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Interregional inventor networks as studied by patent coinventorships

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Abstract

We study the structure of the interregional inventor networks in Sweden by examining the residence of inventors and coinventors involved in Swedish patent applications to the European Patent Office. Several factors are found to influence the spatial *affinity* of regions. We find that spatial affinity extends beyond the region if it has less own R&D-related resources (business R&D, university R&D and patenting); if it is close to the other region and if it is relatively small. The resources of that other region plays a positive role if, in analogue fashion, that region has more R&D-related resources.

JEL classification: O31; O32; R12

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1. Introduction

A fundamental observation of innovative activity is that it is remarkably concentrated in space (Audretsch, 1998; Kelly and Hageman, 1999; Acs et al., 2002). This suggests that external economies associated with knowledge generation, appropriation, diffusion and use are important reasons for the localization of these types of activities. Many empirical studies are concerned with the task of trying to quantify knowledge spillovers, i.e. involuntary flows of knowledge between economic agents. For example, geographically concentrated patent citations have been interpreted as signs of "localized knowledge spillovers".

In this study we use patent data in a different manner. We concentrate on coauthorship of patents, which we believe can be interpreted as indicators of *knowledge exchange*, i.e. intended knowledge flows, between actors within an inventor network. Two principal observations motivate our shift in focus. First, recent studies have called into question the use of citations as signs of knowledge spillovers, an approach initiated by Jaffe et al. (1993). Their main finding, based upon studies of U.S. patent citations, was that there were strong localization effects of knowledge spillovers. In recent contributions it has been questioned whether their results pertain to a too

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high aggregation level (Thompson and Fox-Kean, 2003), or whether not social proximity of inventors gained from earlier patent cooperation, explains most of spillovers as found by Breschi and Lissoni (2003) and Singh (2004). This is in line with other parts of the literature stressing the importance of labor mobility for knowledge flows (Zucker et al., 1998; Almeida and Kogut, 1999; Møen, 2000). Secondly, knowledge transfers should be qualitatively and quantitatively more substantial than citations as indicators of the overall flows of knowledge within an innovation system. After all, even if citations do reflect knowledge spillovers, deliberate cooperation must be of much larger magnitude than casual and random "spillovers". Coauthorship structures therefore seem more adequate for assessing the relative merits to the extent that knowledge travels across space. This said, the aim of this paper is to analyze the factors determining the existence, spatial structure and strength of interregional inventor networks in Sweden based upon patent data.

Each patent application leaves a paper trail in the form of a patent document. Inventors contributing to a patent are listed, along with their addresses, in the databases of the European Patent Office (EPO). Patent applications containing at least one Swedish inventor have in this paper been mapped, along with the location of coinventors using the NUTEK (1998) aggregation of municipalities into 81 local labor market regions.[1] Patents are counted as fractions so that with four inventors, a quarter is allotted each inventor's residential region. The spatial structure of the interregional inventor networks is then assessed as follows. We count the number of links, defined as the number of times two regions are together in patent applications. This establishes the extent of two-directional relationship between the regions. Then we count the number of times a region is involved in links. Supposing then that each region's links with other regions are randomly and uniformly distributed, it is then possible to calculate the extent to which a region has links to other regions in excess of randomly distributed links. We call this number *affinity*, which is calculated from the perspective of both regions, and thus one measure is calculated for each region to each other region. In other words, affinity is the extent to which one region is linked to another in excess of what pure randomness would predict. In this way we control for the fact that links tend to be more frequent from regions with extensive patenting.[2]

With this information at hand, we ask: What determines the spatial structure of interregional inventor networks? That is, how do spatial frictions and different regional characteristics affect affinity? These questions are tackled in a regression framework in an aggregate analysis for all patents and separately for 30 different patent technology groups. There are several reasons why a technology division makes sense, the propensity to patent differs (Scherer, 1983), and the sensitivity to e.g. distance could differ. According to the authors' knowledge a systematic technology division has not been conducted before in a study of interregional coinventorships.

In principle most researchers are connected directly or indirectly to other researchers. Thus network theory is called upon to provide a framework within which interregional inventor networks can be understood and analyzed. Section 2 outlines such a framework. Using this theory, a number of region-specific assets are identified that should be included in analyses of interregional inventor networks, as outlined above. These factors include: headquarters, infrastructure and access to knowledge workers. Headquarters are often located close to R&D activities (Stutz and de Souza, 1998). This function is often viewed as central in corporations, due to the need for communication across organizational units (Malecki, 1997). Research is also an area that may need special monitoring. For instance, Schumpeter (1934) emphasizes the need for businessmen to be close to the technology developers because they often lack the vision to see what is economically marketable, which may obviously create a tension between the two groups. Physical infrastructure, or lack thereof, influences the time and cost involved in establishing and maintaining inventor networks. Thus, time distance is obviously an important factor in an evaluation of the spatial structure and strength of interregional inventor networks. In this context it is important not only to consider travel time by road, but also flight time between regions with access to an airport. Third, the importance of pools of knowledge workers in regions may influence the spatial structure of interregional inventor networks. Only scattered evidence exists on the structures of patent coauthorship. Section 3 reviews the literature to provide material against which we can make some comparisons. Section 4 extensively describes the interregional inventor networks in Sweden, and our data material. Section 5 states our hypotheses about the interregional inventor networks and examines

[1] The terms "coinventorship" and "coauthorship" are used interchangeably to reflect the cooperation between inventors as documented by patent data. In addition, "patents" and "patent applications" as used, both refer to patent applications.

[2] We explain this measure formally in Section 5.

them using regression analysis. The material is analyzed both in the aggregate and over technologies. Section 6 concludes.

2. Invention network theory

2.1. Introduction

The concepts of network and networking have gained considerable popularity in innovation and invention studies during the two last decades.[3] The present section outlines some fundamental elements of an emerging theory of inventor networks.[4] A basic assumption is that all activities in a market economy are organized by means of different links and couplings between economic actors, i.e. as networks. Market competition can be described as a process in which obsolete, non-competitive links, and economic actors are replaced by new and superior links, and economic actors, respectively.

Networks and network relations have four important characteristics (cf. Cappelin, 2003): (i) The relationship (=link) between two nodes is characterized by a precise direction, which identifies either a mutual relationship or a relationship of control or of dependence of a node with respect to another node.[5] (ii) Each node has a specific function, which depends not only on its relationship with other nodes, but also on its position in the overall network. (iii) The relations existing in one network are normally linked to relations in other networks, so that many networks are interconnected with each other. (iv) The relations existing in a specific network are normally affected by the relations existing in the same network in previous periods, due to among other things the existence of cumulative learning (Nelson and Winter, 1982) and of general path dependence.

2.2. Initial definitions

The starting point for our analysis is the micro-level of individual decision makers. As decision makers we identify three types of decision units: individual inventors working independently or in inventor networks, firms and economic agents operating within firms or other organizations engaged in innovative activities. A basic presupposition is that firms and organizations have internal networks for communication and for co-ordination of production and other activities, such as invention and innovation. Certain internal networks consist of links that are arranged for the flow of resources. The links of other internal networks function as channels for exchange of information and knowledge. Moreover, these different internal networks are connected in such a way that firms and organizations are coherent.

2.3. The need for complementary assets in invention

Creating new inventions is a complex task in most technology areas, which in many cases demands the interaction between specialists with different competences. A link to a specialist will normally not be broken unless a specialist with superior competence is found. In such cases, all network members have to overcome the sunk cost advantages of established links, since the establishment of a new link implies investment costs for all remaining network members. Hence, the dynamics of inventor networks are strongly related to competence building and knowledge creation processes in the economy.

The reason why inventor networks are necessary and important is that modern knowledge economies are typically characterized by incomplete and scattered information. No single individual or node can solve all problems. Thus, problem solving, in this case the generation of inventions, is the result of improvements made by various configurations of individual actors, i.e. inventor networks, through an *in itinere* co-ordination or according to heuristic and recursive processes and mutual interactive learning. The learning process encompasses groups of individuals, both within the individual firms and overall in the economy, and it requires the development of links and co-operation between different actors, also outside existing patterns.

Invention processes are based on the integration of various pieces of knowledge possessed by various economic actors within an inventor network with different and complementary knowledge and competences. Learning is the process whereby previously existing knowledge is selected and combined based upon a new perspective. The creation of inventions requires an intense process of interaction (Nonaka and Konno, 1998), which is characterized by transfers of both tacit and explicit knowledge and which requires face-to-face contacts, physical proximity as well as well developed mediated contacts.

In particular, invention calls for the enhancement of complementarities and diversity. The differences between the various actors (nodes) and their knowledge integration are part of an evolutionary process, as the

[3] A network consists of at least two nodes and at least one link.

[4] The discussion in this section is inspired by in particular Johansson (1995).

[5] In the second case we say that the network has a hierarchical character.

different competencies are not static, but rather in continuous evolution. External exchanges feed this evolution, but each actor (node) within an inventor network keeps its own individuality. In fact, it can contribute to the common project, just because it masters a specific know-how, while at the same time it is subject to evolution, by embodying external knowledge, reacting to external stimulus and facing new problems.

2.4. *The cost and optimality decision*

To understand and to explain economic couplings between nodes, where inventors in inventor networks represent a special type of coupling, it is natural to make references to transaction cost theory and the theory of economic contracts. The interaction between economic agents, such as inventors, is often based upon some sort of agreement, which may be interpreted as an economic contract. Long-term (explicit or implicit) contracts between economic agents are usually motivated by the fact that one or several of them must make investments that are transaction-specific. Every exchange is in principle based upon an explicit or an implicit contract. In particular, in exchanges aiming at creating inventions, the contracts may be very important since the contributions of the different agents involved may be difficult to define and since the outcome is genuinely uncertain. This implies that it is usually difficult and uneconomic to formulate complete contracts under these circumstances. Instead the incomplete contracts underlying inventor links/inventor networks have to be supported by mutual economic commitments, ownership relations, other forms of social ties, mutual trust, and/or confidence relations. Thus, formal and informal institutions play a fundamental role for the functioning of inventor networks, since they govern and co-ordinate the relations between nodes, and thus reduce the transaction costs between them.

The links are analyzed as capital objects, which are basically sunk costs. Therefore, networks bring rigidity and structure into the interaction patterns in a market economy. The resources necessary to establish contractual agreements constitute transaction costs (Coase, 1992; Williamson, 2000), which include (i) exclusion costs, (ii) various forms of interaction costs such as negotiation, contract formation, information exchange, contract monitoring, and contract enforcement costs, and (iii) search and disequilibrium costs. In many situations it is possible to reduce transactions costs by means of standardization of interactions. However, this is more difficult within invention networks since inventions are per definition un-standardized.

Our major concern here is interactions between inventors, i.e. inventor networks for the purpose of generating inventions. These networks are generally characterized by durability and sunk cost features. Sunk costs are accepted because investments may reduce long-term uncertainties and transaction costs.

The above discussion focuses on co-operation links, which are durable and have capital properties. Each such link is an inventor link and a system of connected inventor links form an inventor network. According to the theoretical arguments put forward above, we shall expect that co-operation on inventor links between economic agents, i.e. inventors, or between different parts of the same firm are frequent or generic phenomena. An important type of link is the one where ownership of the invention belongs to an individual party. Appropriation of the results is then relatively straightforward. On the other hand, an inventor link is shared as a joint property when two or more parties are involved. This form of relational contracting may be supported by extra-market relations, which bind the parties together. A motive for this solution is a desire to stimulate continuing, long-term interaction. Thus, inventor links and inventor networks can be made self-reinforcing by the mutual interests of the coupled parties.

The capital properties of an inventor link or an inventor network obtain as a consequence of link- or network-specific investments. When two or more parties decide to establish a joint inventor network it is possible to think of this as the outcome of an evolutionary, gradual search and trial process. We may also regard the outcome as a Nash equilibrium of a non-cooperative game, where each party would lose by leaving the network.

Recognizing that inventions are the result of novelty by combination (Weitzmann, 1998; Olsson, 2000) we may draw some general conclusions regarding inventor networks. The principle of novelty by combination implies that expanding an inventor network by bringing in new competencies increases the chances of generating inventions. Thus, large inventor networks should *ceteris paribus* be more productive in terms of inventions than small inventor networks. Metcalfe's law states that there are increasing returns in utility to the number of users in network technologies such as telephones or the Internet. However, this need not necessarily be the case in the current situation. The potential inventive outcome and thus economic value of an inventor network and its inventive capacity increases the more individuals, institutions and organizations participate in an inventor network, if information flows freely within the network. In reality, information does not flow perfectly, certain actors within the network exchange information and maintain contacts more often. Hence, expansion of an inventor network implies that the co-ordination costs may increase rapidly.[6] This implies that there is an optimal, but possibly unknown, size of inventor networks. Since inventions are generated according to the principle 'novelty by combination' the general conditions for generating inventions differ between different technologies. Thus, we shall expect the optimal size of inventor networks to differ between different technologies, depending on how the cost–benefit calculation plays out. To generate inventions in certain technologies there is a need to combine pieces of scientific and/or technological knowledge from various fields, while in other technologies inventions can be developed from a much narrower knowledge base. Each 'invention project' is therefore subject to the attempt to find an optimal organization size subject to technological constraints. The appropriability problem may also limit the size of inventor networks. The larger the number of nodes, the larger the risk that one node will try to appropriate the knowledge created for itself.

2.5. The evolution of inventor networks

Once an inventor network has been established, new ex post reasons arise to keep it intact because of sunk cost conditions. Often the members of an inventor network develop joint knowledge and a specific co-operation language through time. This is an evolutionary effect that can further strengthen the ties between the members of the inventor network and this effect is in particular important when much of the knowledge that is shared has a tacit character. However, this does not imply that members (nodes) never leave inventor networks, or that new members never enter inventor networks, i.e. that inventor networks get new nodes. Furthermore, the relationships between the nodes in an inventor network change over time. This process of adaptation and co-evolution of the relationships between nodes in an inventor network may be defined as a process of learning and of knowledge accumulation. The initial cohesive force of an inventor network is often the result of an investment calculation. All parties involved in setting up an inventor network need to a varying degree to invest in special equipment, special training, procedures and arrangements that are directly motivated to make the network function properly.

Our discussion shows that the existence of inventor networks brings rigidities into invention processes, compared to a situation without them. It creates structure in "the invention system". Moreover, it strongly affects the dynamics of invention systems due to the existence of strong frictional elements. In this context we may just add that scientific revolutions and changes in institutions and communications and transportation infrastructures have the capacity to bring about removal of old inventor networks and replace them with new inventor networks.

Given that inventions are the result of novelty by combination, inventions can be seen as the result of adaptive search and learning processes, which lead to new combinations of the existing knowledge in an inventor network. An innovation occurs when the joint knowledge impulses or signals between the different nodes are not only compatible with the inventor network and its mission and goals, but also overcome a certain threshold of intensity. This allows the inventor network to perceive the stimulus. The network may then decide whether to conflict with it or rather to adapt to it. In fact, whether or not the stimulus is compatible with the existing cognitive system, interactive processing may lead to the identification of an incremental solution to an existing problem, and this stimulates the act of discovery and invention.

On the other hand, a cognitive blockade or lock-in effect may be determined by a too low accessibility or a too low receptivity within the inventor network (Steinmuller, 2000). In particular, accessibility between the nodes in an inventor network is affected by existing infrastructural and institutional conditions. On the other hand, receptivity is related mainly to the scope of the diversified knowledge available within an inventor network, since such knowledge helps to identify useful forms of complementarities in the relations between the different nodes in the inventor network. Time is clearly also a crucial factor, as it facilitates perceiving a continuous stimulus and absorbing and adapting gradually to it.

2.6. The spatial dimension of networks

Up till now we have treated the inventor networks as non-spatial entities. However, inventor networks are spatial configurations where each node has its specific geographic location. Thus, the interaction between the different nodes in an inventor network depends upon the available material infrastructures and the functioning of existing transport and information transfer systems (cf. Button et al., 1998).

The general conditions for bringing competencies into inventor networks differ between functional regions. Generally speaking, it should in principle be much easier to find the competencies necessary for an inventor

[6] See Bolton (2003) for a discussion of benefits and costs of maintaining innovation networks.

network in large dense regions compared to smaller regions.[7] This implies that the probability that the inventor networks are contained within a region is much greater in larger, more population dense, regions than in smaller regions. The probability that inventor networks should contain competencies from other regions is thus expected to be higher in smaller regions than in larger regions. Moreover, it is natural to expect that complementary competencies in all inventor networks mainly should be found in large regions, and in particular, large regions with research universities. Another reason why inventors' competencies (nodes) in larger regions are preferred is that there is a higher probability that these nodes in turn have better connectivity to other inventor networks and thus are better informed than nodes in smaller regions because of the existence of more inventor networks in large regions.

2.7. Conclusions from network theory

Summing up the discussion above we may conclude that an inventor network may be characterized by five main parameters (cf. Cappelin, 2003): (i) the knowledge accumulated and the competence of each node, (ii) the distance, i.e. the friction, between the different nodes of the network, (iii) the connectivity to other interacting networks, (iv) the speed of change of the links and the destruction and creation of links, and (v) the overall trajectory of the overall structure of the network.

In particular, invention may be related to:

- The intensity of the interaction between the various nodes of an inventor network through the existing links; this is related to the interactive characteristics of the invention process, as it is based on interactive learning processes.
- The speed of change of the invention network due to changes in the accessibility of existing links, the disappearance of links and nodes and the establishment of new links and nodes; this is related to the combinatory characteristics of the invention process, which is made by an original combination of pieces of knowledge, which were previously disjoint.

A multitude of actors are involved in networks leading to invention, as stressed by von Hippel (1988), Porter (1990) and Karlsson (1997). New inventions often evolve when networks based on customer–supplier relationships, where supplier refers to the supplier of a potentially new technology, to customers of the applied product, and to non-commercial links to other establishments or head office exist. Non-commercial links refer to the availability of knowledge that can be extracted from participation at fairs, informal meetings, from trade journals, etc.[8] Head office monitoring is important as it concerns the direct influence on the process of developing inventions from a managerial perspective. In other words, new inventions may not necessarily lead to commercially viable products, a point already stressed by Schumpeter (1934).

For a given size of a functional region we expect that the probability that an invention network should be contained within the region increases with the volume of university R&D, the volume of private R&D and the number of highly educated employees in the region. Furthermore, the probability that an invention network in a functional region should be contained within the region decreases with the interregional accessibility of the region.

3. Previous findings

Our review of the empirical literature mainly focuses on examples with special emphasis on either the Swedish inventor networks and/or those using patent data.[9] A large literature is presently developing on social network analysis (Wasserman and Faust, 1994; Scott, 2000). A large literature is presently developing on social network analysis. Network analysis has emerged as an important tool to analyze the way inventors are interconnected. Two contributions identify individual inventors and examine the overlap of patent coauthorship to construct "social proximity" measures. Social proximity reflects earlier collaboration between inventors. For example, if two inventors A and B have cooperated in an earlier patent, it is more likely that a third inventor

[7] With a region we here understand a functional region, which is approximately equal to a commuting region.

[8] Indeed, Freel (2003) provides compelling evidence on the non-homogeneity of networks for innovations. Cassiman and Veugelers (2002) investigate from Community Innovation Survey (CIS) data, the likelihood of entering R&D cooperation when firm-specific appropriability conditions and the public good nature of new knowledge varies. Strategic protection was more important when entering cooperation vertically with customers/suppliers than with research institutes.

[9] Studies in bibliometrics tend to use journal coauthorship to study networks. Some examples include Newman (2001a,b) who study scientific collaboration in physics, biomedical research and computer science, Persson et al. (1997) and Melin and Persson (1998) look at collaborative patterns of researchers at Nordic and European universities respectively and Okubo and Sjoberg (2000) examine internationalization tendencies of coauthorship in researching Swedish firms.

C cooperates with B, if C and A cooperated before.[10] Hence, patent citations may reflect social proximity rather than "genuine" knowledge spillovers. Breschi and Lissoni (2003) examine Italian social proximity through the use of EPO data, and Singh (2004) uses American data, mainly on biotechnology patents from the US patent office (USPTO). Breschi and Lissoni (2003) find that social proximity explains almost the whole localization effect of 366 citations. Singh (2004) finds that the *degree* of social proximity is important for the extent to which it replaces the need for close geographical distance. Thus, for inventors with close social proximity to other inventors (e.g. through earlier research collaboration), distance becomes less important. However, for teams with little social connection, geographical proximity remains important.

Other researchers have used patent data to investigate cooperation in invention. Mowery et al. (1996) examine the change in technological capabilities resulting from international joint-ventures by looking at which technology classes are cited in their patent portfolios, before and after cooperation. They find evidence that cooperation brings these citation profiles closer in line with each other, which was especially clear from equity joint ventures. Gauvin (1995) looks at the extent of international cooperation based on information on several assignees from Canadian patents (this is the only patent office providing this information). Comparing Japanese, American and German main assignees, an interesting finding is that Japanese firms to a larger extent engage in cooperation, and when they do they are to a higher degree involved in cross-sectorial cooperation compared to their American or German counterparts.

Mariani (2000) examines coauthorship relations of 201,531 patents in the European chemical industry, based on EPO data. The main purpose is to compare organizational characteristics, and the degree of localization, examined across countries and regions for a sample of 560 of those patents.[11] Localization refers here to whether all inventors reside in the same region on the listed levels. Delocalization refers to when at least one of a patent's inventors reside elsewhere. She finds that localization is 75.4% on NUTS1 (i.e. national chemical patents), 70.5% on the NUTS2 level and 68.4% on the NUTS3-level. Furthermore, despite the fact that international research cooperation has grown massively in recent decades (cf. Hagedoorn and Schakenraad, 1990), only about 8% of all patents had multiple assignees, i.e. joint ownership of the intellectual property embedded in the patent. In a subsample consisting of multinationals ("Fortune 500 firms"), firms were to a much higher degree engaged in delocalized patents. Their average number of inventors in a patent was 2.5.

The paper by Gay and Picard (2001) analyzes nationalities of coinventors of 602 French patents applied at the USPTO, and the implications of citation distance, conditioned on the degree by which patents are localized completely to France. The paper finds that the residence of coinventors strongly influences the international scope for citations, even when self-citations are excluded.[12]

To sum up, these contributions reflect disparate ways of utilizing patent data to study networks. European studies generally conclude that there are few inventors per patent. A promising line of research connects patent citation data with social proximity analysis. This type of studies may generate results based on micro-data on a level of detail not seen before. In this way, analyses of inventor networks may reveal the span of networks, which actors are involved and whether the outcome is desirable from a policy-perspective point of view.

4. Characterization of the Swedish coinventorship structure

The interregional inventor networks that we analyze in this study by means of patent coauthorships could be one of several kinds of networks pertaining to the organization of knowledge capabilities. The most likely form is of course within-firm organization of technological know-how. In these cases, inventors work solely for one commissioner.[13] A patent could be the result of a research joint-venture, whereby organizations use their complementary capabilities.

It is clear from the listed contributions, that coauthorship of patents is a strict definition of inventor networks. Our effort concerns an investigation of (i) the extent to which patent coauthorships extends over different functional regions, i.e. the existence of interregional inventor networks, and (ii) the factors determining the spatial structure and strength of these interregional inventor networks. Complementary to this, we examine some of the reasons for which patent coauthorship is confined within the own region and examine whether motives for this

[10] This example is taken from Granovetter (1973).

[11] The European Union is by Eurostat divided into NUTS1-NUTS3. In Sweden NUTS1 is the national level, there are 7 NUTS2 regions and 21 NUTS3 regions (counties).

[12] Self-citations are citations to the own organization or an organization affiliated to it.

[13] Of course, some inventors work for none but themselves.

are similar to those governing interregional inventor networks. This is done for all patents as well as patents divided according to technology. Hence it matters little that we do not make a separation of teams and/or organizations.

We now turn to a description of our data. The principal source of information consists of 28,498 "Swedish" patent applications to the EPO. A patent was considered Swedish if at least one of the inventors has an address in Sweden. From this total we were able to assign 99.6% a technological class, and out of 49,852 Swedish inventors we were able to assign 98.8% to a region. We used the "fractional method" for assigning applications to regions, meaning that if for example four inventors were involved in the application, a quarter was allotted each inventor's region.[14] When counting the number of inventors we include non-Swedish, international inventors. Fig. 1 shows the geographical distribution of patent applications per capita (population as of 1998) counted in fractions across 81 local labor market regions defined by NUTEK (1998).

This figure shows that while patenting seems to be generic among many regions, it is more frequent among densely populated regions, in particular Stockholm, Gothenburg, and the Malmö regions, even after adjusting for population size. In the latter region the university town Lund plays an important role for patenting. Other 'hot spots' of patenting include Västerås, west of Stockholm, Uppsala hosting another important university north of Stockholm, and Ludvika. Ludvika and Vasteras host several plants of the Swedish section of ABB. These findings: (a) mimic the "stylized" fact that inventive activity tends to concentrate and (b) suggests that individual companies and the technologies they develop have an impact on the patenting structure.

As stated in Section 1, we fully recognize that the extent of patenting differs both because of different technological opportunities (Dosi, 1988), and because of different propensities to patent (Scherer, 1983). Tables 1 and 2 give ample information about our patent database divided in 30 technological patent classes, and in the aggregate using the definitions of Hinze et al. (1997).

Apart from showing the number of applications and inventors, Tables 1 and 2 show the number of Swedish

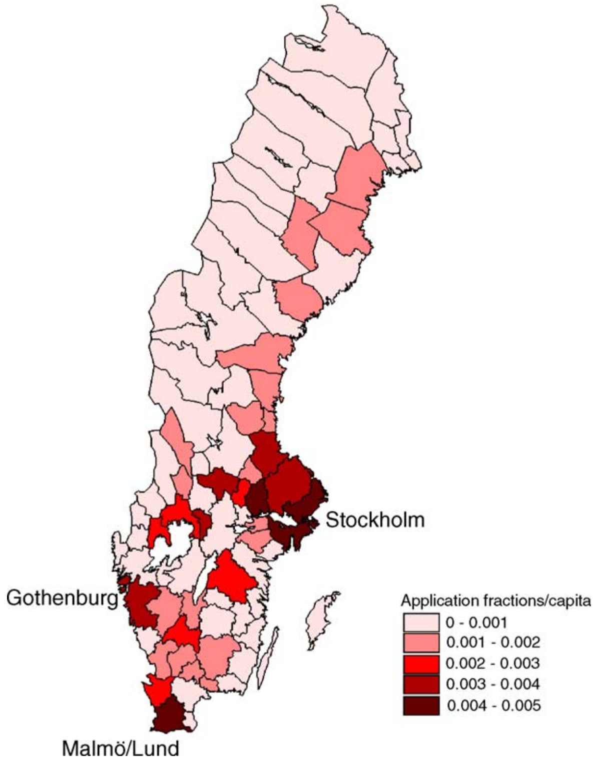

Fig. 1. Number of EPO patent applications (fractions) per capita for Swedish local labor market regions.

and international inventors,[15] the share of international inventors in relation to the total number of inventors, the extent to which Swedish inventors could be classified regionally, and the dispersion across regions measured by the Hirschmann–Herfindahl index (HHI), for each technology. The table shows that much application activity (>1000 applications) were in Electrical engineering, Telecommunication, Control technology, Medical technology, Chemical engineering, Materials processing, Machine tools, Mechanical elements, Handling, Transport, Consumer goods, and Civil engineering. The share of international inventors was 10.45% on average, being less than 2% in Space technology but being close to one third in Polymers and Biotechnology! The number of inventors (incl. international) averaged 1.75, ranging from 1.36 in Consumer goods and Civil engineering to an average of 3 inventors per application in Organic chemistry.

Given that the average number of inventors is less than 2, it is not surprising that the most common team

[14] In the original setup for this paper we 'assigned' a patent to the region of the first inventor. The literature rests ambiguous on whether to count fractions or use the first inventor-method for assigning patents. The motive for changing to fractions was rather, as was pointed out by an Anonymous referee, that in the first setup we only counted links from the first inventor which loses the "between-inventor-linkages".

[15] Danell and Persson (2003) report that Swedish applications with non-Swedish coauthors to the USPTO have tripled since the 1980s. Yet they constitute only 13% of all inventors in those patents.

Table 1
Descriptive statistics about inventors, technologies 1–15

A. Technology	B. Applications	C. Inventors	D. Swedish inventors	E. International inventors	F. International inventors, share (E/C) (%)	G. Swedish inventors per application (S.D.)	H. Regionally classified	I. Regionally classified (H/D) (%)	J. Regional dispersion (HHI)
1. Electrical engineering	1447	3091	2893	198	6.41	2.00 (1.60)	2866	99.07	0.1549
2. Audiovisual techn.	305	486	455	31	6.38	1.49 (0.94)	451	99.12	0.2411
3. Telecommunication	2987	6724	5900	824	12.25	1.98 (1.63)	5832	98.85	0.4238
4. Information techn.	817	1708	1533	175	10.25	1.88 (1.21)	1525	99.48	0.3027
5. Semiconductors	212	531	474	57	10.73	2.24 (1.32)	471	99.37	0.3858
6. Optics	390	784	702	82	10.46	1.80 (1.39)	696	99.15	0.3852
7. Control techn.	1851	3628	3268	360	9.92	1.77 (1.09)	3221	98.56	0.1700
8. Medical techn.	2368	4604	4282	322	6.99	1.81 (1.10)	4237	98.95	0.2429
9. Organic chem..	841	3087	2521	566	18.33	3.00 (1.95)	2489	98.73	0.2633
10. Polymers	255	693	473	220	31.75	1.85 (1.10)	467	98.73	0.1968
11. Pharmaceutics	935	2504	2009	495	19.77	2.15 (1.28)	1982	98.66	0.2361
12. Biotechn.	504	1591	1089	502	31.55	2.16 (1.40)	1076	98.81	0.2473
13. Materials	765	1643	1496	147	8.95	1.96 (1.05)	1460	97.59	0.1423
14. Food Chem.	219	526	415	111	21.10	1.89 (1.41)	406	97.83	0.2029
15. Basic materials chem.	275	604	522	82	13.58	1.90 (1.18)	519	99.43	0.1678

Table 2
Descriptive statistics about inventors, technologies 16–30

A. Technology	B. Applications	C. Inventors	D. Swedish inventors	E. International inventors	F. International inventors, share (E/C) (%)	G. Swedish inventors per application (S.D.)	H. Regionally classified	I. Regionally classified (H/D) (%)	J. Regional dispersion (HHI)
16. Chemical engineering	1138	2080	1907	173	8.32	1.68 (1.21)	1885	98.85	0.1589
17. Surface techn.	409	928	806	122	13.15	1.97 (1.12)	791	98.14	0.1501
18. Materials processing	1265	2596	2234	362	13.94	1.77 (1.12)	2216	99.19	0.0972
19. Thermal processes	705	1097	1040	57	5.20	1.48 (0.83)	1022	98.27	0.1338
20. Environmental techn.	286	522	480	42	8.05	1.68 (1.01)	476	99.17	0.1786
21. Machine tools	1195	1877	1779	98	5.22	1.49 (0.80)	1759	98.88	0.0949
22. Engines	685	1120	1067	53	4.73	1.56 (0.98)	1062	99.53	0.2397
23. Mechanical elements	1289	1923	1803	120	6.24	1.40 (0.75)	1791	99.33	0.1157
24. Handling	1864	2850	2634	216	7.58	1.41 (0.74)	2613	99.20	0.1111
25. Food processing	528	786	757	29	3.69	1.43 (0.90)	749	98.94	0.1591
26. Transport	1401	2225	2072	153	6.88	1.48 (0.88)	2028	97.88	0.1217
27. Nuclear engineering	207	401	384	17	4.24	1.86 (1.04)	379	98.70	0.3220
28. Space techn.	380	732	718	14	1.91	1.89 (1.18)	696	96.94	0.1637
29. Consumer goods	1351	1895	1838	57	3.01	1.36 (0.71)	1821	99.08	0.1760
30. Civil engineering	1492	2143	2036	107	4.99	1.36 (0.72)	2013	98.87	0.1140
Not classified	132	289	265	24	8.30	2.01 (1.37)	264	99.62	0.3099
Aggregate	28,366	55,668	49,852	5816	10.45	1.75 (1.21)	49,263	98.82	0.1600

"size" behind an application is one inventor, which is the case in 14,551 applications, teams of two occur in 7336 applications, 3411 applications have three inventors, 1685 applications have four, 724 have five and so on.[16]

The results of Mariani (2000) provide an opportunity for comparison of the size of inventor groups. She found that of 201,531 applied and approved chemical patents in Europe, only 25.4% were developed by single inventors. The average number of inventors was 2.5 for a sample of 560 patents. Furthermore, as those patents become more nationally delocalized (i.e. spread over more than one NUTS3 region), more inventors are involved. The number of inventors in "Swedish" chemical patents seems to be somewhat lower. In their study on the social network of Italian inventors, Breschi and Lissoni (2003) report for a sample an average of about 1.9 Italian inventors per patent. Again, the average number of inventors in Swedish patents (1.75) is somewhat fewer.

Further interesting information from Tables 1 and 2 regards the regional dispersion of different technologies. This is calculated using the Hirschmann–Herfindahl index, which is explained by the formula:

$$\mathrm{HHI}_k = \sum_r s_{rk}^2, \qquad (1)$$

where s_{rk} represents the share of applications in technology k, and region r is one of our 81 local labor market regions. The index ranges between 0 and 1, where 1 is obtained when all applications in a certain technology are in one region. Judging from this index, the most concentrated activities are in telecommunications, semiconductors, and optics. The most dispersed technologies are machine tools, materials processing, and handling.

5. Interregional networks and the affinity concept

We now discuss properties of the interregional inventor networks in Sweden. A central concept in this endeavor is *affinity*. As explained before, affinity refers to the number of links between two regions, deducting the expected number conditional on that a link starts in a certain region. The total number of regions are here 82, where 81 of them are our 81 local labor market regions, and the 82nd a 'foreign' region.[17] Expressed differently,

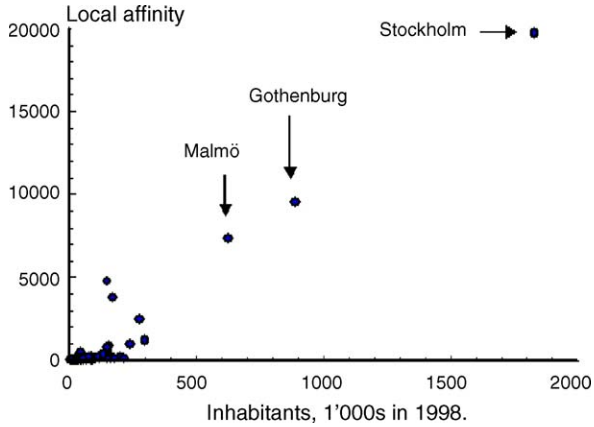

Fig. 2. Local affinity in Swedish regions in relation regional population size.

given that a link has region i as its starting point and there are 82 regions, the probability that the link ends in region j is 1/82. Suppose then that there are n_i links starting from region i. The observed number of links from i to j can be written l_{ij}. Hence, the non-random part from i to j, conditioned upon that the starting region is i is written:

$$A_{ij} = l_{ij} - \frac{n_i}{82}, \qquad (2)$$

which is how we define affinity. Local affinity is a concept that here refers to "within-region" affinity, which is likely to be higher than interregional affinity, since people are more likely to cooperate within the region of their residence. Fig. 2 shows local affinity on the y-axis and the size of regions (inhabitants) in 1998 on the x-axis. Each dot represents the specific inhabitant–local affinity combination for each of the 81 local labor market regions. The relation between regional size and localization seems to be close to linear, especially with respect the larger regions. A simple linear regression of the relationship between local affinity and population gives us:

$$A_{rr} = \underset{(-5.1259)}{-477.8979} + \underset{(29.6290)}{10.7339} N_r, \quad R^2 = 0.9184, \qquad (3)$$

where A_{rr} refers to local affinity in region r and N_r to its population in thousands of people in 1998. t-values are shown below the estimates. There is indeed a highly significant relationship between population size and local affinity. One region had no patent application fractions in it. Since, it therefore does not make sense to think of affinities from this region to another, it was excluded.

Fig. 3,[18] depicts the interregional inventor networks in Sweden as measured by affinity. The thickness of the

[16] Note that these inventors do not necessarily have to be unique, i.e. inventors may appear in more than one application.

[17] A natural extension of this paper is to study international networks, which would then involve dividing this foreign component into country-specific parts.

[18] This figure was made with the help of Netdraw and Ucinet6 (Borgatti et al., 2002).

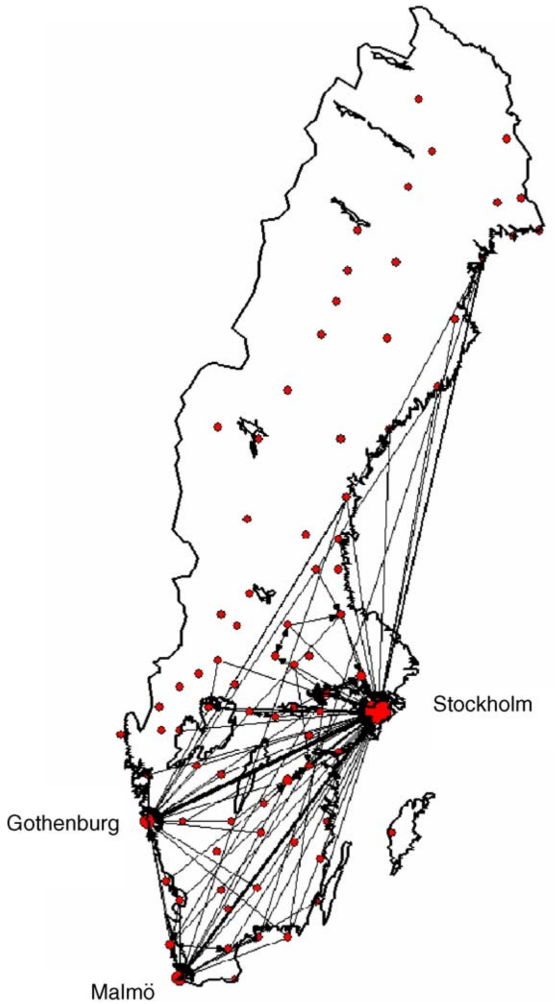

Fig. 3. Affinity for Swedish regions based on patenting. Thicker lines show stronger connections.

lines in Fig. 3 shows the degree of interregional affinity.[19] The arrows, which could run both ways, indicate the direction in which affinity is important. In addition, the sizes of the nodes reflect the amount of patent applications in fractions assigned to the region. The three largest regions – Stockholm, Gothenburg and Malmö – are seemingly central nodes in the Swedish inventor networks. Due to their size, large regions have more inward arrows, because inventors in smaller regions cooperate more frequently with inventors in larger regions than vice versa. Stockholm has many long-distance connections, and many regions have affinity to her. Similar relationships obtain for Malmö and Gothenburg but their centrality is more locally founded so that they are central nodes in the southern and western parts of Sweden. In the north, the largest regions Umeå and Luleå seem to some extent to be central nodes.

A casual look like this does not reveal why these relationships hold. As indicated, many size effects should be involved. Obviously, the fact that the Stockholm region hosts around 1.850 million people (1999) acts as an attractor in the interregional inventor networks. Therefore, to explain affinities, and try to disentangle effects, we turn to regression analysis.

6. Model outline

In theory we have observations of affinities between all regions. But regions without patenting cannot have affinity to another region. We remove one such region, keeping $80 \times 81 = 6480$ observations.[20] A further issue is how to deal with local affinities. It seems possible that local affinities may be determined by partially different factors than those of interregional networks. In fact, after checking for problems of heteroskedasticity, the most efficient way to deal with this seemed to be to separate between interregional and local affinities.

Our theoretical discussion of inventor networks has highlighted a number of factors likely to affect affinities. Travel time distance is a natural explanatory variable. Extensive travel costs should reduce the incentives for inventor cooperation. There could also be differences in how small and large regions “react” to distance. On the one hand, we would expect inventors in larger regions in their search for invention partners, to have more spatially extended connections since the volume of their search efforts enables them to find their research partners both farther away, and therefore to be better equipped with complementary assets. On the other hand, if resources are to a higher extent to be found locally this means that larger regions may find little reasons to search far away from their own region. Size factors that should have a bearing on affinity include patents, population, educated workers, and private and university research. The full regression model is

$$\begin{aligned} A_{ij} = {} & \alpha_0 + \alpha_1 P_i + \alpha_2 P_j + \alpha_3 N_i + \alpha_4 N_j + \alpha_5 \,\mathrm{HQ}_i \\ & + \alpha_6 \,\mathrm{HQ}_j + \alpha_7 \,\overline{\mathrm{HQ}}_i + \alpha_8 \,\overline{\mathrm{HQ}}_j + \alpha_9 R_i + \alpha_{10} R_j \\ & + \alpha_{11} U_i + \alpha_{12} U_j + \alpha_{13} E_i + \alpha_{14} E_j + \alpha_{15}\, \mathrm{e}^{-\lambda t_{ij}} \\ & + \alpha_{16} N_i \,\mathrm{e}^{-\lambda t_{ij}} + \alpha_{17} \frac{N_i}{N_j} \mathrm{e}^{-\lambda t_{ij}} + \epsilon_{ij}, \end{aligned} \tag{4}$$

[19] Only those links showing the highest affinities could be shown because the links would otherwise be hard to distinguish.

[20] Note that observation zero is also a measure of affinity (or non-affinity in this case), and that affinities are measured in both directions between two nodes.

where N denotes population, P the patents, HQ the headquarters, $\overline{\mathrm{HQ}}$ the average size of headquarters, R the private R&D in man-years, U the university R&D in man-years, E are number of people with more than 2 years of university education, λ is a distance sensitivity parameter, and t_{ij} is the travel time between region i and j. For all our variables, i denotes the region where affinity originates and j denotes the region *to* which region i's affinity is measured.

Size variables in region j are expected to raise affinity as a general rule, since resources there should make them more attractive. However, for size variables in regions from where affinity originates, the effect on affinity may work in two ways. More resources in region i would, on the one hand, make it less likely that affinity is sought to any other region. This should therefore have a negative effect on affinity and can be described as a static effect. On the other hand, more resources in region i may influence affinity positively due to a "demand" effect, i.e. more cooperation with other regions is sought, and can hence be labeled a dynamic effect. Of these effects it seems likely that those more likely to be directly related to the network activity as such, such as private R&D, should be relatively more conducive to higher "demand" for networking and could therefore affect affinity positively. The same relationship seems likely for the number of patents in region i. The size variables U and E are probably more directly related to resources and could therefore affect affinity negatively. When it comes to headquarters, and their size, HQ_i and HQ_j is the number of companies with judicial belonging in i and j. $\overline{\mathrm{HQ}}$, is the average size of headquarters in a region. We expect that more headquarters in region i will *lower* affinity because there will be stronger centralization and monitoring of research activities to that region. Also, more headquarters in region j will most likely lower affinity, because researchers will then probably more likely move to headquarters there and not stay in region i. Average headquarter size is measured by the number of companies divided by the total number of employees of the region. The reasoning for this variable is similar to that of the number of headquarters. Bigger headquarters in i will lead to less affinity and bigger headquarters in j will also lead to smaller affinity. Generally, we expect time distance to influence interregional affinity negatively ($\alpha_{15} > 0$). The term $\frac{N_i}{N_j}\,\mathrm{e}^{-\lambda t_{ij}}$ of Eq. (4) is used to test the possibility that time distance may have different effects depending on the relative size of region i to that of region j. We expect that when region i is relatively larger than j, that they should be more sensitive to distance ($\alpha_{17} < 0$). Similarly, the term $N_i\,\mathrm{e}^{-\lambda t_{ij}}$ is included to test the possibility that for large regions i affinity could be more negatively affected by distance. The reason is that larger regions have better worked out transportation infrastructure and more resources to search and establish networks within the region.

Time distance, t_{ij}, has merited special consideration. It consists of weighted travel times between functional regions. Two types of travel time data have been used: (1) Road travel time data from The Swedish National Road Administration (1998). (2) Flight travel time from the Swedish Civil Aviation Administration (2003). For the flight time measure, it replaces road travel time whenever two regions are directly connected by air connections, given that it is faster than traveling by road. An assumption here is that inventors in neighboring regions do not consider it worth the time to go to a neighboring region and use its airport, since there are considerable time losses involved in flying from accessing airports. For road traveling times, we use the fact that each region consists of a number of municipalities, whereof we have road travel times for traveling between all Sweden's municipalities. Thus, a number of road travel times exist for each pair of regions. We use commuting as weights of these possibilities such that:

$$t_{ij}^{\mathrm{w}} = \frac{\sum_r \sum_s M_{rs} t_{rs}}{\sum_r \sum_s M_{rs}}, \quad r \in i, \quad s \in j, \tag{5}$$

where M_{rs} is the number of commuters between municipality r and s and t_{rs} its respective commuting time. Thus, t_{ij}^{w} is the most common commuting road traveltime between region i and j. In addition, a number of regions have only zeros in the observations on the number of commuters between the contained municipalities (mostly regions far from each other). Yet, they may have research networks. Then in the above formula t_{ij}^{w} will become zero. To avoid this happening, the average of commuting times between all municipalities in the two regions is used, which we write t_{ij}^{a}:

$$t_{ij}^{\mathrm{a}} = \frac{\sum_r \sum_s t_{rs}}{n_{ij}}, \quad r \in i, \quad s \in j, \tag{6}$$

where n_{ij} is the number of links between regions, i.e. the sum of the number of pair-wise combinations between the municipalities in them. The road traveling time between two regions i and j are then

$$t_{ij}^{\mathrm{r}} = \begin{cases} t_{ij}^{\mathrm{w}} & \text{if } t_{ij}^{\mathrm{w}} > 0, \\ t_{ij}^{\mathrm{a}} & \text{if } t_{ij}^{\mathrm{w}} = 0. \end{cases} \tag{7}$$

The flight times between all functional regions were collected from the web-pages of the Swedish Civil Aviation Administration (2003). If more airports were available in a region, the shortest flight time was used. Finally, the

Table 3
Variable descriptives

Variable	Description	N	Min.	Max.	Mean	S.D.
A_{ij}	Affinity; conditional affinity between region *i* and *j*	6480	−343.5122	19718.49	−1.3315	303.8793
N	Population 1000s in *i*, 1998	81	3.281	1829.74	109.3126	232.6577
P	Patent applications 1000s in *i*	81	0.2857	9324.0246	330.2399	1149.2712
HQ	Number of companies 1000s in *i*, 1996	81	0.117	72.097	3.2814	8.7408
$\overline{\text{HQ}}$	Average size of HQs: $\text{EMPL}_i/\text{HQ}_i$, 1996	81	2.5176	11.0367	5.6973	1.7976
R	1000 man-years in business R&D in *i*, 1995	81	0	14.5371	0.5132	1.8927
U	1000 man-years in university R&D in *i*, 1995/1996	81	0	4.7830	0.2090	0.8026
E	1000 people with university education >2 years in 1996	81	0.176	323.628	12.5759	38.7378
λ	Time sensitivity parameter: $\lambda=0.017$ if $i\neq j$, $\lambda=0.1$ if $i=j$	6480	0.017	0.1	0.018	0.0092
t_{ij}	Minimum of road and flight-travel time in minutes	6480	8.5913	1126.9	384.0013	259.8919
$e^{-\lambda t_{ij}}$	Distance-weighted parameter	6480	0	0.7733	0.0581	0.1187
$N_i\, e^{-\lambda t_{ij}}$	Interaction term: pop. size and time distance	6480	1.2039E−007	1098.7508	10.4886	57.4301
$\frac{N_i}{N_{jk}}\, e^{-\lambda t_{ij}}$	Interaction term: relative pop. size and time distance	6480	2.4049E−010	53.7054	0.2095	1.4026

Data sources are EPO for patent applications, whereas population, number of headquarters, headquarter average size, business R&D and university R&D have been compiled based on various statistical databases from Statistics Sweden.

shortest time of road and flight was used as our measure of the time involved in traveling between two regions in Sweden:

$$t_{ij} = \min\{t_{ij}^{\mathrm{r}}, t_{ij}^{\mathrm{f}}\}. \tag{8}$$

On the other hand it is not unproblematic to mix road and flight travel times, since flying is usually more expensive, and hence any decision to cooperate is not on quite the same footing. The following regressions were therefore run also without flight times, but without qualitative effects on our results. For brevity, we therefore only report the results using definition (8). The exponential term $e^{-\lambda t_{ij}}$ is used to describe the particular response of commuting to time distance extensively reported on by e.g. Ohlsson (2002) and confirmed in many studies. The λ -values have the interpretation of sensitivity to time distance. It takes one of two values: $\lambda=0.1$ if region *i* and region *j* are the same and $\lambda=0.017$ if they differ. These values are based on empirical estimates from Åberg (2000) and Hugosson (2001). These λ-values have also been used by Andersson and Ejermo (2004, 2005), to spatially discount accessibility to knowledge resources. The higher λ-value for intraregional time distance reflects the higher propensity to cooperate with inventors within the region. Table 3 gives a brief description of our variables and reports some summary statistics.

As stated, several variables are size variables. It is therefore informative to see the extent of intercorrelation of the variables to judge the sincerity of multicollinearity. Table 4 shows the correlation matrix of relevant variables.

As expected, there are signs of strong multicollinearity between many of the variables. If all variables are included in a regression, we would therefore expect some

Table 4
Pairwise correlation matrix of variables

Variable	N_i	P_i	HQ_i	$\overline{\text{HQ}}_i$	R_i	U_i	E_i
N_i	1						
P_i	0.983	1					
HQ_i	0.992	0.992	1				
$\overline{\text{HQ}}_i$	0.322	0.302	0.302	1			
R_i	0.971	0.975	0.976	0.301	1		
U_i	0.839	0.839	0.818	0.142	0.818	1	
E_i	0.987	0.993	0.997	0.288	0.973	0.838	1

of them to turn out insignificant. We therefore run variants of the main regression, to study the stability of coefficients. Likely candidates for exclusion are variables which are highly correlated and are not significant in the full model where all variables are included. In addition, when we started running the regressions, we discovered severe problems of heteroskedasticity. One source for this has already been reported on. Initially we mixed local affinities (i.e. "intraregional") with interregional ones. Heteroskedasticity results if the variance in each of these groups is different. When separating the two groups heteroskedasticity was substantially but not completely reduced. Some intuitive reasoning behind the source for this heteroskedasticity led us to how to do something about it. Clearly, regions with very little patenting activity have larger variance in their affinity towards other regions, since the few regions to which they actually have affinity are more "random".[21] An analysis of the residuals confirmed this. It was found that a weighted least squares regression using P_i^w with w with a value of

[21] This happens as a result of the discrete nature of affinities.

around 0.3 removed almost all heteroskedasticity.[22] We find the results of the interregional networks regressions in Table 5. The full model was run as Model 1. However, from the policy maker's perspective interest rests in variables which can be affected directly. N_i, N_j, P_i, P_j, HQ_i, and HQ_j do not belong to this category, and can be considered as control variables. In addition to the full model, we consider four smaller models where combinations of the control variables are excluded.

Model 2 excludes population:

$$\begin{aligned}A_{ij} = {} & \beta_0 + \beta_1 P_i + \beta_2 P_j + \beta_3\,\mathrm{HQ}_i + \beta_4\,\mathrm{HQ}_j \\ & + \beta_5\,\overline{\mathrm{HQ}}_i + \beta_6\,\overline{\mathrm{HQ}}_j + \beta_7 R_i + \beta_8 R_j + \beta_9 U_i \\ & + \beta_{10} U_j + \beta_{11} E_i + \beta_{12} E_j + \beta_{13}\,\mathrm{e}^{-\lambda t_{ij}} \\ & + \beta_{14} N_i\,\mathrm{e}^{-\lambda t_{ij}} + \beta_{15}\frac{N_i}{N_j}\,\mathrm{e}^{-\lambda t_{ij}} + \epsilon_{ij}.\end{aligned}$$

Model 3 excludes population and patents:

$$\begin{aligned}A_{ij} = {} & \gamma_0 + \gamma_1\,\mathrm{HQ}_i + \gamma_2\,\mathrm{HQ}_j + \gamma_3\,\overline{\mathrm{HQ}}_i + \gamma_4\,\overline{\mathrm{HQ}}_j \\ & + \gamma_5 R_i + \gamma_6 R_j + \gamma_7 U_i + \gamma_8 U_j + \gamma_9 E_i + \gamma_{10} E_j \\ & + \gamma_{11}\,\mathrm{e}^{-\lambda t_{ij}} + \gamma_{12} N_i\,\mathrm{e}^{-\lambda t_{ij}} + \gamma_{13}\frac{N_i}{N_j}\,\mathrm{e}^{-\lambda t_{ij}} + \zeta_{ij}.\end{aligned}$$

Model 4 excludes population and number of headquarters (but we keep their average size)

$$\begin{aligned}A_{ij} = {} & \delta_0 + \delta_1 P_i + \delta_2 P_j + \delta_3\,\overline{\mathrm{HQ}}_i + \delta_4\,\overline{\mathrm{HQ}}_j + \delta_5 R_i \\ & + \delta_6 R_j + \delta_7 U_i + \delta_8 U_j + \delta_9 E_i + \delta_{10} E_j \\ & + \delta_{11}\,\mathrm{e}^{-\lambda t_{ij}} + \delta_{12} N_i\,\mathrm{e}^{-\lambda t_{ij}} + \delta_{13}\frac{N_i}{N_j}\,\mathrm{e}^{-\lambda t_{ij}} + \vartheta_{ij},\end{aligned}$$

and Model 5 excludes population and R&D:

$$\begin{aligned}A_{ij} = {} & \theta_0 + \theta_1\,\mathrm{HQ}_i + \theta_2\,\mathrm{HQ}_j + \theta_3\,\overline{\mathrm{HQ}}_i + \theta_4\,\overline{\mathrm{HQ}}_j \\ & + \theta_5 U_i + \theta_6 U_j + \theta_7 E_i + \theta_8 E_j + \theta_9\,\mathrm{e}^{-\lambda t_{ij}} \\ & + \theta_{10} N_i\,\mathrm{e}^{-\lambda t_{ij}} + \theta_{11}\frac{N_i}{N_j}\,\mathrm{e}^{-\lambda t_{ij}} + \upsilon_{ij}.\end{aligned}$$

Many results appear to be robust across specifications. In particular, for almost all results, coefficients for region j are much higher, seemingly validating the proposition made that size variables in j should have a more positive effect than in i. This seems true in particular for variables P, R, and U. Affinity is positively affected when more of these resources exist in region j. For P and U all the results are significant on the 1% level. For R it is not significant in Model 4, significant on the 10% level in 2 cases, and on the 1% level in one case. The population variable is negative and highly significant in Model 1, the only model where it is included. Because of strong collinearity with the other variables we do not think excluding this variable poses any major problem. Patents in region i had a negative and strongly significant effect on affinity. This means that the "supply" effect which we discussed above, seems to be stronger. That is, when more patenting occurs in region i, affinity seems to become lower because more resources are available within the region rather than having to be sought outside the region. We will examine whether this pattern prevails when we consider only local affinity. A similar result was also found for R&D. This variable affected affinity negatively when more R&D-resources were available in region i and had high significance levels.[23] Also for university R&D the supply effect dominates, since affinity is negatively affected in Models 3–5 from more university R&D in region i, whereas coefficients are not significant in Models 1 and 2. The education variable shows little coherence judging from its effects. For region i its effect is negative in two cases and positive in one. For region j though, the effect is negative and significant (on varying levels) in three cases. A problem with this variable is that it captures all higher education and not necessarily that relevant for inventor networks. A different kind of size variable is that of headquarters. Similar to the education variable this variable carries some noise. The intention of this variable is to capture R&D-monitoring effects, but most companies are not involved in inventor networks and we could not presently account for this. This variable showed only limited stability. For region j there does nonetheless seem to be some indication that monitoring may reduce affinity as we hypothesized, but the coefficients are only significant in about half of the cases (including average size of headquarters), and for region i the effect even goes in the opposite direction in one case (Model 2). Finally, time distance has a very strong negative effect on affinity and is highly significant in all five models where we include this variable. Hence, we can strongly support the hypothesis that distance matters, since coefficients are highly significant. For regions i which are large irrespective of the size of regions j, this effect furthermore seems to be stronger; they have even smaller affinity with distance. But for regions that are *rel-*

[22] The value of w for each regression was chosen as to minimize heteroskedasticity as judged from a Breusch–Pagan heteroskedasticity test. The value used in actual practice varied between 0.29 and 0.32, depending on model.

[23] Only for Model 4 was this coefficient only significant on the 10% level.

Table 5
Estimation results, interregional affinity and aggregate models

Model	Constant	P_i	P_j	N_i	N_j	HQ_i	HQ_j
1	−0.5965 (0.17)	−0.0477 (12.54)***	0.0317 (6.45)***	−0.0921 (3.98)***	−0.0604 (2.12)**	6.1811 (4.77)***	0.2265 (0.14)
2	−0.6856 (0.19)	−0.0497 (13.01)***	0.0343 (6.94)***			2.2410 (2.66)***	−2.5588 (2.46)**
3	9.9873 (2.75)***					−1.8826 (2.31)**	−1.0693 (1.00)
4	0.9047 (0.26)	−0.0460 (12.91)***	0.0318 (6.57)***				
5	0.7669 (0.22)	−0.0500 (13.08)***	0.0363 (7.55)***			0.9413 (1.31)	−2.0146 (2.03)**

Model	$\overline{HQ}_i$	$\overline{HQ}_j$	R_j	R_j	U_i	U_j
1	0.3726 (0.85)	−0.6156 (1.60)	−0.0033 (3.07)***	0.0026 (1.68)*	0.0023 (1.54)	0.0144 (7.28)***
2	0.0962 (0.22)	−0.8716 (2.33)**	−0.0032 (2.90)***	0.0027 (1.74)*	−0.0015 (1.26)	0.0124 (7.78)***
3	−1.6102 (3.59)***	−0.5853 (1.51)	−0.0034 (3.00)***	0.0057 (3.55)***	−0.0075 (6.72)***	0.0159 (9.79)***
4	−0.0701 (0.16)	−0.9313 (2.49)**	−0.0016 (1.75)*	0.0016 (1.05)	−0.0029 (2.78)***	0.0140 (9.65)***
5	−0.0587 (0.13)	−0.8559 (2.29)**			−0.0024 (2.07)**	0.0127 (8.04)***

Model	E_i	E_j	$e^{-\lambda t_{ij}}$	$N_i\, e^{-\lambda t_{ij}}$	$(N_i/N_j)\, e^{-\lambda t_{ij}}$	n	R^2
1	−0.4182 (2.09)**	−0.5946 (2.26)**	16.6767 (2.89)***	0.2697 (27.84)***	−5.8678 (19.89)***	6400	0.69
2	0.0497 (0.30)	−0.3584 (1.52)	15.8096 (2.69)***	0.2687 (28.02)***	−5.7649 (19.71)***	6400	0.69
3	−0.3620 (2.19)**	0.1329 (0.56)	17.8415 (2.90)***	0.2622 (27.05)***	−5.5241 (18.78)***	6400	0.68
4	0.3972 (4.00)***	−0.8312 (6.05)***	15.8889 (2.71)***	0.2659 (27.79)***	−5.7332 (19.67)***	6400	0.69
5	0.2141 (1.39)	−0.4151 (1.77)*	15.5776 (2.65)***	0.2687 (28.00)***	−5.7400 (19.62)***	6400	0.69

Absolute value of t-statistics are in parentheses.
* 10% significance level marked.
** 5% significance level marked.
*** 1% significance level marked.

atively larger, the distance effect is actually smaller on affinity. Reversing this reasoning, while distance always affects affinity negatively, when region i is smaller relative to region j, affinities is more negatively affected by distance. Phrasing this in relation to our theoretical discussion it means that relatively smaller regions are severely constrained by their higher search costs and are more hindered by distance.

7. Local affinities

When we turn to examination of local affinities it is no longer possible to use all variables as outlined by Model 1, since regions i and j are now the same and perfect multicollinearity would arise between certain variables. Hence, we rewrite the Models 1–5 as 1′–5′ with only one of the pairwise variables included for each model. Instead the following models are used.

- Model 1′

$$A_{ii} = \hat{\alpha}_0 + \hat{\alpha}_1 P + \hat{\alpha}_2 N + \hat{\alpha}_3 \,\mathrm{HQ} + \hat{\alpha}_4 \overline{\mathrm{HQ}} + \hat{\alpha}_5 R + \hat{\alpha}_6 U + \hat{\alpha}_7 E + \hat{\alpha}_8 \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\alpha}_9 N \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\epsilon}_{ii}.$$

- Model 2′

$$A_{ii} = \hat{\beta}_0 + \hat{\beta}_1 P + \hat{\beta}_2 \,\mathrm{HQ} + \hat{\beta}_3 \overline{\mathrm{HQ}} + \hat{\beta}_4 R + \hat{\beta}_5 U + \hat{\beta}_6 E + \hat{\beta}_7 \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\beta}_8 N \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\epsilon}_{ii}.$$

- Model 3′

$$A_{ii} = \hat{\gamma}_0 + \hat{\gamma}_1 \,\mathrm{HQ} + \hat{\gamma}_2 \overline{\mathrm{HQ}} + \hat{\gamma}_3 R + \hat{\gamma}_4 U + \hat{\gamma}_5 E + \hat{\gamma}_6 \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\gamma}_7 N \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\zeta}_{ii}.$$

- Model 4′

$$A_{ii} = \hat{\delta}_0 + \hat{\delta}_1 P + \hat{\delta}_2 \overline{\mathrm{HQ}} + \hat{\delta}_3 R + \hat{\delta}_4 U + \hat{\delta}_5 E + \hat{\delta}_6 \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\delta}_7 N \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\vartheta}_{ii}.$$

- Model 5′

$$A_{ii} = \hat{\theta}_0 + \hat{\theta}_1 \,\mathrm{HQ} + \hat{\theta}_2 \overline{\mathrm{HQ}} + \hat{\theta}_3 U + \hat{\theta}_4 E + \hat{\theta}_5 \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\theta}_6 N \,\mathrm{e}^{-\lambda t_{ii}} + \hat{\upsilon}_{ii}.$$

The results are shown in Table 6.

We find that more patenting in the region seems to enhance local affinity significantly. Thus, one may indeed speak of a local supply effect. When more inventive activity goes on locally, the region turns inward to find research partners. Regional R&D also seems to have this effect, since the coefficient is positive and highly significant in Model 1′ and significant on the 10% level in Models 2′ and 3′. Higher population tends to keep affinities local in Model 1′.[24] The effects of number of headquarters and their average size show no stability across regression models. Number of headquarters has a negative and significant effect only in Model 1, but this may probably be attributed the multicollinearity effect, since the coefficient changes sign, seemingly randomly in Models 2′–4′. Average headquarter size is positive and significant only in Model 3′, whereas the coefficient sign again seems unstable among the other models. University R&D has a positive and significant sign in Model 3′ but is negative and significant in Model 1′. Number of highly educated has a negative effect on local affinity in Model 4′ and is insignificant in the other models. Quite importantly, time distance also shows no coherent pattern in terms of its effect on affinity. This means that the strong result we obtained from interregional inventor network does not carry over to the local level. There is however a very intuitive explanation for this result. The unit of analysis is the local labor market region which is *defined* by ease of interaction within it. This means that the average time distance for traveling within it may not be a limiting factor for interaction. Thus, the only remaining robust result is that local patenting affects affinity positively. What could then explain local affinity? Likely candidates could probably be found among organizational characteristics and company structures, but needs further exploration.

7.1. Division by technology

In view of earlier discussions, we have reasoned that properties of technologies could influence our results. We therefore specify the models based on the 30 patent technologies listed before, and now run regressions using the interregional relationships. Since we have reasoned that population is a catch-all variable for many size-effects, we run one model where we include it, one where we exclude it, and a third where we also exclude number of headquarters. We call these estimated models T1–T3, specified as follows. Model T1 is

$$A_{ij,k} = \rho_0 + \rho_1 P_{i,k} + \rho_2 P_{j,k} + \rho_3 N_i + \rho_4 N_j + \rho_5 \,\mathrm{HQ}_i + \rho_6 \,\mathrm{HQ}_j + \rho_7 \overline{\mathrm{HQ}}_i + \rho_8 \overline{\mathrm{HQ}}_j + \rho_9 R_i + \rho_{10} R_j + \rho_{11} U_i + \rho_{12} U_j + \rho_{13} E_i + \rho_{14} E_j + \rho_{13} \,\mathrm{e}^{-\lambda t_{ij}} + \rho_{14} N_i \,\mathrm{e}^{-\lambda t_{ij}} + \rho_{15} \frac{N_i}{N_j} \,\mathrm{e}^{-\lambda t_{ij}} + \mu_{ij},$$

[24] This result mirrors what we found in Fig. 2 and the regression between local affinity and population reported on in Section 5.

Table 6
Estimation results, intraregional/local affinity and aggregate models

Model	Constant	P_i	N_i	$\mathrm{HQ_i}$	$\overline{\mathrm{HQ}}_i$	R_i
1′	45.8637 (0.14)	3.5001 (7.35)***	16.8208 (4.00)***	−575.2820 (3.70)***	−46.8371 (0.77)	0.4366 (3.33)***
2′	141.8465 (0.51)	3.0958 (5.90)***		−222.8311 (1.58)	6.1267 (0.11)	0.2912 (1.86)*
3′	−468.4270 (1.08)			−194.0505 (1.08)	154.6798 (2.04)**	0.3145 (1.77)*
4′	36.1744 (0.13)	3.0386 (5.74)***			−0.1180 (0.00)	0.2453 (1.58)
5′	74.3043 (0.23)	3.2666 (6.09)***		−155.2401 (1.10)	22.7259 (0.37)	

Model	U_i	E_i	$e^{-\lambda t_{ij}}$	$N_i\, e^{-\lambda t_{ij}}$	n	R^2
1′	−0.4523 (2.30)**	35.0802 (1.49)	1012.4688 (0.78)	−33.9181 (2.41)**	80	0.98
2′	0.1128 (0.70)	−0.6655 (0.03)	−322.2925 (0.28)	4.9985 (0.48)	80	0.97
3′	0.4217 (2.32)**	36.2666 (1.32)	−3509.9248 (2.19)**	30.1163 (2.30)**	80	0.97
4′	0.2220 (1.50)	−31.9959 (2.16)**	264.9963 (0.24)	−5.2227 (0.63)	80	0.97
5′	0.1736 (1.10)	−15.2227 (0.64)	−881.7590 (0.69)	9.2776 (0.85)	80	0.97

Absolute value of t-statistics are in parentheses.
* 10% significance level marked.
** 5% significance level marked.
*** 1% significance level marked.

where $k=1, \ldots, 30$ stands for the specific patent technology in question. Model T2 is

$$\begin{aligned} A_{ij,k} &= \omega_0 + \omega_1 P_{i,k} + \omega_2 P_{j,k} + \omega_3\,\mathrm{HQ}_i + \omega_4\,\mathrm{HQ}_j \\ &\quad + \omega_5\,\overline{\mathrm{HQ}}_i + \omega_6\,\overline{\mathrm{HQ}}_j + \omega_7 R_i + \omega_8 R_j + \omega_9 U_i \\ &\quad + \omega_{10} U_j + \omega_{11} E_i + \omega_{12} E_j + \omega_{13}\, e^{-\lambda t_{ij}} \\ &\quad + \omega_{14} N_i\, e^{-\lambda t_{ij}} + \omega_{15} \frac{N_i}{N_j}\, e^{-\lambda t_{ij}} + \varsigma_{ij}, \end{aligned}$$

and Model T3 is specified as

$$\begin{aligned} A_{ij} &= \tau_0 + \tau_1 P_{i,k} + \tau_2 P_{j,k} + \tau_3\,\mathrm{HQ}_i + \tau_4\,\mathrm{HQ}_j \\ &\quad + \tau_5\,\overline{\mathrm{HQ}}_i + \tau_6\,\overline{\mathrm{HQ}}_j + \tau_7 R_i + \tau_8 R_j + \tau_9 U_i \\ &\quad + \tau_{10} U_j + \tau_{11} E_i + \tau_{12} E_j + \tau_{13}\, e^{-\lambda t_{ij}} \\ &\quad + \tau_{14} N_i\, e^{-\lambda t_{ij}} + \tau_{15} \frac{N_i}{N_j}\, e^{-\lambda t_{ij}} + \varsigma_{ij}. \end{aligned}$$

Thus, we run 30×3 regressions. Due to continuing problems of heteroskedasticity, and that the source of this could not be pinned down to one variable as before, we ran a procedure in STATA (rreg) that performs the regressions iteratively in order to deal with heteroskedasticity.[25] Table 7 summarizes the number of positive and negative values that are significant on at least the 10% level for each parameter and all three models.[26]

The separate technology regressions show feature regularities and irregularities. A general observation is that changing things in region j, the region to which j has affinity, does not have statistically significant effects for affinity. What matters for technological affinity is what is going on in the region where affinity originates. Some results give us an indication on what is important in region i. We should also bear in mind differences resulting from the exclusion of the population variable as in Model T2, and the exclusion of number of headquarters in T3. The number of patent applications in region i has a consistently negative effect on affinity. This echoes the result we obtained from the aggregate regressions.

Table 7
Count of the number of significant (≤10% level) coefficients, with respective sign for 30 different patent technologies

Variable	Model T1		Model T2		Model T3	
	+	−	+	−	+	−
$P_{i,j}$	0	30	0	27	0	27
$P_{i,k}$	0	0	0	0	0	0
N_i	13	17	–	–	–	–
N_j	0	0	–	–	–	–
HQ_i	17	13	15	12	–	–
HQ_j	0	0	0	0	–	–
$\overline{\mathrm{HQ}}_i$	19	10	19	8	18	8
$\overline{\mathrm{HQ}}_j$	0	0	0	0	1	0
R_i	13	17	11	13	13	12
R_j	0	0	0	0	0	1
U_i	12	16	11	15	8	18
U_j	0	0	0	0	0	0
$e^{-\lambda t_{ij}}$	10	6	4	4	4	6
$N_i\, e^{-\lambda t_{ij}}$	0	0	3	5	6	4
$\frac{N_i}{N_j}\, e^{-\lambda t_{ij}}$	12	15	4	4	5	5

[25] The first step of this procedure is to eliminate gross outliers. Second, weights are computed iteratively in a way that reduces the influence of leverage observations using Huber and bi-weight procedures.
[26] The full estimation results by technology can be obtained upon request from the authors.

More patenting activity in region *i* tends to make regions turn inward for research partners. Headquarters, when included, have somewhat more positive than negative effects on affinity. Average headquarter size has similar effects but are more frequently positive. R&D shows many cases of both positive and negative sign. Here it seems clear that more information about the nature of R&D could perhaps provide a clearer picture. University R&D, on the other hand, tends to unambiguously favor local inventor networks, or less affinity to other regions when it is present in region *i*. Number of educated people also is problematic in the sense of consistent patterns. Another less clear effect is with time distance. Whereas time distance (the term $e^{-\lambda t_{ij}}$) has a predominantly negative influence on affinity in Models T1 and T2, its effect turns slightly in favor of a positive effect in Model T3. The other time distance effects also seem to be hard to attach consistent meaning. A quick look at rankings of distance sensitivity across technologies reveals that Control technology consistently scores among the *least* distance sensitive technologies. On the other end of the scale, Electrical engineering and Machine tools are technologies where affinity is consistently most negatively affected by distance. It seems clear that better data, especially such that give more detailed information on education, business R&D, and university R&D that can be related to technologies could shed better light on the relationships on the technology-level.

8. Summary and conclusions

This paper set out to explain the structure and strength of interregional inventor networks as measured by affinity between inventors coauthoring patents across Swedish regions. We have found that affinities in general are strongly affected by travel time distance. Affinities extend more often to regions which have high patenting, when they have high R&D levels, and to those with more university R&D, in line with our hypotheses. Less clear effects were obtained for education and headquarter variables, but these are more 'noisy' from construction and likely to be less accurate in terms of their inventor network prediction power. For regions who extend affinity, more resources, it was reasoned, could have both the effect that there would be more 'demand' for networking with other regions, but they could also display higher local affinity. This latter effect seemed to be clearly dominating. Regions with more patenting, business R&D, and university R&D have fewer outgoing affinities and instead tend to turn 'inward', at least in a relative sense. With respect to technology, some effects related to the starting region's assets seemed to remain, but the outcome of results were largely unclear and seem to indicate that better material, i.e. on a technology level, is needed.

What policy conclusions can be drawn? First of all, distance matters. Distance matters for the way that R&D, and R&D-networks are configured. Secondly, there is a role for university R&D. It seems unlikely that networks change overnight when more university R&D is put in a region, but its location seems to influence how networks of inventors operate. Third, if a region conducts more R&D-related activities (patenting, business R&D, and university R&D) relatively more 'inward' or local networking occurs.

Our analysis has not been done on a company structure basis. Of course, the location of headquarters and historical reasons for locating in certain regions, bring about path dependence that should be important to take into consideration. That is, the story may also be one of how past location affects the direction and development of inventor networks. We think this is an important future research issue that requires more elaborated databases with detailed information on affiliation and ability to follow individual inventors over time to be able to be addressed.

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