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*Title Page (with author details)

Impacts of collaboration and network indicators on patent quality: The case of Canadian Nanotechnology Innovation

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This article studies the impact of collaboration and co-inventorship network characteristics of Canadian nanotechnology inventors on the quality of their inventions. We investigate the impact of four types of variables on patent quality, using the number of claims as a proxy for quality: (a) the presence of highly central inventors; (b) the presence of star inventors; (c) repeated collaboration; (d) international collaboration. We show that the presence of more central inventors and of stars in the research team has a positive influence on patent quality, while repeated collaboration has a negative impact. Patents owned by foreign organisations, controlling for whether assignees are firm, yields patents of higher quality.

Keywords: innovation, collaboration, patent quality, knowledge networks, social network analysis, nanotechnology, Canada

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This article studies the impact of collaboration and co-inventorship network characteristics of Canadian nanotechnology inventors on the quality of their inventions. We investigate the impact of four types of variables on patent quality, using the number of claims as a proxy for quality: (a) the presence of highly central inventors; (b) the presence of star inventors; (c) repeated collaboration; (d) international collaboration. We show that the presence of more central inventors and of stars in the research team has a positive influence on patent quality, while repeated collaboration has a negative impact. Patents owned by foreign organisations, controlling for whether assignees are firm, yields patents of higher quality.

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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) 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, high invention rates and possibly higher value innovations. A large number of historical examples are documented in the literature: for instance, the wide informal knowledge trading between engineers in competing minimill firms in the US steel industry (von Hippel, 1987; Schrader, 1991), and the knowledge sharing in a cluster of wireless communication firms in Denmark (Dahl and Pedersen, 2004), but the most commonly cited example is the open knowledge sharing culture in Silicon Valley (Saxenian, 1994).

The concept of collective invention is convenient for describing the dynamics of knowledge sharing through various innovation networks. The network of innovators is an interpersonal network of individuals, who collaborate and exchange information to produce innovations and scientific knowledge. These inventors and scientists work in universities, research centers or industrial R&D departments. There is usually no formal agreement among the researchers; however, they frequently take part in the development of a patent or the creation of a scientific article. Social network analysis is increasingly used to analyze the way these innovators are interconnected. 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 (Agrawal *et al.*, 2006). The patent documents and bibliometric data can thus be exploited to map the complex web of social ties among innovators, to measure the extent of collaboration behaviour and to construct representations of innovation networks.

This paper is a part of a project aimed at understanding the influence of collaboration and of networks on innovation creation and on the quality of innovation in Canadian nanotechnology, measured by patents. While networks are an important indicator of the „insertion of inventors into the broader social structure of relationships[1], the importance, form and localisation of the relationships are also relevant. This work investigates the impact of four types of variables on patent quality: (a) network centrality of an inventor of the team in the Canadian co-inventorship network; (b) the presence of star inventors within the patent team; (c) repeated collaboration between team members; (d) international collaboration. Different network structures and characteristics have different impacts on knowledge sharing between individuals and their organisations, thereby greatly influencing innovation creation. The evolution of the network structure and of the collaboration patterns of inventors has an impact on innovation quality. We show that patents generated by inventors that are more widely connected and more central (and hence potentially have access to a larger pool of knowledge) but have collaborated less repeatedly in the past, produce inventions of greater quality. In addition, the presence of star inventors in the research team has a positive influence on patent quality. We also suggest that patents owned by foreign organisations, controlling for whether assignees are firms, yields patents of higher quality.

The article is organised as follows. Section 2 describes the theoretical framework underlying the study. Section 3 introduces the data and the methodology used in the analysis that follows. Section 4 presents the evolution of the four indicators of collaborative patterns. Section 5 presents the statistical analysis aiming to identify the factors that explain patent quality. Finally, section 6 concludes.

2. Theoretical framework

Sociologists have been using social network analysis to study the behaviour of individuals for a great number of years (see for instance Granovetter, 1973; Burt, 1987, 1992). Following in their footsteps, Breschi and Lissoni (2004 and 2005) and later Balconi *et al.* (2004) constructed the network of collaborative relationships linking Italian inventors using data on patent co-inventorship from the European Patent Office (EPO). The links between individuals have however been modelled in the literature in a number of different ways. Cantner and Graf (2006) proposed to build the networks of innovators based on technological overlap, which is a measure

[1] We are grateful to the editors for this turn of phrase.

of closeness of the technological field of two scientists. They also described the evolution of the innovator network of the town of Jena in Germany using information on scientific mobility. Singh (2005) inferred collaborative links among individuals using a social proximity graph, which he also constructed from patent collaboration data. Other researchers, Fleming *et al.* (2007) for instance, adopted the co-inventorship of patents as an appropriate device to derive maps of social relationships between inventors and to build their networks. In this study, we adopt the co-inventorship of patents as links between inventors to create the network of ties between these individuals.

Nevertheless, there is a number of limitations regarding the use of patents. Based on interviews with inventors, Fleming *et al.* (2007) warned that patent co-inventorship links differ significantly in their strength and information transfer capacity. In addition, since their decay rates vary greatly, a substantial number of old ties remain viable even if the relation does not exist anymore. Moreover, measuring collaboration using solely patent co-inventorship links may admittedly omit a number of relationships between inventors that chose to only patent a proportion of their inventions (Sorenson *et al.*, 2006) while protecting the remainder of their intellectual property with other more appropriate means (Levin *et al*., 1987; Klevorick *et al*., 1995). However, according to McNiven (2007), 88% of the intellectual property instruments used by Canadian nanotechnology companies are reported to be patents or pending patents. An important limitation of patent information is its inability to infer the interaction mechanisms and processes between inventors or the quality of these interactions (Murray, 2002). Finally, another shortcoming of the patent use for the study on innovation is the fact that inventor affiliation information does not generally appear in patent documents and its identification thus requires a second source of information.

While the majority of the inventors named on industrial patents are probably employees of the assignee, there is an increasingly important phenomenon of academic patenting that should not be neglected. In fact, the characteristics of the network structures differ depending on whether they contain purely industrial or also academic researchers. A wide literature on the so-called „academic" patents exists (see the survey of Foray and Lissoni, 2010 for instance). Balconi *et al.* (2004) observe 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. Although we have not yet identified the academic inventors in our database, we suspect that in a relatively new field such as nanotechnology, the proximity to science (Meyer, 2000) implies that academics have a non negligible contribution to patenting. The network structure should therefore resemble that of Balconi *et al.* (2004).

Numerous authors have used patent „quality" measures as a proxy for patent „value" (whether technological or economical) to study what influences the importance of a patent using a number of indicators such as citations (Trajtenberg, 1990), patent family size (Lanjouw *et al.*, 1998), patent renewal decisions (Wang *et al.*, 2010), the number of claims (Lanjouw and Schankerman, 2004) or complex combinations of the above (Bonaccorsi and Thoma, 2007). The findings from the aforementioned research studies nevertheless reveal some interesting properties of the innovation networks. Wang *et al.* (2010) for instance use a network of patent citations to show that a high brokerage (intermediary position measured by betweenness centrality) has a negative impact on the patent renewal decision in the early stage of a patent"s life and a non significant impact in the mature stage. When citations are used as a proxy for patent quality, the impact of brokerage has a positive effect on patent quality. Different patent quality measures are thus influenced differently by various indicators. Considering these impacts of centrality measures, we hypothesise that a better network position of inventors has a positive impact on patent quality:

H1 An inventor in a more central position contributes to patents of a higher quality.

Cohen and Levinthal (1990) suggested that it may be necessary not only to invest in basic research inside the firms, but also to hire the best possible research personnel, which they call "star scientists". Supporting this argument, Zucker *et al.* (1998b) show that rates of firm founding and of new product introduction are related to the connections of the companies to "star" university scientists. Zucker *et al.* (1998a) also confirm that the number of products in development and on the market are positively influenced by collaborative research (evidenced by coauthored publications) with star scientists. The authors further show that 50% of stars affiliated with firms have patented discoveries versus only 15.6% of the non affiliated university stars. The patenting of discoveries by stars is an indication of expected commercial value of their discoveries. Extending the concept of star scientist to star inventor, we hypothesise that:

H2 The presence of a star inventor and a larger number of star inventors in the patent team enhances patent quality.

Newman (2001) 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. Former collaborations are also found to be determinant of the future success. 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, which should result in greater innovativeness. Cowan *et al.* (2005) claimed that previous collaborations increase the probability of a successful collaboration and Fleming *et al.* (2007) argued that an inventor‟s past collaboration network will strongly influence subsequent productivity. Not only should repetitive collaborations have a positive impact on the company‟s innovative production, it should also have an impact on the scope of patents. With repetitive collaboration, however, interactions between individuals may become more of a routine, rendering stepping off the beaten track more difficult as time goes by (Cattani and Ferriani, 2008), forcing a certain cognitive alignment (Baum and Ingram, 2002). While there is a wide literature on repeated collaboration and trust-building (see for instance Gulati, 1995; Kogut, 1989), very few authors address the impact of repeated collaboration on patent quality or patent value. Because of the routinisation of collaboration that it implies, we thus hypothesise that repeated collaboration has a negative impact on patent quality and that it overcomes the potential benefits from acquiring new collaborators (and hence to potentially have access to new knowledge).

H3 The presence pairs of inventors that have repeatedly worked together in the patent team decreases patent quality.

Other researchers who adopted the network approach have also included geographical aspects into their models. Gittelman (2007) 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. While it is not the scope of the paper to tackle the interaction between geographical proximity and social proximity, Gittelman‟s argument suggests that foreign owned patents, which imply a more dispersed research team, would tend to generate more commercially valuable technologies emanating from patents with possibly a greater number of claims. We therefore propose the following hypothesis:

H4 Foreign ownership of a patent increases patent quality.

3. Data and methodology

3.1 Data

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. As such, it is a very unique and comprehensive dataset. The Nanobank patent database is based on data extracted from the United States Patents and Trademarks Office (USPTO) database. This is the only patent database which provides the geographical location of the address of 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), which we define as Canadian nanotechnology patents, regardless of the assignee‟s location. We have employed additional filters[2] using the keyword

[2] The resulting nanotechnology patent database therefore includes the patents that have both been identified in Nanobank and by using the keywords used by Porter *et al.* (2008).

search strategy of Porter *et al.* (2008), which enabled us to select only the patents which are strictly related to nanotechnology and created a Canadian nanotechnology patent database which comprises 1443 patents from 1979 to 2005. Because we use the intersection of two datasets that were built using two different methodologies and keyword strategies, we are confident that we truly measure nanotechnology patents in Canada. The concept of social network analysis defined above was used to identify the connections between all the nanotechnology inventors of these patents and to construct representations of the networks. The use of the social network analysis program PAJEK was instrumental in building these representations of innovation networks and in analyzing their architectures. The analysis of these collaborative networks enables us to understand the co-inventorship characteristics of the inventors in Canadian nanotechnology clusters.

We have created 11 subnetworks corresponding to five-year moving windows starting from 1989 and finishing in 2004 (as shown in Figure 1) in order to track the evolution of the collaboration and network properties over time. 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 chose to work with the subnetworks created during an interval of five years as we assume that relationships between any co-inventors who appeared together on one USPTO patent lasts 5 years on average during which information and scientific knowledge can be actively exchanged. Five-year moving windows thus more accurately reflect the evolutionary structure of a collaboration network. As Canadian nanotechnology patenting in the period prior to 1989 is rather sporadic, our sample starts 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. Furthermore, we also removed from the sample the patents which do not have an assignee yet. As a consequence, our sample consists of 1218 patents, to which 1794 inventors have contributed.

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 to nanotechnology research only recently. The figure also includes the number of patents which were used for building the particular subnetwork of each time interval. The number of patents has increased faster (15.62% per year) than the number of inventors (15.29% per year) hence suggesting that the sector benefits from a critical mass of inventive individuals.

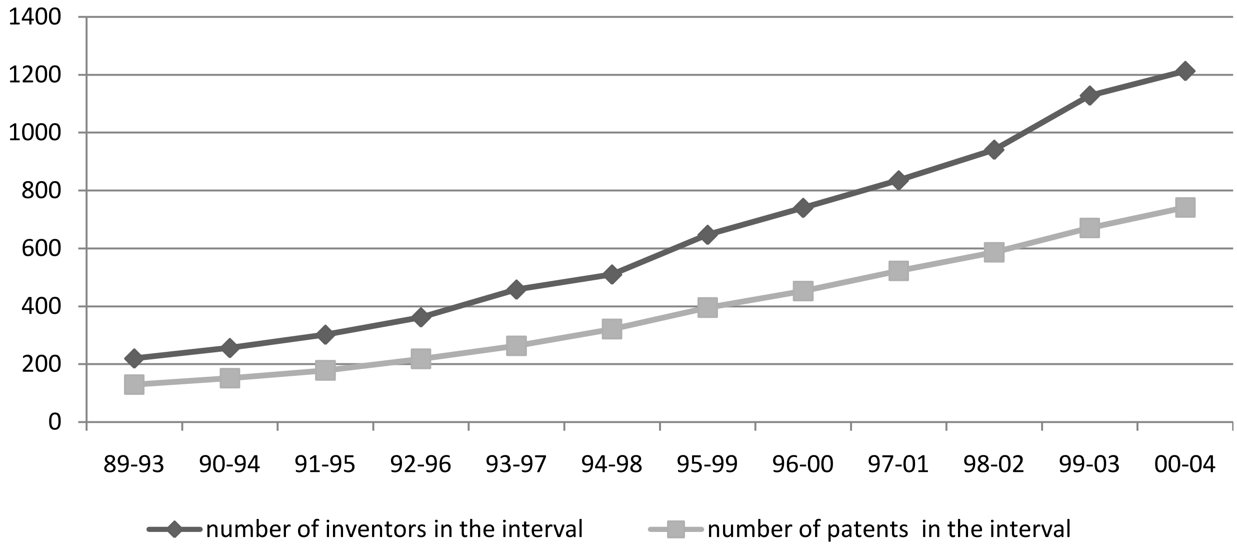

Figure 1: Number of inventors and patents used in each subnetwork

3.2 Model

In this article we use the number of claims as an indicator of a patent quality. Patent claims are a series of numbered expressions describing the invention in technical terms and defining the extent of the protection conferred by a patent (the legal scope of the patent). A high number of patent claims is an indication that an innovation is broader and has a greater potential profitability. It has been frequently suggested and empirically demonstrated (see for example Tong and Frame, 1994) that the number of claims is significantly and consistently indicative of higher value patents. The conclusions of most of the papers on patent value reviewed by van Zeebroeck and van Pottelsberghe de la Potterie (2011, in press) are supportive of the positive association of the number of claims with patent value. Lanjouw and Schankerman (2004) have suggested that specifically in the biotechnology field, the number of claims is the most important indicator of patent quality. However, there are some shortcomings related to the use of claims as a patent quality indicator as well. According to Lanjouw and Schankerman (2001), the number of claims also depends on the technology field (drugs and health, chemical, and electronic inventions have more claims per patent, while patents protecting mechanical and other types of inventions have fewer claims), the ownership types (in each field the US-owned patents have on average a higher number of claims than foreign-owned ones, while Japanese-owned patents have on average the lowest number of claims) and on the time (the mean number of claims per patent has increased over time).

In our analysis, the number of claims is used as a proxy for the patent quality, and hence as a measure of the success of the innovation process. Because the dependent variable is a count measure, we use the pooled cross-section[3] data to estimate the number of claims of each patent. A Poisson regression is generally appropriate for this purpose (Hausman *et al.*, 1984):

$$\Pr(Y = y) = \exp \lambda(x) \left[\frac{\lambda(x)}{y!} \right]$$

The particularity of this model resides in the fact that both the probability of a given number of events, $\Pr(Y = y)$, and the variance of the number of events is equal to the $\lambda(x)$. The Poisson process therefore makes a strong assumption that the variance is equal to the mean, which implies that there is no overdispersion (when the variance exceeds the mean) in the sample. In general, the negative binomial is generally employed to correct for this overdispersion which causes for the standard errors to be underestimated, and hence for significance of the coefficients to be overestimated. The negative binomial formulation usually takes the form:

$$\lambda = \exp(\pi x)\varepsilon$$

where ε, the error term follows a Gamma distribution. The specification of the overdispersion is therefore:

$$Var[Y] = E[Y](1 + \alpha E[Y])$$

[3] We have omitted the subscript t from the equations because only 328 organisations have more than one patent. We are thus analysing the data as a cross-section rather than as a panel, but accounting for possible time effects with year dummy variables.

Because the claims of each individual patent are considered in this analysis, a firm that has been granted a patent will appear more than once in the database. To account for the non independence of the observations generated by this formulation, our model allows for intragroup correlation, each corresponding to an individual firm. Using the cluster option of the *nbreg* procedure of Stata 10 allows the observations to be independent between groups, but not necessarily within groups. We are aware that a number of inventors may have worked for various organisations, which would hence compromise our assumption of independence across groups. This phenomenon is however relatively infrequent throughout the database.

In contrast to the stable augmentation observed for the number of inventors and the number of patents, Figure 2 shows that the average number of claims has declined during the first half of the sample and steadily increased in the second half of the sample.

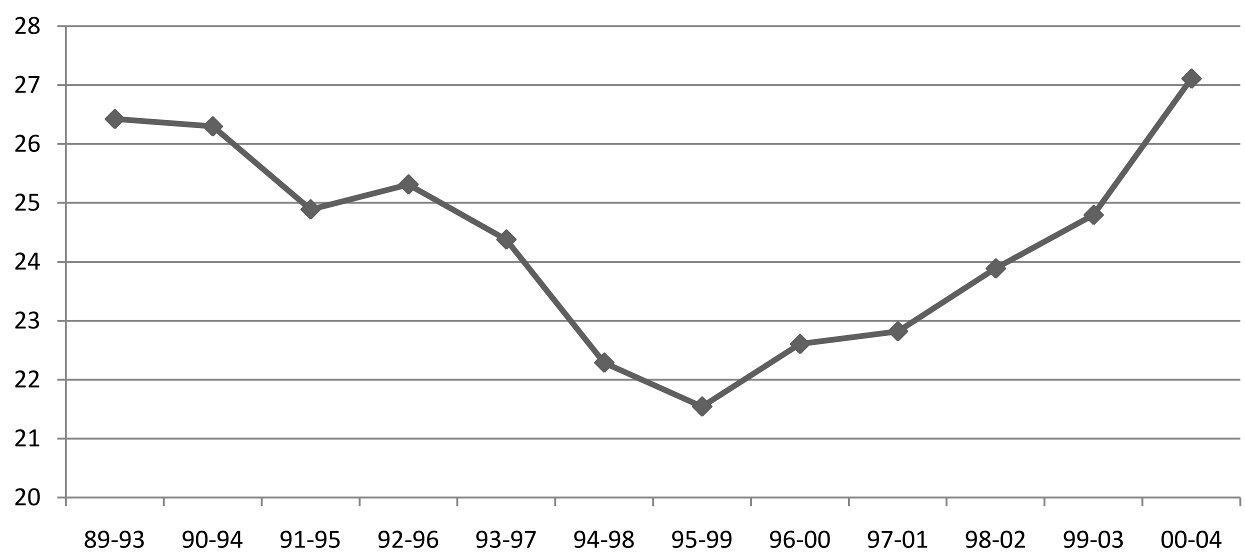

Figure 2: Average number of claims per patent in each subnetwork

3.3 Explanatory variables

The independent variables used in the negative binomial regressions to explain the number of claims of a patent are described below. A number of variables are used to test each hypothesis. The variables are presented in the order of the hypotheses that they contribute to validating.

The first hypothesis takes into consideration the collaborator‟s collaborators, their collaborators, and so on. Here we first adopt a network approach in which a structure of the entire net of complex relationships is analyzed and characterized. There are two main indicators of centrality which can be measured in disconnected networks: degree centrality and betweenness centrality. *Degree centrality* of an inventor in a co-patenting network is based on the number of co-inventors with whom this inventor has collaborated. 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. These inventors are highly important for a firm because of their numerous direct connections and thus their ability to potentially shape the company"s economic outcome. We thus expect this variable to have a positive effect on patent quality (H1). Degree centrality however does not always correlate with the power and influence an inventor might have over the network. This is better measured by betweenness centrality.

Betweenness centrality of a vertex is defined as the proportion of all shortest distances between pairs of other vertices in the network that include this vertex (de Nooy *et al.*, 2004). An inventor is more central if a large proportion of the shortest paths between pairs of other inventors in the subnetwork have to „go through him". In other words, if one person at one end of the network wanted to „send" a message to another person in another part of the network, the shortest path would be the one which involves the smallest number of intermediaries to „transmit" the message. The individuals often found on these shortest paths have higher values of betweenness centrality. 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. As such, an important intermediary should have a positive influence on patent quality (H1). An inventor with many direct connections (high degree centrality) might not be very powerful as an intermediary (not very high betweenness centrality) and in terms of access to information he might be in fact dependent on others.

For the first two measures of individual centrality within the network, we calculate the average value over the team contributing to each patent, as well as the maximum value corresponding to the individual that is the most central. The first indicator measures the degree centrality of an inventor (*AveDegcent* and *MaxDegcent*), *i.e.* the number of direct connections of that inventor, while the second measure characterises the degree to which an inventor acts as an intermediary for the network (*AveBtwcent* and *MaxBtwcent*). Four different indicators will therefore contribute to the testing of the first hypothesis (H1).

The most central inventors are not necessarily the most prolific inventors. Most inventive output in nanotechnology is produced by a small proportion of the most prolific inventors. These highly productive scientists are generally called "star scientists" and their important role has been much discussed in the literature. In this paper, we define these prominent researchers in our dataset based on patent quantity only. We thus extend the concept of star scientist to star inventor. To test the second hypothesis (H2), we use two types of indicators corresponding to four variables. The first counts the number of patents per inventor and takes the average over the patent team (*AvePatperinv*) and the maximum value among these inventors (*MaxPatperinv*). This simple indicator allows the identification of star inventors, those individuals that have contributed to 20 or more patents. Having identified the stars, we measure the number of star inventors (*NbStar*) involved in the patent production and include a dummy variable to identify whether the patent team involves at least one star inventor (*dStar*). In order not to exacerbate the bias attributed to the fact that in the beginning of the sample, inventors may already be star inventors, we sum the patents of each inventor since 1979, and not 1989. Otherwise, experienced inventors who retired in the early 1980s would not appear as star inventors. That said, there are two ways to consider the „quality" of inventors. The first consists in counting the number of patents to which each inventor has contributed up to the year of the patent examined („experience measure"). The road to stardom hence becomes gradual for these career-prolific inventors. The second focuses on the intrinsic potential capacity of the inventor and considers that if an inventor eventually becomes a star it is because he or she is an extraordinary individual to start with. We therefore count the total number of patents of this individual, regardless of the patent granting date, to identify the stars („career measure"). Unfortunately, as we cannot foresee the future, inventors who started their career towards the end of the sample will never qualify for stardom in this case. While for the former, experience would be the key ingredient to increasing patent quality, for the latter, innovation potential is the most important aspect. Having run the regressions with both types of quality measures, we found that despite its flaws, the latter measure has the most influence on the number of claims of a patent. These are the results presented in this paper.

An important aspect of the research aims to identify whether repeated collaboration (H3) contributes to increasing the quality of patents. We construct a variable that counts the number of prior co-invention occurrences between any two inventors (*PriorColl*). We then calculate the maximum number of these occurrences associated with each inventor of each patent team (*MaxPriorColl*) as well as the average across the research team (*AvePriorColl*). Two indicators are thus used to validate the third hypothesis (H3). Our first analysis showed a negative impact of more frequently repeated collaboration. A further investigation revealed that there was a wide gap between patents owned by firms and patents owned by other institutions. To take these differences into account, we introduce an interactive dummy variable, *dFirm*, to modulate the number of prior collaborations between any two inventors of the team. This dummy variable takes the value 1 if the patent assignee is a firm and 0 otherwise.

Finally, to account for the foreign ownership of patents (H4), we include a dummy variable that takes the value 1 if the patent assignee is foreign and the value 0 otherwise (Canadian), *dForeign*. Because a number of foreign assignees are firms, the dummy variable described in the previous paragraph also plays the role of a control variable to that effect. We have investigated whether the patent team involved foreign inventors as well as the proportion of these foreign inventors in the team, but none of these measures were significant in the regressions.

The descriptive statistics of these variables are presented in appendix. Because these variables vary considerably during the 15 years of our sample, the next section present the evolution of the main indicators that will be used in the regressions. As a consequence, year dummy variables are also added to the regression to take into consideration all other aspects of the indicators" evolution that are not explained by the other independent variables.

4. Descriptive statistics on the evolution of collaborative patterns

Although our data does not permit the use of standard panel data analyses, which would take into consideration the evolution of the characteristics, time is nevertheless important in the regression analysis that follows. As such, simple descriptive statistics (Table 2) are not explicit enough to get a feel of the data. In this section we thus present the four sets of indicators which characterize the nanotechnology collaborative relationships corresponding to each of the four hypotheses presented above. While the first hypothesis relates to the position of an individual in the network, the last three hypotheses require the disassembling of the entire network into collaborating pairs to describe the nature and frequency of collaborative activities between these innovating couples. Let us consider each family of variables in turn.

4.1 Inventor centrality position (H1)

Before turning to the centrality measures, let us examine collaboration in general. The average size of collaboration teams, as represented here by the *average number of co-inventors in one patent*, has gradually increased from less than 2.8 to well over 3.4 co-inventors per patent (Figure 3). For the entire period examined, there is on average 3.34 inventors per patent. This implies that Canadian inventors have increased their tendency to collaborate more intensively and to share information with a greater number of researchers than in the past. This may also represent the increasingly complex nature of nanotechnology projects requiring larger teams.

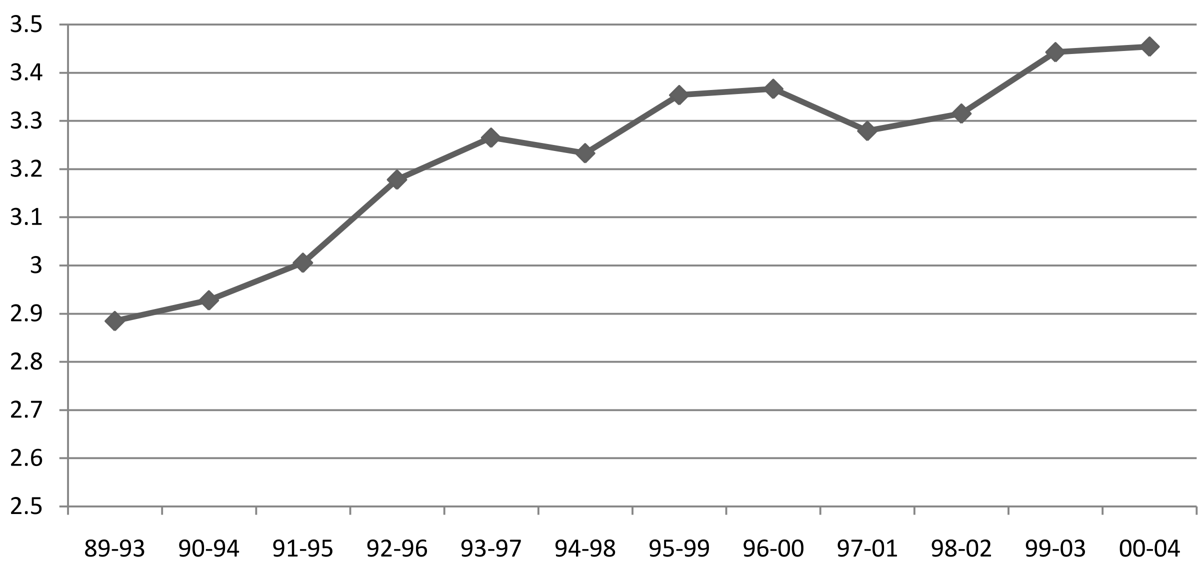

Figure 3: Average number of co-inventors in a patent per five-year period

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. The yearly average measure of betweenness centrality presented in the graph below (Figure 4) is normalised, while the yearly average measure of degree centrality is not. In the regressions, we will use the normalised values for both indicators. A non normalised measure of degree centrality is easier to relate to as it simply represent the average number of direct collaborators of an individual within the network during a 5-year period.

Both measures of centrality have a fairly clear decreasing tendency from 1992 onwards. One possible explanation resides in 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. These inventors may play a very important role within their specialization and may exert a great control over the local specialized subnetwork. For instance, they would be the first to be aware of any new development in the field. In general, the number of intermediaries is increasing, implying a greater redundancy in terms of access to knowledge.

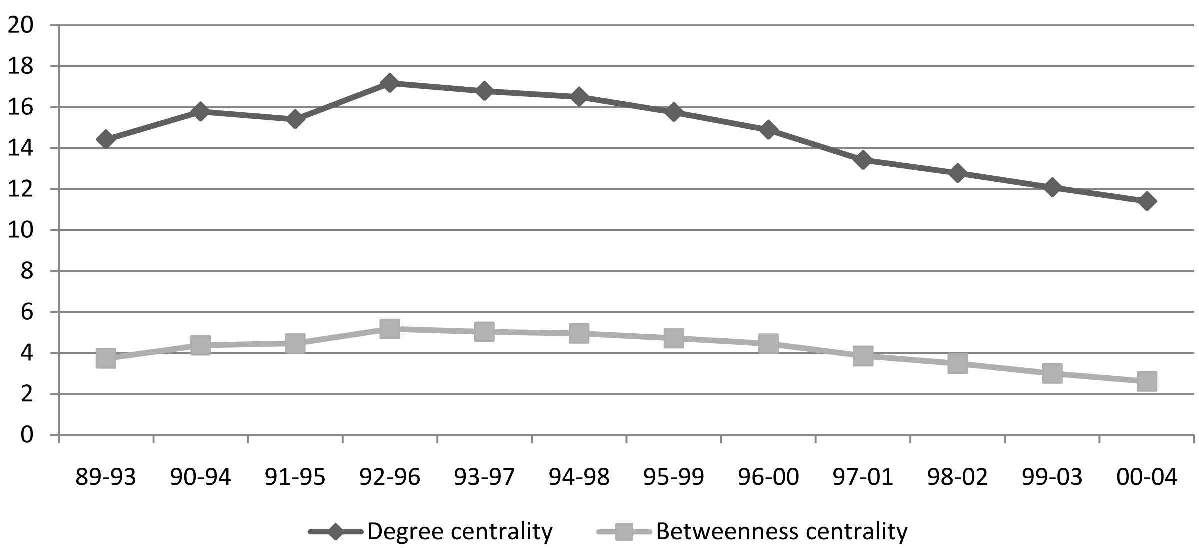

Figure 4: Indicators of average degree centrality and betweenness centrality (normalised and X 10 000) in each subnetwork

4.2 Star inventors (H2)

Even though the number of star inventors has been steadily rising, their share in the total number of inventors has decreased substantially (from about 6% to almost 1%). The share of patents which were created in collaboration with star inventors (see Figure 5) rises initially (from 30% to almost 36%) but then starts its downward trend and reaches almost 22% in the most recent years. As the nanotechnology fields develops, the importance of star inventors diminishes. This is in part due to the fact that we cannot measure the number of patents that early career inventors of the latter part of the sample will produce in the future. This is a limitation of our study. We have no means of identifying these potential future star-inventors.

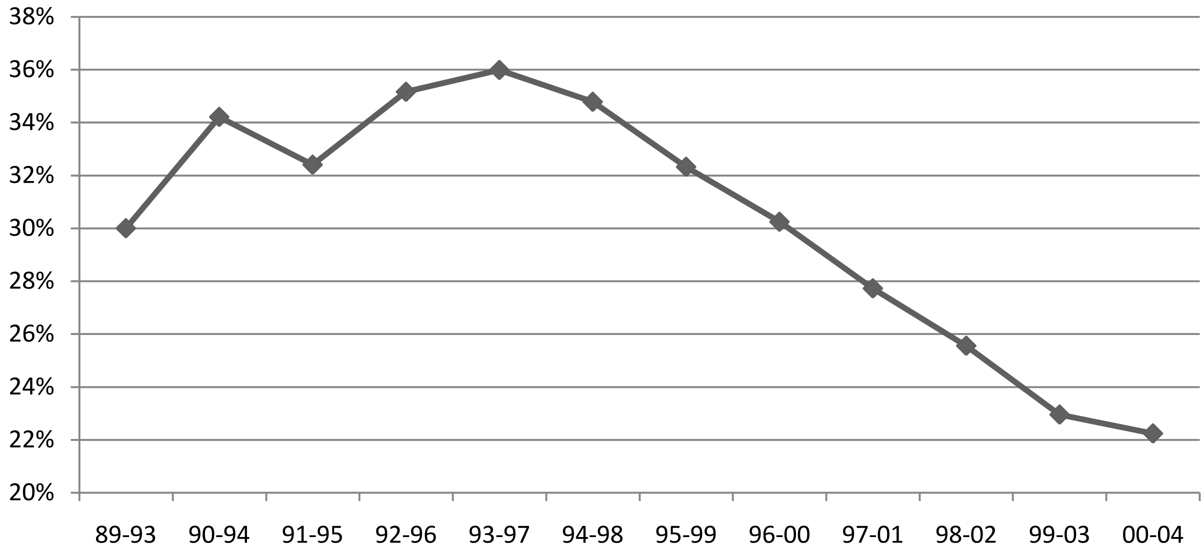

Figure 5: Share of patents created in collaboration with at least one star inventor

4.3 Repeated collaboration (H3)

Figure 6 shows both the number of collaborative links (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 number of the collaborations increases faster than the number of collaborating pairs is indicative of an increased intensity of cooperation activity throughout the years. In other words, repeated collaboration is becoming more frequent in Canadian nanotechnology.

Around 34% of all the collaborative relations between pairs of inventors in period examined involve repetitive collaborations. In some cases the collaborative 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 are named inventors on 50 patents together). The highest number of patents filed together by the same inventors during any five-year period is 35. Most of the relationships between a pair of inventors are, however, one time collaborations (resulting in only 1 patent). Figure 7 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% of all collaborations in recent years.

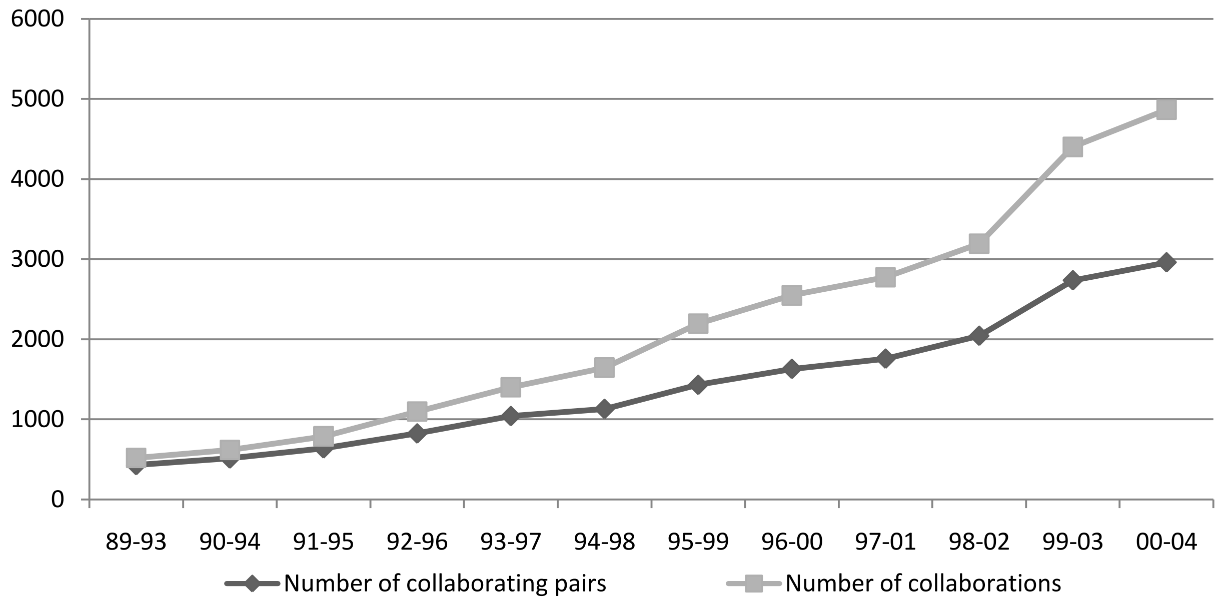

Figure 6: Number of collaborating pairs and collaborations per five-year period

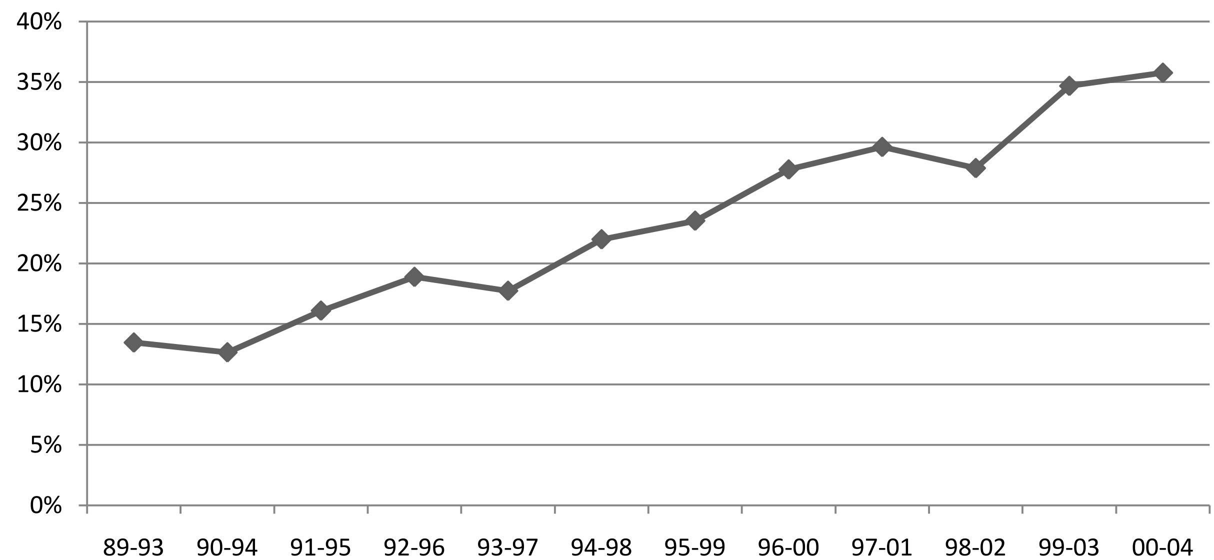

Figure 7: Proportion of repeated collaborations with the same partners per five-year period

4.4 International collaboration (H4)

Finally, we have located the addresses of all inventors in the database to identify the proportion of this collaboration that occurs across frontiers. International research relationships represent relatively high shares of collaborative activities (20%-30%). The overall collaboration pattern has changed slightly over time, the two most important developments being the gradual decrease in the frequency of the international joint research partnerships in the first half of the sample followed by an increasing internationalization in the latest years (see Figure 8). The evolution of the proportion of foreign collaboration is surprisingly similar to that of the number of claims per patent presented above in Figure 2. This strong similitude, on average would tend to support Gittleman‟s (2006) argument according to which dispersed research groups produce more commercially valuable technologies, potentially with a greater number of claims. Unfortunately, this relation never materialised in the regressions[4].

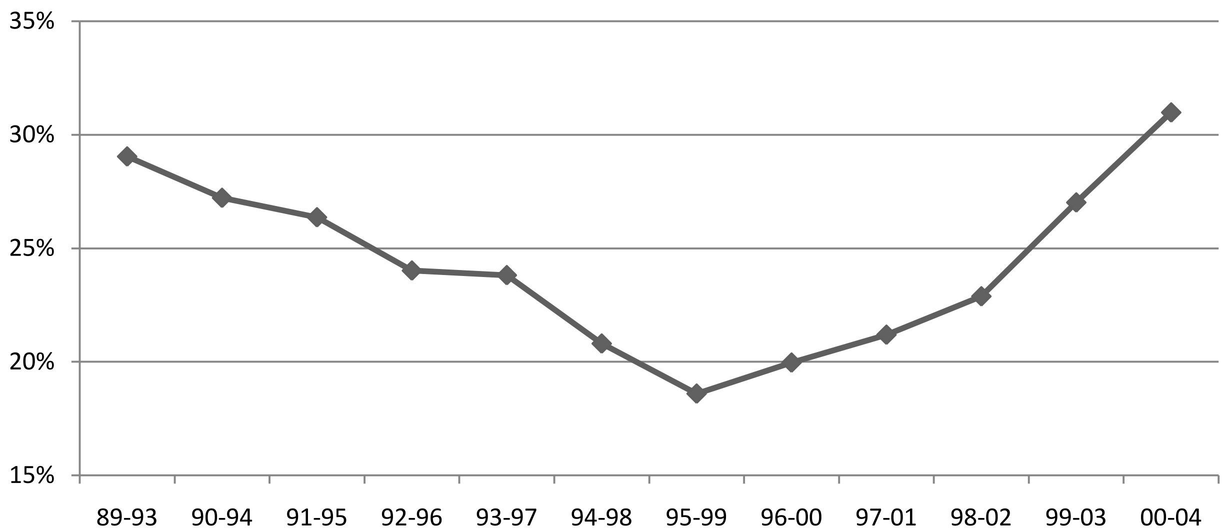

Figure 8: Proportion of the collaborations that involve foreign inventors

Not only do Canadian inventors collaborate with foreign inventors, but also a large proportion of the patents are owned by foreign entities, although the trend is decreasing and a larger proportion of the intellectual property remains in Canada (see Figure 9). The V-shaped curve of international collaboration is thus not observed in terms of foreign ownership of patents.

[4] In our regression analyses, we have tested both whether patent teams were composed of Canadian and foreign inventors and whether assignees were foreign to measure the importance of international collaboration on patent quality. Although the former is more representative of the geographical spread of teams, the variable was never significant in the regressions, while the latter was significant. As a consequence, only the results with the significant foreign ownership dummy variable will be presented.

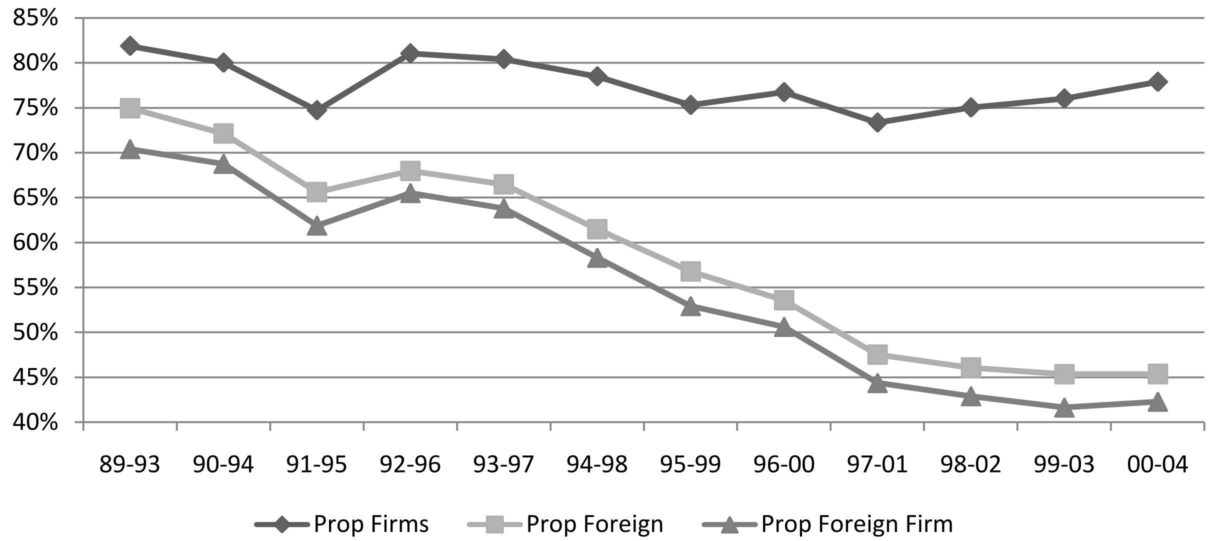

Figure 9: Proportion of patents owned by firms, foreign organisations and foreign firms

5. Results

In general, the regression results (see Table 1) confirm most of our hypotheses with a few notable exceptions. Whether we consider the average degree centrality of inventors of the patent team, or the degree centrality of the most central inventor of the team, both measures have a positive influence on the number of claims of the patent to which they have contributed. The first hypothesis (H1) is thus validated. The same cannot be said for the intermediary position (betweenness centrality) of individual inventors. While the average measure is not significant, the maximum value is positive and significant. It would thus appear that what influences most the value of a patent is to have at least one good „intermediary", whose betweenness centrality is high. Because the average value is not significant, we suggest that too much redundancy, caused by a large number of „intermediaries" in the team „through which" knowledge potentially flows, does not influence patent value.

To follow on the measure of inventor quality, we find that the fact that a team has contributed to more patents (*AvePatperinv*) on average does not influence patent value. Using the maximum number of patents per inventor only yields a weakly significant positive impact. In contrast, the fact that within the team there is at least one star inventor and the more stars there are both have a positive influence on the number of claims associated with a patent, hence validate the second hypothesis (H2). It is not so much the number of patents that counts but the potential for a large contribution to patenting that influences patent value. Star inventors thus have an impact.

Turning now to repeated collaborations, we find that in general, the more any two inventors have collaborated in the past (whether the maximum or the average value is used), the less the patent to which they have also contributed is likely to present more claims, i.e. the coefficient of *MaxPriorColl* is negative[5]. Our third hypothesis (H3) is thus validated. To test whether this is true for patents owned by firms, we include an interactive dummy variable (*MaxPriorColl* x *dFirm*) in the regression to account for prior collaboration only when assignee organisations are firms. Including such an interactive term in the regression implies that the resulting coefficient of the variable relating to prior collaboration for the firms is the sum of the coefficients of *MaxPriorColl* and of *MaxPriorColl* x *dFirm*. Because the sum of the coefficients remain negative, we can say that controlling for the type of assignee, prior co-invention has a lesser negative effect for firms. One of the most plausible explanations for this result is that repeated co-invention limits the opportunities of a team to tap into new knowledge, hence reducing the potential value of the resulting innovation, hence supporting the intuition of Cattani and Ferriani (2008) on the co-participation in movie production. New knowledge is accessible from inventors to which the team members are connected (measured by the centrality indicators) and by new team members. Although the sum of the coefficients of *AvePriorColl* and of *AvePriorColl* x *dFirm* (the results of which are presented in the appendix) yields a slightly larger negative value than that of *MaxPriorColl* and of *MaxPriorColl* x *dFirm*, because the mean *AvePriorColl* is 55% of the mean value of *MaxPriorColl*, the overall contribution (the mean value multiplied by the sum of the coefficients) to patent quality is less negative. This suggests that new team members to the firm (who contribute to reducing the overall mean of the variable) probably bring fresh knowledge to the team, but not enough to change the overall sign of the joint coefficient.

[5] The results with the mean number of prior collaborations (*AvePriorColl*) across the research team are presented in appendix.

Table 1: Regression results

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AveDegcent	0.0101 ***							
		(0.0032)							
	MaxDegcent		0.0074 ***						
			(0.0014)						
H1	AveBtwcent			0.0082					
				(0.0063)					
	MaxBtwcent				0.0077 ***				
					(0.0026)				
	AvePatperinv					0.0022			
						(0.0022)			
	MaxPatperinv						0.0031 *		
							(0.0016)		
H2	NbStar							0.0969 ***	
								(0.0290)	
	dStar								0.2196 ***
									(0.0638)
	MaxPriorColl	-0.0358 ***	-0.0362 ***	-0.0313 ***	-0.0323 ***	-0.0335 ***	-0.0368 ***	-0.0424 ***	-0.0434 ***
		(0.0112)	(0.0112)	(0.0110)	(0.0112)	(0.0113)	(0.0112)	(0.0110)	(0.0111)
H3	MaxPriorColl x dFirm	0.0279 **	0.0293 **	0.0275 **	0.0259 **	0.0296 ***	0.0297 ***	0.0346 ***	0.0369 ***
		(0.0121)	(0.0121)	(0.0118)	(0.0120)	(0.0115)	(0.0116)	(0.0113)	(0.0118)
H4	dForeign	0.1302 **	0.1053 *	0.2183 ***	0.1797 ***	0.2280 ***	0.1946 ***	0.1864 ***	0.1713 **
		(0.0617)	(0.0587)	(0.0694)	(0.0594)	(0.0750)	(0.0713)	(0.0681)	(0.0712)
	dFirm	0.1454 **	0.1345 **	0.1732 ***	0.1689 ***	0.1687 ***	0.1576 **	0.1534 **	0.1442 **
		(0.0624)	(0.0630)	(0.0621)	(0.0612)	(0.0644)	(0.0637)	(0.0624)	(0.0629)
	Constant	2.6950 ***	2.7096 ***	2.7144 ***	2.7212 ***	2.7156 ***	2.7174 ***	2.7508 ***	2.7580 ***
		(0.1614)	(0.1644)	(0.1563)	(0.1567)	(0.1582)	(0.1583)	(0.1641)	(0.1713)
	Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
	ln(alpha)	-1.1862 ***	-1.1950 ***	-1.1706 ***	-1.1814 ***	-1.1681 ***	-1.1738 ***	-1.1844 ***	-1.1843 ***
		(0.1681)	(0.1755)	(0.1660)	(0.1701)	(0.1677)	(0.1669)	(0.1729)	(0.1746)
	Clusters	328	328	328	328	328	328	328	328
	N	1218	1218	1218	1218	1218	1218	1218	1218
	Mean Wald chi2(20)	258.32	294.22	173.18	206.16	183.26	219.60	204.69	199.46
	Log pseudolikelihood	-4803.41 ***	-4798.75 ***	-4811.92 ***	-4806.00 ***	-4813.40 ***	-4810.21 ***	-4804.41 ***	-4804.53 ***

Note: ***, **, * represent significance at the 1%, 5% and 10% levels respectively.

Finally, our results also support Gittelman‟s (2007) assertion that foreign collaboration fosters more commercially valuable innovation. Our fourth hypothesis (H4) is thus also validated. Year dummy variables were included in all the regressions but are mostly non significant with the exception of the four most recent years where they have a positive and significant effect.

6. Conclusions

The purpose of this work was to study the influence of various collaboration indicators between inventors on the quality of the invention output. Four sets of indicators were introduced to track the changes of the Canadian nanotechnology collaboration patterns during the period of 1989-2004 using five-year moving-average windows: inventor centrality within the collaboration network, star-inventorship, repeatedness of collaboration, and international collaboration. These indicators reveal important evolutionary changes of the collaborative environment in Canadian nanotechnology.

We study two properties of the position of inventors within the nanotechnology collaboration network: degree and betweenness centrality. As time progresses, we observe that on average, individuals occupy less central positions (average degree centrality and betweenness centrality are both decreasing). This is probably a consequence of the increasing nanotechnology specialization as the field develops and more applications in a wide range of domains are found. Although this reflects our impression from consulting nanotechnology scientists, this remains a speculation and our current research consists in identifying the various niches of expertise, both academic and industrial, in Canada. Inventors in highly centralized networks make use of a clear network centre which enables knowledge to spread easier. The observed decreasing average centrality could thus contribute to slowing down knowledge transmission through the network. When we examine the impact of both centrality measures on patent quality, we however find that, more central inventors contribute to increasing patent quality (H1). From a management point of view, however, our results suggest that inventors should be encouraged to develop more relationships with important knowledge sources, *i.e.* highly connected individuals.

We observe that Canadian nanotechnology inventors have an increasing tendency to build collaborative ties with a higher number of partners and to collaborate on nanotechnology projects more intensively than they have done in the past. The presence of star-inventors on a patent team has a positive influence on the quality of the resulting invention (H2). Although we are not able to properly measure whether an individual has the making of a star-inventor (recent inventors have not registered enough patents), we suspect that the impact would be even stronger if we could measure their future production. Applications of nanotechnology are becoming more complex requiring larger collaborative teams. These collaboration indicators possibly imply 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 collaboration teams with fresh knowledge from distinct research environments leads to an increased opportunity for innovative recombination of that knowledge and thus enhances inventors‟ future creativity. If the fresh knowledge is provided by a team composed of a greater number of star-inventors, patent quality is also enhanced.

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 lead to a more profound research relationship, which may involve an exchange of information of higher quality (*e.g.,* a rare or undisclosed knowledge), but unfortunately tends to limit access to novel knowledge, if these inventors are not also well connected to a number of other inventors (in a more central position in the network). Our results show a negative effect of repeated co-inventorship on the patent quality (H3). Firms would thus benefit from building more diverse teams of inventors that have not collaborated in the past. For instance, involving two star-inventors that have worked on a number of projects together would not have the same benefit as involving two unrelated star-inventors. If the average proportion of repeated collaboration continues to rise (as shown by Figure 7), this tendency should worry firms concentrating in nanotechnology development activities.

Another aspect of team diversity stems from international collaboration. Although we could not show that teams composed of foreign inventors had a positive influence on patent quality as the strong similarity between Figure 2 and Figure 8 would have us believe, we nevertheless show that patents of foreign assignees are of a higher quality (H4), the delocalisation of invention teams being implied by foreign ownership. As the Canadian expertise continues to develop, and the proportion of foreign ownership continues to diminish (as shown in Figure 9), we recommend that international collaboration remains a non negligible part of the way inventors work.

An important limitation of this work resides in the lack of information about the inventors themselves. A large literature has studied academic patenting and found scientists-inventors to be more central and to play an important role in knowledge diffusion through the network. We are currently in the process of merging our patent data with scientific article data that contains the affiliation of all authors in order to distinguish the inventors that are academics from those that are not. Distinguishing between the academic stars and the industrial stars may shed some light on who are the real star inventors and how they become stars. The second limitation of this study lies in the patent quality proxy used for patent value. Although a number of scholars use the number of patent claims as a proxy, increasingly, hybrid measures that combine numerous indicators are preferred to infer patent quality. We are therefore in the process of gathering patent citations as well as patent renewal information to verify the robustness of our results. Another line of future research is concerned with the contribution of each type of inventor to the value of future patents. For instance, is there a difference between the effect of repeated collaborations between academic inventors, who generally have access to a larger scientific network, and that of industrial inventors?

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7. Appendix

Table 2: Descriptive statistics (mean, standard deviation and correlations)

Variable	Mean	Std. Dev.	1	3	4	5	6	7	8	9	10	11	12	13	14
1 NbClaims	24.22	(16.70)	1.00												
3 AvePatperinv	13.19	(17.37)	0.09	1.00											
4 AveDegcent	12.14	(12.58)	0.19	0.83	1.00										
5 NbStar	0.65	(1.09)	0.16	0.70	0.79	1.00									
6 MaxPatperinv	21.47	(27.07)	0.13	0.90	0.87	0.83	1.00								
7 MaxDegcent	18.27	(18.86)	0.22	0.69	0.94	0.76	0.83	1.00							
8 AveBtwcent	3.61	(6.19)	0.10	0.75	0.76	0.58	0.76	0.67	1.00						
9 MaxBtwcent	7.77	(12.60)	0.15	0.64	0.78	0.68	0.79	0.79	0.90	1.00					
10 dFirm	0.80	(0.40)	0.16	0.27	0.34	0.25	0.31	0.35	0.20	0.22	1.00				
11 dForeign	0.49	(0.50)	0.19	0.48	0.64	0.45	0.54	0.65	0.46	0.51	0.33	1.00			
12 dStar	0.33	(0.47)	0.19	0.77	0.80	0.85	0.84	0.79	0.58	0.62	0.30	0.50	1.00		
13 MaxPriorColl	4.06	(8.02)	0.07	0.69	0.56	0.64	0.69	0.49	0.50	0.53	0.19	0.29	0.58	1.00	
14 AvePriorColl	2.22	(5.07)	0.03	0.72	0.45	0.38	0.53	0.31	0.45	0.31	0.15	0.21	0.46	0.79	1.00

Note: Average and Maximum degree centrality and betweenness centrality have been normalised (X 10 000)

Table 3: Regression results with the mean number of prior collaboration

		(1')	(2')	(3')	(4')	(5')	(6')	(7')	(8')
H1	AveDegcent	0.0093 ***							
		(0.0025)							
	MaxDegcent		0.0065 ***						
			(0.0012)						
	AveBtwcent			90.4651					
				(56.0373)					
	MaxBtwcent				63.3072 ***				
					(19.5203)				
H2	AvePatperinv					0.0041 *			
						(0.0024)			
	MaxPatperinv						0.0026 **		
							(0.0012)		
	NbStar							0.0744 ***	
								(0.0257)	
	dStar								0.2066 ***
									(0.0657)
H3	AvePriorColl	-0.0641 ***	-0.0636 ***	-0.0570 ***	-0.0574 ***	-0.0666 ***	-0.0643 ***	-0.0692 ***	-0.0734 ***
		(0.0229)	(0.0232)	(0.0219)	(0.0220)	(0.0227)	(0.0224)	(0.0215)	(0.0214)
	AvePriorColl x dFirm	0.0526 **	0.0556 **	0.0484 **	0.0500 **	0.0535 **	0.0543 **	0.0612 ***	0.0633 ***
		(0.0233)	(0.0238)	(0.0226)	(0.0225)	(0.0221)	(0.0224)	(0.0219)	(0.0219)
H4	dForeign	0.1273 **	0.1080 *	0.2142 ***	0.1802 ***	0.2099 ***	0.1935 ***	0.1854 ***	0.1673 **
		(0.0618)	(0.0593)	(0.0681)	(0.0605)	(0.0746)	(0.0717)	(0.0690)	(0.0700)
	dFirm	0.1404 **	0.1298 **	0.1701 ***	0.1622 ***	0.1596 **	0.1540 **	0.1492 **	0.1406 **
		(0.0635)	(0.0640)	(0.0628)	(0.0621)	(0.0650)	(0.0645)	(0.0632)	(0.0637)
	Constant	2.7136 ***	2.7317 ***	2.7177 ***	2.7383 ***	2.7166 ***	2.7318 ***	2.7652 ***	2.7681 ***
		(0.1561)	(0.1619)	(0.1505)	(0.1555)	(0.1523)	(0.1532)	(0.1632)	(0.1689)
	Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
	ln(alpha)	-1.1884 ***	-1.1943 ***	-1.1740 ***	-1.1811 ***	-1.1738 ***	-1.1758 ***	-1.1828 ***	-1.1865 ***
		(0.1698)	(0.1761)	(0.1666)	(0.1705)	(0.1675)	(0.1685)	(0.1735)	(0.1758)
	Clusters	328	328	328	328	328	328	328	328
	N	1218	1218	1218	1218	1218	1218	1218	1218
	Mean Wald chi2(20)	257.44	293.25	172.94	205.91	197.23	229.02	211.71	210.23
	Log pseudolikelihood	-4802.27 ***	-4799.20 ***	-4810.02 ***	-4806.18 ***	-4810.20 ***	-4809.10 ***	-4805.33 ***	-4803.33 ***

Note: ***, **, * represent significance at the 1%, 5% and 10% levels respectively.