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Spatial Inventor Networks As Studied by Patent Coinventorship[1]

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Spatial Inventor Networks as Studied by Patent Coinventorship

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Abstract

We study the structure of the spatial inventor networks in Sweden by examining the residence of inventors and coinventors in Swedish patent applications to the European Patent Office. Several factors are found to influence the spatial *affinity*. We find that spatial affinity is strongly influenced by the general size of the nodes, as measured by population. In addition, affinities are strongly influenced by distance, but different technologies responded differently to distance. The most distance sensitive technology, i.e. with the highest agglomeration of co-inventors, was almost three times as sensitive to distance as the least sensitive. Interestingly, "Information technology" was the least distance sensitive technology, which would be in line with predictions of "the death of distance". Higher affinity was also registered for many technologies when more university researchers were employed in one of the regions. Hence, a technology division is appropriate for understanding the span of innovation networks over regions, and how these could develop in response to policy initiatives.

Key words: Inventor networks, localization, patents, Sweden, affinity
JEL classification: O31, O32, R12

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1 Introduction

A fundamental observation of innovations is that they are 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 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 (2003). This is in line with other parts of the literature stressing the importance of labour 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 map the networks of inventors in Sweden and try to illuminate factors that may influence their structure. To this end we use patent data.

Each patent application leaves a paper trail in the form of a patent document.

Inventors contributing to a patent, along with their adresses are listed in the databases of the European Patent Office (EPO). Patent applications containing at least one Swedish inventor have been mapped, along with the location of co-inventors using the NUTEK (1998) aggregation of municipalities into 81 functional regions. A patent's "home region" is the region in which the first Swedish inventor in the list of inventors resides. This paper tries to assess factors explaining the structure of inventor networks. The process by which this is done can be illustrated as follows. Consider all patents with a specific region as home region. Then count the number of *co-inventors* to patent applications of the home-region, residing in a certain region, and divide this number by *all* the inventors. We then get a measure of how connected the second region is to the home-region. This measure is called *affinity* in the paper. Affinities can therefore be interpreted as probabilities that inventor networks extend across distinct regions.

With this information at hand, we ask: What determines the affinity of regions? That is, how do spatial frictions and different regional characteristics affect the likelihood for cooperation in inventor networks?[1] These questions are answered in the aggregate for all patents and for different patent technologies. Patents are divided into 30 technology groups, and region affinities are examined on a technology-level. There are several reasons why a technology division makes sense. Compared to the small existing literature on patent coinventorship, a systematic technology division has not been conducted before. From a more theoretical perspective, economists are increasingly recognizing that knowledge has a tacit dimension, a concept introduced by Polanyi (1966). The term tacit knowledge is used to refer to knowledge that is difficult and costly to codify (Nelson and Winter, 1982), and hence tend to remain embodied in people (von Hippel, 1994). This kind of knowledge is contextual, in the sense that while some people may find it trivial and easy to articulate, others do not (Cowan et al., 2000). Epistemic communities of science develop a language of their own, reinforcing tacitness, not only in the sense that it is difficult to articulate (Dosi, 1988), but also because hands-on learning-by-doing, and learning-by-observing, is needed in these communities. This makes it inefficient

[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.

for such communities or teams, to be separated by large geographic distances. Many authors have observed that tacitness is a fundamental property in advanced communities of science, such as teams for nuclear bomb development, or DNA engineering (Collins, 1974, Gorman, 2002). Thus, knowledge transfer in these communities cannot merely be reduced into transfer of codified messages (Callon, 1995). We may expect that tacitness, and hence the need for proximity, is higher for technologies which are more deeply rooted in science. Technology can be defined as "the application of new knowledge learned through science to some practical problem." (Audretsch et al., 2002). However, as will be seen, it is not an easy task to infer the degree of scientific sophistication from merely observing the names of patent technologies. Such inference must therefore be casual and interpreted with care. In addition, a technology division is appropriate because the scientific framework upon which technologies are based bring about different technological opportunities (Dosi, 1988). Different technology areas have different propensities to patent (Scherer, 1983) also because the effectiveness of patenting is viewed differently. The organization of knowledge, "optimal" inventor group sizes, and hence the extent of cooperation within inventor networks, and so on, is also likely to differ depending on technology.

In principle most researchers are connected directly or indirectly to other researchers. Thus network theory is called upon to provide a framework within which an innovation network 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 to test for affinity, 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 causes of affinity. It is in this context 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 within both the originating region and the co-operating regions may influence affinity. 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 Swedish patent inventor networks, and our data material. Section 5 states our hypotheses about the inventor networks and examines them using regression analysis. The material is analysed both in the aggregate and over technologies. Section 6 concludes.

2 Network Theory

2.1 Introduction

The concepts of network and networking have gained considerable popularity in innovation studies during the two last decades.[2] The present section outlines some fundamental elements of an emerging theory of innovation networks.[3] A basic assumption is that a market economy is organised by means of different links and couplings between economic agents, 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 characterised 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.[4] (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

[2] A network consists of at least two nodes and at least one link.
[3] The discussion in this section is inspired by in particular Johansson (1995).
[4] In the second case we say that the network has a hierarchical character.

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 networks, firms and economic agents operating within firms or other organisations engaged in innovative activities. A basic presupposition is that firms and organisations have internal networks for communication and for co-ordination of production and other activities. 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 organisations are coherent.

2.3 The Need for Complementary Assets

Introducing new innovations into the market place is a complex task, 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 an established link. Hence, the dynamics of innovation networks are strongly related to competence building and knowledge creation processes in the economy.

The reason why innovation networks are necessary and important is that a market economy is typically characterised by incomplete and scattered information. No single individual or node can solve all problems. Thus, in a market economy, problem solving, i.e. the generation of innovations, is the result of improvements made by various configurations of individual actors, i.e. innovation 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 in the overall economy, and it requires the development of links and co-operation between different actors, also outside existing institutional channels.

Innovation processes are based on the integration of various pieces of knowledge possessed by various economic actors within an innovation 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 innovations implies an intense process of interaction (Nonaka and Konno, 1998), which is characterised 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, innovation 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 different competencies are not static, but rather in continuous evolution. External exchanges feed this evolution, but each actor (node) within an innovation 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

Attached to the internal networks of firms and organisations one can observe links that extend beyond the boundaries of the organisation. Such links connect various economic units to each other. To explain such couplings we have to make references to transaction cost theory and the theory of economic contracts. The interaction between economic agents 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 innovations, 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 innovation links/innovation 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 innovation networks, since they govern and co-ordinate the relations between nodes, and thus reduce the transaction costs between them.

The links are analysed 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). Transaction costs 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 standardisation of interactions. However, this is rendered more difficult within innovation networks since innovations are per definition un-standardised.

Our major concern here is interactions between economic agents within innovation networks for the purpose of generating innovations. These networks are generally characterised by durability and sunk cost features. They are motivated by needs to reduce uncertainties and transaction costs. The ultimate form of an innovation link is an ownership link. In this way the interaction within an innovation network is internalised within the same firm. A firm as a whole is in this perspective an innovation network that has been integrated to one organisation. All such processes of formation, remoulding and decomposition of firms are essential parts of the evolution of the economy's innovation networks based on self-organisation principles.

The above discussion focuses on co-operation links, which are durable and have capital properties. Each such link is an innovation link and a system of connected innovation links form an innovation network. According to the theoretical arguments put forward above, we shall expect that co-operation on innovation links between economic units or between different parts of the same firm are frequent or generic phenomena. Such an innovation link is shared as a joint property between two parties and the same prevails for an innovation network that contains more than two parties. 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, innovation links and innovation networks can be made self-reinforcing by the mutual interests of the coupled parties.

The capital properties of an innovation link or an innovation network obtain as a consequence of link- or network-specific investments. When two or more parties decide to establish a joint innovation 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, i.e. each party would lose by leaving the network.

Recognising that innovations are the result of novelty by combination (Weitzmann, 1998, Olsson, 2000) we may draw some general conclusions regarding innovation networks. The principle of novelty by combination implies that expanding an innovation network by bringing in new competencies increases the chances of generating innovations. Thus, large innovation networks should *ceteris paribus* be more productive in terms of innovations than small innovation networks. For network technologies, Metcalfe's law states that the utility increases with the number of users, such as telephones or the internet. However, this need not necessarily be the case in the current situation. The potential economic value of an economic network and its innovative capacity increases the more individuals, institutions and organisations participate in an economic 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 innovation network implies that the co-ordination costs may increase rapidly.[5] This implies that there is an optimal size of innovation networks. As the general conditions for generating innovations differ between different fields, we shall expect the

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

optimal size of innovation networks to differ between different fields.

The appropriability problem may also limit the size of innovation 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 Networks

Once an innovation network has been established, new ex post reasons to keep it intact arise because of sunk cost conditions. Often the members of an innovation 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 innovation 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 innovation networks, or that new members never enter innovation networks, i.e. that innovation networks get new nodes. Furthermore, the relationships between the nodes in an innovation network change over time. This process of adaptation and co-evolution of the relationships between nodes in an innovation network may be defined as a process of learning and of knowledge accumulation. The initial cohesive force of an innovation network is often the result of an investment calculation. All parties involved in setting up an innovation network need to invest in special equipment, procedures and arrangements that are directly motivated to make the network function properly. This includes special training of personnel.

Our discussion shows that the existence of innovation networks brings rigidities into innovation processes. It creates structure in the "innovation market". Moreover, it strongly affects the dynamics of market competition. Competition does not disappear although a strong frictional element has been identified. In this context we may just add that scientific revolutions and structural changes in the market place have the capacity to bring about removal of old innovation networks and replace them with new innovation networks.

Given that innovations are the result of novelty by combination, innovations can be seen as the result of adaptive search and learning processes, which lead to new combinations of the existing knowledge in an innovation network. An innovation occurs when the joint knowledge impulses or signals between the different nodes are not only compatible with the innovation network and its mission and goals, but also overcome a certain threshold of intensity. This allows the innovation 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 innovation.

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 innovation network (Steinmuller, 2000). In particular, accessibility between the nodes in an innovation 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 innovation network, since such knowledge helps to identify useful forms of complementarities in the relations between the different nodes in the innovation 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 Role for Spatial Conditions

Up till now we have treated the innovation networks as non-spatial entities. However, innovation networks are spatial configurations where each node has its specific geographic location. Thus, the interaction between the different nodes in an innovation 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 innovation networks differ between functional regions. Generally speaking it should in principle be much easier to find the competencies necessary for an innovation network in larger regions compared to smaller regions. This implies that the probability that the innovation networks are contained within a region is much greater in larger regions than in smaller regions. The probability that innovation 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 innovation networks mainly should be found in large regions, and in particular, large regions with research universities. Another reason why competencies (nodes) in larger regions are preferred is that there is a higher probability that these nodes have better connectivity to other innovation networks and thus are better informed than nodes in smaller regions.

2.7 Conclusions

Summing up the discussion above we may conclude that an innovation network may be characterised 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, innovation may be related to:

- The intensity of the interaction between the various nodes of an innovation network through the existing links; this is related to the interactive characteristics of the innovation process, as it is based on interactive learning processes.
- The speed of change of the innovation 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 innovation 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 innovation, as stressed by von Hippel (1988), Porter (1990) and Karlsson (1997). New products could evolve if there are networks pertaining to customer-supplier relationships, where supplier refers to the supplier of a potentially new technology, customers of the applied product, non-commercial links to other establishments or head office. Non-commercial links refer to the availability of knowledge that can be extracted from participation at fairs, informal meetings, from trade journals, etc. [6] Head office monitoring is important as it concerns the direct influence on the process of developing a new product, from a managerial perspective. In other words, new products may not necessarily be commercially viable, a point already stressed by Schumpeter (1934).

For a given size of a functional region we expect that the probability that an innovation 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 innovation 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 innovator networks and/or those using patent data. [7] A large literature is presently developing on social network analysis (Wasserman and Faust, 1994, Scott, 2000). Network analysis has emerged as an important tool to analyse the way inventors of patents are interconnected. Two contributions identify individual inventors and examine the overlap of patent co-authorship 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

[6] Indeed, Freel (2003) provides compelling evidence on the non-homogeneity of networks for innovations. Cassiman and Veugelers (2002) investigates 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.

[7] 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 Sjöberg (2000) examine internationalization tendencies of coauthorship in researching Swedish firms.

a third inventor C cooperates with B, if C and A cooperated before.[8] 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 (2003) 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 (2003) 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 inventive cooperation. 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 idea purpose is to compare organizational characteristics, and the degree of localization, examined across countries, and regions for a sample of 560 of those patents.[9] Localization refers here to whether all inventors reside in the same region on the listed levels. Delocalization referes to when at least one of a patent's inventors reside elsewhere. She finds that localization is 75.4 per cent on NUTS1 (i.e. national chemical patents), 70.5 per cent on the NUTS2 level and 68.4 per cent

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

[9] 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).

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 per cent 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 co-inventors 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 co-inventors strongly influences the international scope for citations, even when self-citations are excluded. [10]

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, 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 patent co-authorship networks that we analyze in this study 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. [11] 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. We have *not* from our empirical material,

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

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

mainly patent applications to the EPO, identified individuals, the teams they belong too, nor their company affiliation. Although this is in principle possible, it is a demanding task to say the least. This would be an error if we were interested in the impact of knowledge flows on other actors (through e.g. citations), since a lot of the data naturally concerns patents assigned to the same or similar teams of inventors. Our effort should therefore be interpreted as an investigation of the extent that regions are networked together as an aggregate. The focus is on regional aggregates, and the function that regions play in the localization of inventors, although we also decompose the material by technological sector. Hence it matters little that we don't make a separation of teams and/or organizations.

We now turn to a description of our data. Our main data source consists of 22,230 patent applications to the EPO, which we were able to assign both a technological class and a region. A patent is considered Swedish if at least one of the inventors has an address in Sweden. Each patent has been assigned to a "host-region" by the first regionally classifiable inventor in the list of all inventors of an application. Since we are here interested in regional relationships we have excluded all information on international inventors from the analysis. [12]

Figure 1 shows the frequency distribution of applications (left staple) and total number of inventors (right staple) in groups of inventors per patent ranked by the size-class of the number of inventors per application. Clearly, the most common size of inventor teams is one inventor, with 13,816 or 62 per cent of all applications. Furthermore, summing the number of patents for size-classes 1-3 inventors, they make up 94 per cent of all applications. Summing all inventors (i.e. including coinventors), shows that of a total of 36,290 Swedish inventors in EPO patent applications [13] , 38 per cent belong to the one-inventor group, while 83 per cent, or 30,036 inventors, belong to the size-classes 1-3 inventors. On average there are 1.63 Swedish inventors involved in the production of a patent.

Regional properties of the data are particularly interesting for us. Figure 2

[12] Danell and Persson (2003) report that Swedish applications with non-Swedish coauthors to the USPTO have tripled since the 1980's. Yet they constitute only 13 per cent of all inventors in those patents.
[13] Note that these are aggregate numbers and not necessarily unique inventors.

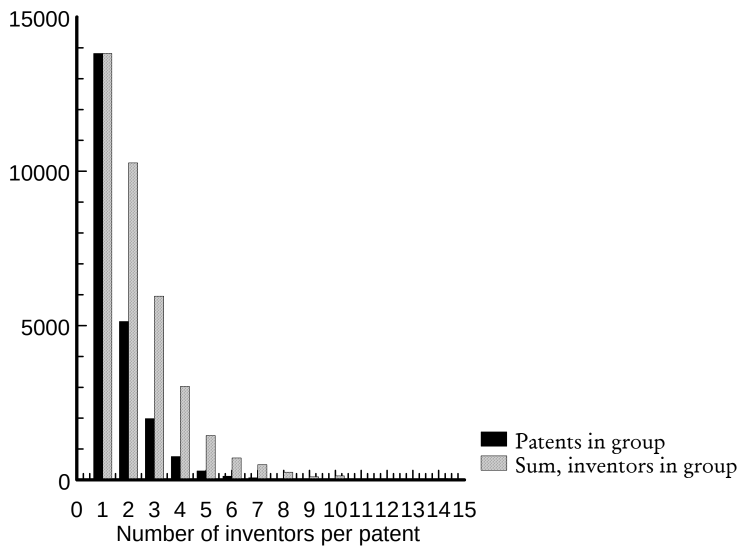

Fig. 1. Inventors in Swedish EPO applications. The full bars show the number of applications, in groups arranged by the number of inventors. Grey bars show the total number of inventors (incl. co-inventors) in respective groups.

shows regional differences in the number of coinventors in 81 Swedish local labour market regions, as specified by NUTEK (1998).

Some interesting differences emerge. As a general observation, there are fewer inventors per patent in northern Sweden. In two of three cases the reason is that only one patent was produced. Also, in some areas in the south fewer inventors are involved in each patent. These areas are relatively less populated compared to other areas in the south, but generally much more populated than most regions in the north. It seems likely that the most densely populated regions (Stockholm-Uppsala, Göteborg and Malmö-Lund) have a somewhat larger number of inventors per patent. Thus, high access to potential inventors seem to foster larger inventor teams. In some cases, the total number of patents is high while the number of coauthors is also high. This is true for the Uppsala-region (avg. 1.97 inventors), with a strong position in biotech and pharmaceuticals, Västerås and Ludvika (2.17, 1.74 inventors per patent, respectively) home to several plants of the Swedish section of ABB. Karlskoga, Sundsvall and Karlstad also rank high; each with a few hundred patents, and around 1.8 inventors per patent. The standard deviation over the regions was 0.42 and the median 1.35, suggesting a skewed distribution of the coinventorship pattern. This suggests that individual companies and

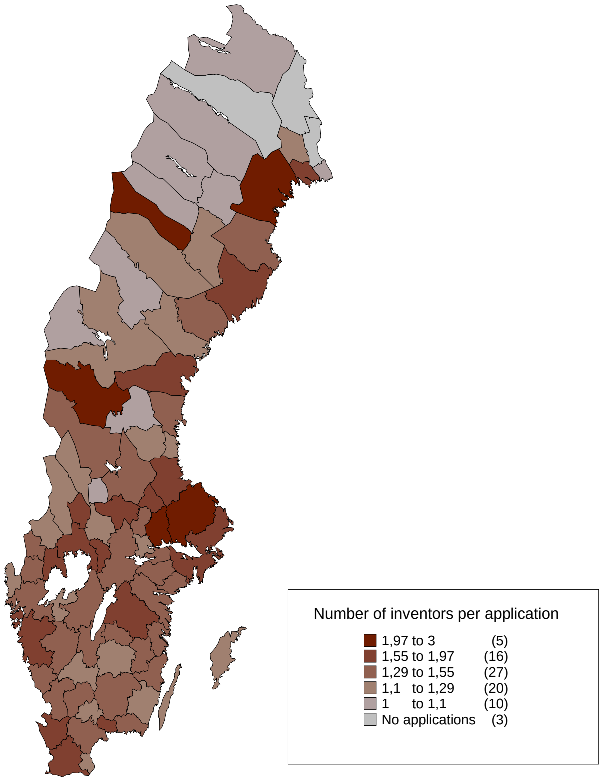

Fig. 2. The number of Swedish inventors per patent in Swedish regions.

their technologies have an impact on the coauthorship structure. As stated in the introduction, 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). There are substantial differences in industries, in the way patenting is viewed as effective of protecting new knowledge (Levin et al., 1983, 1987, Arundel, 2001). We therefore divide the material in 30 technological patent classes using the definitions of Hinze et al. (1997), see Table 1. Because of the generally few inventors/patent (see Figure 1), the median value was 1 inventor/patent for all technologies except classes 5, 9, 13-15, 17 and 27 where the median was 2.

Table 1
Coauthors in patents by technology.

Technology class	No. patents	Inventors/patent	Std.dev.	Technology class	No. patents	Inventors/patent	Std.dev.
1. Electrical engineering	1 178	1.92	1.51	17. Surface techn.	303	1.87	1.09
2. Audiovisual techn.	246	1.44	0.90	18. Materials Processing	994	1.65	1.01
3. Telecommunication	2 184	1.83	1.27	19. Thermal Processes	564	1.39	0.75
4. Information techn.	477	1.72	1.06	20. Environmental techn.	357	1.52	0.90
5. Semiconductors	152	2.13	1.31	21. Machine tools	963	1.41	0.75
6. Optics	306	1.58	1.11	22. Engines	536	1.44	0.84
7. Control techn.	1 489	1.63	0.97	23. Mechanical Elements	1 016	1.35	0.72
8. Medical techn.	1 823	1.65	0.96	24. Handling	1 498	1.35	0.67
9. Organic Chem.	670	2.67	1.87	25. Food Processing	400	1.41	0.94
10. Polymers	196	1.76	1.02	26. Transport	1 069	1.39	0.78
11. Pharmaceutics	728	2.03	1.24	27. Nuclear Engineering	172	1.79	1.00
12. Biotechn.	394	2.03	1.37	28. Space techn.	311	1.83	1.14
13. Materials	631	1.79	0.96	29. Consumer Goods	1 124	1.29	0.61
14. Food Chem.	184	1.73	1.00	30. Civil Engineering	1 217	1.30	0.65
15. Basic Materials Chem.	241	1.77	1.07	All	22 230	1.63	0.30
16. Chemical Engineering	807	1.61	1.14	Median across tech.		1.65	

In the introduction we discussed that tacit knowledge is likely to play an important role in technological areas which are strongly driven by scientific development. However, it is difficult to draw inference on tacitness based on names of technological areas. Some of them seem to be more science-based than others. Examining this table casually gives the impression that many of the technologies on the left side of the table seems more science-based, and also require a higher number of coinventors per patent. For example, patenting in "Consumer goods", "Handling", "Transport", "Machine tools" and "Food processing" have 1.29-1.41 inventors/patent each, compared to 2.67 for "Organic chemistry" or "Pharmaceutics" and "Biotechnology" each with 2.03 inventors per patent. Some caution is required before jumping to conlusions; the name of the class may be deceptive and further analysis of this topic would be needed.

The results of Mariani (2000) provide an opportunity for comparison of the size of inventor groups. She finds that of 201,531 applied and approved chemical patents in Europe, only 25.4 per cent 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 Swedish inventors seem to be somewhat fewer in the chemical sector. The datasets are not quite comparable, because our data do not include non-Swedish inventors. However, if we use the result, reported on by Danell and Persson (2003), that 13 per cent of inventors involved in Swedish patents to the USPTO were non-Swedish, we can approximate the total average inventor number of inventors per Swedish patent by $1.63/0.87 \approx 1.87$.

In their study on the social network of Italian inventors, Breschi and Lissoni (2003) report for a subsample an average of about 1.9 Italian inventors per patent. Thus, the Swedish coinventorship structure seems roughly consistent with their findings. It seems as if more densely populated areas, whether within Sweden (as shown by Figure 2), or compared to other countries (Italy, as in Breschi and Lissoni (2003) or the rest of Europe as in Mariani (2000)), are conducive to a higher number of coinventors.

We now discuss properties of the Swedish coinventor networks. The degree of localization refers to the coinventors living in the home region of the patent, i.e.

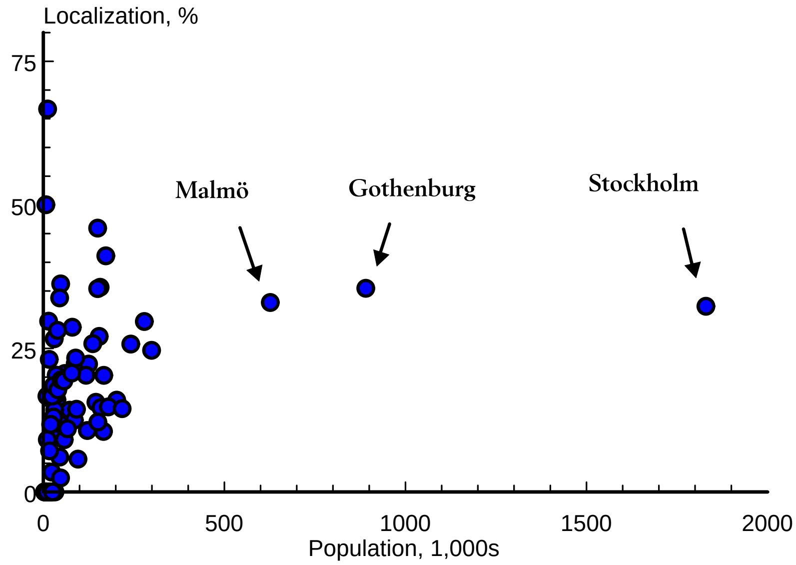

Fig. 3. The degree of localization related to size of the different regions in terms of population in thousands 1998.

local affinity. Figure 3 shows the localization measured in per cent on the y-axis and the size of regions in 1998. It is difficult to draw precise conclusions about the relationship between size of regions and localization, even though there seems to be a tendency for larger regions (Stockholm, Göteborg, Malmö etc) to have a higher degree of localization. Peripheral regions often have extreme localization rates, because there are very few (Gotland) or no (Simrishamn) patents assigned to them. In these cases, high localization can occur because all coinventors reside in the same region, or because the only coinventor lives in the same region. On the opposite side of the scale, low localization is in some cases the result of non-existent coinventors.

A simple linear regression [14] of the relationship between localization and population shows:

$$l_r = \underset{(9.4093)}{15.1105} + \underset{(2.7891)}{0.0172} N_r, \qquad R^2 = 0.0929 \tag{1}$$

, where l_r refers to the degree of localization in region r and N_r to population, thousands of people in 1998. t-values are shown below the estimates. There

[14] The regression excludes three regions which do not have patent applications, and therefore no localization.

is indeed a positive relationship, significant on the 5 per cent level. This relationship shows that increasing regional population increases the localization degree, but only by 0.018 %, when population increases by 1,000.[15]

Figure 4, depicts the networks of Swedish inventors.[16] The lines show the affinities between regions. As explained earlier, the affinity between region i and region j is the sum of the share of coauthors residing in region j when region i is the home region. When regions function as residence of coinventors (region j), we will refer to them as cooperating regions. Region affinity, through a logit transformation, is the variable we use as our dependent variable in the regression analyses.

The thickness of the lines in Figure 4 shows the degree of affinity. The arrows indicate the direction in which the affinity relation dominates, i.e. to which region affinity is the largest. To keep the exposition as clear as possible, only affinities higher than 3 per cent are shown. Some names of region nodes have been indicated. The three largest regions - Stockholm, Göteborg and Malmö - are central nodes in the Swedish inventor network. Due to their size, large regions will have more inward arrows, because they are often cooperating regions for smaller regions, while the reverse relationship is less frequent. Stockholm has many long-distance connections, and is a cooperating region for many regions in Sweden. Malmö and Göteborg are both locally cooperating regions, i.e. central nodes in the southern and western parts of Sweden, and Malmö is also a cooperating region for many regions far away. In the north, the largest regions Umeå and Luleå are to some extent 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 this system. Therefore, to explain affinities, and try to disentangle effects, we turn to regression analysis.

[15] Three regions without patents are excluded from the regression, but shown in Figure 3.
[16] The graph was made with the help of Netdraw and Ucinet6 (Borgatti et al., 2002).

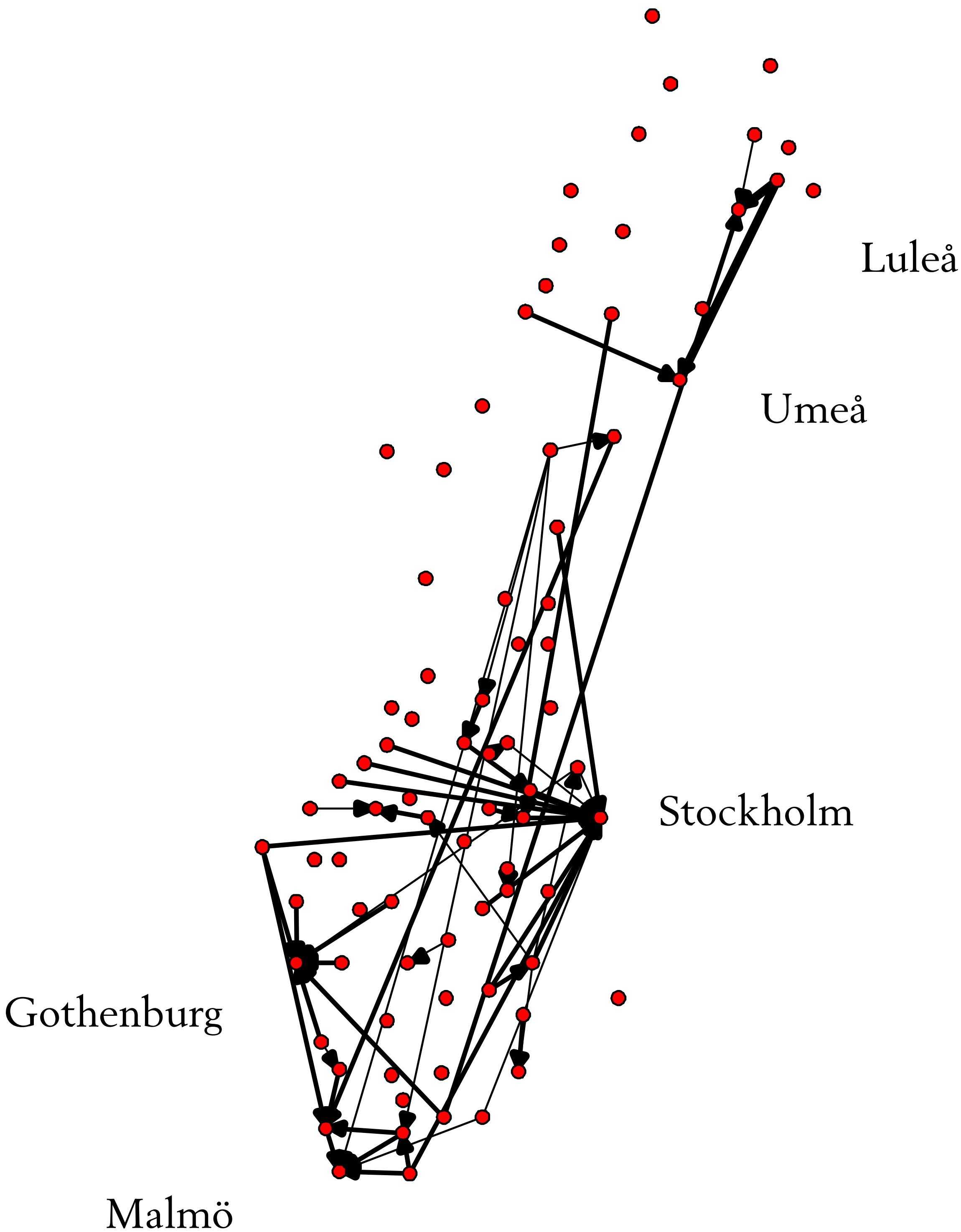

Fig. 4. Coauthorship networks in patenting for Swedish regions. Thicker lines show stronger connections.

5 Model outline

In theory we have 81 x 81 observations of affinities. But regions without patenting cannot have affinity to another region. We remove three such regions, keeping 6,318 observations.[17] Our theoretical discussion of innovation networks has highlighted a number of factors likely to explain affinities. Travel time distance is a natural explanatory variable. Extensive travel costs should reduce the incentives for inventor cooperation. On the other hand, we would expect inventors in larger regions in their search for innovation 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 better equipped with complementary assets. Of the size factors that we have reasons to believe affect affinity we include patents, population, educated workers, private and university research. How should we define our dependent variable? It should capture the extent of cooperation between regions on the one hand, on the other it should also reflect the extent to which a region does not cooperate. For this reason, we divide the number coinventors with the total number of inventors. The affinity variable is formally written

$$A_{ij} = \frac{C_{ij}}{I_i}, \qquad i, j = 1, ..., 81 \tag{2}$$

where C_{ij} denotes the number of co-authors in cooperating region j of a patent where region i is the home region and I_i is the total number of Swedish inventors in a patent application originating from region i. The measures answers the question: How many of the co-inventors reside in region j for a patent originating in region i? Note that:

$$C_{ij} \subset I_i \tag{3}$$

Therefore, A_{ij} is strictly lower than 1. It is useful to make a logit transformation, L_{ij}, of the dependent variable, so that the predicted values will remain within the range 0-1. However, C_{ij} is often 0 (no co-operation) and in these cases we therefore change A_{ij} to a small number: 10^{-10}.

[17] 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.

$$L_{ij} = \begin{cases} \ln\left(\frac{A_{ij}}{1-A_{ij}}\right) & \text{if } 0 < A_{ij} < 1 \\ \ln\left(\frac{10^{-10}}{1-10^{-10}}\right) & \text{if } \quad A_{ij} = 0 \end{cases} \tag{4}$$

When $0 < A_{ij} < 1$, the denominator $1 - A_{ij}$ can be thought of as the aversion of region j to region i. The full, ordinary least squares, regression model is:

$$\begin{aligned} L_{ij} = &\alpha_0 + \alpha_1 N_i + \alpha_2 N_j + \alpha_3 P_i + \alpha_4 P_j + \alpha_5 HQ_i + \alpha_6 HQ_j \\ &+ \alpha_7 \overline{HQ}_i + \alpha_8 \overline{HQ}_j + \alpha_9 R_i + \alpha_{10} R_j \\ &+ \alpha_{11} U_i + \alpha_{12} U_j + \alpha_{13} e^{-\lambda t_{ij}} + \alpha_{14} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \varepsilon_{ij} \end{aligned} \tag{5}$$

where N denotes population, P patents, HQ headquarters, $\overline{HQ}$ average size of headquarters, R private R&D in man-years, U university R&D in man-years, λ is a distance sensitivity parameter and t_{ij} is the travel time between region i and j. For all our variables i and j denote home and cooperating regions respectively.

Most size variables are expected to raise affinity. Population is measured in thousands for 1998. These variables are expected to raise affinity if they increase (α_1, $\alpha_2 > 0$).[18] The number of patents produced is also expected to raise affinity (α_3, $\alpha_4 > 0$). If many patents are produced in the cooperating region, we conclude that inventors reside there, indicating the availability of a 'pool of knowledge-workers'. In the other direction, more patents produced in the home region will more likely trigger cooperation. HQ_i and HQ_j is the number of companies with judicial belonging in i and j. We expect that more headquarters in the home region will lower affinity ($\alpha_5 < 0$), because there will be stronger centralization and monitoring of research activities. More headquarters in the cooperating region will most likely raise affinity ($\alpha_6 > 0$), because researchers are likely to co-locate with headquarters in the cooperating region. $\overline{HQ}$, is the average size of headquarters in a region. It is measured by the number of companies divided by the total number of employees of the region. This variable catches the importance of the relative size of headquarters; larger headquarters will be more prone to monitor R&D close-by and thus we expect $\alpha_7 < 0$ and $\alpha_8 > 0$. R denotes R&D man-years in busi-

[18] Note that affinity also rises when the logit transformation rises.

ness and U R&D man-years in the university sector. We expect that both research variables in the home and destination regions will raise affinity so that $\alpha_9, \alpha_{10}, \alpha_{11}, \alpha_{12} > 0$. One may suspect that there will be multicollinearity among several of our variables, so we will exclude variable(s), to see whether this affects our estimates.[19]

Generally, we expect time distance to influence affinity negatively ($\alpha_{13} > 0$). The term $\frac{N_i}{N_j} e^{-\lambda t_{ij}}$ of equation (5) is used to test the possibility that time distance may have different effects depending on the relative size of the home region to that of the cooperating region. We expect home regions relatively larger than cooperating regions to have affinities directing towards them, or in other words be more distance sensitive ($\alpha_{14} < 0$). The reason is that they 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 regions. Two types of time data have been used: 1. Road travel time data from the 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 airport lines, given that it is faster than travelling by road. An assumption here is that inventors in neighbouring regions don't consider it worth the time to go to a neighbouring region and use its airport, since there are considerable time losses involved in flying from accessing airports. For road travelling times, we use the fact that each region consists of a number of municipalities, whereof we have road travel times for travelling 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:

[19] We also considered including number of highly educated people (three years or more of university education). Educated people should theoretically more often be involved in patent networks. However, the variable carries a fair amount of "noise" because the Swedish educated workforce is to a large degree employed by the public sector, people generally not involved in patenting. We therefore excluded the variable. In addition, we found that its correlation was extremely high with population, to some extent justifying this approach.

$$t_{ij}^{w} = \frac{\sum_r \sum_s M_{rs} \cdot t_{rs}}{\sum_r \sum_s M_{rs}}, \qquad r \in i, s \in j \tag{6}$$

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 travel-time 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 are used, which we write t_{ij}^{a}:[20]

$$t_{ij}^{a} = \frac{\sum_r \sum_s t_{rs}}{n_{ij}}, \qquad r \in i, s \in j \tag{7}$$

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

$$t_{ij}^{r} = \begin{cases} t_{ij}^{w} \text{ if } t_{ij}^{w} > 0 \\ t_{ij}^{a} \text{ if } t_{ij}^{w} = 0 \end{cases} \tag{8}$$

The flight times between all functional regions were collected from the webpages of the Swedish Civil Aviation Administration (2003). If more airports were available in a region, the shortest flight time was used. Finally, the shortest time of road and flight was used as our measure of the time involved in travelling between two regions in Sweden:

$$t_{ij} = \min\{t_{ij}^{r}, t_{ij}^{f}\} \tag{9}$$

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

[20] Although this may introduce biases, they are likely to be negligible, because regions with no commuting are far from each other, and hence the weights become relatively unimportant.

also without flight times, but without qualitative effects on our results. For brevity, we therefore only report the results using definition (9). 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 the home and cooperating region are the same and $\lambda = 0.017$ if they differ, based on the empirical results of Åberg (2000) and Hugosson (2001). These λ-values have also been used by Andersson and Ejermo (2003, 2004), to spatially discount accessibility to knowledge resources. The higher λ-value for intraregional time-distance reflects the higher propensity to cooperate within the region.

Table 2 gives a brief description of our variables and reports some summary statistics.

Table 2

Variable descriptives. 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.

Variable	Description	N	Min	Max	Mean	Std. dev.
A_{ij}	affinity; share of coinventors in j for a patent in i	6,318	0	0.6667	0.0031	0.0248
L_{ij}	logit transformation $L_{ij} = \ln\left(\frac{A_{ij}}{1-A_{ij}}\right)$	6,318	-23.0259	0.6931	-21.3358	5.2904
N_i	population. 1,000s in i, 1998	81	3.281	1,829.74	109.3126	232.6577
N_j	population. 1,000s in j, 1998	- " -	- " -	- " -	- " -	- " -
P_i	patent applications 1,000s in i	81	0	7.394	0.2744	0.9199
P_j	patent applications 1,000s in j	- " -	- " -	- " -	- " -	- " -
HQ_i	number of companies 1,000s in i 1996	81	0.117	72.097	3.2814	8.7408
HQ_j	number of companies 1,000s in j 1996	- " -	- " -	- " -	- " -	- " -
$\overline{HQ}_i$	average size of HQs: $EMPL_i/HQ_i$ 1996	81	2.5176	11.0367	5.6973	1.7976
$\overline{HQ}_j$	average size of HQs: $EMPL_j/HQ_j$. 1996	- " -	- " -	- " -	- " -	- " -
R_i	1,000 man-years in business R&D in i 1995	81	0	14.5371	0.5132	1.8927
R_j	- " - in j 1995	- " -	- " -	- " -	- " -	- " -
U_i	1,000 man-years in university R&D in i 1995/96	81	0	4.7830	0.2090	0.8026
U_j	- " - in j 1995/96	- " -	- " -	- " -	- " -	- " -
λ	time sensitivity parameter. $\lambda = 0.017$ if $i \neq j$; $\lambda = 0.1$ if $i = j$	6,318	0.1	0.017	0.018	0.0092
t_{ij}	minimum of road and flight-travel time in minutes	6,318	8.5913	1126.9	375.848	253.807
$e^{-\lambda t_{ij}}$	distance-weighted parameter	6,318	0	0.7733	0.059	0.1194
$\frac{N_i}{N_{jk}} e^{-\lambda t_{ij}}$	interaction: relative pop. size and time distance	6,318	0	53.7054	0.2139	1.42

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 3 shows the correlation matrix of relevant variables.

Table 3
Pairwise correlation matrix of variables.

Variable	L_{ij}	N_i	P_i	HQ_i	$\overline{HQ}_i$	R_i	U_i
L_{ij}	1.0000						
N_i	.2580	1.0000					
P_i	.2378	.9846	1.0000				
HQ_i	.2389	.9924	.9907	1.0000			
$\overline{HQ}_i$	.1410	.3139	.3058	.2969	1.0000		
R_i	.2393	.9709	.9748	.9764	.2993	1.0000	
U_i	.2296	.8383	.8398	.8179	.1343	.8175	1.0000

As expected, there are signs of strong intercollinearity between many of the variables. Hence, if we include all in a regression, we would expect some of them to turn out insignificant. [21] We therefore run variants of the main regression, to study the stability of coefficient and to consider subsets. Likely candidates for exclusion are variables which are highly correlated and are not significant in the full model where all variables are included. We find all results in Table 4. The full model was run as Model 1. For this model, we find that the coefficients for P_i and P_j, $\overline{HQ}_i$ and $\overline{HQ}_j, R_i$ and R_j, U_i and U_j are not significant, and display high correlation. Our interest from the policy maker's perspective are variables which can be affected directly. $N_i, N_j, P_i, P_j, HQ_i, HQ_j$ do not belong to this category, and can from the econometric perspective 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:

$$L_{ij} = \beta_0 + \beta_1 P_i + \beta_2 P_j + \beta_3 HQ_i + \beta_4 HQ_j + \beta_5 \overline{HQ}_i + \beta_6 \overline{HQ}_j + \beta_7 R_i + \beta_8 R_j + \beta_9 U_i + \beta_{10} U_j + \beta_{11} e^{-\lambda t_{ij}} + \beta_{12} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \epsilon_{ij} \tag{10}$$

[21] Following Klein's rule of thumb that $R_z^2 > R^2$ where z is the R^2 from running a regression where z is the dependent variable on the other explanatory variables, we get extremely high R_z^2 for N_i, P_i, HQ_i, R_i and U_i, thus confirming the presence of multicollinearity.

Model 3 excludes population and patents:

$$
\begin{aligned}
L_{ij} = &\gamma_0 + \gamma_1 HQ_i + \gamma_2 HQ_j + \gamma_3 \overline{HQ}_i + \gamma_4 \overline{HQ}_j + \gamma_5 R_i + \gamma_6 R_j + \gamma_7 U_i \\
&+ \gamma_8 U_j + \gamma_9 e^{-\lambda t_{ij}} + \gamma_{10} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \zeta_{ij}
\end{aligned} \tag{11}
$$

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

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

and Model 5 excludes population and R&D:

$$
\begin{aligned}
L_{ij} = &\theta_0 + \theta_1 P_i + \theta_2 P_j + \theta_3 HQ_i + \theta_4 HQ_j + \theta_5 \overline{HQ}_i + \theta_6 \overline{HQ}_j \\
&+ \theta_7 U_i + \theta_8 U_j + \theta_9 e^{-\lambda t_{ij}} + \theta_{10} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \epsilon_{ij}
\end{aligned} \tag{13}
$$

Table 4

Estimation results, aggregate model. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
constant	-24.6459 (0.2582)***	-24.8418 (0.2576)***	-24.6348 (0.2609)***	-24.573 (0.2592)***	-24.9057 (0.2573)***
N_i	0.0259 (0.0028)***	-	-	-	-
N_j	0.0297 (0.0032)***	-	-	-	-
P_i	-0.3024 (0.6486)	-1.0383 (0.6687)	-	-0.1296 (0.4254)	-0.8444 (0.6407)
P_j	0.1130 (0.7225)	-0.7320 (0.7374)	-	0.2755 (0.5055)	-0.6742 (0.6873)
HQ_i	-0.5854 (0.1054)***	0.1161 (0.0676)*	0.0293 (0.0434)	-	0.1516 (0.064)
HQ_j	-0.6612 (0.1222)***	0.1280 (0.0711)*	0.0668 (0.05)	-	0.1378 (0.0687)
$\overline{HQ}_i$	0.0527 (0.0334)	0.1676 (0.0307)***	0.1548 (0.0315)***	0.1584 (0.0314)***	0.1704 (0.0308)***
$\overline{HQ}_j$	0.0094 (0.0323)	0.1490 (0.0287)***	0.1412 (0.0293)***	0.1416 (0.0292)***	0.1495 (0.0288)***
R_i	0.0002 (0.0002)	0.0003 (0.0002)	0.0002 (0.0002)	0.0004 (0.0002)**	-
R_j	0.0000 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	0.0002 (0.0002)	-
U_i	0.0002 (0.0002)	0.0009 (0.0002)***	0.0008 (0.0002)***	0.0009 (0.0002)***	0.0010 (0.0002)***
U_j	0.0000 (0.0002)	0.0008 (0.0002)***	0.0008 (0.0002)***	0.0008 (0.0002)***	0.0009 (0.0002)***
$e^{-\lambda t_{ij}}$	14.4538 (0.8654)***	15.0058 (0.9068)***	15.083 (0.9068)***	15.1374 (0.9054)***	14.9956 (0.9072)***
$\frac{N_i}{N_{jk}} e^{-\lambda t_{ij}}$	-0.2659 (0.0918)***	-0.3764 (0.1056)***	-0.3784 (0.1056)***	-0.3700 (0.1035)***	-0.3798 (0.1059)***
nobs.	6318	6318	6318	6318	6318
df	6303	6305	6307	6307	6307
R^2	0.2952	0.2603	0.2596	0.259	0.2598
$\bar{R}^2$	0.2936	0.2589	0.2584	0.2578	0.2587
F-value	188.57	184.87	221.08	220.47	221.41

Since the dependent variable has been changed by the logit transformation, the interpretation of the above coefficients should be thought of as the effect of changing an independent variable on the odds-ratio of success, i.e. change in the affinity of two regions relative to the "aversion" between them.

Some results appear robust across specifications: population affects the odds-ratio positively and is strongly significant in both home and cooperating region when it is included, in line with expectations. Excluding population, however, makes average size of headquarters become positive and highly significant, both in the home and cooperating region. This means that the affinity is highest between two regions with relatively large companies. The number of patent applications in home and cooperating region do not seem to exert any influence on affinities as the parameters are generally insignificant. In addition, the number of headquarters shows no coherent pattern, since it is highly significant and negative when population is included, but rarely significant (but positive) when population is excluded. This is not surprising, since it is a common sign of multicollinearity for parameters to be unstable. In the correlation matrix we find that the correlation between HQ and N is 0.9924, an almost perfect correlation. The second robust result concerns the effect of distance. Distance lowers affinity on the 1 per cent level in all Models 1-5. An increase in the average time-distance by 10 minutes, from the average of actual values, 376 minutes, to 386 minutes, lowers affinity by 0.00098, using $\lambda = 0.017$ and 15 as a rough average of the time distance estimates in Table 4. [22] Also, the interaction term of the time distance variable and relative population size shows up as expected. If we examine the affinity between two regions using the average time of travelling between them of 376 minutes, changing the regions from the Stockholm region being the home region (1,829,740 citizens 1998), and the smallest region being the cooperating region (Sorsele, 3,281 inhabitants) compared to two average regions, we find that affinity increases by 0.08540, using the parameter value -0.37. Relatively smaller home regions compared to cooperating regions have a smaller sensitivity to distance, meaning that their affinities stretch over larger distances. In other words, their complementary competencies are often found in large regions. Business R&D does not seem

[22] This was calculated from $\exp(Lij2)/\left[1+\exp(Lij2)\right] - \exp(Lij1)/\left[1+\exp(Lij1)\right]$,where $Lij2 = 15 \cdot \exp(-0.017 \cdot 386)$ and $Lij1 = 15 \cdot \exp(-0.017 \cdot 376)$.

to have an influence of affinities, although positive it is only significant on the 5 per cent level for the home region in Model 4. University R&D on the other hand does seem to have some effect when population is excluded. Regions generally exhibit higher affinity when both home and cooperating region have more university R&D. For instance, changing values from average to highest university R&D in the home region (keeping the average value for the cooperating region) raises affinity by 0.00103, using parameter values of 0.0009 and 0.0008 for U_i and U_j respectively.

5.1 Division by Technology

In view of earlier discussions, we have reasoned that properties of technologies could influence our results. We therefore specify the model above based on the 30 technologies listed before. Because we have reasoned that population is a catch-all variable for many size-effects, we run first one model where we exclude it, but keep the other variables:

$$\begin{aligned} L_{ij,k} = &\rho_0 + \rho_1 P_{i,k} + \rho_2 P_{j,k} + \rho_3 HQ_i + \rho_4 HQ_j \\ &+\rho_5 \overline{HQ}_i + \rho_6 \overline{HQ}_j + \rho_7 R_i + \rho_8 R_j \\ &+\rho_9 U_i + \rho_{10} U_j + \rho_{11} e^{-\lambda t_{ij}} + \rho_{12} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \mu_{ij} \end{aligned} \tag{T1}$$

where $k = 1, ..., 30$ stands for the specific technology in question. Note that patents in the home and cooperating region are in the specific technology area considered. In a second variant we also remove the HQ-variables, because they seem to be highly correlated with private R&D, and we believe private R&D to be the main determinant of the distribution of the network.

$$\begin{aligned} L_{ij,k} = &\omega_0 + \omega_1 P_{i,k} + \omega_2 P_{j,k} + \omega_3 HQ_i + \omega_4 HQ_j \\ &+\omega_5 \overline{HQ}_i + \omega_6 \overline{HQ}_j + \omega_7 R_i + \omega_8 R_j \\ &+\omega_9 U_i + \omega_{10} U_j + \omega_{11} e^{-\lambda t_{ij}} + \omega_{12} \frac{N_i}{N_j} e^{-\lambda t_{ij}} + \varsigma_{ij} \end{aligned} \tag{T2}$$

Thus, we run 30 x 2 regressions shown in Tables A-L of the Appendix. Table 5 summarizes the number of positive and negative values that are significant on at least the 10 per cent level for each parameter and both models.

Table 5
Count of the number of significant ($\leq$ 10 per cent level) coefficients, with respective sign for 30 different patent technologies. .

	Model T1		Model T2	
Variable	+	-	+	-
$P_{i,k}$	20	0	19	0
$P_{j,k}$	17	0	17	0
HQ_i	0	5	x	x
HQ_j	1	3	x	x
$\overline{HQ}_i$	1	3	1	3
$\overline{HQ}_j$	0	1	0	2
R_i	2	1	2	2
R_j	0	0	1	1
U_i	7	1	6	1
U_j	9	0	11	0
$e^{-\lambda t_{ij}}$	30	0	30	0
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	0	29	0	29

Table 5 shows some interesting differences compared to the aggregate cases we have considered so far. We find for instance, that patents in both home and cooperating region now significantly affects the outcome in most cases, giving credit to the approach of splitting the data by technology. Of course, the presence of patenting in a certain technology will most likely be a source of affinity, whereas on the aggregate level this attraction factor is confounded due to aggregation of all technologies. It should be illuminating to look at how distance sensitivity varies across technologies. Table 5 reveals that all technologies are distance sensitive, that is, inventors do tend to co-locate, since the parameter for $e^{-\lambda t_{ij}}$ is positively significant in all cases. Parameter values do vary quite a lot, differing with almost a factor of 3 from lowest to highest. The five least distance sensitive technologies, in increasing order of sensitivity are Information technology, Optics, Basic materials chemistry, Biotechnology and Thermal processes. The five *most* distance sensitive in increasing order are Handling, Materials Processing, Electrical engineering, Pharmaceutics and Control technology. The ranking of technologies is almost unchanged in Model T2. It is suggestive that *Information technology* displays the least distance sensitivity from this material, given that some authors proclaim that information technology will mean the "death of distance". Actors involved in patenting of this technology are more spread over the country than for other patent technologies, after controlling for other factors. One could speculate that inventors in information technologies are better at using their own technology, and hence use codified information to a larger extent than other inventors. How does distance sensitivity affect the pattern of networks as time distance between regions change? Repeating the experiment from aggregate, that is changing the average time from 376 to 386 with parameter values 2.1559 (Information technology, Model T1) changes affinity by -0.00014. Instead, using the parameter value 6.0130 (Control technology) changes affinity by -0.00039. This means that the effect on affinity is nearly three times as big. Otherwise, it is difficult to distinguish any patterns in terms of 'tacitness', i.e. that technologies based more on scientific content should have a higher distance sensitivity, casually observed as most technologies on the left side of Table 1. There could be many reasons for this. This paper has not considered the organizational setup of inventors. Distance of inventor networks is likely to be highly dependent on historical locations of firms, and therefore inventors' residence. In addition, we have not been able to measure the 'scientific sophistication' or degree of 'tacitness' embedded in any technology. This may well be an issue for future research.

The sign of the variable "number of headquarters" and average size of headquarters, are rarely significant. Especially the latter is a major difference compared to the aggregate setup. A possible explanation could be that headquarters are not divided by sector nor technology, hence a lot of "noise", i.e. non-research activities and/or mix of different types of R&D-firms, are included in the measure. Average headquarter size may also suffer from this problem.

University and private R&D do however enter with the predicted signs in some cases. For certain technologies affinity seems to be higher with higher presence of university and private research. The following list indicates across which technologies this result is robust, here defined as of having at least 10 per cent significance, whether population is included or not. Higher university research in the home region increases affinity for Electrical Engineering, Medical Technology, Mechanical Elements, Food Processing, Nuclear Engineering. It also has a negative home-region effect for Space technology. Higher university research in the cooperating region increases affinity in Electrical

Engineering, Information technology, Semiconductors, Optics, Control Technology, Engines, Food Processing and Nuclear Engineering. In addition, when private research increases in the home region, affinity becomes lower for Mechanical Elements, but there are no effects registered otherwise and not for the cooperating region effect in particular. How can we explain these results, the fact that university R&D seems to better explain affinity than private R&D? An obvious interpretation has to come from the data. It may be that although R&D is formally registered to certain regions, the actual R&D activity takes place at another. It is also illustrative that researchers do seem to need close access to university R&D in many technologies.

6 Summary and Conclusions

This paper set out to explain inventor networks as measured by affinity across Swedish regions. We have found as a general rule that affinities are strongly affected by distance, and that population acts as a strong attraction factor. By dividing patents according to technology, our models gained considerably in efficiency. Technologies showed marked differences in distance sensitivity, although it is less clear whether this result can be related to a notion of 'tacitness' - this issue has not really been examined in more depth in the paper. A factor of three separate the most from the least distance sensitive technology when it comes to affinity. We find it intriguing that the least distance sensitive patent technology was "Information technology". An interpretation of this result must be somewhat speculative, but it seems close at hand to believe that inventors in this technology could be less bounded by geographical distance, due to their skills in information management, which makes them better able at codifying knowledge. If this technology is of the "general purpose technology" type (Bresnahan and Trajtenberg, 1995), and its use continues to diffuse into other areas, they too would probably become less distance sensitive. These results give us an immediate venue for future research. How have inventor networks developed over time? If the above conjecture is true, and the improvement of information technology has gone on for some time, it should show up in our data over time. Another dimension over which the analysis could be carried out, is to study the role of international networks, i.e. what is the share and distance over which collaboration occurs internationally?

Technologies were also responding differently to whether in particular university R&D was present in the region. This suggests different capabilities to draw on the local pool of knowledge. Probably, inventors do to some degree have connections with local universities. These results show that establishment of university research cannot automatically be thought to generate networks with other regions, which could ultimately lead to more patenting. Technologies where affinities tend to increase when inventors are located close to universities include Electrical Engineering, Medical Technology, Mechanical Elements, Food Processing, Nuclear Engineering, Information Technology, Semiconductors, Optics, Control Technology and Engines. Private R&D was surprisingly not inducive to higher affinities.

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. Reverse causality could in principle also affect our results, so that location of inventors affect, for instance, the location of university research.

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Appendix A Estimation results by technology

Appendix A.1 Results without population

Table A
Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 1-5. Population not included.

Variable	Electrical engineering	Audiovisual techn.	Telecommunication	Information techn.	Semiconductors
constant	-23.003 (0.2047)***	-23.3845 (0.315)***	-22.3721 (0.273)***	-23.0304 (0.2534)***	-22.9354 (0.6074)***
$P_{i,k}$	0.0082 (0.0022)***	0.0381 (0.0206)*	0.0020 (0.0011)*	0.0051 (0.0058)	0.0216 (0.0102)**
$P_{j,k}$	0.0071 (0.0029)**	0.0067 (0.0332)	-0.0010 (0.0022)	-0.0038 (0.0133)	0.0569 (0.0589)
HQ_i	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
HQ_j	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0000)	-0.0003 (0.0001)**
$\overline{HQ}_i$	-0.0302 (0.0227)	0.0239 (0.0379)	-0.0928 (0.0290)**	-0.0252 (0.0253)	-0.032 (0.0825)
$\overline{HQ}_j$	-0.0117 (0.017)	0.0184 (0.0236)	-0.0372 (0.0266)	0.0044 (0.0235)	0.0123 (0.0381)
R_i	0.0001 (0.0002)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
R_j	0.0000 (0.0002)	0.0000 (0.0002)	0.0004 (0.0003)	0.0002 (0.0003)	0.0007 (0.0006)
U_i	0.0003 (0.0001)**	0.0002 (0.0001)	0.0002 (0.0001)*	0.0001 (0.0001)	0.0001 (0.0001)
U_j	0.0003 (0.0002)**	0.0002 (0.0002)	0.0003 (0.0002)	0.0006 (0.0003)**	0.0024 (0.0007)***
$e^{-\lambda t_{ij}}$	5.5059 (0.7422)***	2.6665 (0.6435)***	5.1917 (0.8668)***	2.1559 (0.6155)***	3.7423 (1.0387)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.2193 (0.0468)***	-0.0991 (0.031)**	-0.1719 (0.0467)***	-0.1262 (0.0383)***	-0.1201 (0.0374)**
nobs.	4294	2188	3079	2269	973
df	4281	2175	3066	2256	960
R^2	0.1323	0.0733	0.1472	0.1131	0.2937
$\bar{R}^2$	0.1299	0.0682	0.1439	0.1084	0.2849
F-value	54.4124	14.3293	44.0999	23.9829	33.2735

Table B

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 6-10. Population not included.

Variable	Optics	Control techn.	Medical techn.	Organic Chem.	Polymers
constant	-23.3783 (0.3545)***	-22.9737 (0.2381)***	-23.2621 (0.2793)***	-22.9422 (0.5859)***	-23.3053 (0.3095)***
$P_{i,k}$	0.0004 (0.0092)	0.0133 (0.0042)**	0.006 (0.0032)*	0.0073 (0.0051)	0.0125 (0.0107)
$P_{j,k}$	-0.0359 (0.0252)	0.0029 (0.0053)	0.003 (0.0054)	0.0329 (0.0232)	0.0689 (0.0382)*
HQ_i	0.0000 (0.0000)	-0.0001 (0.0000)*	-0.0001 (0.0000)*	0.0000 (0.0000)	0.0000 (0.0000)
HQ_j	0.0000 (0.0001)	-0.0001 (0.0000)	-0.0001 (0.0001)	-0.0001 (0.0001)	0.0001 (0.0001)
$\overline{HQ}_i$	0.021 (0.043)	-0.0366 (0.0245)	0.0534 (0.0358)	-0.0367 (0.0748)	0.0217 (0.0496)
$\overline{HQ}_j$	-0.0048 (0.0239)	0.024 (0.0221)	-0.0234 (0.0209)	-0.0346 (0.0351)	-0.0208 (0.0159)
R_i	0.0001 (0.0001)	0.0001 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	-0.0002 (0.0001)
R_j	0.0003 (0.0003)	0.0002 (0.0002)	0.0001 (0.0003)	-0.0001 (0.0005)	-0.0004 (0.0003)
U_i	0.0000 (0.0001)	0.0000 (0.0002)	0.0003 (0.0001)**	0.0001 (0.0001)	0.0002 (0.0001)
U_j	0.0007 (0.0003)*	0.0005 (0.0002)**	0.0011 (0.0003)***	0.001 (0.0007)	0.0004 (0.0004)
$e^{-\lambda t_{ij}}$	2.3752 (0.6888)***	6.013 (0.7479)***	4.8057 (0.6975)***	4.8233 (1.1875)***	3.7271 (0.9605)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1099 (0.0354)**	-0.2097 (0.0446)***	-0.1499 (0.0429)***	-0.139 (0.0413)***	-0.1001 (0.035)**
nobs.	1783	4294	3970	1216	1864
df	1770	4281	3957	1203	1851
R^2	0.0988	0.1193	0.1583	0.2726	0.118
$\bar{R}^2$	0.0926	0.1169	0.1558	0.2654	0.1123
F-value	16.1625	48.343	62.0353	37.5759	20.6416

Table C

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 11-15. Population not included.

Variable	Pharmaceutics	Biotechn.	Materials	Food Chem.	Basic Materials Chem.
constant	-22.5838 (0.3753)***	-21.8824 (0.627)***	-23.4617 (0.3618)***	-23.3195 (0.5391)***	-23.1303 (0.2446)***
$P_{i,k}$	0.0085 (0.0051)*	0.0406 (0.0207)*	0.018 (0.0044)***	0.0081 (0.0054)	0.0021 (0.0102)
$P_{j,k}$	0.0459 (0.0213)**	0.0166 (0.0502)	0.0323 (0.0092)***	0.0879 (0.0304)**	0.0576 (0.0242)**
HQ_i	0.0000 (0.0000)	-0.0001 (0.0001)	-0.0001 (0.0000)**	0.0000 (0.0000)	0.0000 (0.0000)
HQ_j	-0.0001 (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)*	0.0000 (0.0001)	0.0000 (0.0001)
$\overline{HQ}_i$	-0.0614 (0.0439)	-0.1942 (0.0882)**	0.0419 (0.0478)	0.0353 (0.0737)	-0.0227 (0.0272)
$\overline{HQ}_j$	-0.0485 (0.0317)	-0.0322 (0.0258)	0.0239 (0.0258)	-0.04 (0.0306)	0.0067 (0.0191)
R_i	0.0001 (0.0001)	0.0005 (0.0003)*	0.0002 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
R_j	0.0005 (0.0005)	-0.0002 (0.0003)	0.0003 (0.0002)	0.0001 (0.0004)	-0.0002 (0.0003)
U_i	0.0000 (0.0002)	-0.0009 (0.0006)	0.0001 (0.0001)*	0.0002 (0.0001)	0.0001 (0.0001)
U_j	-0.0001 (0.0007)	0.0018 (0.0015)	0.0002 (0.0002)	0.0004 (0.0004)	0.0001 (0.0002)
$e^{-\lambda t_{ij}}$	5.5388 (1.1627)***	2.4569 (1.0419)**	4.8357 (0.8624)***	4.7166 (1.1737)***	2.4509 (0.5946)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1531 (0.0437)***	-0.0821 (0.0315)**	-0.0353 (0.0934)	-0.0934 (0.0393)**	-0.1052 (0.0356)**
nobs.	1540	1135	2836	1459	2917
df	1527	1122	2823	1446	2904
R^2	0.2603	0.3012	0.114	0.1537	0.0833
$\bar{R}^2$	0.2544	0.2937	0.1103	0.1467	0.0795
F-value	44.7706	40.2981	30.2791	21.8862	21.9936

Table D

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 16-20. Population not included.

Variable	Chemical Engineering	Surface techn.	Materials Processing	Thermal Processes	Environmental techn.
constant	-22.7789 (0.2311)***	-22.6845 (0.2592)***	-23.361 (0.3107)***	-23.0198 (0.1787)***	-22.8837 (0.2481)***
$P_{i,k}$	0.0240 (0.0071)***	0.0304 (0.0129)**	0.0119 (0.0034)***	0.0136 (0.0059)**	0.0122 (0.0073)*
$P_{j,k}$	0.0200 (0.0093)**	0.0571 (0.0253)**	0.0153 (0.0051)**	0.0229 (0.0101)**	0.0555 (0.017)**
HQ_i	-0.0001 (0.0000)***	-0.0001 (0.0000)**	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
HQ_j	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0000)	-0.0001 (0.0001)**
$\overline{HQ}_i$	-0.0200 (0.0239)	-0.0418 (0.0305)	0.0076 (0.038)	-0.0093 (0.02)	-0.0218 (0.0317)
$\overline{HQ}_j$	-0.0191 (0.0184)	-0.0249 (0.0191)	-0.0046 (0.0242)	-0.0087 (0.0146)	-0.0171 (0.0191)
R_i	0.0002 (0.0001)*	0.0002 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
R_j	-0.0001 (0.0002)	-0.0001 (0.0002)	0.0000 (0.0002)	0.0001 (0.0002)	0.0004 (0.0003)
U_i	0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)
U_j	0.0002 (0.0002)	0.0001 (0.0002)	-0.0001 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)
$e^{-\lambda t_{ij}}$	3.6879 (0.6158)***	3.5418 (0.7533)***	5.4435 (0.7729)***	2.6358 (0.5485)***	3.1654 (0.6502)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1362 (0.0368)***	-0.1182 (0.0378)**	-0.174 (0.0421)***	-0.1106 (0.0336)**	-0.1154 (0.0314)***
nobs.	4294	2836	3808	4051	3322
df	4281	2823	3795	4038	3309
R^2	0.0761	0.0641	0.1059	0.0558	0.0906
$\bar{R}^2$	0.0735	0.0601	0.1031	0.053	0.0873
F-value	29.3778	16.1013	37.4679	19.8958	27.4846

Table E

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 21-25. Population not included.

Variable	Machine tools	Engines	Mechanical Elements	Handling	Food Processing
constant	-23.0407 (0.2268)***	-23.1945 (0.1678)***	-23.5016 (0.1903)***	-23.0904 (0.2294)***	-22.8901 (0.2139)***
$P_{i,k}$	0.005 (0.0022)**	0.011 (0.0052)**	0.0185 (0.0047)***	0.0051 (0.002)**	0.0127 (0.0087)
$P_{j,k}$	0.0052 (0.003)*	0.0014 (0.0109)	0.0135 (0.0075)*	0.0047 (0.0026)*	0.018 (0.0135)
HQ_i	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-0.0001 (0.0000)
HQ_j	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-0.0001 (0.0000)
$\overline{HQ}_i$	-0.0234 (0.0247)	0.0033 (0.0202)	0.0366 (0.0198)*	-0.0085 (0.0221)	-0.0239 (0.0224)
$\overline{HQ}_j$	-0.0008 (0.0233)	0.0052 (0.0138)	0.0013 (0.0161)	-0.013 (0.021)	0.0047 (0.0142)
R_i	0.0001 (0.0001)	0.0000 (0.0001)	-0.0004 (0.0001)**	0.0000 (0.0001)	0.0001 (0.0001)
R_j	0.0000 (0.0002)	0.0000 (0.0002)	-0.0002 (0.0002)	0.0002 (0.0002)	0.0001 (0.0001)
U_i	0.0000 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)**	0.0000 (0.0001)	0.0002 (0.0001)**
U_j	0.0003 (0.0002)	0.0003 (0.0002)*	0.0001 (0.0001)	0.0001 (0.0001)	0.0004 (0.0002)**
$e^{-\lambda t_{ij}}$	5.1389 (0.7272)***	2.8758 (0.6155)***	3.8611 (0.5586)***	5.2762 (0.6871)***	2.8954 (0.5514)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1549 (0.0392)***	-0.1294 (0.0381)***	-0.0933 (0.0291)**	-0.1667 (0.0434)***	-0.0846 (0.0279)**
nobs.	4618	3241	5023	4537	4213
df	4605	3228	5010	4524	4200
R^2	0.0788	0.0794	0.0756	0.0963	0.0497
$\bar{R}^2$	0.0764	0.076	0.0734	0.0939	0.047
F-value	32.8407	23.1992	34.1624	40.1923	18.3156

Table F

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 26-30. Population not included.

Variable	Transport	Nuclear Engineering	Space techn.	Consumer Goods	Civil Engineering
constant	-23.0888 (0.1995)***	-23.4075 (0.5045)***	-22.4776 (0.301)***	-23.0988 (0.1754)***	-23.1808 (0.1402)***
$P_{i,k}$	0.0052 (0.0043)	0.0146 (0.0054)**	0.0152 (0.0045)***	0.0068 (0.0051)	0.0093 (0.007)
$P_{j,k}$	0.0188 (0.006)**	0.0345 (0.0188)*	0.0289 (0.0105)**	-0.0088 (0.0066)	0.0116 (0.0074)
HQ_i	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
HQ_j	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0001)	0.0001 (0.0000)**	0.0000 (0.0000)
$\overline{HQ}_i$	-0.0190 (0.0208)	0.0095 (0.0761)	-0.0758 (0.0363)**	-0.0148 (0.0174)	0.0102 (0.0152)
$\overline{HQ}_j$	-0.0077 (0.0177)	0.0055 (0.0235)	-0.0582 (0.0217)**	-0.0233 (0.0156)	-0.0115 (0.0144)
R_i	0.0001 (0.0002)	-0.0001 (0.0001)	0.0000 (0.0001)	-0.0002 (0.0001)	-0.0001 (0.0001)
R_j	-0.0002 (0.0002)	-0.0002 (0.0004)	0.0000 (0.0003)	-0.0001 (0.0001)	-0.0001 (0.0001)
U_i	0.0001 (0.0001)	0.0002 (0.0001)*	-0.0001 (0.0000)**	0.0001 (0.0001)	0.0002 (0.0001)
U_j	0.0002 (0.0001)	0.0009 (0.0004)**	0.0000 (0.0002)	0.0002 (0.0001)	0.0000 (0.0001)
$e^{-\lambda t_{ij}}$	4.8547 (0.6647)***	3.8414 (1.2712)**	3.0934 (0.8141)***	4.7061 (0.6255)***	4.3863 (0.6046)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1573 (0.0381)***	-0.0611 (0.0259)**	-0.0769 (0.0287)**	-0.164 (0.0393)***	-0.1682 (0.0437)***
nobs.	4942	1297	2431	5023	5670
df	4929	1284	2418	5010	5657
R^2	0.0963	0.1435	0.0890	0.0987	0.0819
$\bar{R}^2$	0.0940	0.1355	0.0845	0.0965	0.0799
F-value	43.7452	17.9283	19.6838	45.7147	42.0386

Appendix A.2 Results without population and without headquarters

Table G
Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 1-5. Population and headquarters excluded.

Variable	Electrical engineering	Audiovisual techn.	Telecommunication	Information techn.	Semiconductors
constant	-23.0561 (0.1806)***	-23.4474 (0.2924)***	-22.475 (0.2247)***	-23.1051 (0.1869)***	-23.2325 (0.6003)***
$P_{i,k}$	0.008 (0.0022)***	0.026 (0.0151)*	0.0014 (0.0008)*	0.0028 (0.0044)	0.0141 (0.0086)
$P_{j,k}$	0.007 (0.0029)**	0.0091 (0.0268)	-0.0009 (0.002)	-0.0036 (0.0126)	0.0104 (0.0565)
$\overline{HQ}_i$	-0.0266 (0.0218)	0.0271 (0.0377)	-0.0849 (0.026)**	-0.0187 (0.0215)	-0.0192 (0.0831)
$\overline{HQ}_j$	-0.0118 (0.017)	0.019 (0.0226)	-0.0369 (0.0266)	0.0047 (0.0227)	-0.0018 (0.0384)
R_i	0.0000 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)
R_j	0.0000 (0.0001)	0.0000 (0.0001)	0.0004 (0.0002)**	0.0002 (0.0002)	-0.0003 (0.0004)
U_i	0.0003 (0.0001)**	0.0002 (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
U_j	0.0003 (0.0002)**	0.0002 (0.0002)	0.0003 (0.0002)	0.0006 (0.0003)**	0.0022 (0.0007)**
$e^{-\lambda t_{ij}}$	5.5006 (0.7379)***	2.6752 (0.6484)***	5.1876 (0.8555)***	2.1521 (0.6191)***	3.582 (1.0464)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.2254 (0.047)***	-0.1047 (0.0315)***	-0.1723 (0.0462)***	-0.1271 (0.0381)***	-0.1153 (0.0364)**
nobs.	4294	2188	3079	2269	973
df	4283	2177	3068	2258	962
R^2	0.1321	0.0724	0.147	0.1129	0.2735
$\bar{R}^2$	0.0752	0.0673	0.1437	0.1082	0.2644
F-value	65.19	16.9917	52.8717	28.7373	36.2157

Table H

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 6-10. Population and headquarters excluded.

Variable	Optics	Control techn.	Medical techn.	Organic Chem.	Polymers
constant	-23.3592 (0.3379)***	-23.1827 (0.2275)***	-23.383 (0.2661)***	-23.0028 (0.5252)***	-23.3106 (0.3233)***
$P_{i,k}$	0.0020 (0.0085)	0.0099 (0.004)**	0.0056 (0.0032)*	0.0071 (0.0048)	0.0089 (0.0102)
$P_{j,k}$	-0.0339 (0.021)	0.0003 (0.0055)	0.0027 (0.0053)	0.0291 (0.0207)	0.0591 (0.0400)
$\overline{HQ}_i$	0.0215 (0.0434)	-0.0231 (0.0244)	0.0556 (0.0357)	-0.0335 (0.0689)	0.0356 (0.0518)
$\overline{HQ}_j$	-0.0032 (0.0234)	0.0246 (0.0222)	-0.0274 (0.0205)	-0.0394 (0.0346)	-0.0197 (0.0160)
R_i	0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0002)	0.0000 (0.0001)	-0.0001 (0.0001)
R_j	0.0003 (0.0003)	0.0000 (0.0002)	-0.0001 (0.0002)	-0.0003 (0.0003)	-0.0002 (0.0002)
U_i	0.0000 (0.0001)	0.0000 (0.0002)	0.0003 (0.0001)*	0.0001 (0.0001)	0.0002 (0.0001)*
U_j	0.0007 (0.0003)**	0.0005 (0.0002)**	0.0010 (0.0003)***	0.0011 (0.0007)	0.0005 (0.0004)
$e^{-\lambda t_{ij}}$	2.3990 (0.6852)***	5.9570 (0.7464)***	4.7356 (0.6934)***	4.7444 (1.1829)***	3.8088 (0.9625)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1102 (0.0346)**	-0.2218 (0.0454)***	-0.1667 (0.0425)***	-0.1378 (0.0383)***	-0.0995 (0.0344)**
nobs.	1783	4294	3970	1216	1864
df	1772	4283	3959	1205	1853
R^2	0.0986	0.1169	0.1554	0.2717	0.1160
$\bar{R}^2$	0.0925	0.1144	0.1528	0.2644	0.1103
F-value	19.3831	56.696	72.8426	44.9538	24.3154

Table I
Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 11-15. Population and headquarters excluded.

Variable	Pharmaceutics	Biotechn.	Materials	Food Chem.	Basic Materials Chem.
constant	-22.6619 (0.3623)***	-22.2071 (0.5736)***	-23.7479 (0.3622)***	-23.3969 (0.5534)***	-23.0153 (0.2207)***
$P_{i,k}$	0.0074 (0.0046)	0.0137 (0.008)*	0.0134 (0.004)***	0.0095 (0.0045)**	-0.0011 (0.0105)
$P_{j,k}$	0.0388 (0.0197)**	0.0232 (0.0473)	0.0257 (0.0087)**	0.0847 (0.0291)**	0.0570 (0.0252)**
$\overline{HQ}_i$	-0.0651 (0.0456)	-0.1552 (0.0836)*	0.0629 (0.0479)	0.0447 (0.0761)	-0.0312 (0.0263)
$\overline{HQ}_j$	-0.0575 (0.0328)*	-0.0327 (0.0258)	0.0234 (0.0258)	-0.0417 (0.0305)	0.0072 (0.0191)
R_i	0.0000 (0.0001)	0.0001 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)
R_j	-0.0001 (0.0002)	-0.0001 (0.0003)	-0.0001 (0.0001)	-0.0001 (0.0002)	-0.0001 (0.0001)
U_i	0.0000 (0.0002)	-0.0001 (0.0003)	0.0001 (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)
U_j	0.0000 (0.0007)	0.0016 (0.0014)	0.0001 (0.0002)	0.0003 (0.0004)	0.0001 (0.0002)
$e^{-\lambda t_{ij}}$	5.2965 (1.1488)***	2.4871 (1.0026)**	4.7186 (0.8595)***	4.6517 (1.1801)***	2.4517 (0.600)***
$\frac{N_i}{N_j} e^{-\lambda t_{ij}}$	-0.1531 (0.0418)***	-0.0837 (0.0315)**	-0.0493 (0.0944)	-0.0871 (0.0349)**	-0.0952 (0.0333)**
nobs.	1540	1135	2836	1459	2917
df	1529	1124	2825	1448	2906
R^2	0.2540	0.3001	0.1075	0.1529	0.0816
$\bar{R}^2$	0.2481	0.2926	0.1037	0.1459	0.0778
F-value	52.0598	48.1944	34.0266	26.1361	25.8199

Table J

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 16-20. Population and headquarters excluded.

Variable	Chemical Engineering	Surface techn.	Materials Processing	Thermal Processes	Environmental techn.
constant	-23.0621 (0.2214)***	-22.8774 (0.2464)***	-23.2966 (0.3026)***	-23.0751 (0.1653)***	-22.9682 (0.2253)***
$P_{i,k}$	0.0061 (0.0057)	0.013 (0.0114)	0.0123 (0.0032)***	0.0131 (0.0046)**	0.0128 (0.0061)**
$P_{j,k}$	0.0157 (0.0078)**	0.0521 (0.0227)**	0.0157 (0.0048)**	0.0169 (0.0082)**	0.0393 (0.0142)**
$\overline{HQ}_i$	0.0035 (0.0239)	-0.0211 (0.0298)	0.0054 (0.0378)	-0.008 (0.0199)	-0.0217 (0.0305)
$\overline{HQ}_j$	-0.0173 (0.0187)	-0.0237 (0.0193)	-0.0033 (0.0245)	-0.0063 (0.0148)	-0.0192 (0.0195)
R_i	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
R_j	-0.0002 (0.0001)	-0.0002 (0.0001)	0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
U_i	0.0002 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)
U_j	0.0002 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	0.0001 (0.0001)	0.0000 (0.0001)
$e^{-\lambda t_{ij}}$	3.6075 (0.6143)***	3.4895 (0.7443)***	5.4702 (0.772)***	2.5955 (0.5426)***	3.0185 (0.643)***
$\frac{N_i}{N_j}e^{-\lambda t_{ij}}$	-0.1476 (0.0381)***	-0.1316 (0.0386)***	-0.1649 (0.0385)***	-0.1096 (0.0321)***	-0.1076 (0.0284)***
nobs.	4294	2836	3808	4051	3322
df	4283	2825	3797	4040	3311
R^2	0.0718	0.0618	0.1053	0.055	0.0829
$\bar{R}^2$	0.0692	0.0578	0.1025	0.0522	0.0796
F-value	33.1307	18.6085	44.6881	23.5132	29.9293

Table K

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 21-25. Population and headquarters excluded.

Variable	Machine tools	Engines	Mechanical Elements	Handling	Food Processing
constant	-23.0418 (0.2099)***	-23.2027 (0.1604)***	-23.468 (0.1815)***	-23.0959 (0.2214)***	-23.0239 (0.1975)***
$P_{i,k}$	0.0050 (0.0022)**	0.0115 (0.0056)**	0.0186 (0.0047)***	0.0053 (0.0018)**	0.0018 (0.0063)
$P_{j,k}$	0.0053 (0.003)*	0.0012 (0.0113)	0.0138 (0.0074)*	0.0041 (0.0023)*	0.0052 (0.0097)
$\overline{HQ}_i$	-0.023 (0.0242)	0.0021 (0.0202)	0.0356 (0.0196)*	-0.0088 (0.022)	-0.0157 (0.0213)
$\overline{HQ}_j$	-0.0007 (0.0232)	0.0058 (0.0137)	0.003 (0.0163)	-0.0135 (0.021)	0.0038 (0.0142)
R_i	0.0001 (0.0001)*	-0.0001 (0.0001)	-0.0004 (0.0001)***	0.0000 (0.0001)	0.0000 (0.0001)
R_j	0.0000 (0.0001)	0.0001 (0.0002)	-0.0001 (0.0002)	0.0001 (0.0001)	-0.0001 (0.0001)
U_i	0.0000 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)**	0.0000 (0.0001)	0.0002 (0.0001)*
U_j	0.0003 (0.0002)*	0.0003 (0.0002)*	0.0001 (0.0001)	0.0001 (0.0001)	0.0004 (0.0002)**
$e^{-\lambda t_{ij}}$	5.1452 (0.7237)***	2.8963 (0.6167)***	3.8885 (0.5618)***	5.2479 (0.6821)***	2.8532 (0.5458)***
$\frac{N_i}{N_j} e^{-\lambda t_{ij}}$	-0.156 (0.0375)***	-0.1361 (0.0372)***	-0.0907 (0.0282)**	-0.1619 (0.0403)***	-0.0883 (0.0278)**
nobs.	4618	3241	5023	4537	4213
df	4607	3230	5012	4526	4202
R^2	0.0788	0.0789	0.0789	0.0960	0.0470
$\bar{R}^2$	0.0764	0.0755	0.0752	0.0752	0.0752
F-value	39.4086	27.6677	42.932	48.0637	20.7234

Table L

Estimation results by technology. White's heteroscedasticity consistent standard errors are in parenthesis. 10 per cent significance level marked *, 5 per cent with ** and 1 per cent with ***. Technologies 26-30. Population and headquarters excluded.

Variable	Transport	Nuclear Engineering	Space techn.	Consumer Goods	Civil Engineering
constant	-23.0801 (0.1885)***	-23.4213 (0.4987)***	-22.4398 (0.295)***	-22.9561 (0.1590)***	-23.1834 (0.1364)***
$P_{i,k}$	0.0050 (0.0043)	0.0145 (0.0055)**	0.0149 (0.0045)***	0.0105 (0.0034)**	0.0079 (0.0043)*
$P_{j,k}$	0.0184 (0.0062)**	0.034 (0.0189)*	0.0283 (0.0105)**	0.0002 (0.0046)	0.0130 (0.0052)**
$\overline{HQ}_i$	-0.0191 (0.0207)	0.0141 (0.0740)	-0.0764 (0.0362)**	-0.0198 (0.0168)	0.0110 (0.0157)
$\overline{HQ}_j$	-0.0073 (0.0178)	0.0077 (0.0244)	-0.0547 (0.0213)**	-0.0216 (0.0156)	-0.0120 (0.0148)
R_i	0.0001 (0.0001)	-0.0001 (0.0000)**	0.0001 (0.0000)*	-0.0001 (0.0001)	-0.0001 (0.0001)
R_j	-0.0002 (0.0001)*	-0.0001 (0.0002)	0.0002 (0.0001)	0.0001 (0.0001)	-0.0001 (0.0001)
U_i	0.0001 (0.0001)	0.0003 (0.0001)**	-0.0001 (0.0000)**	0.0001 (0.0001)	0.0002 (0.0001)
U_j	0.0002 (0.0001)	0.0009 (0.0004)**	0.0001 (0.0002)	0.0002 (0.0001)*	0.0000 (0.0001)
$e^{-\lambda t_{ij}}$	4.8628 (0.6630)***	3.8853 (1.2351)**	3.1472 (0.8102)***	4.7788 (0.6339)***	4.3894 (0.6042)***
$\frac{N_i}{N_j} e^{-\lambda t_{ij}}$	-0.1575 (0.0373)***	-0.0609 (0.0241)**	-0.0740 (0.0275)**	-0.1693 (0.0398)***	-0.1692 (0.0435)***
nobs.	4942	1297	2431	5023	5670
df	4931	1286	2420	5012	5659
R^2	0.0962	0.1432	0.0882	0.0967	0.0818
$\bar{R}^2$	0.0752	0.0752	0.0752	0.0752	0.0752
F-value	52.4853	21.4934	23.4091	53.6544	50.4145