Collaboration and Network Indicators in Canadian Nanotechnology ±

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Abstract

The purpose of this work is to investigate the role of the collaboration and the innovation networks in the efficiency of knowledge diffusion among Canadian nanotechnology inventors. We introduce two sets of indicators which allow tracking the changes in the Canadian nanotechnology collaboration network in the period of 1989-2004. We observe that the Canadian nanotechnology inventors have an increasing tendency to build cooperative ties with higher number of partners, to collaborate with them more intensively and to form larger collaboration teams. They also tend to return for subsequent collaborations to the same partners with whom they have collaborated within the past five years. We identify the prominent researchers in Canadian nanotechnology and propose to take into consideration the patent quality when identifying star scientists. We note that many of the superior scientists in nanotechnology have not produced any USPTO nanotechnology patent. We also propose indicators which characterize the structural properties of the nanotechnology collaboration network. We observe a fragmentation of the network over time, caused by an increasing specialization of the nanotechnology field.

Keywords: innovation, collaboration, knowledge networks, social network analysis, geographical pattern, patents, nanotechnology, clusters, Canada

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1. Introduction

As an alternative to the three classical locations where innovation takes place (which are non-profit institutions, profit-seeking firms and the minds of individual inventors), Allen (1983) has introduced the concept of collective invention. The key to understanding a phenomenon of collective invention is in the exchange and free circulation of knowledge and information within groups of socially connected (but often competing) agents rather than in the inventive efforts of particular firms or individuals. The open sharing of information thus results in a fast knowledge accumulation and high invention rates. A large number of historical examples were documented in the literature: For instance, the wide informal knowledge trading between engineers in competing minimill firms in the US steel industry was described by von Hippel (1987) and by Schrader (1991), and the knowledge sharing in a cluster of wireless communication firms in Denmark by Dahl and Pedersen (2004), but the most commonly cited example is an open knowledge sharing culture in Silicon Valley studied by Saxenian (1994).[1]

The concept of collective invention is convenient for describing the dynamics of knowledge diffusion through various innovation networks. The network of innovators is an inter-personal network of individual innovators, who collaborate and exchange information in order to produce innovations and scientific knowledge. These are the inventors and scientists working at the universities, in research centers or industrial R&D departments. The methods of social network analysis[2] have been used to analyze the way these innovators are interconnected. There is usually no formal agreement among the researchers; however, they frequently take part in the development of a patent or the creation of scientific article. Within the research community which investigates the innovation networks it is widely presumed that two innovators, who have worked together on at least one patent or one scientific article, will keep in touch afterwards in order to exchange information or to share some knowledge assets. The patent documents and

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[1] For other examples of collective invention see Lamoreaux and Sokoloff (1997).

[2] Social network analysis is the mapping and measuring of relationships and flows between people, groups, organizations, computers or other information/knowledge processing entities. The nodes in the network are the people or groups, whereas the links show relationships or flows between the nodes. Social network analysis provides both a visual and a mathematical analysis of complex human systems (Krebs, 2006).

bibliometric data could thus be exploited to map the complex web of social ties among innovators and to construct the innovation networks.

The network of scientists, whose links are established by their co-authorship of scientific articles, may be the largest social network ever studied (Newman, 2001a). Newman (2001a) was the first (to our knowledge) to use four databases of scientific papers in physics, biomedical research and computer science constructed networks of collaboration between scientists in each of these disciplines and studied a variety of statistical properties of these networks to describe the network structure. In his subsequent papers (Newman, 2001b; Newman, 2001d), he continued his research on scientific networks, exploring a variety of nonlocal network properties and measures. Newman (2001c) then examined empirically the time evolution of scientific collaboration networks in physics and biology. Breschi and Lissoni (2003 and 2004) and later Balconi *et al.* (2004) constructed the network of collaborative relationships linking Italian inventors using data on co-inventorship of patents from EPO (European Patent Office). They built bipartite graph of applicants, patents and inventors. Using this graph, they could derive various measures of social proximity between cited and citing patents. Beaucage and Beaudry (2006) constructed the network of Canadian biotechnology inventors based on the similar methodology as Balconi *et al.* (2004). Cantner and Graf (2006) proposed to build the networks of innovators based on technological overlap, which is a measure of closeness of the technological field of two scientists. They also described the evolution of the innovator network of Jena, Germany using the information on scientific mobility. Singh (2005) inferred collaborative links among individuals using a social proximity graph, which he also constructed from patent collaboration data. Many other researchers[3] adopted the co-inventorship of patents as an appropriate device to derive maps of social relationships between inventors and to build their networks. Based on interviews with inventors, Fleming *et al.* (2006), however, warned that patent co-inventorship links differ significantly in their strength and information transfer capacity. Also, since their decay rates vary greatly, a substantial number of old ties remain viable even if the relation does not exist anymore.

The findings from the aforementioned research studies have revealed some interesting properties of the innovation networks. Most importantly, apparent differences in collaboration

[3] For instance Mariani (2000), Ejermo and Karlsson (2006); Gauvin (1995) and Fleming *et al.* (2006).

patterns according to the nature of subjects under study were observed. The characteristics of the network structures differ depending on whether they contain purely industrial or also academic researchers. Balconi *et al.* (2004) observed that networks of inventors within industrial research are usually highly fragmented. On the other hand, the networks constructed by Newman (2001a) were much clustered, but since he based them on scientific co-authorship we assume that these were mainly academic networks. Newman (2001b) also observed that for most scientific authors the majority of the paths between them and other scientists in the network go through just one or two of their collaborators. This is in agreement with Balconi *et al.* (2004) who found that academic inventors that enter the industrial research network are, on average, more central than non-academic inventors - they exchange information with more people, across more organizations, and therefore play a key role in connecting individuals and network components. Academics also have a tendency to work within larger teams and for a larger number of applicants than non-academic inventors (Balconi *et al.*, 2004).

Newman (2001c) showed that the probability of a pair of scientists collaborating increases with the number of other collaborators they have in common, and that the probability of a particular scientist acquiring new collaborators increases with the number of his or her past collaborators. Nevertheless, Cantner and Graf (2006) did not find a relation between previous and present cooperations with the same partners, suggesting that collaborations in the studied region are not persistent. Former collaborations are also found to be determinant of the future success. Cowan *et al.* (2005) claimed that previous collaborations increase the probability of a successful collaboration and Fleming *et al.* (2006) argued that an inventor’s past collaboration network will strongly influence subsequent productivity.

Some of the researchers who adopted the network approach have also included geographical aspects into their models. Gittelman (2006) argued that the geography of the research collaborations has distinct impacts on the firms’ scientific contribution and their inventive productivity. The work of the collocated research teams results in scientifically more valuable knowledge, whereas the more dispersed research groups are more likely to produce commercially valuable technologies. Beaucage and Beaudry (2006) characterized three major Canadian biotechnology clusters in terms of their innovation network structures and proposed the likely influence of the distinct geographical collaborative patterns on the knowledge generation and innovation production.

Another line of research related to the innovation networks involves theoretical simulation studies, in which researchers build innovation network models to simulate knowledge diffusion through the network. Cowan and Jonard (2003) have developed a model of knowledge diffusion and studied the relationship between the structure of the network across which knowledge diffuses and the distribution power of the innovation system. Cowan *et al.* (2004) have continued with the simulation study of knowledge flows and compared the mean knowledge growth under different network architectures (ranging from the highly clustered to the one that has no spatial structure). In order to capture the observed practice of informal knowledge trading proposed by von Hippel (1987) and Schrader (1991) mentioned above, Cowan and Jonard (2004) modeled knowledge diffusion as a barter process in which agents exchange different types of knowledge only if it is mutually profitable. They examined the relationship between network architecture (characterized by different levels of path length and cliquishness) and diffusion performance. Morone and Taylor (2004) identified the limitations of Cowan and Jonard's model (2004) and improved it by introducing a network structure that changes as a consequence of interactions. They investigated the dynamics of knowledge diffusion and network formation. Finally, Cowan *et al.* (2007) modeled the formation of innovation networks as they emerge from bilateral decisions. They developed a model of alliance formation and examined the nature of the networks that emerge under different knowledge and information structures. One of the most important conclusions of these studies is that the existence of a network structure can significantly increase the long-run knowledge growth rates. The finding that the architecture of the network over which innovators interact influences the extent of diffusion and thus the innovative potential of the whole network is also the main theme of our research.

This paper is a part of our project aimed at understanding the role of collaboration networks in the knowledge generation, in the innovation creation and in the growth of high technology clusters in Canada. This work introduces various indicators which characterize the collaboration behaviour of Canadian nanotechnology inventors and the diffusion of knowledge through the nanotechnology innovation network built from patent co-inventorship data. The constructed network allowed us to examine the geographical aspects of the collaborative behaviour of the inventors in Canadian nanotechnology clusters as well. The article is organised as follows: section 2 introduces the data and the methodology used in this study, section 3 presents the set of collaboration indicators and the collaborative patterns, section 4 introduces the set of network indicators and section 5 concludes.

2. Data and methodology

In order to build the network of Canadian nanotechnology inventors we used the patent co-inventorship data contained in the Nanobank database. Nanobank is a public digital library comprising data on nanotechnology articles, patents and federal grants, as well as firms engaged in using nanotechnology commercially. The Nanobank patent database is based on the data from the United States Patents and Trademarks Office (USPTO) database. This is the only patent database which provides the geographical location of the residence for each inventor (unlike the Canadian Intellectual Property Office database (CIPO) or the European Patent Office (EPO)). The use of the USPTO database instead of the CIPO for the analysis of the Canadian nanotechnology may have caused a certain bias in the data, but we consider it minimal, since Canadian inventors usually patent both in Canada and in the US. The much larger and easily accessible nanotechnology American market offers them a greater potential than the nanotechnology market in Canada.

From the Nanobank database we have selected the patents in which at least one inventor resides in Canada (5067 patents). We have employed additional filters, which enabled us to select only the patents which are strictly related to nanotechnology[4] and created a Canadian nanotechnology patent database which comprises 1443 patents. The concept of social network analysis defined above was used to create connections between all the nanotechnology inventors of these patents and to construct the networks. The use of the social network analysis program PAJEK was instrumental in building the innovation networks and in analyzing the network architectures. An analysis of these collaborative networks enabled us to understand the collaborative behaviour of the inventors in Canadian nanotechnology clusters.

[4] For the exact description of our selection methodology see Schiffauerova and Beaudry (2008).

In the paper we have created two different kinds of networks: First, the *complete network*, which includes all 1968 nanotechnology inventors in our database which are listed as inventors or co-inventors on any patent issued in the period of 1979 and 2005. Here we have assumed that once inventors unite and collaborate on the research leading to one patent they continue to be in contact afterwards and are able to exchange information acquired long after the patent had been granted with all the collaborators they ever had. This allows us to disregard the time of collaboration and consider all links among inventors in the network to be active simultaneously.

Second, in order to track the evolution of the collaboration and network properties over time we have created 11 *subnetworks corresponding to five-year moving windows* starting from 1989 and finishing in 2004 (as shown in Figure 1). As Canadian nanotechnology patenting in the period preceding the year of 1989 is rather sporadic we decided to start with the first year where at least 20 Canadian nanotechnology patents were issued. In addition we did not include the year 2005 as it is only partially covered by Nanobank. Constructing the network for each year separately would alter the connectivity of the networks. Using only the patents granted in a given year would not capture the relationships created before and maintained through this particular year. We selected to work with the subnetworks created during the interval of five years since we assume that this is an average period length during which the relationship between any co-inventors who appeared together on one USPTO patent lasts and during which information and scientific knowledge could be actively exchanged. Five-year moving windows thus more accurately reflect the structure of a collaboration network.

We analyze the cooperation relationships existing in each of these five-year intervals. Figure 1 shows the size of each of the eleven subnetworks corresponding to the five-year intervals. The size is determined by the number of inventors (vertices) which are present in the subnetwork. Some of the inventors are included in all of the subnetworks (if they worked on several patents spread throughout the years), some of them just in the few initial ones after which their nanotechnology scientific interest faded away and some have started contributing into nanotechnology research only recently. The figure includes also the number of patents which were used for building the particular subnetwork in each interval.

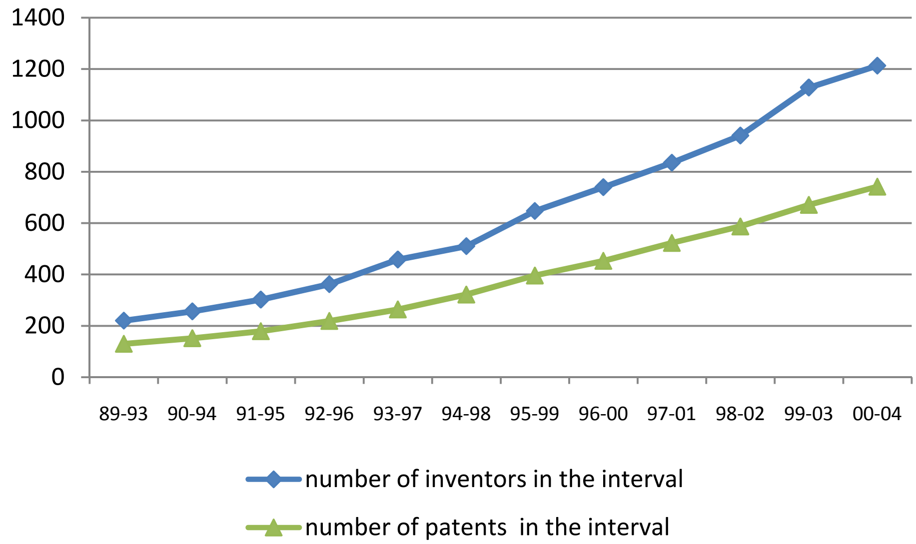


Figure 1: Number of inventors and patents used in each subnetwork

In the following two sections we introduce two sets of indicators which characterize the collaborative relationships in nanotechnology: collaboration indicators and network indicators. In order to create the *collaboration indicators* we needed to disassemble the entire network into collaborating pairs and to describe the nature and frequency of collaborative activities between these innovating couples. Special focus is put here on the geographical aspects of these collaborations. Contrary to the collaboration indicators in which only the cooperation ties between each two inventors are considered, the *network indicators* go beyond the collaborating couple and take into consideration also the collaborator`s collaborators, their collaborators, and so on. Here we adopt a network approach in which a structure of the entire net of complex relationships is analyzed and characterized.

3. Collaboration indicators

The study of the knowledge flows and the information exchange among the collaborating inventors consists in the characterization of the collaboration links between them. The network of Canadian nanotechnology inventors (the full network) includes 4920 collaborative links (represented by edges in the network graphs). It is important to distinguish between the terms of the collaborative link and the collaboration. Collaborative link (or a tie, or a relation) represents a connection between a pair of inventors, which involves one or more instances of co-invention of a nanotechnology patent. Collaboration, on the other hand, represents here a connection between a pair of inventors for the purpose of co-invention of one single nanotechnology patent. Each collaborative relation may thus involve one or more collaborations, as there can be one or more patents granted to any collaborating couple. Collaboration partner or collaborator is then defined as a co-inventor of at least one nanotechnology patent registered at the USPTO. The following indicators of collaboration are based on the characteristics of the collaborative links, collaborations and collaborators.

3.1 *Indicators of collaboration intensity*

Figure 2 shows both the number of cooperative links (collaborating pairs) existing in each interval as well as the total number of all collaborations which took place between all of these pairs. The fact that the count of the collaborations increases faster than the number of collaborating pairs is indicative of an increased intensity of cooperation activity in Canadian nanotechnology throughout the years. Figure 3, which features the gradually increasing values for both *average numbers of collaborators* and *collaborations per inventor*, further confirms that.

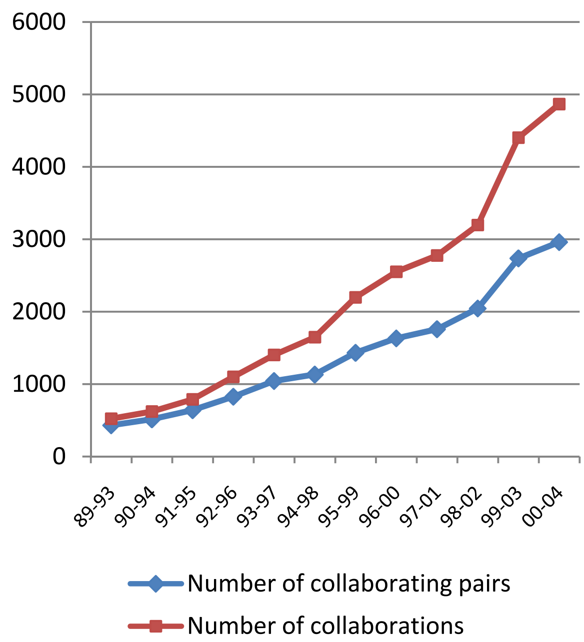


Figure 2: Number of collaborating pairs and collaborations in each subnetwork

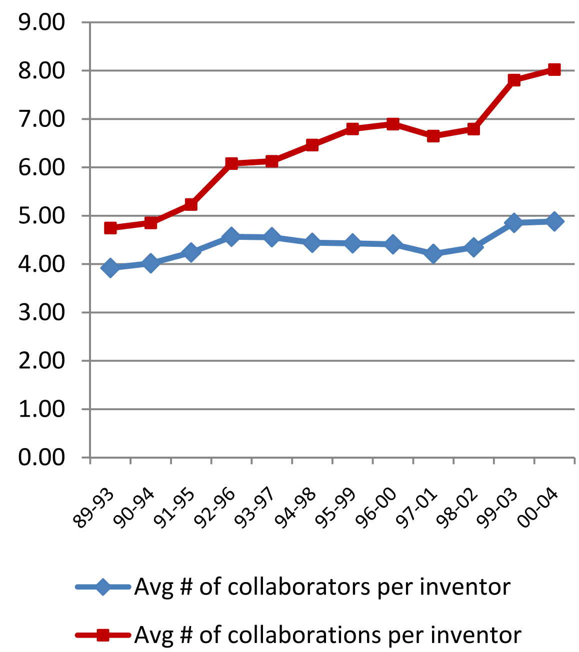


Figure 3: Average number of collaborators and collaborations per inventor in each subnetwork

Slightly higher values are observed in the full network: An inventor in a Canadian nanotechnology network has on average 5 collaboration partners, which is comparable with the average number of collaborators per inventor found by Beaucage and Beaudry (2006) who observed 5.12 collaboration partners per Canadian biotechnology inventor. We calculated an average number of collaborators per inventor for the networks of Balconi *et al.* (2004, calculated from p.139, Table 5) in order to compare it with our full network. Our calculation shows that the networks of Balconi *et al.* (2004) have on average 2.09 collaborators per inventor, considerably less than the 5 collaboration partners observed in our network. The difference could be explained by the distinct samples of patents selected for the analysis: Contrarily to our narrowly focused patent sample (nanotechnology), in the study of Balconi *et al.*, the industry range is quite broad. Newman's findings (2001a) differ even more from our results. He observed a much larger number of collaborators in his innovation networks; especially for the scientists in experimental disciplines (an average high-energy physics scientist had 173 collaborators during a five year period!). Nevertheless, the fact that his networks were created from the co-authorship of the scientific articles and not the patents may explain the discrepancy. The average number of authors in this discipline is also relatively high compared with the number of inventors on a typical patent.

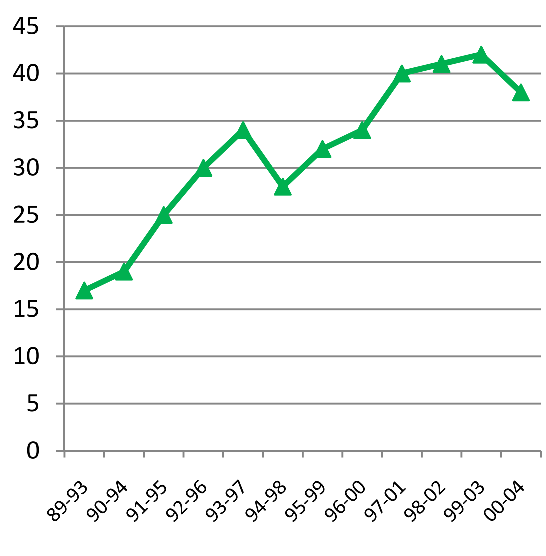


Figure 4: Maximum number of collaborators per inventor in each subnetwork

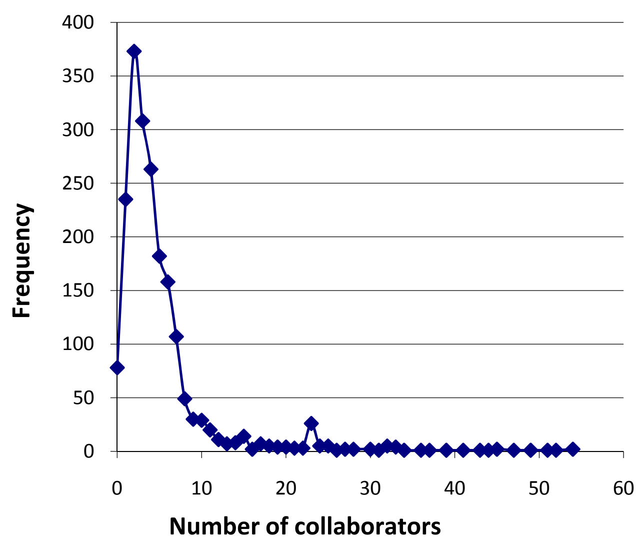


Figure 5: Frequency distribution of the number of collaborators per inventor in the entire network

Some inventors in our network also have a considerably higher number of relationship ties: the highest one amounting to 54 co-inventors. Figure 4 illustrates the *maximum number of collaboration partners per inventor* in each interval-based subnetwork . The most collaborative inventor had only 17 collaborators in the oldest subnetwork, but later this number has more than doubled when one inventor has been engaged in the joint research projects with 42 different collaborators during the five year period. Most inventors naturally not only never reach such high collaborating scores, but their collaborator counts are even well below the subnetwork averages (see Figure 5 for the distribution of the frequencies of collaborators in the full network). Canadian nanotechnology inventors most commonly have one (12%), two (19%), three (16%) or four (13%) collaborators. Only a small amount of inventors (4%) do not collaborate on their patent(s) with anybody, and only a few (8%) have more than 10 co-inventors.

3.2 Size of the collaboration teams

The size of collaboration teams is here represented by the *average number of co-inventors in one patent.* The entire Canadian nanotechnology network has on average 3.34 inventors per patent. The evolution of the team size in five-year periods is shown in Figure 6. It has increased from less than 2.8 to well over 3.4 co-inventors. This implies that Canadian inventors have slightly increased their tendency to collaborate more intensively and to exchange information with other researchers than in the past. For comparison we also provide the average number of co-inventors in a patent calculated per year of granting (see Figure 7). The evolution here seems to be more dramatic, since the five- year period aggregation smoothens the huge differences in the means of individual years. Also note that in *Figure 7* we included the patents issued before 1989, when the total counts of patents were often very low and the averages are thus not highly representative.

The largest number of co-inventors in one patent in our nanotechnology patent database is 24, but this appeared only on two separate occasions. It is of interest to note that the largest number of authors on a single paper found by Newman (2001a) was 1681 co-authors, nearly 188x times the average number of scientists on a typical paper in the studied database (high-energy physics). Scientific papers have traditionally been authored by more numerous co-authors than patents, since joint article authorship was found to reflect a variety of things other than exchange of information and research collaboration.[5] Even though the legal requirements for

[5] Cockburn and Henderson (1998) suggest that article co-authorship may be offered as a quid pro quo for supplying information or resources, it can serve as a means of resolving disputes about priority, it may also be an

article co-authorship and patent co-inventorship are officially very similar, the numbers of article co-authors are on average much higher than the numbers of co-inventors of the patent which reflects the same discovery or invention. Ducor (2000) found that the number of article co-authors is on average more than three times higher than the number of inventors on the corresponding patent.

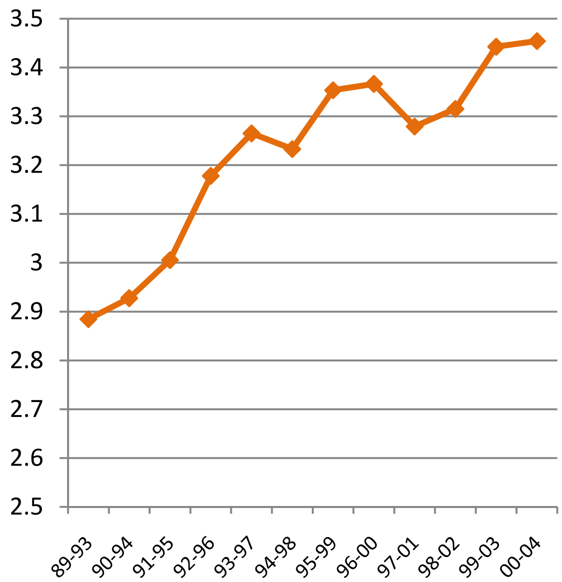


Figure 6: Average number of co-inventors in a patent in each subnetwork

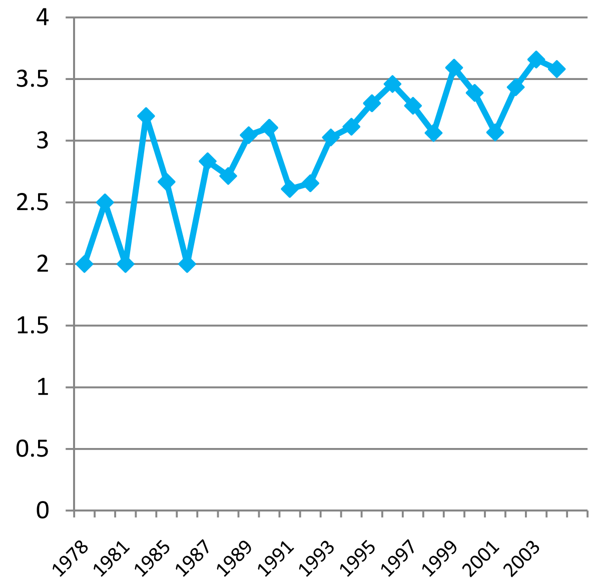


Figure 7: Average number of co-inventors in a patent per year measured in the year of granting

3.3 Repetitiveness of collaboration with the same partner

Around 34% of all the collaborative relations between pairs of inventors in the complete Canadian nanotechnology network involve repetitive collaborations. In some cases the cooperative relationships proved to be very fruitful, as the most frequent collaboration between a pair of inventors was repeated 50 times (i.e., the collaborating pair had obtained 50 patents together). Figure 8 displays the *maximum number of collaborations repeated with the same partner* in each interval. The highest number of patents filed together by the same authors during any five-year period is 35. Most of the relationships between a pair of inventors are, however,

acknowledgement of an intellectual debt, it may just be listing of laboratory directors or other project leaders as authors or it may reflect an effort to gain legitimacy, or admission to networks of other researchers.

one time collaborations (i.e., they resulted in only 1 patent). Figure 9 shows the *share of the repetitive collaborations* out of the total number of collaborations starting at around 15%, then steadily increasing in time and reaching 35% in recent years. Repeated collaborations with the same partner foster mutual trust and confidence. A higher frequency of collaboration between two inventors hence leads to a more profound research relationship, which may involve an exchange of information of higher quality and a transmission of a greater amount of valuable scientific knowledge.

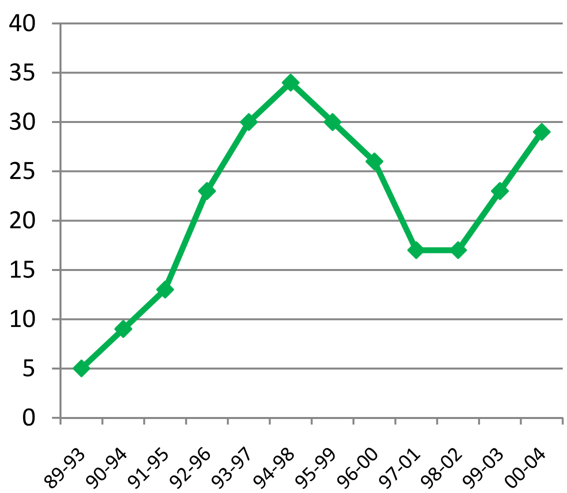


Figure 8: Maximum number of collaborations with the same partner in each subnetwork

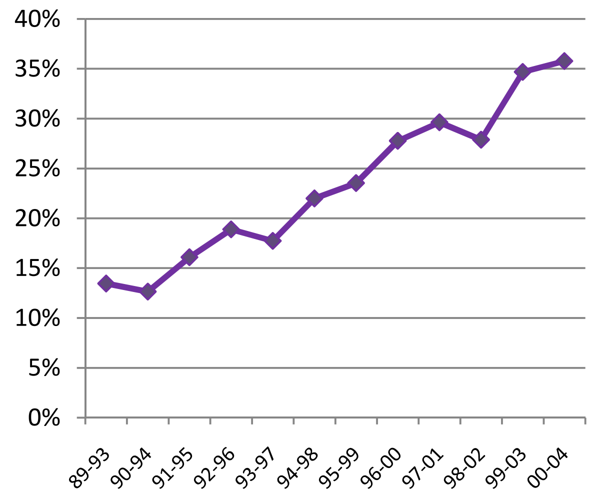


Figure 9: Percentage of repeated collaborations with the same partners in each subnetwork

3.4 Geographical aspects of collaboration

Since an important part of our research deals with geographical aspects of collaboration, we have located the residence addresses of all inventors in the database and found that nanotechnology activity in Canada is concentrated in several regions. We have identified eight Canadian nanotechnology clusters[6] of which four are important nanotechnology agglomerations, while the other four are smaller regions moderately active in nanotechnology. We classified geographically the collaborations according to their location as collaborations inside clusters (both inventors in a collaborating pair are from the same cluster), outside clusters (one inventor in

[6] The cluster in this study is defined as a geographically continuous region active in nanotechnology (as measured by the patent production).

a pair resides in a different cluster or elsewhere in Canada) and outside Canada (one inventor in a pair resides abroad). The proportions among these types of collaborations constitute a *collaboration pattern* of the Canadian nanotechnology inventors, which is our main geographical indicator. Figure 10 shows the evolution of the indicator during each five-year moving interval. It suggests that most nanotechnology cooperation (60%) takes place within a very short geographical distance - inside clusters - but only around 10-15% of collaborations are carried out among inventors residing in distinct specific Canadian clusters. International research relationships represent relatively high shares of collaborative activities (20%-30%). The overall collaboration pattern has slightly changed over time, the most important change being the gradual increase in the frequency of the inter-cluster joint research partnerships (the percentage has almost doubled throughout the years).

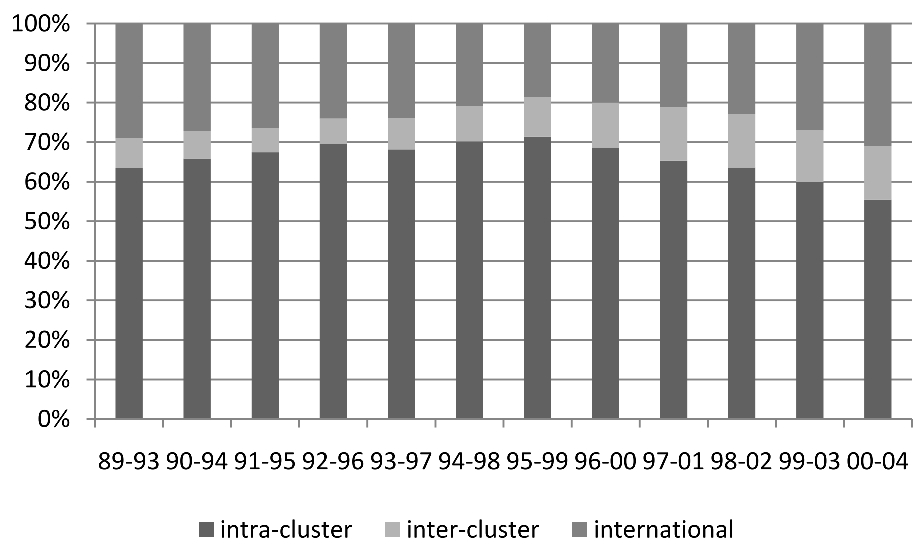
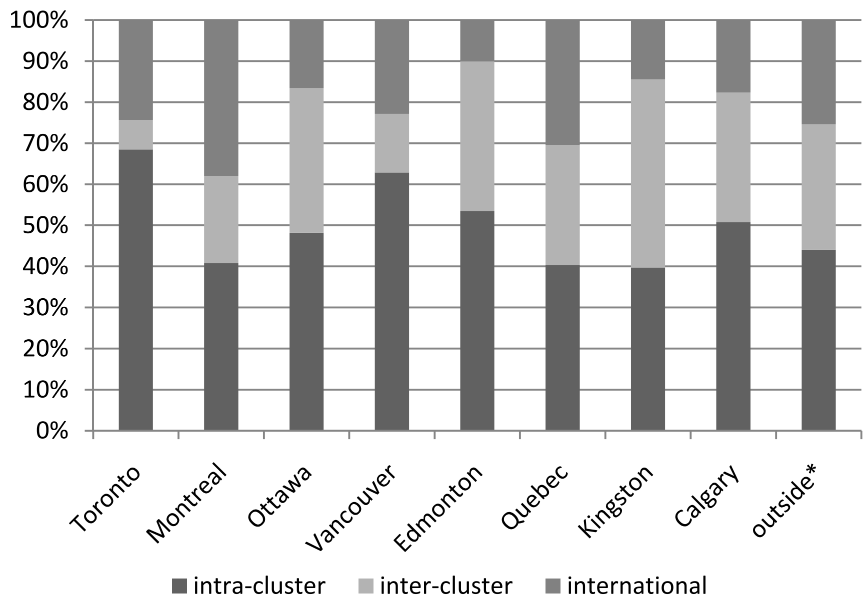


Figure 10: Change in the collaboration pattern of Canadian nanotechnology inventors over time

We have also calculated these proportions separately for each cluster. The results displayed in Figure 11 show that the collaborative pattern are much more disparate for distinct clusters than for distinct time periods. In Toronto, which is the cluster with the highest number of nanotechnology inventors (41% of all the inventors residing in Canadian clusters), around 68% of collaborations between pairs of inventors take place within the cluster, where sufficient knowledge has already been accumulated. In 24% of collaborations, the expertise is sought abroad and only 7% of collaborative interests are directed towards partners in other clusters or elsewhere in Canada. Other nanotechnology agglomerations are much smaller than Toronto in terms of inventor counts and the percentage of their intra-cluster collaborations is lower as well (40-54%). Researchers in these clusters probably do not find all the needed expertise inside their own clusters and thus have to look for collaborators outside the cluster or outside Canada more frequently. The figure also shows that some of the Canadian inventors who decide to collaborate outside their clusters prefer to do so with foreign inventors. The preference of foreign over domestic collaborators is most evident for the larger clusters (Toronto, Montreal and Edmonton) which also show the smallest percentages of collaborating pairs where each inventor comes from a distinct cluster. However, in smaller agglomerations (Calgary, Edmonton, Kingston and also Ottawa) inventors who wish to collaborate outside their clusters still prefer to keep their collaborative ties inside Canada.



*outside: inventors residing in Canada but outside the clusters

Figure 11: Collaboration pattern of Canadian nanotechnology inventors in each cluster

3.5 Collaboration with star scientists

Most inventive output in nanotechnology is produced by only a few percentages of the most prolific inventors. These highly productive scientists are called "star scientists" and their important role has been much discussed in the literature[7]. We defined these prominent researchers in our dataset based on patent quantity only, or based on both the quantity and quality simultaneously. Moreover, we included the examination of the most prominent researchers based on their record of forward citations in scientific articles.

According to the number of patents as the only discriminatory factor we identified 40 prolific inventors (with 15 or more patents), out of which 23 are considered to be star inventors (with more than 20 patents) and 4 of them are deemed "superstars" (with more than 50 patents). Note that the most productive inventor in Canadian nanotechnology has registered 87 nanotechnology patents at the USPTO. This is considerably more than any other researcher in the group *(*see Figure 7*)*, we may be measuring a "lab director effect" here.

We then incorporated patent quality as a second discriminatory factor and created a Quantity and Quality Patent Index (QQ Index), which takes into consideration both the patent counts and the mean patent value for each inventor[8]. This indicator modifies the number of patents according to the gap between the average number of claims of a particular inventor and an average number of claims for all the inventors in the database. According to this QQ Index, we have identified 37 QQ-prolific inventors (with QQ Index value of 20 or more), out of which 18 are QQ-star inventors (with minimal QQ Index value of 30) and 3 inventors are called QQ-superstars (with QQ Index values of 50 or more).

The third indicator, which is the number of forward citations to the researchers' articles, represents the scientist's ability to contribute to the knowledge development. *ISI Web of Knowledge*[SM] provides a list of individuals that have made fundamental contributions to the

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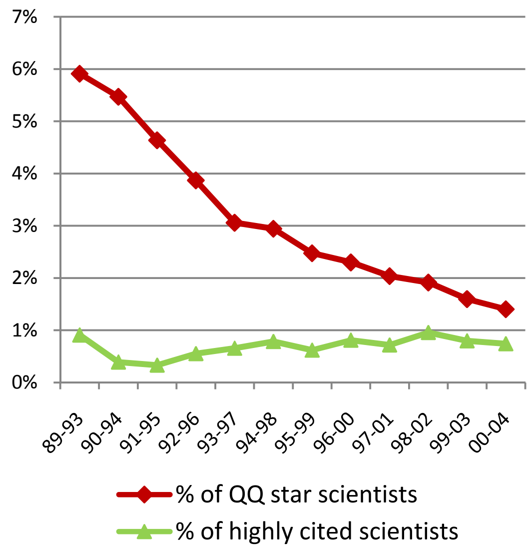
7 Zucker and Darby (1996), Zucker *et al.* (1996), Zucker *et al.* (1998a) and Zucker *et al.* (1998b) show the importance of star scientists in the biotechnology sector and emphasize the positive effects on the performance of the firms collaborating with the stars. Moreover, Zucker *et al.* (1998b) and Prevenzer (1997) argue that in the biotechnology sector, star scientists often capitalize on their knowledge through firm start-ups.

8 Quantity and Quality Patent Index (QQ Index): $QQIndex_i = \frac{N_i * C_i^{avg}}{C^{avg}}$, where

$QQIndex_i$…the value of the QQ Index indicator for inventor *i*
N_i……..…..the number of the USPTO patents invented or co-invented by inventor *i*
C_i^{avg} …......the average number of patent claims for all the USPTO patents invented or co-invented by inventor *i*
C^{avg}……......the average number of patent claims for all the inventors in the database

advancement of science and technology in recent decades. The list includes only the researchers with a really extraordinary accomplishment, since it comprises less than 0.5% of all publishing researchers in the database. We have blended the data from the list of the highly cited scientists in nanotechnology into our database of inventors. We have found that 12 of our inventors are also highly influential scientists and scholars. However, none of these 12 highly cited inventors is a producer of an extraordinarily high number of patents. In fact, many of the ones present in our database have invented or co-invented only 1 patent. Moreover, the fact that we found only 12 matching scientists in both lists suggests that there are many highly influential nanotechnology researchers (as acknowledged by their citing colleagues) who never filed any patent application at the USPTO. We assume that these highly cited scientists come mostly from an academic environment, where the publication performance is more appreciated and more rewarding than impressive patent scores. The scientists with the most prolific publication record may thus often neglect the patent application opportunities.

This methodology has enabled us to identify in total 60 prominent inventors. 48 of them are either prolific or QQ-prolific scientists, where 29 are scientists were indicated as prolific by both measures concurrently. The remaining 12 are the highly cited scientists. Our special focus was on the QQ-stars and QQ-prolific inventors and the levels of collaboration with other inventors and between each other. Even though the number of QQ-star inventors has been steadily rising, their share in the total number of inventors has decreased substantially (from 6% to almost 1%) over the years (see Figure 12). As for the collaboration indicators, first we measured the *share of patents which were created in collaboration with QQ star scientists* (see Figure 13). This measure has been rising initially (from 30% to almost 36%) but then it has started its downward course and reached almost 22% in the recent years. Note that even though there are around twice as many QQ-prolific scientists (37) as QQ-star scientists (18) in the database, the *share of patents created in collaboration with QQ-prolific scientists* is only slightly higher than the share of the patents created in collaboration with QQ-star scientists. This again points towards the importance of the QQ-star scientists and their role in the knowledge diffusion. Finally, the *share of the patents created in collaboration with highly cited scientist*s has a generally increasing tendency as well.



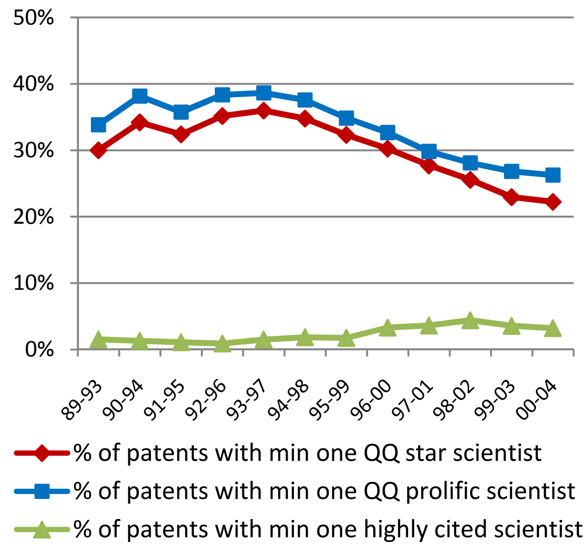


Figure 12: Share of inventors which are QQ-stars or highly cited scientists

Figure 13: Share of patents created in collaboration with at least one QQ-star, QQ-prolific or highly cited inventor

Furthermore, we investigated *how many QQ-star scientists usually collaborate together*. Out of all the patents created in collaboration with QQ-star scientists, the shares of the ones co-invented by 2 or 3 QQ-star scientists have been increasing over time, while collaboration of 4 or more QQ-star scientists together is becoming less popular as is also the presence of only one QQ-star in the research group (see Figure 14).

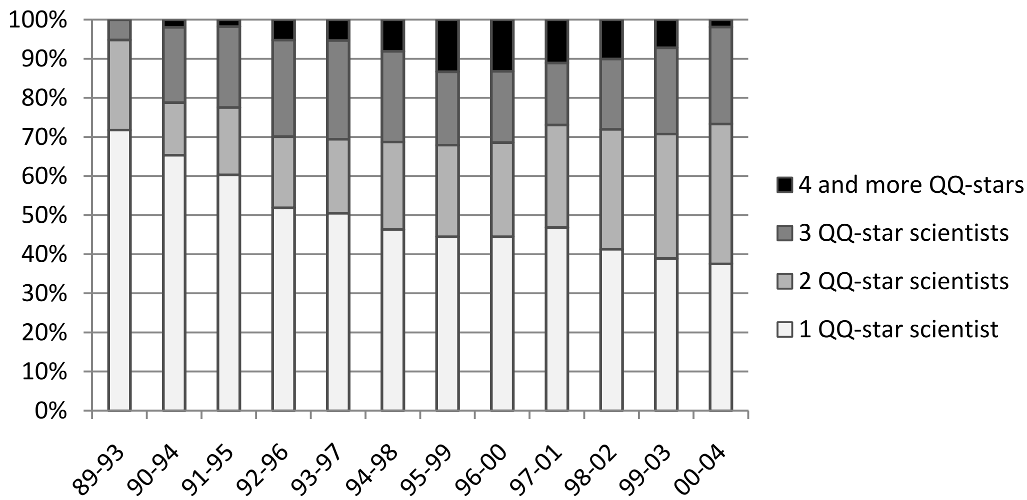


Figure 14: Shares of patents created in collaboration with 1, 2, 3 or 4 and more QQ-star scientists

To conclude, even though the absolute number of collaborations with QQ-star scientists has been rising over time, their share is in fact decreasing, since increasingly more inventors with low patent scores tend to file patent applications. Around 20-35% of patents have been created while collaborating with at least one QQ-star scientist. The mutual collaboration among 2 or 3 QQ-star scientists is increasing in popularity.

4. Network indicators

An important advantage of the network approach consists in the fact that indicators derived from it take into consideration all the network relationships and not only the immediate collaborators or collaborations. As such network indicators are able to evaluate the transmission efficiency of the network structure and consequently the creation and diffusion of knowledge among researchers within the entire network. The following section presents some of the basic indicators used to characterize the nanotechnology innovation network.

4.1 Network fragmentation

In order to understand the importance of fragmentation in the collaboration network, let us first introduce the concept of components. A component is defined as a maximal connected subnetwork (Wasserman and Faust, 1994). It is a part of the network which includes a maximum number of vertices which are all directly or indirectly connected by links. Within a component all inventors are directly or indirectly interconnected and they are thus considered to collectively contribute to the innovation process. *Figure 15* displays two examples of such components present in the network, which provide evidence of a strong inter-cluster cooperation. The group of inventors from Edmonton in Component #4 to the left collaborates with inventors from Vancouver and Montreal. One inventor connects this group to another group of inventors from Ottawa, Calgary and Montreal, which involves one international collaborator. Component #6 to the right shows one central inventor from Kingston who connects together three collaborating subgroups. One is purely Kingstonian. The second group involves mainly Calgary inventors with one foreign inventor. The third subgroup is much more diverse as it includes inventors from the Edmonton, Montreal, Ottawa and Vancouver clusters as well as inventors from outside the clusters and from outside Canada. The figure shows that inventors from very distant parts of Canada (and even from a different country) may actually be much better interconnected and thus able to exchange scientific knowledge, than inventors which are collocated within close geographical proximity (within the same cluster) but are not contained within the same component (no communication between the components is assumed).

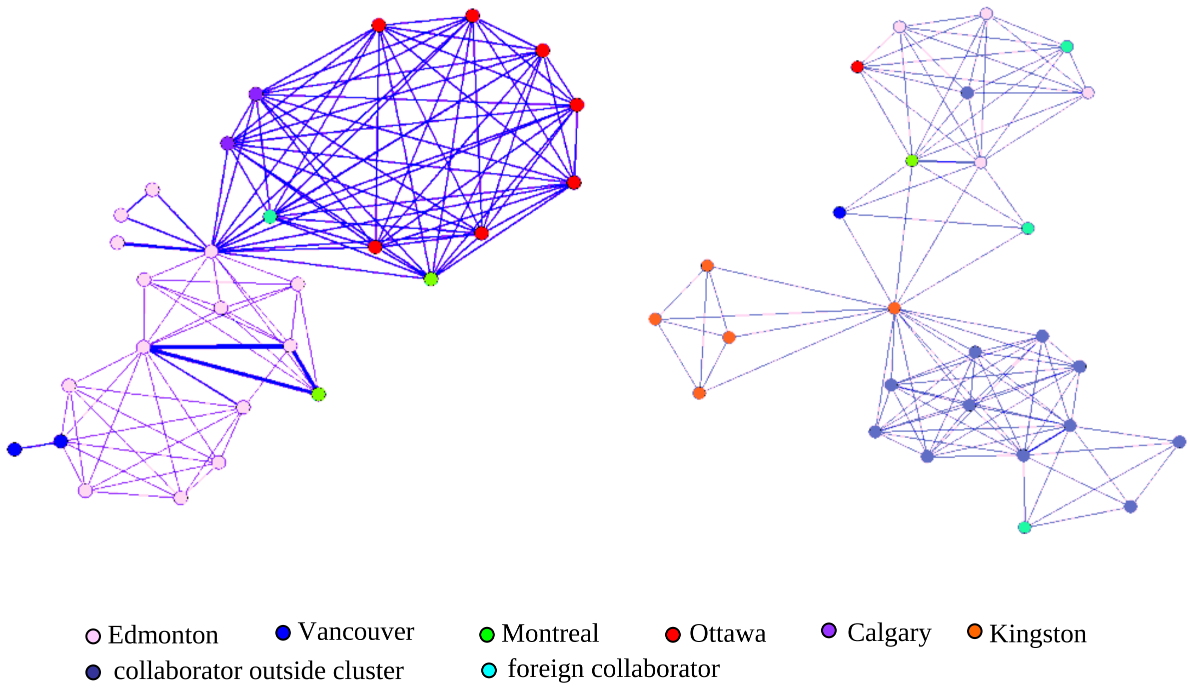


Figure 15: The fourth and sixth largest components (Components #4 and #6)

For the fifteen-year span of our sample, the complete network of Canadian nanotechnology inventors comprises 407 components, while the number of components in the five-year moving intervals grows from 48 to around 265 (see Figure 16). Obviously, the number of components in the network is not a good measure of fragmentation, since more important networks will often have more components than smaller ones and still may be much less fragmented. An important network structure indicator is therefore the *average size of the component*. It indicates how many inventors in the network can on average exchange information with each other through direct or indirect cooperation links among them. Figure 17shows that the average component size in each subnetwork does not fluctuate much and is usually somewhere between 4.3 to 4.7 inventors. These numbers are only slightly smaller than an average component calculated for the entire network, which is 4.84.

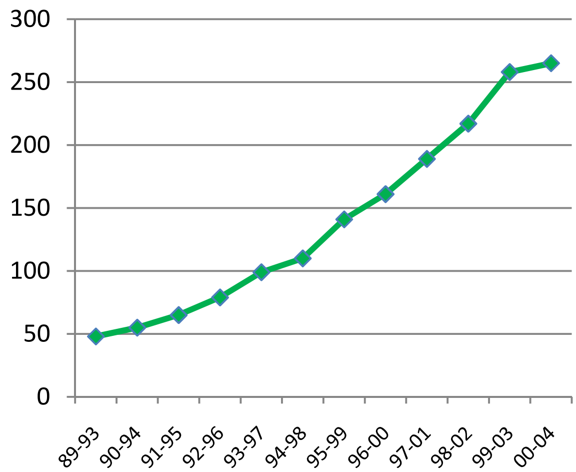


Figure 16: The number of components in each subnetwork

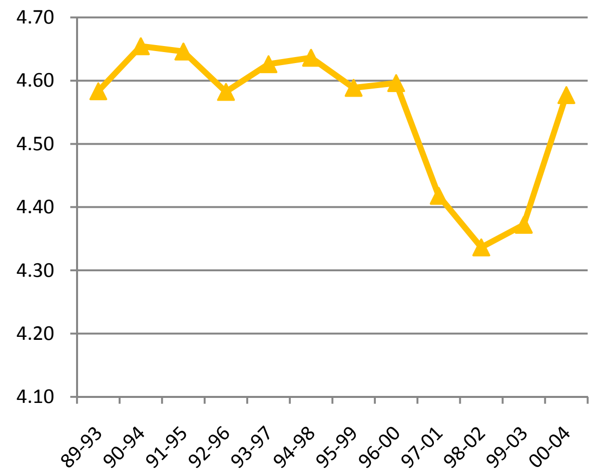


Figure 17: Average component size in each subnetwork

Nevertheless, there are significant differences in the component sizes. In the complete network there is only one component of a substantial size and the rest of the components are relatively small: The largest component includes 336 inventors, the second one consists only of 30 inventors and the third of 29 inventors. The distribution of the component sizes of the in the full nanotechnology network is shown in Figure 18: the first dot to the left far above the others identifies the largest component and the rest of the dots represent the components at least 10 times smaller appearing as a continuous line.

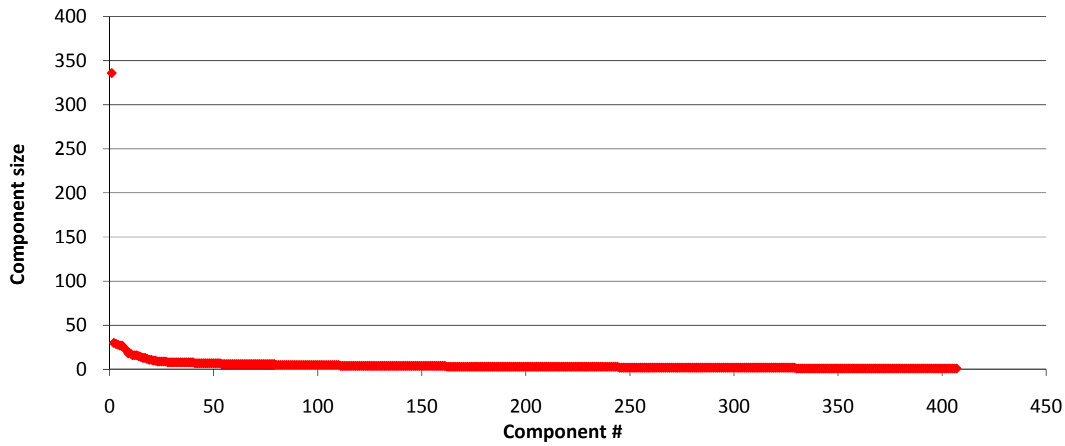


Figure 18: Distribution of component sizes in the complete network

The existence of one component of a much greater size than the others is in fact quite a common component structure in collaboration networks and the *size of the largest component* is an important network indicator. Inventors in a network with a large component can exchange scientific knowledge much easier than in other networks. The evolution of the two largest component sizes is shown in Figure 19. The size of the largest component has almost doubled during these years, from 82 to 154 interconnected inventors. The size of the second largest has tripled, but is still nowhere near the size of the dominant component.

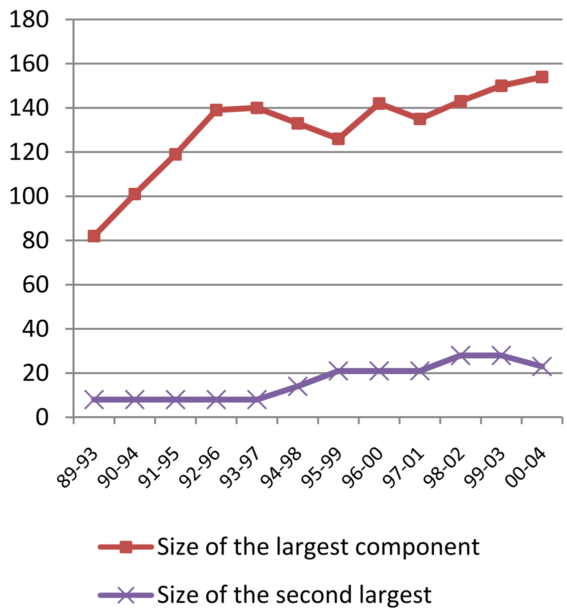


Figure 19: Sizes of the two largest components in each subnetwork

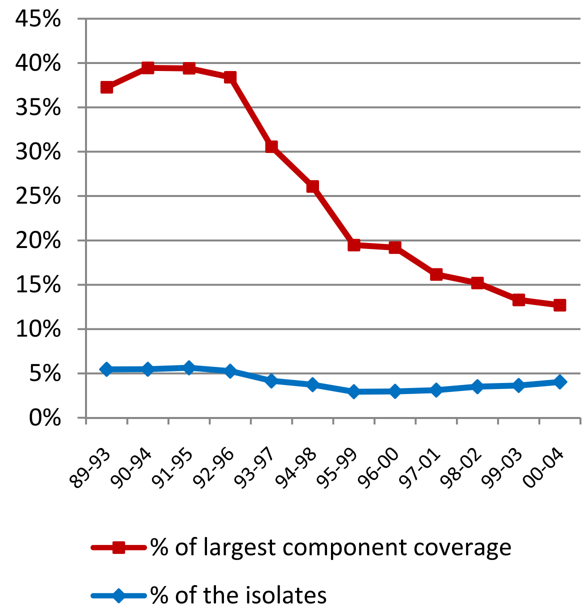


Figure 20: Share of inventors that compose the largest component and share of single inventors in each subnetwork

The *largest component coverage* is how we call an indicator which evaluates the relative size of the largest component. The largest component in the complete network of Canadian nanotechnology inventors is formed by 17% of all inventors (or around 18% of non-single inventors). The evolution of the proportion of inventors contained in the largest component in each subnetwork is shown in Figure 20. As more inventors patent their ideas, the largest component proportionately includes less and less inventors. In the first subnetwork (corresponding to the first five-year moving interval) the most important component was composed of around 38% of inventors. Later, the largest component reached almost 40% of inventors and then gradually dropped to around 13% in recent years. This is in fact surprising since we expected that the largest component coverage will rise with time together with the increasing sizes of the subnetworks. This may be explained by the wide breadth of applications existing in nanotechnology. We may be observing fragmentation of the subnetworks because of various nanotechnology specialisations and the development of new fields.

Indeed, researchers often found a giant component in huge collaboration networks. In all seven scientific networks which he studied, Newman (2001a) observed a giant component of scientists, which gathers 90% of all scientists. His networks were also built from the five-year period data; however they were based on article co-authorships with a majority of inventors being academic scientists. The article-based networks usually have a distinct network structure (denser and more clustered) from the patent-based ones. Balconi *et al.* (2004), who did construct their networks from the EPO patent database, observed that the largest component in one of the subsectors gathers almost 60% of the non-single inventors, and it is followed by a second component which is 50 times smaller. The second largest one in our network is only 11 times smaller than the first one. Balconi *et al.* (2004), however, did not observe this large component in all their studied networks (subsectors) either. In some of the networks (of similar sizes as our full network) the largest component comprised only 2-3% of inventors and the second largest component was once or twice smaller as the largest one. The existence of the giant component was also confirmed by Putsch (2006). The network analysis of Fleming *et al.* (2006) revealed the emergence and disappearance of giant components in patent collaboration networks. He found emerging giant component in Silicon Valley, whose size increases dramatically, but did not find a similar one in Route 128.

The number of isolates (single patent components) is the last measure of fragmentation to be discussed here. An isolate component consists of a single inventor who has not collaborated with anybody else. In the complete network, only around 4% of all components (78 components) are isolates. *Figure 20* shows the evolution of the percentage of inventors who do not have any collaborator in their five-year interval subnetwork. The value of the share fluctuates slightly, but a general tendency seems to be quite stable (around 4%-5%) and slowly decreasing with time.

The main characteristics and structure of the 20 largest components in the network are shown in Table 1. From the composition numbers it is obvious that most of the components consist of the inventors residing in several distinct clusters. This is particularly true for the larger components, some of which are geographically spread all over the country and abroad as well. Nevertheless, some of the components (e.g., Components #5, #12, #14), mostly the smaller ones, present solely intra-cluster cooperation within Canada. When an inventor from outside the cluster cooperates, he is mainly foreign. In fact, 19 of the 20 components presented include at least one foreign collaborator. Note that some of these international components consist of completely majority of foreign inventors with only one or two Canadians (e.g., Components #7 or #11). These are probably much larger foreign components in which a few Canadian inventors participate. For instance, the whole Component #7 is based on collaboration on one single patent and is composed of 24 inventors, out of which 23 are foreign and only one is Canadian.

Table 1: Main characteristics and composition of the 20 largest components in the Canadian nanotechnology innovation network

Component #	*#1*	*#2*	*#3*	*#4*	*#5*	*#6*	*#7*	*#8*	*#9*	*#10*
Number of inventor	336	30	29	28	27	27	24	22	18	18
Number of patents	492	24	30	18	13	5	2	26	13	15
Patents per inventor	1.5	0.8	1	0.6	0.5	0.2	0.1	1.2	0.7	0.8
Average number of claims	29.1	16.8	18.8	10.3	19.8	28.2	13	30.9	34	14.8
Number of inventors in each cluster										
Toronto	156						1		11	10
Montreal	11	21		2		1		10		
Ottawa	31		4	7		1				1
Vancouver				2	21	1				
Edmonton			15	14		4			6	
Quebec		7						1		
Kingston	3		7			5				
Calgary	2			2						
out-of-cluster	7	1	1		2	12				
abroad	126	1	2	1	4	3	23	7	1	7

Component #	*#11*	*#12*	*#13*	*#14*	*#15*	*#16*	*#17*	*#18*	*#19*	*#20*
Number of inventors	16	16	16	15	14	13	13	12	11	11
Number of patents	4	5	14	6	29	17	4	12	5	5
Patents per inventor	0.3	0.3	0.9	0.4	2.1	1.3	0.3	1	0.5	0.5
Average number of claims	18	24.4	20	14.3	29.8	9.3	24.5	36	17.8	33.6
Number of inventors in each cluster										
Toronto	2		3	13		11	5		6	
Montreal								5		
Ottawa								1	5	
Vancouver		6			9					4
Edmonton										
Quebec			2							
Kingston										
Calgary										
out-of-cluster		3			1		1			
abroad	14	7	11	2	4	2	7	6		7

Table 1 also shows two additional indicators which characterize each component: first one concerns innovative productivity of the inventors (the ratio of patents per inventor) and the second one describes patent quality (average number of patent claims). The most productive component (Component #15) has 14 inventors whose repeated collaborating resulted in 29 patents. The biggest component (#1) is the second most productive – 336 inventors from many diverse clusters created 492 patents. Its mean patent quality also belongs among the highest. Foreign components (Components #7 and #11) show very low ratios of patents per inventor and thus belong among the least productive ones. Nevertheless, this does not mean that the foreign inventors are less productive; rather it confirms that the large components composed mainly of foreign inventors have likely produced much greater number of patents, which are not considered here due to the absence of Canadian co-inventors.

4.2 Network density

Structural cohesion refers to the degree to which vertices are connected among themselves. The most common measure of cohesion is network density, which is the number of existing links in the network expressed as a proportion of the maximum number of possible links. This indicator is however not suitable for comparison of the networks of different sizes, and therefore we measured density by the average degree of a network. The degree of a vertex is the number of links directly connected to the vertex and represents the number of direct collaborators with whom an inventor has cooperated on at least one patent. The larger the number of direct co-inventors of each inventor, the tighter is the network structure. The *average degree of a network* then denotes the average of the degrees of all vertices and it in fact also shows the average number of co-inventors in each subnetwork, which we discussed earlier. Another indicator of the structural cohesion which we used is the ratio *edges/vertices* (the number of the collaboration links in each network divided by the number of inventors). Both indicators show practically the same phenomenon and Figure 21shows that the trend points towards denser networks. This means that the access of Canadian nanotechnology inventors to knowledge has been improving over time. In denser networks inventors can directly or indirectly reach a greater amount of knowledge and a larger number of inventors. Consequently the possibility for two inventors to get in touch through a chain of personal acquaintances is higher as well.

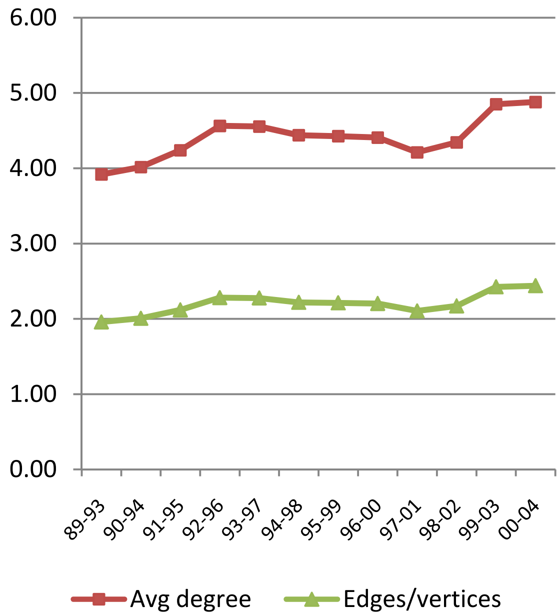


Figure 21: Indicators of density in each subnetwork

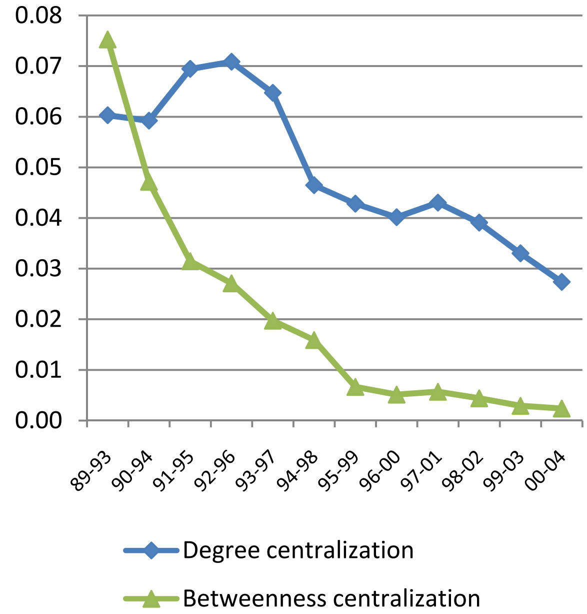


Figure 22: Indicators of centralization in each subnetwork

4.3 Network centralization

Indicators of the network structure characterize the degree of the network centralization. A highly centralized network has a clear boundary between the center and the periphery. The center of a highly centralized network allows more efficient transmission of information, which consequently spreads fairly easily. Centralization of a network is defined as the variation in the degree centrality of vertices, divided by the maximum degree variation which is possible in a network of the same size (de Nooy *et al.*, 2004).

There are two main indicators of network centralization which could be measured in disconnected networks: degree centralization and betweenness centralization. *Degree centralization* of a network is based on the variation in degree centrality of vertices in a network, where degree centrality of a vertex is in fact equal to the degree of the vertex defined above. Inventors with higher values of degree centrality are found in more central positions in the subnetwork. They are directly connected to more inventors and thus have more potential sources of scientific knowledge at their disposal and better opportunities to spread information further. This makes them important for the transmission of information through the network. Analogous to degree centralization, *betweenness centralization* of a network is based on the variation in betweenness centrality of vertices in the network. Betweenness centrality of a vertex is defined as a proportion of all shortest distances between pairs of other vertices that include this vertex (de Nooy *et al.*, 2004). An inventor is more central if a lot of the shortest paths between pairs of other inventors in the subnetwork have to go through him. Betweenness centrality is therefore based on the inventor's importance to other inventors as an intermediary and it measures his control over the interactions between other inventors and thus over the flow of knowledge in the subnetwork. *Figure 22* shows the evolution of both indicators of centralization. Even though degree centralization fluctuates to a certain point, they both have a fairly clear decreasing tendency. It may be explained by an increasing specialisation of nanotechnology: a few highly central inventors are slowly disappearing and more inventors in less central positions within numerous nanotechnology specializations emerge. As a consequence, the communication within the network of Canadian nanotechnology inventors is getting less efficient with time as is the ability to spread knowledge throughout the network.

4.4 Geodesic distances

The geodesic distance is defined as the shortest path between two vertices, it is the length of a geodesic between them and depends on the number of intermediaries needed for an inventor to reach another inventor in the subnetwork. A short path length in innovation networks should improve knowledge production and knowledge diffusion (Cowan and Jonard, 2004; Fleming *et al.*, 2004), since knowledge can move to the different parts of a network more quickly and spread more rapidly among inventors. Moreover, as Cowan and Jonard suggest, decreased path length will cause knowledge to degrade less by bringing new sources of ideas and perspectives from farthest parts of the network to the inventors.

An indicator of the *average distance of a network* denotes the average of all shortest paths among all the vertices in the network. It could however be measured only in fully connected networks, as the distance between two unconnected vertices is not defined (it does not exist). First we calculated the average distance only between reachable vertices while excluding those to which no path exists. The results for each subnetwork in Figure 23show that the information travels among the connected inventors increasingly faster than before. Aware that the calculation which excludes the unreachable vertices may bring a certain bias to the results (any highly disconnected network should yield lower scores for geodesic distances), we calculated the average distance in every largest component of each subnetwork and obtained similar results. It could be expected that the average path length in the larger components will get longer as well and the decreasing path lengths seen in the figure are thus rather surprising. They may however be an indication of a continual improvement in the subnetwork structure which enables increasingly more efficient knowledge diffusion as time progresses.

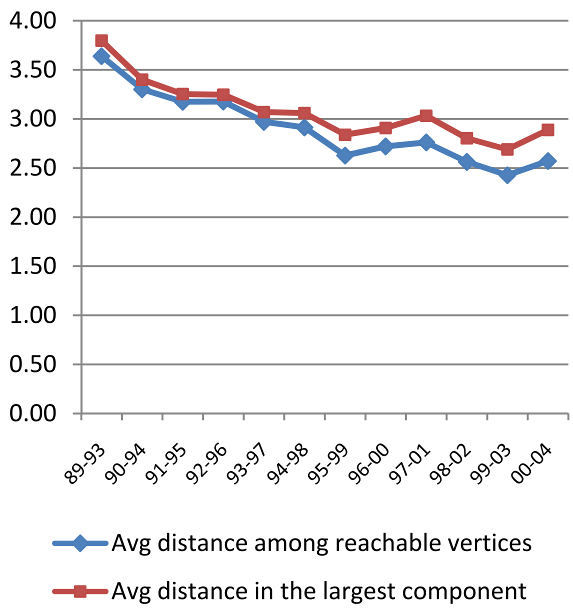


Figure 23: Indicators of average distance in each subnetwork

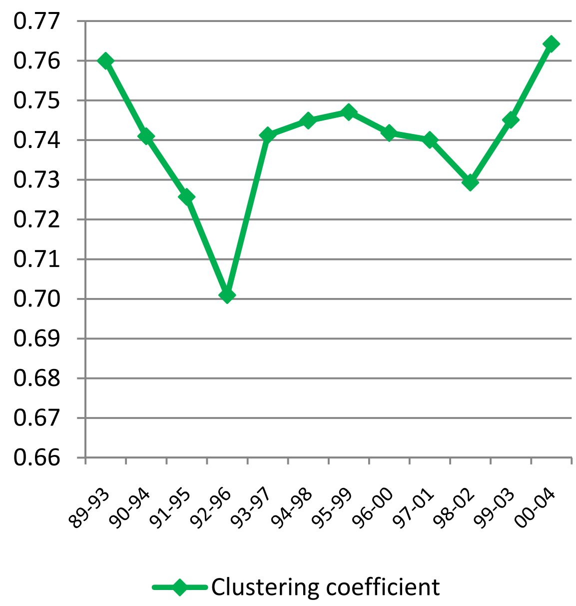


Figure 24: Indicator of cliquishness in each subnetwork

4.5 Network cliquishness

Cliquishness (clustering) is a property of local network structure which refers to the likelihood that two vertices that are connected to a specific third vertex are also connected to one another. Clustered networks have tendency towards dense local neighbourhoods, in which individual inventors are better interconnected with each other. Such networks exhibit a high transmission capacity, since a great amount of knowledge could be diffused rapidly (Burt, 2001). Moreover, a high degree of cliquishness in an innovation network supports friendship and trust-building, and hence facilitates collaboration between the innovators. Uzzi and Spiro (2004) and Schilling and Phelps (2007) argue that higher degree of clustering enhances system performance and knowledge diffusion.Cowan and Jonard (2003) however point out the existence of negative clustering effects stemming from the loss due to repetition, as the information exchanged in highly clustered neighbourhoods is often redundant. Moreover, empirical findings of Fleming *et al.* (2006) confirm the negative impact of the higher degree of clustering in the network on innovative productivity. They suggest that the optimal degree will apparently depend on a variety of factors.

In order to capture the network cliquishness first we measured the degree of local clustering for each vertex with egocentric density of a vertex. Egocentric density of a vertex is the fraction of all pairs of the immediate neighbours of a vertex that are also directly connected to each other. Afterwards we calculated the *average egocentric density* of each subnetwork. As you can see in *Figure 24*, the degree of clustering fluctuates in time and does not have any clear tendency. The role of a high degree of cliquishness in the information transmission is still not obvious, but work is currently on the way to investigate its importance in the innovation production.

5. Conclusions

The purpose of this work was to study social networks of Canadian nanotechnology inventors, in which a co-inventorship of one or more nanotechnology patents registered at the USPTO represents a collaborative tie between two innovators. In order to explore the collaboration characteristics and network properties we have introduced two sets of indicators which allowed tracking the changes in the Canadian nanotechnology collaboration network in the period of 1989-2004. These indicators revealed not only the evolution of the collaborative environment in Canadian nanotechnology, but also the geographical patterns of the inventors` collaborative behaviour. Moreover, the indicators enabled us to evaluate the collaboration network efficiency in the knowledge diffusion.

We observe that the Canadian nanotechnology inventors have an increasing tendency to build cooperative ties with a higher number of partners and to collaborate with them on the nanotechnology projects more intensively than they have done so in the past. The sizes of the cooperation teams working on the projects leading to the nanotechnology patent applications are getting bigger as well. These collaboration indicators suggest that Canadian nanotechnology inventors have been increasingly able to diffuse greater amounts of valuable scientific knowledge among a higher number of other inventors and therefore both to emit and to absorb more knowledge spillovers. Nurturing the collaboration teams with a fresh knowledge from distinct research environments leads to an increased opportunity for an innovative recombination of that knowledge and enhances thus the inventors` future creativity. Nanotechnology inventors also tend to return for subsequent collaborations to the same partners with whom they have already collaborated within the past five years. Repeated collaborations with the same partner foster mutual trust and confidence. A higher frequency of collaboration between two inventors hence leads to a more profound research relationship, which may involve an exchange of information of higher quality (e.g., a rare or undisclosed knowledge).

We have also examined the prominent researchers in Canadian nanotechnology clusters. We proposed to take into consideration the patent quality when identifying the prolific inventors, and developed a measure which includes both the patent count and the patent value in the equation. Furthermore, we have also identified the scientists whose publications are the most highly cited. We discovered that the most prominent researchers and scientists superior in the nanotechnology field do not usually produce patents or register them at the USPTO. We offered an explanation based on the differences in the reward systems in academic and industrial environments. Investigation of the evolution of the collaboration with the QQ star scientists has shown that even though the absolute number of collaborations with QQ-star scientists has been rising over time, their share is in fact decreasing, since increasingly more inventors with low patent scores tend to file patent applications. In general, around 20-35% of patents have been created while collaborating with at least one QQ-star scientist. Also we noticed that the mutual collaboration among 2 or 3 QQ-star scientists is increasing in popularity.

We also examined the evolution of the structural network properties in time and related them to the likely efficiency of the nanotechnology innovation network in terms of knowledge diffusion. First we described the changes in the pattern of fragmentation of the nanotechnology network which have developed during the 15 year period. Even though the size of the largest component in the network has been increasing with time in its absolute value, it has contained fewer inventors proportionally to the network size in each of the studied intervals. The large components allow a longer reach to the inventors who could thereby benefit from non-redundant knowledge originating in remote locations. The decreasing relative size of the largest component means that the network structure does not offer the best possible opportunity for capturing the distant information, which the inventors in the network of such size could have. Nonetheless, the smaller components have been growing relatively much faster and the mean component size has remained in fact fairly unchanged throughout the time. Also, the share of isolate components – the inventors not connected to any other collaborating partner and thus working in isolation - has slightly decreased during the studied period. We concluded that the described development of the network fragmentation is caused by an increasing specialization of nanotechnology. As new fields are emerging the inventors are disconnecting themselves from the main component and regrouping into the smaller components representing specialized branches.

We have also proposed four other network indicators which characterize the properties of the structure of the nanotechnology collaboration network: density, average distance, centralization and cliquishness (clustering). We observe that the Canadian nanotechnology network has become denser with time, i.e. more cohesive and tight. This suggests that inventors have become more closely interconnected among themselves and their chances for knowledge exchange have thus been enhanced. Also, the average distances in the network are getting shorter and knowledge could thus be transferred faster and through less intermediaries. On the other hand, the structure of the Canadian nanotechnology network is becoming less centralized as the time progresses, which is probably also due to the increasing nanotechnology specialization. Inventors in the highly centralized networks make use of a clear network centre which enables knowledge to spread easier. The decreasing centralization should hence slow down knowledge transmission through the network. Finally, we have not observed any trend in the changes of the network`s local clustering. A definite relationship between the cliquishness and the knowledge diffusion has however still not been fully established.

The impact of the network structure on the ability to transmit information through the network has already been studied, and some researchers have even explored the relationship between some network properties and innovation, but due to contradictory results a consensus has yet to be reached. The exact role of the network architecture in the knowledge creation and especially in the innovation generation thus still remains to be determined. At the present time we are working on the econometric model in order to establish an unambiguous relationship between network structure and innovative propensity.

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