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THE SPATIAL DISTRIBUTION OF INNOVATION NETWORKS

Mats Wilhelmsson

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Abstract

Innovation networking has become both more feasible with improved telecommunication and more important as it usually produces research of higher quality. However, the spatial distribution of academic networks and innovative networks are not uniform. Despite overwhelming evidence on the benefits of collaboration, patent data from 1994-2001 in Sweden demonstrate that innovation networks are not very common. In addition, the pattern of innovative networks is very fragmented. Our results indicate that innovation networks are more likely to exist in densely populated areas with a diversified industry. Face-to-face contacts in such areas seem to promote networking. Moreover, science-oriented industries appear to benefit more from proximity to universities when it comes to collaboration. However, the size of the market does not matter at all when it comes to collaboration, more important is the density and diversity of the market.

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1. Introduction

Policy makers have always been faced with problems about how to promote growth and enhance regional economic development. Twenty years ago, Romer (1986) in a seminal paper stressed the importance of human capital on economic growth. However, the precise linkage between academic research, knowledge and economic growth is unclear. A number of studies have focused on the role of higher education and innovation as the key "transport mechanism." (e.g. Andersson et al, 2004). On the other hand, Storper and Venables (2004), and Owen-Smith and Powell (2004) argued that innovation networks are a way of transferring knowledge.

Collaboration and co-authorship within academic research has become more feasible as telecommunication has improved over the years. For example, Gaspar and Glaeser (1998) reported that the proportion of co-authored articles in four well-established economic journals has increased from less than five percent in the early 1960s to above 50 percent in the early 1990s. Moreover, Andersson and Persson (1993) reported that the number of internationally co-authored articles has increased by almost 15 percent per year. The proportion of co-authored articles is also high in a journal such as *The Annals of Regional Science*. In the middle of 2000, the share of co-authored articles was around 60 percent compared to around 50 percent in the beginning of 1990.

Innovative networks have also become more important as they normally produce research of superior quality. For example, Stephan (1996) shows that innovation networks do produce "better" research. According to Acs (2000), networks are also associated with a greater degree of innovation. Thus, innovative networks generate more new knowledge, better innovations and therefore more wealth. Henceforth, there has been a growing interest in innovation networks and its implications for the creation of new knowledge.

The spatial distributions of academic and innovative networks are not uniform. For example, Andersson and Persson (1993) explain the spatial pattern of academic collaboration across national borders vis a vis the size of the academic environment, its proximity to other academic venues and language similarity. Even within a country, we can observe regional differences in network density.

What in the regional context can explain differences in innovation network density? The purpose of this paper is among other things to investigate this question. An essential issue for policy makers is to understand what explains and enhances regional networking. Thus, the aim of this research is to contribute to a better understanding of how important innovative networks are for the efficiency of research and what factors in the regional context promote scientific networking. In particular, we want to analyze existing innovative networks in Sweden over the period 1994-2001 and consider such questions as: is it more likely that urbanized areas have more networks compared to less urbanized areas or can networks be seen as substitutes for agglomeration economies? A key point here is that face-to-face communication within agglomerations seems to encourage changes of ideas and networking (see, for instance, Saxenian, 1994 and Fujita and Thisse, 2002). Moreover, concentration of firms appears to facilitate networking and appears to increase the state of knowledge in the industry (Porter, 1990). Hence, we want to relate innovation networks to measures of localization and urbanization, to the industrial composition and size distribution of firms, and to the regional distribution of human capital.

The main objective in this paper is twofold: (1) to perform a descriptive analysis of innovation networks and (2) to analyze the regional determinants of the existence of innovation networks. The first objective will be analyzed by using social network analysis, which will give us measurements concerning network density. The second objective will be handled by relating network density to regional labor market characteristics.

The rest of the paper is organized as follows: Section 2 presents a literature review concerning the economic growth model, human capital, innovation, networks and agglomeration economies. In Section 3 we will discuss the methods used in the paper, including the social network analysis; and in Section 4, we present the data together with a descriptive analysis. In Section 5, the econometric analysis is presented; and in Section 6, the paper is ended with conclusions and a discussion of policy implications.

2. A Literature Review

Externalities flowing from human capital in regional development had a scientific revival with endogenous growth models starting with Romer (1986, 1990), Lucas (1988) and Grossman and Helpman (1991).

Griliches (1979, 1998), Jaffe (1986, 1989), Anselin, Varga and Acs (1997), Acs (2002) and Andersson et al (2004) have all modeled this effect of externalities in a production-function framework using industrial and/or university research as inputs. They found significant and positive effects from university research on output, which they interpreted as evidence of knowledge transfers arising from the existence of a university.

However, the precise linkages between academic research, knowledge transfers and economic growth remain unclear. In the words of Jaffe et al (2002), the “transport mechanism” is not well understood. Empirical studies have attempted to quantify these knowledge transfers from research to innovating firms through various proxies, such as investigate the patenting of university innovations, examine the impact of university science parks and determine whether spin-off activities have taken place.

Others, such as Storper and Venables (2004) and Owen-Smith and Powell (2004) argue that innovation networks are a way of transferring knowledge. From empirical studies, the conclusion is reached that research-collaboration networks are an important mechanism for firms to use in order to engage in industry-science relations (Henderson, Jaffe and Trajtenberg, 1993). Empirical findings also indicate that performance is better among companies that collaborate (see e.g.Rothwell et al, 1974, Hagedoorn and Schankenraad, 1994, Shan et al, 1994, Walker et al, 1997, Stuart, 2000, Fritsch and Franke, 2004, Owen-Smith and Powell, 2004). Moreover, some results indicate that collaborating companies are tend to be likely to be more innovative compared to non-collaborative companies and are more likely to be engaged in a greater number of projects.

As said, statistics on patents have been used to study quantitative changes of inventive activities over time and space as a proxy for knowledge spillovers (see Jaffe, 1986, Jaffe and Trajtenberg, 2002). The number of patent applications and patents granted is considered to be an important indicator of competitiveness, since patents are the primary instruments used to protect the commercial value of innovations. For example, Jaffe investigated American- approved patents with regard to the companies' research and development (R&D). He found that a transfer of knowledge occurs among companies in regions with a high production of patents. Companies performing research in areas where a considerable amount of research is carried out by other companies will, in general, receive more approved patents per dollar spent on R&D than companies in areas where relatively little research is carried out by other companies. Thus, clusters of companies performing R&D will produce knowledge spillover effects.

In Andersson et al (2005b) the spatial distribution of new knowledge production is studied. Commercial patents granted in Sweden during 1994-2001 are analyzed using a panel of (100) one hundred labor market areas. Patent activity is related to measures of localization and urbanization, to the industrial composition and size distribution of firms, and to the regional distribution of human capital. The analysis confirms the importance of human capital and research facilities in stimulating regional patent output. Importantly, the results also document the importance of agglomeration and spatial factors in influencing patent activity: Patent activity increases in larger and denser labor markets and in regions in which a larger fraction of the labor force is employed in medium-sized firms. The results also indicate that patents activity is greater in labor markets with more diverse employment bases and in those, which contain a larger share of national employment in certain industries, confirming the importance of urbanization and localization economies in stimulating patent activity.

The notion that the concept of agglomeration is important in the spatial economies is well known. For example, Alfred Marshall focused on factors determining regional growth such as ‘agglomeration effects’ and ‘spillover effects’. In the agglomeration model, industrial clustering occurs because, in the words of Hoover (1937), there are external economies of localization and urbanization. The reason for these external economies, according to Marshall (1925), is that in an agglomeration, firms are able to share labor and other inputs (better matching); and in an agglomeration, knowledge is spread more efficiently. A number of empirical analyses support the importance of urbanization economies for enhancing the information of new knowledge—that is, Rosenthal and Strange (2004) and Hanson (2001). For example, Hanson’s results indicate the presence of “localized human-capital externalities.”

There is nothing in the agglomeration model that says that collaboration between firms or inventors within a firm is more frequent in areas where, for example, we exhibit agglomeration economies. Nevertheless, knowledge is more efficiently spread within a network, which indicates that networking could be more common in agglomerations. However, Johansson and Quigley (2004) argue that “networks among economic actors dispersed over space may act as a substitute for agglomerations of actors at a single point.” This means that agglomeration may not be as important for networking as one might believe. Innovative networking may take place because of a lack of agglomeration. Thus, networks can be thought of as a substitute for agglomeration.

Gordon and McCann (2000) describe industrial clustering from three different theories/models, namely: traditional agglomeration theories, industrial-complex systems and social network theories. Their argument is that clustering can arise from different reasons; and when it comes to policy recommendations, it is important to be aware of this in the investigation of a particular labor market. As Gordon and McCann say, the spatial dimension in social-network models is not clear. However, their conclusion is that the social-network model predicts more networking in an area with less agglomeration. Specifically, investing in networks is more important for firms outside the big agglomerations. Therefore, networking, and especially cross-border networking, should be more common in labor markets that lack agglomeration economies. Hence, innovation networks, which include members across labor markets and national borders, are more likely to be developed in areas where agglomeration economies are weaker. For example, Gordon and McCann's empirical study concerning London, England shows that the spatial distribution of innovation collaboration has no relationship to the industrial clustering in the areas.

In a theoretical article, Meagher and Rogers (2004) set up a very interesting and compelling model demonstrating how networking affects innovativeness. Their model is based on organizational theory, and their simulation results show that "network density can effect innovativeness but only when there are heterogeneous firms." Specifically, it seems that both agglomeration and industrial diversity play a role in explaining innovation networking and potential outcomes. The authors' results concerning the size of the market show that the size *per se* does not play an important role in fostering innovativeness. It is the density that matters.

How about geographical proximity? How important is closeness? For example, will face-to-face contact be less important in the future, as information technology is improved? Gasper and Glaeser's (1998) results indicate the opposite. Improved communication technology makes some face-to-face contacts unnecessary; but it will also increase the frequency of contacts between individuals, which will result in more face-to-face contacts in other respects. The argument is that telecommunication technology and face-to-face contacts are not substitutes but complements. Storper and Venables (2004) even argue that face-to-face contact is "a missing aspect of mechanisms that are considered to generate agglomeration." This is in the line of our argument that the network (which facilitates face-to-face contacts) is an important part of the transfer mechanism. Their game theoretical analysis with two researchers, and has three Nash equilibria. One involves both researchers putting in exactly the same amounts of effort. The other two are equilibria where one researcher put in all the effort, and the other put in no effort at all. Storpers and Venables' argument is that face-to-face contacts guarantee that we do not end up in a solution with free-riders, that is, where only one researcher puts in all the effort.

3. Methodology and Models

Our proposition is that innovation networks can, to a high degree, be explained by regional and local factors such as agglomeration, density and industrial composition, together with the educational level of the workforce. Moreover, our proposition is that innovation collaboration varies by industry and is more important in industries close to the sciences, such as biotechnology. Furthermore, our proposition is that distance matters in the sense that researchers are more likely to collaborate with other inventors within the same labor market, but that proximity has become less important over time.

Two very distinct methods are in this paper. First, we are going to use the toolbox of social network analysis. Here, only a limited descriptive part of the toolbox is used. By utilizing social network analysis, our aim is to construct a number of measures or indexes that characterize innovative networks and their variation in space. The second method is that of econometric analysis. One model will be estimated, analyzing the following question: ”can the variation in space when it comes to networking be explained by urban economic determinants by using a negative binomial regression model”?

Social Network Analysis

Social network analysis is not very common in the regional economic literature. However, the method has become more and more popular. Examples using empirical social analyses within Economics are Owen-Smith et al (2002), Balconi et al (2004), Ejermo and Karlsson (2006) and Cantner and Graf (2006).

The basic social network analysis, which will be used partly here, examines the nodes and the links, and the relationship between them. In the context of innovation networks, the nodes are the inventors and the links are the relationship between the inventors. The links (or egdges, ties) show the interconnectedness and the distance between the innovators. Details concerning the methodology can be found in Wassermann and Faust (1994). A short description can also be found in Balconi et al (2004) and Cantner and Graf (2006).

A number of different measures can be used to characterize a network. Here we will especially use measures such as: Network Density, Geodesic Distance, Network Centrality, Isolates, Components and Size of the Largest Component (see Marsden, 1990)[1].

The network density is defined as the number of existing links between nodes in a region divided by the maximum possible number of links in that region:

$$d_{i,t,k} = \frac{l_{i,t,k}}{n_{i,t,k}(n_{i,t,k} - 1)} \qquad (1)$$

where l is equal to observed number of links in region i, year t and product type k. The letter n is equal to the number of inventors in the same region, period and product type. If d increases, the density of the networks in the region is higher.

For example, assume that there are three inventors in the region. Two of them collaborate and have one patent. The other does not collaborate with anybody and has one patent. That means that we have two links between two nodes. The total number of links is six, that is, the density of the network is equal to one third. The number of components is equal to two; hence, two disconnected networks exist. The size of the largest component is equal to the number of nodes, in this case two. The geodesic distance between two nodes in a component is the minimum number of links between them. The diameter of the largest component is estimated as the largest geodesic distance in that component. In our example, we have one isolate, that is, one one-inventor patent. Centrality of the network is a measurement of how much the network revolves around a node. For example, we can expect that in some regions with a strong employer, the networks are more centralized.

[1] Ucinet has been used as software for the social network analysis (see Borgotti et al, 2004).

We are using three different measurements to estimate the degree of networking. The first two measurements focus on the nodes, explicitly, the inventors. The first measurement is estimated by dividing the number of inventors by the number of patents; and the second measurement by the number of inventors minus the isolates by the number of patents. Both these measures quantify the average size of the networks. Lastly, the third measurement is focused on the links (ties) between the nodes and is called in the social network literature the network density, and defined as in Equation 1 above.

Some recent empirical studies investigating innovative networks and partly using the social network analysis methods are Simmie et al (2002), Balconi et al (2004), Kaufmann (2007), and Ejermo and Karlsson (2004). Balconi et al investigate the role of academia in innovation networks. They do that by performing a social network analysis of Italian patent data. Their conclusion is that the formation of networks is very scattered and fragmented in Italy. The exception is science-oriented technology fields, such as within the chemical industry. Mansfields' (1995) results are thereby supported by their findings. His results also indicate that a substantial portion of the innovations within high-technology sectors is a result of academic- research collaboration.

Semmie et al (2002) investigate innovation in five West-European cities. Their main objective is to find answers as to why some cities or regions are more successful when it comes to innovation rates. As do Gordon and McCann, they first identify the theories that explain why innovations are concentrated in space and then compare these theories with the outcome from the survey. Findings in the survey seem to confirm that networks in the forms of business networks are important. However, the authors conclude that the theories seem to enlarge the importance of local networks. International and regional networks seem to be more important.

Kaufmann (2007) analyzed innovation networks within the Vienna urban area. His conclusion seems to indicate that there is a difference between firms located in the city and those in the suburban areas, and that the urban area cannot be described as one single metropolitan innovation system. Earlier, Catner and Graf (2006) investigated research collaboration within an urban area. Their study is carried out on Jena in Germany and is an application of social network analysis and network regression. Their results indicate, for example, that a shared knowledge base is vital when it comes to joint research projects.

In a recent paper by Ejermo and Karlsson (2006), the interregional structure of inventor networks in Sweden was investigated. They measure how close the relationship is between two regions. This measure is called affinity, and it is defined as the difference between the number of observed links from one region to another and the number of potential links. Hence, it measures how closely related two labor markets are when it comes to collaboration in research. The data they are using are all the patent applications with at least one inventor from Sweden and filed at the European Patent Office (EPO). They found out that when it comes to inventor networks, the relationship between two labor markets is highly influenced by the distance between the two labor markets. However, the variation in distance sensitivity is large, across different technologies. Inventors in a region with R&D resources are less likely to collaborate with inventors in other regions that lack similar resources. Moreover, their results indicate that inventors in large agglomerations are less likely to collaborate with inventors in small labor markets. Fritsch (2001) also emphasized in his study in Germany that spatial proximity is important for collaboration among firms.

Econometric Analysis

We will use a number of models to be able to answer the research questions. The basic model is a negative binomial regression model that will be used to analyze the spatial distribution of network density and other network measures that vary in space. The reason we are using the count model is that we have zero counts, that is, in some labor markets the number of innovation networks is equal to zero.

Albeit there is not much in the theory that indicates that networking should vary in space, empirically, the findings show that the degree of innovative networking does vary in space. The coefficient of variation is substantial. In our explanation model, we are trying to relate the spatial variation in network density by measures such as agglomeration, diversity, industrial composition and education level of the workforce.

Many of the independent variables are themselves correlated, and a simple univariate comparison may be highly misleading. We can relate for example, network counts, η_{it}, by labor market, *i*, and year, *t*, to these factors by estimating a count model.

$$\operatorname{prob}\left(\eta_{\mathrm{it}} = \mathrm{y}_{it}\right) = \frac{e^{\mu_{it}\lambda_{it}}\left(\mu_{it}\lambda_{it}\right)^{\mathrm{y}_{it}}}{\mathrm{y}_{it}!} \tag{2}$$

$$\log\lambda_{it} + \log\mu_{it} = X\beta, \tag{3}$$

where the probability that the count η_{it} is equal to y_{it} is expressed in equation (2).

The vector *X* represents characteristics of the labor market *i* at time *t*, and β is a vector of parameters. If μ_{it} = 1, the mean and the variance of the count distribution are equal, and equation (2) is a straightforward Poisson model. If the mean and variance of the count distribution are unequal, parameters of the model may be represented as a straightforward negative binomial count model.[2] The coefficients of the count model are estimated by maximum likelihood methods. The method has earlier been utilized in for example, Andersson et al (2005b).

4. Data and Descriptive Analysis

Data

During the last few decades, data on patents have come to play an important role as a basis in investigating the innovation-producing process. Griliches' surveying paper (1990) evaluates patent statistics as economic indicators. He emphasizes that a patent represents “a minimal quantum of invention that has passed both the scrutiny of the patent office as to its novelty and the test of the investment of effort and resources by the inventor.” However, of the patents granted, many “reflect minor improvements of little economic value,” while some of them “prove extremely valuable.” Furthermore, he points out that a data set on patents is only a subset of all inventions, since not all valuable inventions are patented. However, it is not unreasonable to believe that approved patents are a better proxy for economic value and the quality of the innovation, than the ones not approved.

For the purposes of this study, (since) as patents have the advantage that they can be measured, innovation is defined as the commercial patent applications or awarded patents in Sweden. The data is based upon applied or approved patents registered to the Swedish Patents and Registration Board (PRV) or the European Patent Office (EPO) during the period 1994-2001[3].

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[2] This follows, for example, if it is assumed that μ_{it} follows a gamma distribution, $\mu_{it} \sim Gamma(1/\alpha, \alpha)$. If $\alpha=0$, the model is poisson. If $\alpha > 0$, the model is negative binomial.

[3] Ejermo and Karlsson (2006) are using a similar data set concerning Sweden. The difference in this study compared to their study is that we do not use patent applications, but approved patents, and not only patents from EPO.

Each patent in our database has information on the application firm and its address, plus all the inventors with their addresses. As in Balconi et al (2004), Ejermo and Karlsson (2006), and Cantner and Graf (2006), we implicitly assume that inventors on the patent application know each other and share knowledge with each other. We also have a code indicating the product type of the patent. Here we will use the same classification as in Andersson et al (2005a), which is a classification that is more closely related to economic activities[4].

Two different data sets are constructed. The first data set includes all approved patents over the years 1994 to 2001 and is an inventor data set. To be precise, it includes all the inventors to one and each of the approved patents. Each inventor is considered to be an observation[5]. The patents are the way of identifying the research networks. Each observation is classified as a particular product type and as to whether it is a publicly traded corporation or a large firm (based on market capitalization on the Stockholm stock market) supplemented. The data set is used in the social network analysis. The second data set utilizes the first one in the construction of a labor market data set. A key variable is a measurement concerning the innovative networking used. This measure has been estimated for each labor market and time period. The data set has been supplemented with a number of variables describing the labor market level (see Andersson et al, 2005b).

TABLE 1 IN HERE

[4] The product type definition is original based upon the International Patent Classification system created in 1997. The classification we are using can be found in the appendix.

[5] The total number of inventors is not the unique number of inventors. The unique number of inventors has been identified by using the name of the inventors. If the inventor has a unique name, she/he is considered to be a unique inventor. If two inventors with the same name have different job and home addresses, they are considered to be unique. If they have the same job address and/or home address, they are not considered to be unique.

The inventor data set consists of around 22,000 inventors. Almost 40 percent of them are one-inventor patents[6]. Some of the inventors have been involved in more than one patent. In the data set there are almost 14,000 unique inventors (or 63 percent). The number of patents is equal to 13,631 patents. If we exclude the isolates, only 4,961 patents (or 36 percent) is a result of collaboration. Out of the networking patents, almost half are collaboration across labor market borders. Around 2,000 collaborations are between individual inventors in different labor markets. More than every fifth of each of the inventors comes from the group”*Performing Operations*.” This group includes such procedures as polishing; cleaning; separation; and work with cement, clay, plastic, hand tools, pressing, and printing, etc. The next largest group is *Mechanical Engineering* and *Information Technology*.

The second data set, the labor market data set, is presented below. The labor market areas are defined by the Swedish Labor Ministry on the basis of commuting patterns, using methods analogous to those used to define MSAs in the United States. Most, but not all, of Sweden’s one hundred labor market areas contain a central city and a number of surrounding jurisdictions.

TABLE 2 IN HERE

The variable market size is measured as the number of employment in the non-agricultural sector. Density is used as a measure of agglomeration and is measured as employment per squared kilometer. Diversity is estimated as the Hirfindahl-index[7]. The share of employment within the manufacturing sector measures the specialization in the labor market, and the two measures of human capital are the proportion of PhD's and the number of researchers at the university, respectively.

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[6] Here a one-inventor patent is used as a synonym to ”isolate”, which may or may not be true.

[7] $H_i = \sum_{s=1}^{S_i} \left(\frac{e_{si}}{e_i} \right)^2$, where S is the total number of industries within region *i* and e is the number of employment.

On average (across labor markets and over time), there is slightly more than one inventor per patent (*NW-1*). If we are excluding the isolates, the average number of inventors per patents (*NW-2*) is equal to 1.3. The maximum number of inventors per patent in one labor market is almost ten inventors and the minimum is zero (with zero patents). In other words, there is quite a large variation among the labor markets. The third measure, the density of network (*NW-3*), is the measure that has the largest variation around its mean. The average number of 0.12 can be interpreted as a percentage. Hence, on average the observed network size is around 12 percent of the potential network size[8].

Descriptive Statistics

If we turn our attention to the first data set, it can be observed that more than 80 percent of the inventors originate from corporations and half of them from large firms. The researcher very seldom comes from small firms or is a private person. This pattern is especially clear in the *Pulp and Paper* industry and in the *Electricity* industry.

TABLE 3 IN HERE

It can be observed that collaboration is not common. Almost 65 percent of the approved patents are a result of one-inventor research. In other words, out of 13,600 patents, almost 8,700 are isolates. If we consider the collaborations, that is, the approved patents with more than one inventor, we can conclude that many of the collaborations are based on networks with innovators residing in different labor markets. Around 40 percent of the networks cross-border labor markets and seven percent cross national borders. However, very few of the patents are a result of

[8] As we are using the measure on labor markets, some labor markets will have a network density larger than 1. In other words, they have more observed links than potential links. Observed links are estimated as all links including links to other labor markets, but potential links are only measured within the labor market.

research between different firms[9]. The international collaboration is frequent in less than 10 percent of the patents and has been stable over the studied period. Approximately three percent of the inventors (or 700) work in other countries than Sweden. Near 200 of them work in one of the other Scandinavian countries and more than 300 from other West-European countries.

Collaborations are more prevalent in the *Chemistry/Metallurgy* group. This is also the product type where the most collaboration is found across labor market and national border. In the *Fixed Construction* group, collaborations are more seldom, and if the patent is a result of a research network, it is most likely formed with researchers within the same labor market.

The labor market data set reveals that networking varies in space. We know that the spatial distribution of new knowledge can be explained to a large degree by agglomeration, together with diversity and the regional distribution of human capital (Andersson et al, 2005b). The question is whether innovative networking in itself can be explained by agglomeration economies or by the lack of agglomeration economies.

Social Network Analysis

The social network analysis presented in the present paper is fairly limited. Our main objective is to estimate a measure of networks. As said, three different measures of networking will be used. Two simple ratio measures relating the number of inventors to the number of patents will be estimated (measuring the average size of the networks). The third measure comes from the social network analysis literature and is defined in Equation 1 as the network density. In the table below, some network statistics are presented.

TABLE 4 IN HERE

[9] What we do not identify in our data base is joint ventures between firms resulting in the formation of new research corporations.

The average number of patents per labor market and year is almost 17 patents, and the total number of patents is equal to 13,630 over the period. The standard deviation is very high, and the maximum number of patents is equal to 680 patents, whereas the lowest number is equal to zero. The standard deviation is lower if we only look at the patents resulting from collaboration. Now, the average number of patents per labor market and year is around 11 patents. The number of nodes is equal to almost 26 on average. Here the variation around its mean value is even higher. The observed number of links is equal to 38 per labor market and year. If we look at the number of links over the period and across all labor markets, we can observe that the number of links or ties is equal to more than 30,000. This can be compared to the potential number of links, which is equal to 485,298,870 links. This indicates that the average network density is relatively low but comparable to the number Balconi et al (2004) present concerning networks of Italian inventors. The network density is much higher on average per year and per labor market. We can also observe that the density is rather stable over time (see figure below).

FIGURE 1 IN HERE

In the table below, some network statistics have been estimated for five labor markets in Sweden. The first three are the three largest metropolitan areas in Sweden (Stockholm, Gothenburg and Malmö). The fourth labor market represents an area with a highly specialized industrial sector (compared to the more diversified labor markets for the first three). The fifth labor market represents a small labor market containing a university.

TABLE 5 IN HERE

The number of patents in Stockholm over the eight-year time period is 4,154 patents. It is more than twice as much as in Gothenburg and more than four times as many as in Malmö. The number of inventors equals 6,708 in Stockholm. To a large extent, the patents are one-inventor patents. The number of isolates is equal to 2,628. Nearly 1,500 of the patents are a result of collaboration between two or more inventors. The number of components (networks) is equal to 2,513. Around 750 have more than one inventor, and around 300 are components with three or more inventors. The size of the largest component is equal to 55 nodes, and the network density is only equal to 0.0001. In Stockholm, the fragmentation (including the isolates) is equal to 99.9 percent (99.7 if we exclude the isolates). In other words, only 0.3 percent of the inventors (nodes) in Stockholm can reach each other. The number of inventors per patent in all metropolitan regions is close to 1. The number of innovators per component is equal to 1.7 in Stockholm. The network density is low, but we can observe that it decreases by the size of the labor market. The network density in Västerås is higher compared to Stockholm, and the fragmentation is high in all labor markets except in Västerås. The figures also show that the network centralization is much higher in Västerås, indicating that the networks to a higher degree cluster to a node or a small number of nodes. This can also be seen in that the number of components with more than three inventors is very frequent. One reason could be that Västerås is a very specialized city with ABB as the major employer, and that a number of the innovative networks revolve around a few inventors at ABB.

Proximity

The average geographical distance between nodes has almost doubled over the years 1994 to 2002. In 1994, the average distance between two inventors was less than 60 kilometers compared to more than 120 kilometer in 2001[10]. Hence, proximity seems to be less important today compared to ten years ago. Across labor markets and over the years, the average distance between inventors is around 90 kilometers. Researchers within the industries of *Metallurgy,*

[10] The distance to international inventors has not been estimated.

Information Technology, *Electricity*, and *Paper and Pulp* are all above the average, that is to say, collaboration is more distant in these sectors. The sectors *Mechanical Engineering* and *Sports and Amusements* are very local in the sense that the inventors in the network have close proximity to each other.

5. Econometrics Analysis

The Regional Network Density Model

We analyze the systematic relationship between the network density in the one hundred labor market areas and the four broad classes of determinants: agglomeration, human capital, diversity and industrial structure. As seen in the literature review, the link between these four groups and the innovative networks is not obvious, but our hypothesis is that they all can explain to some degree the density of innovation networks.

The base model concerning the regional network density explanation model is presented below. As a dependent variable, three different measures of network density are used; and as independent variables, market size, measures of agglomeration and diversity are used. We also use the specialization in the labor market by share of employment within the manufacturing sector and two measures of human capital. The preferred model is the negative binomial one, as the over-dispersion parameter (α), is significantly different from zero,

TABLE 6 IN HERE

The overall results indicate that diversity matters positively, together with a larger share employment within the manufacturing sector, while market size affects the number of innovative collaborations negatively. Regardless of measures concerning network density, the results are robust. We also observe a strong indication that employment density matters in a positive way, specifically, if employment density is greater, network density is more common. Higher education seems to have a positive effect on networking, but the number of researchers at a university does not affect it. Even though the parameters concerning the time effects are significantly different from zero in some cases (not presented in the table), the estimates concerning employment density, scope, diversity and so on are almost constant compared with a model without fixed time effects. The fixed time effects pick up a significant effect in the models where *NW-1* and *NW-2* are used as a measure of size of the networks. The density of networks measured as *NW-3* cannot be explained by time, that is, the network density is not stronger or weaker over the studied period.

In some sense, our results appear to confirm the theoretical results by Meagher and Rogers (2004). In other words, it seems that both agglomeration, measured as population density, and industry diversity play a role in explaining networking. Our results do not support what Gordon and McCann (2000) and Johansson and Quigley's (2004) conclusion holds, that is, that networking should be more important in less dense area. On the other hand, market size has a negative impact on networking since we can detect that innovation networks are less common in large metropolitan areas. Hence, networks can be thought of as a substitute for market size and as a complement to density and diversity.

There is no reason to believe that the relationship between the existence of research networks and regional determinants is equal across industries. Contrarily, it seems likely, for example, that science-oriented sectors are more dependent on a highly educated workforce compared to less science-oriented industries.

Below, the date set has been split into three subsets, namely, the sectors *Medical Science, Transporting* and *Information Technology*.

TABLE 7 IN HERE

One important observation is that the variation is not very large in the three subsets. However, there seems to be a difference concerning the formation of innovative networks and the determinants that explain the regional variation. Within the *Information Technology* sector, employment density is not very important in explaining network density. Moreover, it seems that the diversity and educational level of the workforce is of central importance in the *Transportation* sector. Diversity does not play a crucial role in the sector *Medical Science*; instead specialization within the manufacturing sector is indispensable. The market size measured is of no importance in any of the sectors presented here.

Regional Network Proximity Model

Given that you are networking, is it more likely that your network is within the same labor market if you are working in a labor market with high density? This is the question the next model aims to answer. In other words, to what degree is proximity important in the formation of innovative networks? Earlier results (Fritsch, 2001, and Ejermo and Karlsson, 2006) have shown that proximity is important in the formation of innovative networks in countries such as Sweden and Germany. In our data, the correlation between the density of networking and distance between nodes is positive, that is to say, if networking is more common in a labor market, inventors are also more likely to collaborate across labor market borders. In the model below, we are relating the average distance between inventors across labor markets and over time, and the same regional determinants utilized earlier. We have estimated four different models. First, a model is controlling for fixed time effects and another model controlling for both fixed time effects and labor market specific effects. The reason for using the latter is due to the fact that given collaboration across labor markets, northern regions will always have longer “collaboration distance.” By including fixed regional effects, some of the spatial effect will be controlled for (model D2 and D4). Second, we have estimated the models using the average distance between nodes (D1 and D2) with and without isolates (D3 and D4).

TABLE 8 IN HERE

The results indicate that proximity can be explained very well by regional specific determinants. Regardless of model, if employment density increases in the labor market, the average distance between inventors will rise. In other words, researchers in dense areas will not only collaborate more, they will also collaborate over longer distance. The size of the market works the other way around, as well. Larger markets (given the density and all the other variables) will reduce the average distance linking the nodes.

A third result that seems clear is that as the proportion of PhD's in the labor market increases, collaboration distances also increase. In the model in which we are controlling for fixed labor market effects, the estimates concerning diversity are significantly different from zero. The estimate is negative, indicating that diversity is a substitute for proximity. Hence, distance between researchers seems to increase if the home-market lacks diversity. If the home-market is much diversified, the inventors do not need to collaborate across labor markets borders.

6. Conclusion and Policy Implication

How does knowledge spillover? One way of knowledge transfer is within the innovation network.

We examined patent data from 1994-2001 in Sweden. Even with strong evidence on the benefits of collaboration, innovation networks are not very frequent. Our results appear to verify the theoretical results of Meagher and Rogers (2004) and indicate that innovation networks are more likely to be present in densely populated areas with diversified industry. It appears that agglomeration measured both as employment density and as industry diversity, plays a role in explaining networking. In other words, face-to-face contacts (or at least a possibility of face-to-face contacts) do seem to promote networking. Market size has a negative impact on networking in that we can observe that innovation networks are less common in large metropolitan areas, ceteris paribus. Hence, networks can be thought of as a substitute for market size, and as a complement to density and diversity, as argued in Gordon and McCann (2000) and Johansson and Quigley (2004).

In the model explaining the differences in network proximity, the results indicate that employment density increases the average distance between inventors. Researchers in dense areas not only will collaborate more, they will also collaborate over longer distances. The size of the market works the other way around as well. Moreover, as the proportion of PhD's in the labor market increases, collaboration distances increase. Workforces with higher educational degrees will not only be more likely to collaborate, but they will also collaborate over longer distances. Diversity seems to be a substitute to proximity. These results are in some sense in contradiction with Ejermo and Karlsson (2006) who argue that regions with R&D resources are less likely to collaborate with inventors in regions lacking similar resources. Their results also indicate that inventors in large markets are less likely to collaborate with inventors in small markets. Our conclusion is that they are less likely to collaborate all together.

What are our policy implications? One implication from our results is that innovation hubs can play an important role, both in increasing the quality of research and in increasing innovativeness as density and diversity increase. However, as Meagher and Rogers (2004) point out, it can be hard to duplicate the success of Silicon Valley with innovation hubs, as network density seems only to have an affect if the industry in question already has a significant spillover effect. Another result that appears significant is that distance matters. Cross-border research collaboration is not that common, especially over national borders. Andersson and Persson's (1993) and Gaspar and Glaeser's (1998) results concerning co-authorship indicate that distance has become less important over time. Our estimates support their results. Cross-border collaboration is much more common in 2001 compared to 1994, even as the geographical distance of the links are longer, and this development should be encouraged since it seems to promote innovativeness.

Appendix: Classification

Industry	New-code	IPC-code
Human necessities	C1	A-A61-A63+C05
Medical or veterinary science; hygiene	C2	A61
Sports, games; amusements	C3	A63
Performing operations	C4	B-B60-B61-B62-B63-B64-B82
Transporting	C5	B60 to B64
Nanotechnology	C6	B82
Chemistry; metallurgy	C7	C-C05-C07-(C12M to C12S)
Organic chemistry	C8	C07
Biochemistry	C9	C12M to C12S
Textiles; paper	C10	D
Fixed constructions	C11	E
Mechanical engineering; lighting, heating; weapons	C12	F
Physics	C13	G-G05-G02-G06-G09C-G11
Information technology	C14	G02+G06+G09C+G11+H04
Controlling; regulating	C15	G05
Electricity	C16	H-H04

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Table 1. The Inventor Data Set

Variable	Definition	Statistics	
Inventor	Name of the inventor	22,030	
Patent-id	Patent identification number	Na	
LA	Labor market code	Na	
Applied	The year the patent were applied	1995	
Approved	The year the patent were approved	1998	
Isolates	1 if one-inventor patent	8,670	40 %
Time	No. of years between applied and approved patent	2.5 years	
Firm	1 if joint-stock company, else 0	18,018	81 %
Cap	1 if large market capitalization publicly traded company, else 0	9,267	42 %
C1	1 if Human Necessities	1710	8 %
C2	1 if Medical science; hygiene	1818	8 %
C3	1 if Sport; games; amusements	175	<0 %
C4	1 if Performing Operations	4657	21 %
C5	1 if Transporting	1547	7 %
C6	1 if Nanotechnology	0	0 %
C7	1 if Metallurgy	865	4 %
C8	1 if Organic chemistry	94	<0 %
C9	1 if Biochemistry	57	<0 %
C10	1 if Textiles, Paper	908	4 %
C11	1 if Fixed Constructions	1569	7 %
C12	1 if Mechanical Engineering	2422	11 %
C13	1 if Physics	1622	7 %
C14	1 if Information Technology	2481	11 %
C15	1 if Controlling; regulating	61	<0 %
C16	1 if Electricity	2043	9 %
Unique	Identification number: unique inventor	13,877	63 %
Cross-LA	Cross-border collaboration over LA	2,039	15 %
Cross-Inter	Co-operation over national borders	341	3 %
Cross-Firm	Co-operation between companies	48	<1 %

Table 2. The Labor Market Data Set

Variable	Definition	Mean	Standard deviation
NW-1	Networking (=inventor per patent)	1.097	0.637
NW-2	Networking (=inventor per patent excluding isolates)	1.341	1.182
NW-3	Networking (=network density)	0.117	0.361
Emp	Total employment (0000)	3.861	10.866
Higher ed	Proportion of employees with post graduate education	0.065	0.024
R&D Univ.research	Researchers at universities	0.004	0.024
Density-emp	Employment per square kilometers in the labor market area	11.029	13.594
Diversity	Hirfindahl-index for 24 business sectors	0.117	0.0222
Share-manuf. industry	Proportion of employees working in the manufacturing industry	0.224	0.102

Labor market's share of employment in the industry divided by its share of total employment. The labor market area data are available annually from Statistics Sweden.

Table 3. Inventor origination and product types.

Product	Inventors	Corp.	Large Cap	Patents	Isolates	Collaborations	Cross-border LA	Cross-border Inter	Distance
	No.	No.	No.	No.	%	No.	No.	No.	Kilometer
Human Necess.	1710	1103	238	1220	76	325	51	10	75
Medical science	1818	1458	798	1075	57	464	61	9	62
Sport; games	175	64	4	144	81	27	3	0	36
Perf. Oper.	4657	3793	1431	3091	68	983	137	22	52
Transporting	1547	1171	682	1088	72	308	53	5	47
Metallurgy	865	758	337	468	49	240	46	10	117
Organic chem.	94	76	22	41	37	26	4	2	79
Biochemistry	57	44	8	21	38	13	1	1	74
Textiles, Paper	908	869	578	431	44	243	37	10	116
Constructions	1569	999	153	1181	77	273	42	2	42
Mech. Engin.	2422	2008	1059	1609	67	527	69	8	33
Physics	1623	1311	596	982	60	392	54	5	61
IT	2481	2379	1910	1192	50	597	51	16	305
Controlling	61	56	40	39	64	14	4	1	153
Electricity	2043	1928	1411	1049	50	613	77	12	101
Total	22030	18018	9267	13631	64	4961	690	113	91

Table 4. Networks statistics for approved patents in Sweden 1994-2001 and average per year and labor market.

	Total	Average	Standard deviation	Max
Patents	13,630	16.85	58.31	680
Patens-isolates	4,961	10.64	36.18	407
Nodes	22,030	26.66	96.32	1144
Nodes-isolates	13,360	10.64	36.18	407
Links	31,747	38.01	170.21	2511
NW1	1.6163	1.0969	0.6372	5.4048
NW2	2.6930	1.3412	1.1824	9.4091
Networks Density (NW3)	0.0006	0.1171	0.3605	4.0000

Figure 1. The density of networks over time and across labor markets

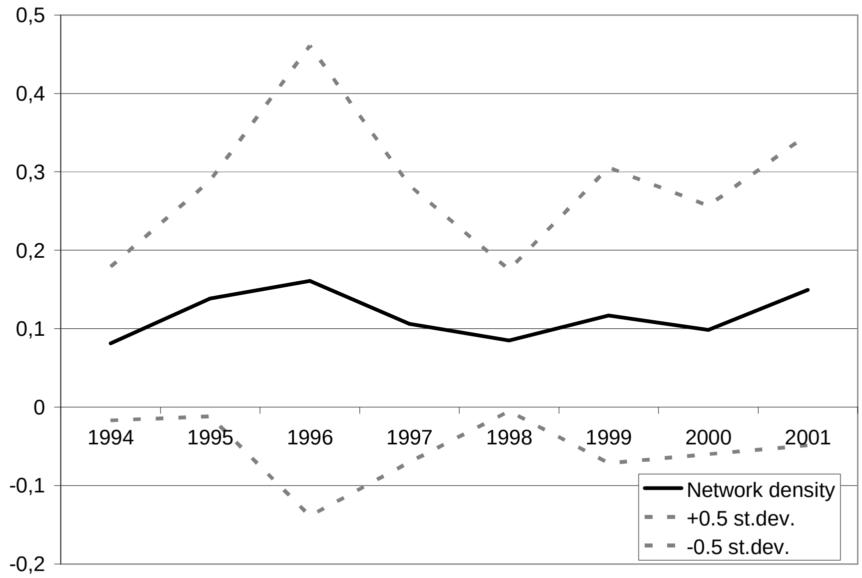

Table 5. Social network analysis over the period 1994-2001 in five labor markets.

	Descriptive Statistics	Stockholm	Gothenburg	Malmö	Västerås	Umeå
1	Patents	4,154	1,797	834	517	112
2	Nodes (innovators)	6,708	3,063	1,391	1,097	154
3	Unique Nodes	4,258	1,764	932	541	119
4	Prop. Unique nodes (3)/(2)	0.63	0.58	0.67	0.49	0.77
5	Isolates (= one-inventor patents)	2,628	1,038	260	235	84
6	Nodes minus isolates (2)-(5)	4,080	2,025	884	862	70
7	Patents minus isolates (1)-(5)	1,526	759	327	282	28
8	Components	2,513	990	557	245	95
9	Components w. three or more nodes	304	129	62	93	5
10	Size	55	100	26	43	3
11	Network density	0.0001	0.0003	0.0005	0.0017	0.0017
12	Fragmentation	99.9%	99.5%	99.7%	96.6%	99.6%
13	Network centralization	0.06%	0.24%	0.52%	1.56%	1.38%
14	(3)/(1)	1.02	0.98	1.11	1.04	1.06
15	(3)/(8)	1.69	1.78	1.67	2.21	1.25

Note: Here is isolates defined as one-inventor patents. However, even if an inventor has a patent by himself, he could be included in a network (component).

Table 6. Negative Binomial Estimates of Innovation Network Counts.

	NW1	**NW1**	**NW2**	**NW2**	**NW3**	**NW3**
Density-emp	0.0050	0.0043	0.0077	0.0064	0.0379	0.0420
	(3.10)	(1.14)	(2.97)	(2.13)	(2.71)	(2.10)
Diversity	-1.3529	-1.4147	-6.4704	-6.7490	-2.7936	-2.6570
	(-1.94)	(-0.93)	(-4.77)	(-4.27)	(-0.83)	(-0.68)
Emp	-0.0045	-0.0052	-0.0055	-0.0074	-0.2790	-0.2612
	(-3.61)	(-1.30)	(-2.86)	(-2.39)	(-6.54)	(-2.85)
Higher Ed	9.3373	11.4876	16.3756	22.0056	0.5741	-5.6542
	(6.84)	(4.31)	(8.57)	(9.32)	(0.08)	(-0.46)
R&D Univ. research	2.1189	-1.4583	-1.3104	-10.2307	-41.1089	-32.4992
	(0.58)	(-0.15)	(-0.24)	(-1.26)	(-1.30)	(-0.63)
Share-manuf. industry	2.0327	2.1750	3.1947	3.6068	2.2156	1.8984
	(9.08)	(5.56	(3.86)	(9.67)	(2.36)	(1.55)
Fixed time effects	No	Yes	No	Yes	No	Yes
Log likelihood	-906.38	-904.61	-1086.48	-1075.31	-273.67	-270.88

Note: t-ratio within parentheses. Estimates concerning fixed time effects are not included in the table.

Table 7. Negative Binomial Estimates of Innovation Network Counts (NW3) and different industry sectors.

	Medical Science	**Transportation**	**Information Technology**
Density-emp	0.0213	0.0361	0.0119
	(1.47)	(1.79)	(0.71)
Diversity	-4.6053	-23.2096	-50.3000
	(-0.60)	(-1.98)	(-1.98)
Emp	-0.0378	-0.0840	-0.0470
	(-1.46)	(-1.54)	(-1.43)
Higher Ed	37.2009	22.4278	52.2786
	(3.46)	(2.05)	(3.98)
R&D Univ. research	-47.8050	-3.4622	-25.6066
	(-1.14)	(-0.09)	(-0.60)
Share-manuf. industry	3.2538	-0.0003	-5.0881
	(1.71)	(-0.00)	(-1.15)
Fixed time effects	Yes	Yes	Yes
Log likelihood	-163.10	-174.27	-92.82

Note: t-ratio within parentheses. Estimates concerning fixed time effects are not included in the table.

Table 8. Negative Binomial Estimates of Average Network Distance.

	D1	**D2**	**D3**	**D4**
Density-emp	0.0169	0.0510	0.0122	0.0531
	(2.25)	(6.12)	(2.07)	(6.59)
Diversity	1.9946	-19.3692	-5.2302	-18.7734
	(0.47)	(-5.16)	(-1.28)	(-5.00)
Emp	-0.0113	-0.0237	-0.0116	-0.0215
	(-1.82)	(-3.71)	(-2.02)	(-3.45)
Higher Ed	13.5557	25.2395	21.4536	24.0587
	(1.91)	(4.10)	(3.44)	(4.11)
R&D Univ. research	-37.4942	33.0281	-56.3206	26.6941
	(-2.41)	(1.73)	(-3.85)	(1.44)
Share-manuf. industry	-0.6815	2.0646	0.2190	1.7504
	(-0.65)	(2.45)	(0.22)	(2.14)
Fixed time effects	Yes	Yes	Yes	Yes
Fixed LA effects	No	Yes	No	Yes
Isolates included	Yes	Yes	No	No
Log likelihood	-3166.07	-2254.2824	-3471.41	-2510.47

Note: t-ratio within parentheses. Estimates concerning fixed time and labor market (LA) effects are not included in the table.