text{(A.25)}$$

This leaves us with a 130×1 column vector of external accessibilities to other groups' research available for each group. Now we divide this effect into intra-and interregional accessibilities to external knowledge. First, we calculate only those effects which are internal to the region and subtract this from (A.25). We construct a matrix $\widetilde{\mathbf{T}}$ with dimensions 81×130. This matrix consists of 130 identical column vectors. Each element of the vectors shows the internal time distance of the corresponding row (e.g. any element on row 80 shows the internal time distance in region 80):

$$\widetilde{\mathbf{T}} = \begin{bmatrix} \tau_{1,1} & \tau_{1,1} & \cdots & \cdots & \tau_{1,1} \\ \tau_{2,2} & \tau_{2,2} & \cdots & \cdots & \tau_{2,2} \\ \vdots & & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ \tau_{81,81} & \tau_{81,81} & \cdots & \cdots & \tau_{81,81} \end{bmatrix}$$

We multiply $\mathbf{R}^e$ elementwise with $\widetilde{\mathbf{T}}$ to form intraregional but external knowledge accessibility, $\mathbf{AR}_{ext,1}$ for each group again similar to what has been done before:

$$\widetilde{\mathbf{TRD}}^e = (\tilde{\mathbf{T}}.*\mathbf{R}^e).*\mathbf{D} \quad (A.26)$$

$$\mathbf{A}_{ext,1} = (i_{81}\widetilde{\mathbf{TRD}}^e./\mathbf{N})' \quad (A.27)$$

The dummy **D** again plays the role of only taking into account effects when the group conducts research in the region. Then, to calculate external knowledge from other groups in other regions, we simply subtract $\mathbf{A}_{ext,1}$ from $\mathbf{A}_{ext}$:

$$\mathbf{A}_{ext,2} = \mathbf{A}_{ext} - \mathbf{A}_{ext,1} \quad (A.28)$$

Table A Estimates of the Negative Binomial (Neg. bin.) and the Zero-Inflated Negative Binomial (ZINB) models

Dependent variable: pat_k		
Variable	Neg. bin.	ZINB
Constant	−0.0674 (0.6928)	1.8245 (0.6651)***
R_k	0.0038 (0.0017)**	0.0003 (0.0003)
$A_{\text{int},k}$	−0.0255 (0.0195)	0.0021 (0.0066)
$A_{\text{ext1},k}$	−0.0033 (0.0054)	0.0066 (0.0057)
$A_{\text{ext2},k}$	−0.0002 (0.0005)	0.0066 (0.0005)
$AU_{1,k}$	−0.0029 (0.0070)	0.0069 (0.0096)
$AU_{2,k}$	0.0011 (0.0020)	−0.0007 (0.0019)
Log-likelihood	−182.7714	−170.9029
LR-test	17.93	13.26
Pseudo R^2	0.0468	
No. obs	130	130

Standard errors are in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level respectively

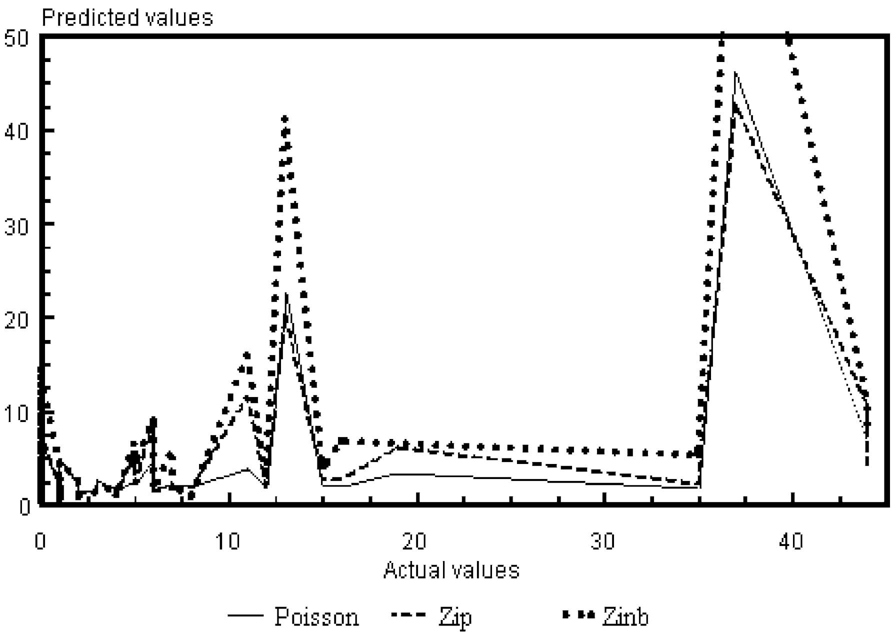

Fig. A Predicted values for the Poisson, Zero-Inflated Poisson and the Zero-Inflated Negative Binomial model. One outlier is not shown for the ZINB model, 75.44 corresponding to actual value 37

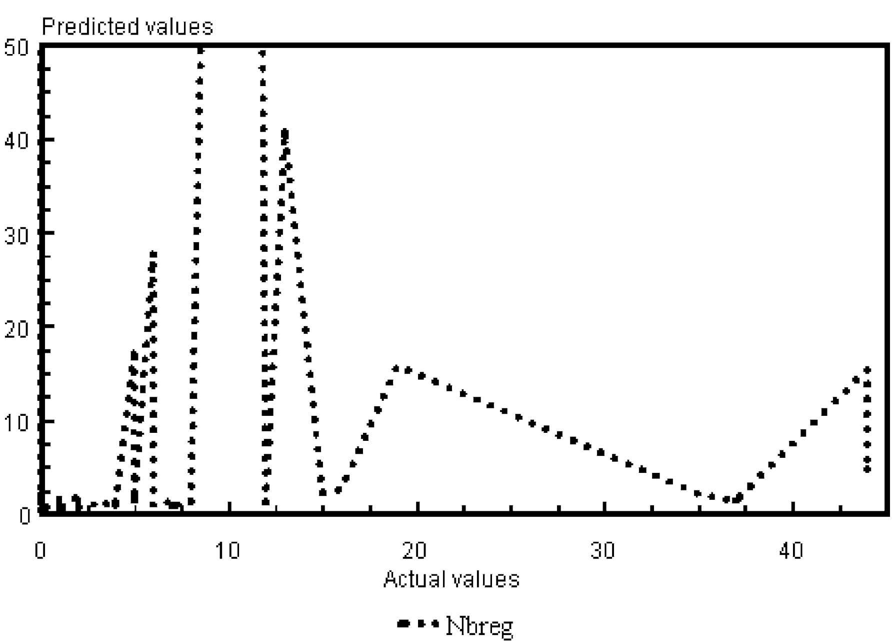

Fig. B Predicted values for the Negative Binomial model. Note: there are some extraordinary outlier predictions outside the range shown. 139,000,000,000, 2,080.196 and 280.6752 corresponding to actual patent values 37, 0 and 11

1.3 Accessibility to university research staff

We now turn to accessibility to research in universities (and other higher education). We start out with an 81×1 column vector, u, each element showing the amount of university research personnel in a region. This is premultiplied with the mean time distance matrix **T** (A.17) to form:

$$\mathbf{Tu} = \begin{bmatrix} Tu_1 \\ \vdots \\ Tu_{81} \end{bmatrix} \tag{A.29}$$

where $Tu_{r\cdot}$ shows region r's total accessibility to university research. Next, we form a matrix $\widetilde{\mathbf{Tu}}$ which we get by postmultiplying by a column identity row-vector i_{130}. This results in an 81×130 matrix, $\widetilde{\mathbf{TU}}$. We then proceed with the same method as above,

$$\mathbf{AU} = (i_{81}(\widetilde{\mathbf{TU}}.*\mathbf{D})./\mathbf{N})' \tag{A.30}$$

which results in a 130×1 vector in which each element represents a group's average accessibility to university research. To separate between intra- and interregional accessibility, exactly the same method is applied as for knowledge accessibility between groups. We label intraregional university research $\mathbf{AU}_1$ and interregional accessibility $\mathbf{AU}_2$.

1 Appendix B: results of the Negative Binomial and the Zero-Inflated Negative Binomial models

Table A presents the results of the Negative Binomial model and the Zero-Inflated Negative Binomial model not included in the main text.

1 Appendix C: prediction graphs of the presented models

Figures A and B show the predicted values plotted on the Y-axis against actual values on the X-axis, for the various models in use. Perfect predictions would result in straight 45° lines from the origo.

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