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The Importance of Collaborative Networks in Canadian Scientific Research

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Abstract

This study investigates co-author and co-inventor collaborations using scientific articles and patents to measure collaborative knowledge production. This paper assesses how a scientist's position within the joint co-publication and co-invention network affects its production and citation impact. Our findings reveal that number of publications is strongly associated with the scientists' position in co-author/inventor networks and that a scientist's technological production actually increases with collaboration in such networks. These academic relationships have a significant impact on the future number of publication citations and appear to benefit the number of patent citations in the same measure.

Keywords: Academic patents, collaboration, nanotechnology, scientific papers

1 Introduction

Knowledge networks play a strategic role in the production of new knowledge. Given that policy makers widely consider that scientists' networks are essential for that purpose, governments have initiated various programs to increase the number of such collaborations.

It is argued that the diffusion of knowledge depends on direct and indirect connections between research actors (Katz, 1994; Katz and Martin, 1997). Academic scientists tend to cluster and collaborate in teams to reduce research infrastructure costs, share knowledge and benefit from new ideas and tacit knowledge. Co-authorship and co-invention networks have attracted much attention in recent years and have emerged in various forms such as joint

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research projects, joint publications and patent applications (Powell and Grodal 2005; Scherngell and Barber 2009; Lee et al., 2011). Intense group research enhances the creation and diffusion of knowledge and decreases the level of uncertainty, particularly in science-based high technologies.

This study focuses on the collaborative activities of academic research. It posits that relationships between scientists within the co-authorship network can become stronger if they have innovative contributions. In addition, co-invention could play a more relevant role in enhancing the visibility of publications, thereby benefiting scientific outputs. For that reason, this research considers that the collaborative behaviours of co-authorship and co-invention occur in a single network.

In examining the effects of scientific and technological collaboration, we contribute to existing related studies. Our study will proceed as follows: first, using the analytical tools of Social Network Analysis (SNA), we investigate the different network structures for academic contributions in order to enrich our understanding of the determinants that prominently drive research productivity; second, we provide a comprehensive picture of two main research activities in universities, publications and academic patents; and third, we study scientific and technological relationships to develop a richer description of the scientific community. Our intention is to help fill a gap in the literature caused by the shortage of detailed analyses of academic patenting and publishing networks and their influence on the productivity of academic scientists.

In the transition to a knowledge-based economy, collaboration plays a vital role in the competitive environment surrounding new technology and new knowledge. Scientists are compelled to expand their collaboration networks in scientific fields and geographical areas. These highly multidisciplinary fields are an interesting context for investigating the impact of collaborative networks. A study of such networks helps clarify their effect on future interactions among scientists and on the joint production of articles or patents. In this paper, we address the nature of these linkages and measure research collaborations via social network analyses to understand whether they can foster the production of knowledge in terms of publishing and patenting.

In recent years, collaborations among scientists and knowledge networks have become a topic of interest to the scientific community. While some studies have pointed out that collaborations have general positive effects on the number or quality of the collaborators' contributions, other scholars found no such support (De Stefano et al., 2013; Glänzel and Schubert, 2005; Hollis, 2001; Landry et al., 1996). The impact of research collaborations among scientists and how these collaborative networks affect research output is still unclear. Despite a substantial body of literature, more specifically on collaborations between universities and industry, more research is required. According to He et al. (2009), the positive correlation between collaboration and research outcomes is more presumed than empirically verified. Scientists have an optimistic belief in the benefits of collaboration, but this needs to be thoroughly investigated to provide clear insight into scientist interaction through networks.

We use social network analysis as a valuable means to systematically assess the importance of collaboration; in other words, we aim to identify how the position of scientists in co-publication and co-invention networks affects the number and the "quality" of publications and patents produced. In these networks, two scientists are considered connected if they have co-authored an article or co-invented a patent. Given that collaboration increasingly occurs through such scientist relations, our goal is to capture their important implications for the diffusion of knowledge as these connections materialize through more formal channels, i.e. co-publication and co-invention.

Drawing on information on 3,252 academic scientists from 10-year panel data, we analyze a sample of Canadian scientists involved in nanotechnology research based on their publications and patents from 1996 to 2005. The results of this study show that both co-authorship and co-invention links provide strong connectedness among scientists in academia. Our analysis reveals that the position of a scientist within collaborative networks can be associated with that individual's performance in terms of number of publications and patents. We also find that a prominent position in such networks is highly related to citation impact, a factor that has been largely used as an indicator of publication/patent quality.

Collaboration and interactions between scientists are of great importance to nanotechnology research as this field draws extensively on knowledge in other areas. These topics have important implications, not only for nanoscience but also for the governance of other technological areas. This paper attempts to integrate and critically evaluate what is known about collaborative networks among scientists who specialize in nanotechnology. These miniature technologies are predicted to drive the next major societal transformation, and most countries have become interested in the economic benefits that nanotechnology development promises. It is a multidisciplinary field drawing from various areas such as materials science, engineering, chemistry, physics, biology, and medicine. Nanotechnology research encompasses multiple disciplines that draw knowledge from diverse knowledge sources and is believed to provide for convergence of disparate science and engineering disciplines (Porter and Youtie, 2009).

The rapid development of nanotechnology has attracted worldwide attention and strategic investment. National nanotechnology programs have been launched in more than 60 countries. By 2015, total funding for nanotechnology activities by government, corporate research and private sources will reach a quarter of a trillion dollars. Governments alone will have invested more than $67.5 billion dollars in this technology (Harper, 2016). As a multipurpose field, nanotechnology has potential applications and enormous scope for commercial expansions. According to OECD statistics (OECD, 2013), the US had the largest number of companies in this industry in 2013, boasting 4,928 nanotechnology active firms, defined as organizations that dedicate at least 75% of their production, goods and services to nanotechnology.

The surge in nanotechnology research has led countries to issue increasing numbers of nanotechnology publications and patents. According to StatNano,[3] China and the US publish about half of the extant papers on nanotechnology, and the US owns about half of all nanotechnology patents. Canada ranks 14th among the top 20 countries in terms of nanotechnology publication, 10th among the top 10 countries in nanotechnology granted patents and 8th in nanotechnology patent applications published by the USPTO in 2016. The share of nanotechnology articles to all articles published by Canada in 2016 is 4.87.

The outline of this paper is as follows. In Section 2, we introduce the theoretical background for this study. Section 3 describes our datasets and methodology, as well as all the

[3] http://statnano.com/

explanatory variables. Section 4 presents an analysis of the results, and Section 5 concludes with a summary of the main findings and presents our policy implication proposals.

2 Conceptual framework

The relationship between science and technology is a subject of ongoing debate. Actors in these two communities connect in various ways and through a complex set of interactions. A line of previous literature investigated the citations to scientific articles from patent applications (Branstetter and Ogura, 2005; McMillan et al., 2000), while scholars in a different stream used interviews and surveys to explore the contributions of university research to industrial innovations (Agrawal and Henderson, 2002). Most of the studies that traced the link between science and technology concentrated on the relationship between university research and industry and how knowledge flows from academia to industry (D'Este and Patel, 2007).

Another stream of literature has addressed the data matching of inventors and authors to assess the effect of individual scientists' performance on patenting and publishing (Azoulay et al., 2006; Van Looy et al., 2006; Breschi et al., 2008; Calderini et al., 2007; Fabrizio and Di Minin, 2008). Murray (2002), using a different methodology, studied the overlap of science and technology by building patent-paper pairs, and found a slight overlap between these scientific and technological networks. Despite these research efforts, studies should further target how research cooperation between scientists in universities influences their different activities given the growing expectations about the contribution of academic research to economic growth and the recent interest on that topic. To our knowledge, literature pertaining to collaborative networks is rare.

Scientists frequently organize collaborations across universities to share their ideas. Such collaborations arise at different levels of individuals and institutions, and are encouraged by policy makers. The broader range of opportunities within collaborative networks accelerates access to pooled resources and skills to stimulate knowledge sharing and new knowledge creation (Bammer, 2008; Katz and Martin, 1997; Stokols et al., 2005). According to Hauptman (2005), academic scholars have limited capabilities and they highly benefit from collaborative networks to improve their productivity. A number of theoretical arguments have been put forward to examine scientific collaboration. Some scholars studied the network analytic perspective by performing collaborative links across regions (Gao et al., 2011; Scherngell and Barber, 2011; Wanzenböck et al., 2013). Another research stream focused on the impact of academic collaborations with industry (Baba et al., 2009; Balconi et al., 2004; Banal-Estañol et al., 2010).

Collaboration in co-authorship networks

Co-authorship is used as one of the most tangible indicators of research collaboration and reliably assists in tracking almost every aspect of scientific networks. It is assumed that when scientists in a research community publish a paper together, the connection between them existed prior to the publication and endures for a period of time. The scientists are therefore more likely to perform research together and to benefit from future joint research and improved scientific productivity. Increased collaboration influences research outputs, in addition to other intra-scientific factors (De Stefano et al., 2013; Glänzel and Schubert, 2005; Melin and Persson, 1996). According to Persson et al. (2004), the rise of collaborative research can be observed from the steady increase in co-authored scientific publications and the number of authors in all subject fields in recent years. Although studies by Laudel (2001) and Katz and Martin (1997) showed that the majority of scientists involved in a publication do not appear as co-authors in that publication, Bellotti (2012) indicated that relationships between scientists involve a set of interactions that is wider than co-authorship. A study by Glänzel and Schubert (2005) suggested that the positive correlation between collaboration and co-authorship gives insight into the structural changes of collaboration. Thus, the question regarding whether these collaborations enhance a scholar's performance is of particular relevance. Some scholars showed that research collaboration has a higher impact on number of publications (Landry et al. 1996; Hollis, 2001), but others did not find a positive correlation (McDowell and Smith 1992).

Hollis (2001) showed that the relationship between collaboration and publication quality appears to be negative after adjusting for the number of authors per publication. Frenken et al. (2005) found that the citation rate of papers is positively correlated with the number of authors. Wuchty et al. (2007) highlighted that the process of knowledge creation has changed and that teams frequently produce more highly cited papers than individual scientists. Similarly, Glänzel and Schubert (2005) shed light on giving and receiving citations and demonstrated that co-publication papers receive more citations on average. However, the existence of a positive relationship between collaboration and research outcomes is unclear.

Collaboration in co-invention networks

In recent years, there has been a growing interest in academic collaboration through co-invention networks. Some studies show a major increase in university scientists listed as inventors, while others have described growing numbers of university Technological Transfer Offices (TTOs) in the last quarter of the 20th century (Crespi et al., 2011; Lissoni et al., 2008). Academic patents have proliferated and have become more economically important since the US introduced the Bayh-Dole Act in 1980, triggering changes in university patenting policies (Sampat, 2006). The creation and diffusion of ideas are central to technological innovation and has prompted the circulation of new knowledge from different sources and organizations. According to Breschi and Lissoni (2005), co-invention is a co-authorship of patents. The assumption regarding these knowledge networks is the same as that for co-authorship given that two academic inventors who work together on even one patent application are more likely to keep in touch to exchange knowledge. In another empirical study, Breschi and Catalini (2010) highlighted the positions that scientists tend to occupy in technological networks, indicating that even just a few links ensure that every scientist is connected in the network. Some scholars analyzed the connections in networks and local cliques to examine the properties of co-invention networks (Cowan and Jonard, 2004; Fleming et al., 2007). Based on co-invention patterns studied by Carayol and Roux (2007), academic networks are highly clustered, and the probability that an inventor's neighbors are connected is rather high.

Nevertheless, there is still an ongoing debate on the impact of in-network collaborations on innovation performance. Zhang et al. (2014) analyzed the patent co-invention data from State Intellectual Property Office of China and observed that co-invention relationships have a significant impact on patent productivity only in provinces that already have a higher number of patents. Singh (2005) showed that the connection among scientists in innovative networks contributes to a positive effect on knowledge flow. Further, working in a team is more likely to lead to a higher number of citations (Wuchty, Jones and Uzzi (2007). Breschi and Lissoni (2009) found that connected patents in co-inventor networks are of higher quality than non-connected patents, as measured by the number of citations they receive.

Co-inventor networks have not been as widely analyzed as co-authorship networks. However, some scholars did examine network clustering and found that higher levels of clustering hinder innovation (Fowler, 2005; Chen and Guan, 2010). Paruchuri (2009) supported an inverted-U relationship between the structural centrality of an inventor in pharmaceutical companies and the inventor's impact on the innovation activities of that firm.

Collaboration is fundamental in academic research

While economic literature generally assumes that collaborative networks facilitate new knowledge creation activities and enhance research productivity, such as access to tacit knowledge, equipment, new ideas, etc. (Bozeman and Corley 2004; Liberman and Wolf, 1998; Thorsteinsdottir 2000), little is known about the efficiency of research collaborations on the output of scientists. Increasing the number of linkages in collaboration patterns is unlikely to add value, as shown by Lee and Bozeman (2005), who cited transaction costs, team members' long delays in completing their part of the research, disappointing results, etc., as problems that scholars face in collaborative research. These difficulties likely reduce the productivity of a research group.

As a fundamental and common feature in academic research, collaboration is important to the course of scientific progress. However, collaborative relationships can have their disadvantages. Collaborators should be very cohesive since the quality of their work depends not only on their relationship but also on their ability to agree on research findings and how to interpret them. Collaboration entails time costs, given that scientists have different opinions yet must come to an agreement on how to formulate their research problems and divide the work. Collaboration also has operational costs, such as transporting equipment to different sites. However, it is a social process that requires personal patience in dealing with new relationships and adapting to different environments. The quality of the scientists' work undoubtedly declines if they fail to achieve a coherent and uniform publication (Franceschet and Costantini, 2010; Katz & Martin, 1997; Sonnenwald, 2007).

It has been suggested that increased involvement in patenting by university scientists may negatively impact on their research activity. The literature shows evidence of complementary action between publishing and patenting in universities. Geuna and Nesta (2006) proved that there is no process of substitution between patenting and publishing and that the most productive scientists in terms of patenting are also those who have the greatest number of academic publications.

The above discussion provides insight into the importance of further investigating research collaborations to a successful knowledge creation process, as these relationships are also crucial to sustainable economic competitiveness. The purpose of our study is to explore how scientist collaboration impacts knowledge creation. To that end, we provide an exploratory analysis on the effect of scientific and technological networks. Using an approach appropriate for the academic realm, we measure the impact of both networks on their main scientific and technological activities to investigate the connectivity between these research networks. Given the importance of academic scientists in assessing the impact of science networks on technological activities and vice versa, this approach may contribute greatly to our understanding of the underlying link between these research networks. It may also be helpful for orienting future policies.

To examine this effect, we use Social Network Analysis (SNA), which is an appropriate approach to study collaboration patterns (Barabási et al., 2002; Moody, 2004; Hummon and Carley, 1993; Newman 2004). A number of scholars (e.g. Abbasi, et al., 2011; Barabasi et al., 2002; Cantner and Graf, 2006; Singh, 2007; Youtie et al., 2013) have studied network measures sourced from social network analysis to investigate how the network position of scientists affects research performance. For example, Wanzenböck (2013) used betweenness centrality to measure the ability to control knowledge flows, and centrality as a proxy to analyze connectedness with central hubs. These measures are calculated to reflect relevant network structures. De Stefano and Zaccarin (2013) highlighted the importance of the structure of networks for the creation and diffusion of knowledge and innovation. Empirical results from a study of a sample academic community in Italy between 2001 and 2008 showed that occupying central positions positively affected performance, but that impact declined beyond a certain threshold (Rotolo and Messeni Petruzzelli, 2013). While Beaudry and Allaoui (2012) found that higher betweenness centrality in academic networks leads to a greater number of publications, a study by Beaudry and Kananian (2013) showed that the mere fact of being surrounded by a more integrated clique of scientific researchers in co-publication networks enhances innovation performance. Forti et al. (2007) compared the network characteristics of academic scientists who have had a patent with colleagues during their career with the traits of those who never filed a patent to understand how the scientific productivity of academic scientists is influenced by their co-invention links.

While scientific communities have received greater attention, very few studies have carefully examined the collaborative networks of co-invention in universities from a network structure perspective. Since the net effect was a priori unclear from a theoretical standpoint due to the opposing forces at stake, we developed empirical analyses to examine how these collaborative networks play a role in enhancing the performance of academic scientists. We characterized co-authorship and co-invention networks and calculated the network measures for extended collaboration to determine the impact of network positions.

3 Data sources and methodology

Data description

Our analysis focused on a sample of nanotechnology patents and publications. As competitors in regard to these types of emerging science-based technologies, universities are at the vanguard of nanotechnology research. With respect to exploring the potential of nanotechnology, and given our focus on collaboration and academic research outputs, examining this field can yield interesting results for appropriating the benefits of collaborations.

To investigate the above issues and build a comprehensive dataset, we extracted data from 1985 to 2005[4] from two main publication and patent application databases, Elsevier's Scopus and the United States Patent and Trademark Office (USPTO). Scopus has a list of scientific articles from a wide variety of publishers and provides information such as title, publication date, abstract, etc. We selected Scopus rather than Web of Science as it also includes conference proceedings which are important in some engineering and scientific

[4] We extracted data originating between 1985 and 2005. Our reason for choosing that end year is that we aimed to have enough citation years after the sample's end date, given that we were examining three periods for citations, i.e. three, five and seven years after grant year for patents. It is not uncommon to find patents that took five years to be granted, and then to count five years of citation periods up to 2015. We also chose 1996 as the start date of our sample because too few nanotechnology papers and patents could be found prior to that date. In addition, the Scopus database substantially changed around 1996 to include more journals.

fields. Moreover, Scopus provides more comprehensive and reliable results and information than Google Scholar[5]. Furthermore, for the period examined, Scopus provides author names linked to their affiliations (something later introduced by Web of Science around 2008-2009), which greatly facilitates the disambiguation of individuals across the publication and invention landscapes. For these reasons, Scopus was selected as the publication database of choice.

In addition, we used USPTO data because inventors, particularly those in Canada, prefer to protect their intellectual property in a large market. Given the proximity of Canada to the United States, inventors submit their patent applications to both the USPTO and the Canadian Intellectual Property Office (CIPO). The other reason for using the USPTO is that it lists address information that can help distinguish whether two inventors with the same name are the same person. It therefore prevents confusion in merging data, whereas CIPO does not provide this information in a consistent manner. Hence, the USPTO is an acceptable substitute for CIPO as it contains considerable data on the affiliation of inventors. To extract Canadian scientists, we turned to publications and patents with at least one participating author/academic inventor who is affiliated with a Canadian institution. Local archives on academic scientists in Canada (Tri-council agencies)[6] were also used to recognize academic scientists.

To find scientists who conduct nanotechnology research, we used a nanotechnology-related keyword search, based on that of Porter et al. (2008),[7] for both publications and patents. We invested a considerable amount of time in performing the disambiguation exercise to determine if individuals with similar names are the same person or whether they changed their address at some point. This involved manually checking individual scientists and inventors against several sources of information (e.g. author and inventor affiliations) to

[5] According to a study of difference between these databases by Minasy et al. (2013), Scopus metrics are found to be slightly higher than that of Web of Science. Yang and Meho (2006) compared the citations of Scopus, Web of Science and Google Scholar and found that Google Scholar has some technical problems that users need to be aware of in order to accurately use the number of citations.

[6] This database covers data from three agencies in Canada: Natural Sciences and Engineering Research Council of Canada (NSERC), Social Sciences and Humanities Research Council of Canada (SSHRC) and Canadian Institutes of Health Research (CIHR).

[7] Their approach to developing a nanotechnology bibliometric search consisted of three steps: first, they created a pilot field scope to define nanotechnology search terms; second, they asked nanotechnology experts to modify, add and retain their field scope; and third, they evaluated these terms and tested them with publication and patent data.

eliminate similar scientists whose names might have been spelled differently on papers or patent documents.

Once the scientists' names were disambiguated, we created a combined network of scientists based on two types of links (co-authorship and co-invention). We built a single network instead of two isolated networks given the correlation between a scientist's positions in both networks and the possibility of (statistical) interaction effects between the networks if network measurements from two distinct networks (co-authorship and co-invention) were included in the statistical analysis. The networks overlap, and ensuing interaction between these networks as well as the correlation between various network measures, were very high and thus affected the robustness of results when treated as separate/distinct entities. For that reason, we combined the co-authorship and co-invention links into a single network to account for the apparent feedback loops between nanoscience and nanotechnology.

The time windows that we considered in constructing the network are three-year[8] intervals to account for extended collaborations and to analyze the network connections among academic scientists. We then used a one-year lag to determine the importance of a scientist's position in the network over time, based on the general underlying idea that if scientists in a research community publish/file a paper/patent together, the connection between them existed prior to the publication/patent and endures for a period of time.

We used social network analysis (SNA) as a tool to provide understanding of these collaboration networks. Several authors have used SNA with bibliometric data in order to present the relationships and interactions within social systems. We built our networks and calculated network measures using Gephi. The construction of our dataset was then completed by matching all these databases.

Variables and estimated model

We evaluate four dependent variables constructed for each scientist and each academic-inventor in a given year *t*: number of articles (*NumPaper*) attributed to each scientist and number of forward citations to these papers (*PaperCit5*) in the subsequent five years,

[8] We checked with five-year intervals and the results for our sample were the same.

number of patents (*NumPatent*) attributed to each academic inventor and number of forward citations (*PatentCit5*) up to five years after their granting year.

We also add a dummy variable for the type of chair (*CanadaChair*) that these scientists occupied at some point in their career that takes the value 0 for no chair, 1 if they occupy an industrial chair and also receive funding from NSERC or CIHR, or for being a Canada Research Chair.[9] The granting of academic research funding can further act as a signal of scientist productivity, and recipient scientists may attract additional funding in subsequent years. The literature generally finds that scientists with prestigious awards and public funding are more prolific contributors to publications and patents (Sauer, 1988; Payne and Siow, 2003; Adams et al., 2005; Jacob and Lefgren, 2007; Blume-Kogut et al., 2009). We therefore include the average amount of funding over three years (*GrantAmount*) in our models to explain scientists' unobserved capabilities that may influence their position in co-authorship or co-invention networks. Further, we create a proxy (*Age*) for the experience of academic scientists, using their first publication/patent to account for the fact that scientists with more experience may be well connected in their networks.

The network attribute measures on which we focus in this study are degree centrality (*DegCent*), eigenvector centrality (*EigenCent*), closeness centrality (*ClosCent*), betweenness centrality (*BetCent*), and individual cliquishness (*Cliqness*). Degree, eigenvector, betweenness and closeness are all measures of a scientist's prominence in a network. By calculating these network measures in our network, we aim to examine whether the position of scientists/academic inventors in these networks correlates with their research performance. We also include the squares of the network measures in our models. There is a possibility that the higher levels of networking may have diminishing or even negative effects on the performance, meaning that at some point there is nothing or at least there is little to gain from interactions. These results demonstrate the overwhelming support of the positive effect of networking on performance. Hicklin et al. (2007) found diminishing returns at the higher levels and demonstrated that the relationship between networking and performance is nonlinear. In another research, Reagans and McEvily (2003) studied the contribution of network structure to the knowledge transfer and their findings indicated the

[9] We also added an ordered measure to our set of instruments for type of funding (Award), which equals 1 if a scientist receives funding through an award and 0 otherwise, but this did not yield significant results.

nonlinear relationship. Their estimations showed that there is no need to have maximum network features to gain from the benefits of the network. The following paragraphs explain the network measures we include in our models in this study.

Degree centrality

A scientist's degree centrality corresponds to the number of other scientists connected directly to that scientist, and can indicate local centrality in a network as well as a scientist's popularity. The normalized measure of scientist degree centrality R_k is given in Eq. (1) where n is the number of scientists in the network and $d(R_i,R_k)$ is a function that equals 1 if scientist R_i is connected to R_k, and 0 otherwise (Freeman, 1979; Chung and Hossain, 2009).

$$C_D(R_k) = \frac{\sum_{i=1}^{n} d(R_i, R_k)}{n-1} \tag{3-1}$$

Eigenvector centrality

Eigenvector centrality, or eigencentrality, is an extension of degree centrality considering that not all vertices are equivalent and that some are more important. The concept of eigenvector centrality disentangles the fact that a scientist may appear more important when linked to other important scientists. This differs from in-degree centrality because receiving many links does not necessarily mean high eigencentrality. In addition, a scientist can have few links but nonetheless be the important linker. Scientists with higher eigenvector centrality are linked to well-connected scientists and influence the others in the network as well. Bonacich (1972) defines the centrality $c(R_k)$ of a node R_k as the positive multiple of the sum of adjacent centralities. The set of formulas can be written in matrix notation as $\forall c = Ac$ when we consider the centrality of all nodes and represent c=($c(v_1)$, … $c(v_n)$) as A in the graph's adjacency matrix. The normalized measure of scientist eigenvector centrality with the Euclidean norm R_k is given in Eq. (3-4) (Ruhnau, 2000).

$$\lambda C(R_k) = \sum_{i=1}^{n} (a_{ik} C(R_k)) \qquad \forall i \tag{3-2}$$

$$C_E(R_k) = \frac{C(R_k)}{\sqrt{\sum_{i=1}^{n} C(R_i)^2}} \tag{3-3}$$

Closeness Centrality

Closeness centrality indicates that a scientist is considered important if that individual is relatively close to all other scientists. This item is therefore based on how long it takes to spread knowledge from one specific node to all other nodes. Freeman (1979) proposed closeness as a measure of network centrality in terms of the distance between various nodes. The normalized closeness centrality of a node R_k is given by Eq. (1) where n is the number of scientists in the network and $d(R_i,R_k)$ is a distance function that equals 1 if scientist R_i is connected to R_k, and 0 otherwise. Closeness is a surrogate measure for the efficiency of communicating with other scientists in the network (Freeman, 1979; Chung and Hossain, 2009).

$$C_c(R_k) = \frac{\sum_{i=1}^{n} d(R_i, R_k)^{-1}}{n-1} \tag{3-4}$$

Betweenness centrality

Betweenness centrality, proposed by Freeman (1979), indicates the number of times a scientist connects to other scientists in a network. The number of shortest paths (geodesics) between two scientists is considered in calculating this measure. Eq. (2) shows the betweenness of R_k where g_{ij} denotes the total number of shortest paths from i to j and $g_{ij}(R)$ denotes the number of geodesics from i to j that pass through R_k (White and Stephan, 1994).

$$C_B(R_k) = \sum_{i}^{n} \sum_{j}^{n} \frac{g_{ij}(R_k)}{g_{ij}} \qquad where\ i \neq j \neq k \tag{3-5}$$

Cliquishness

The clustering coefficient or cliquishness is commonly used to measure the tendency of scientists to cluster together. This indicator, introduced by Watts and Strogatz (1998), is always a number between 0 and 1. Given three scientists (*i, k, j*) in the context of social network analysis, if i and k have a relationship and there exists a relationship between j and k, the clustering coefficient represents the likelihood that i and j are also connected. Eq. (3) shows the clustering coefficient for a particular scientist (R_k), where e is the number of links between neighbours of R_k, and k_k is the degree of R_k (Hanneman and Riddle, 2005; Zhou et al., 2005).

$$CC(R_k) = \frac{2e_k}{k_k(k_k - 1)} \tag{3-6}$$

To assess the impact of collaborations, as measured by the various network measures described above, on publications and patents, we propose the following model:

$$Y_{it} = \alpha + \beta_1 X_{it} + \beta_2 X_{it}^2 + \delta_t d_t + \nu_i + \varepsilon_{it} \qquad \text{(i=1, …N and t=1, …T)} \tag{3-7}$$

Where Y_{it} is a measure of research outputs (*NumPaper*$_{it}$ *and NumPatent*$_{it}$), X_{it} is a set of time-varying network variables, X^2_{it} is the non-linear effect of these explanatory variables where applicable, d_t is a dummy variable for years, ν_i is an individual fixed effect to control for unobserved scientist characteristics, which is constant over time, and ε_{it} is an error term. We use interactive variables to assess potential moderating effects on the relationship between the variables of interest and our dependent variable. We include various combinations of explanatory variables in the model to examine the non-linear relationships and the nonlinear curve in which the slope of the curve changes as the value of one of the variables also changes. The first step in detecting a nonlinearity relationship is more theoretical than technical. We ask questions such as: is the slope of the relationship expected to have the same sign for all values of our independent variables or can we expect the magnitude of the slope to be continuously decreasing or increasing? Making a rough graph shows that increases in one independent variable initially produce increases in our dependent variable, but after some time subsequent increases in this independent variable produce declines in the dependent variable. Estimating the coefficient of independent variables indicates the direction of curvature. Moreover, incremental F tests can check whether polynomial terms are needed to detect nonlinearity.

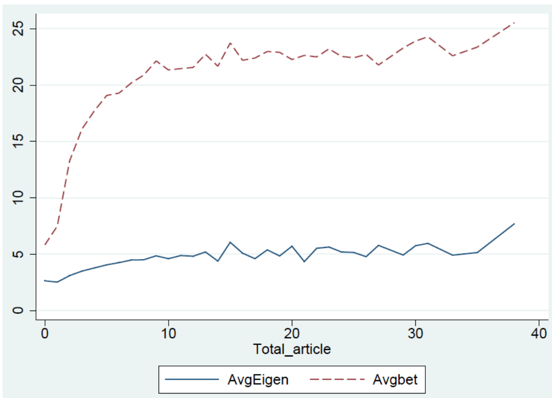
Our first dependent variable has an excess number of ones, more than would be expected in a normal distribution. Our initial tests using ordinary least squares (OLS) on the natural logarithm of the number of articles hence did not perform as well as negative binomial regressions (which were preferred to Poisson regressions because of over dispersion).[10, 11] Similarly, as there are non-negligible numbers of zeros in the observations for the number of patents and the number of citations of papers and patents (more than 70% zeros), we estimate the model using negative binomial regressions (contrary to Poisson, for the same reasons).

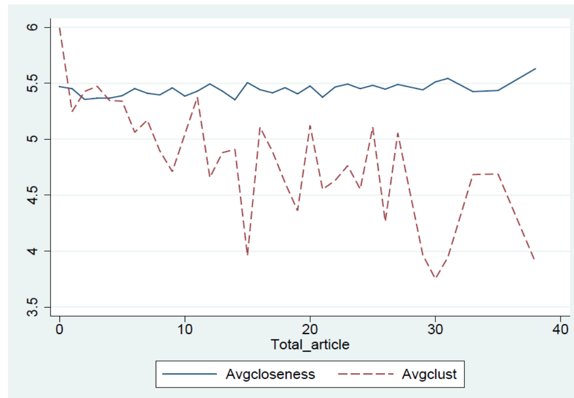
We run several robustness checks on the main models. First, we report tobit regressions to account for the large number of ones and zeros for cross-sections and panel data. Because both types of outputs are "academic" outputs and as such are often related to one another, we also estimate seemingly unrelated regressions (SUR) for cross-sections and panel data in which two unrelated outcome variables are predicted. This method should produce more efficient estimates by weighting the estimates by the covariance of the residuals from individual regressions as it allows for a degree of correlation between the errors.

Before turning to the regression results, we first briefly present the evolution of the network variables (Appendix A presents the descriptive statistics and bivariate correlations of the variables used in this study). We examine our two dependent variables, number of articles and number of patents in terms of the network measures. Figure 1a shows that as the number of articles by scientists increases, average betweenness centrality also increases, i.e. the likelihood that the shortest path between two other scientists in the network goes through the node represented by this scientist increases. This suggests a more important intermediary role of the scientist over the communication between other scientists in the network. In contrast (also observed in Figure 1a), the average eigenvector centrality rises only slightly, indicating that publishing more articles only slightly increases the chance to connect with high-scoring scientists. Average closeness centrality is almost constant and average clustering seems to decrease as the number of articles increases (Figure 1b). Constant closeness centrality indicates that the "time" it takes to spread information from one scientist to all other scientists (measured in terms of the number of nodes/scientists required to reach everyone) is not changed when scientists publish more articles. The tendency of a scientist to

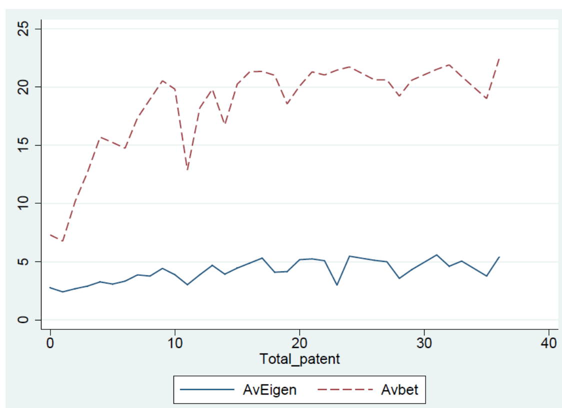
[10] We chose the cross-section versions of these regression models to account for repeated observations as opposed to their panel versions, mainly because the average number of years for each observation is relatively small (only two years).
[11] Vuong tests on zero-inflated negative binomial regressions favoured the non zero-inflated version of the regression models.

create tightly knit groups characterized by a relatively high density of links decreases as average clustering decreases. Comparing these network measures in terms of patent production yields very similar trends, i.e. average betweenness centrality also increases with an increasing number of patents, while average eigenvector centrality shows a steady trend (Figure 1c).





(a) **(b)**



(c)

Figure 1 – Average eigenvector centrality and average betweenness centrality per article (a), average clustering and average closeness per article (b), and average eigenvector centrality and average betweenness centrality per patent (c)

4 Regression Results

Mapping the pattern of collaboration via co-publication and co-invention relationships, we attempt to estimate the network indicators that influence scientist productivity in terms of number of articles and patents and number of citations received by both types of documents. Tables 1 to 4 summarize the results of negative binomial regressions for different model specifications on the number of scientific papers (Table 1) and technological patents (Table 2), and on the number of citations to the former (Table 3) and the latter (Table 4).

The results show that collaborative ties among scientists influence research performance. The positively significant correlations presented in Appendix A reveal that in scientific relationships, scientists who have many collaborations with different scientists and those who frequently cross the collaboration paths of other scientists contribute to more publications and patents. Further, maintaining collaborations within a group of scholars appears to have a positive impact on scientist productivity. The first very crude measure of collaboration is simply an individual scientist's number of co-authors. We observe that this number has a positive impact on the number of articles and citations that these articles receive in the future.[12]

Turning now to the network measures, we find that both degree and eigenvector centrality have a positive impact, suggesting that the number of connections between scientists and their counterparts plays an important role in paper and patent productivity. Closeness centrality, which indicates that a scientist has quick and easy access to all the other scientists in the network, is found to be a valuable predictor of increased publication and even patent production. Betweenness centrality means connecting different groups of scientists as a middle scientist or intermediary, and has a positive impact on the production of publications and patents.

[12] We also added the number of co-inventors, but this variable was never significant.

Table 1 – Impact of collaborations on citations of nanotech papers (*$NumPaper_{it}$*) in Canada – Regression results of the nbreg model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$ln\ (10^3 \times ClosCent_{t-2})$	5.8006 **	9.6690 ***								
	(2.8195)	(2.9897)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-0.5140 **	-0.8336 ***								
	(0.2451)	(0.2589)								
$ln\ (10^4 \times EigenCent_{t-2})$			0.5575***	0.5928***						
			(0.1482)	(0.1499)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			-0.0634***	-0.0603***						
			(0.0166)	(0.0168)						
$ln(10 \times DegCent_{t-2})$					0.9445***	0.9698 ***				
					(0.3044)	(0.3086)				
$[ln(10 \times DegCent_{t-2})]^2$					-0.0875***	-0.0811 ***				
					(0.0286)	(0.0289)				
$ln(10^4 \times BetCent_{t-2})$							0.3478***	0.3858 ***		
							(0.0519)	(0.0626)		
$[ln(10^4 \times BetCent_{t-2})]^2$							-0.0402***	-0.0388 ***		
							(0.0067)	(0.0090)		
$ln(10^3 \times Cliqness_{t-2})$									0.4239 ***	0.4611 ***
									(0.1570)	(0.1473)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.1368 ***	-0.1505 ***
									(0.0286)	(0.0262)
nbAuthors	1.5195 ***	1.5276 ***	1.5508***	1.5543***	1.5520***	1.5454 ***	1.5027***	1.4917 ***	1.4365 ***	1.4356 ***
	(0.0461)	(0.0473)	(0.0438)	(0.0446)	(0.0439)	(0.0445)	(0.0329)	(0.0460)	(0.0451)	(0.0444)
$dCanadaChair_{it}$	0.1719	0.1546	0.0897	0.0976	0.1064	0.1038	0.1255	0.1057	0.1408	0.1006
	(0.1563)	(0.1602)	(0.1600)	(0.1638)	(0.1583)	(0.1596)	(0.1477)	(0.1449)	(0.1368)	(0.1373)
Age_{it-1}	0.0426 ***		0.0496***		0.0475***		0.0344***		0.0163 *	
	(0.0076)		(0.0072)		(0.0077)		(0.0061)		(0.0083)	
$ln(AvgFunding)_{it-1}$		0.0224 ***		0.0213***		0.0207 ***		0.0177 ***		0.0158 **
		(0.0065)		(0.0065)		(0.0065)		(0.0063)		(0.0064)
Constant	-19.339 **	-30.606 ***	-4.2472***	-4.095***	-5.5713***	-5.5343 ***	-3.5127***	-3.4026 ***	-2.6248 ***	-2.5270 ***
	(8.0575)	(8.5913)	(0.3029)	(0.3178)	(0.7797)	(0.8024)	(0.1178)	(0.1188)	(0.2416)	(0.2270)
$ln(\alpha)$	-1.6380 ***	-1.5462 ***	-1.7884***	-1.5982***	-1.6887***	-1.5611 ***	-1.7323***	-1.6883 ***	-1.8178 ***	-1.8232 ***
	(0.1515)	(0.1413)	(0.1675)	(0.1474)	(0.1507)	(0.1398)	(0.1415)	(0.1516)	(0.1724)	(0.1699)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Wald χ^2	1979 ***	1853 ***	2513 ***	2112***	2311 ***	1993 ***	4427 ***	2087 ***	2103 ***	2081 ***
Log likelihood	-2642	-2664	-2624	-2656	-2635	-2661	-2623	-2635	-2601	-2601

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Table 2 – Impact of collaborations on citations of nanotech patents (*$NumPatent_{it}$*) in Canada – Regression results of nbreg model

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$\ln(10^3 \times ClosCent_{t-2})$	48.736 ***	50.108 ***								
	(7.8878)	(7.6572)								
$[\ln(10^3 \times ClosCent_{t-2})]^2$	-4.1357 ***	-4.2511 ***								
	(0.6722)	(0.6535)								
$\ln(10^4 \times EigenCent_{t-2})$			1.4667***	1.4755***						
			(0.3769)	(0.3647)						
$[\ln(10^4 \times EigenCent_{t-2})]^2$			-0.1025***	-0.1029***						
			(0.0379)	(0.0372)						
$\ln(10 \times DegCent_{t-2})$					2.0148**	2.0573 **				
					(0.8184)	(0.8061)				
$[\ln(10 \times DegCent_{t-2})]^2$					-0.1075	-0.1142				
					(0.0718)	(0.0711)				
$\ln(10^4 \times BetCent_{t-2})$							0.7467***	0.7239 ***		
							(0.1215)	(0.1511)		
$[\ln(10^4 \times BetCent_{t-2})]^2$							-0.0331*	-0.0355		
							(0.0173)	(0.0221)		
$\ln(10^3 \times Cliqness_{t-2})$									2.4623 ***	2.4459 ***
									(0.4781)	(0.4754)
$[\ln(10^3 \times Cliqness_{t-2})]^2$									-0.5651 ***	-0.5555 ***
									(0.0851)	(0.0814)
nbAuthors	-0.0031	0.0003	-0.0245	-0.0231	-0.0800	-0.0712	-0.0926	-0.0750	0.0177	0.0220
	(0.1139)	(0.1144)	(0.1105)	(0.1107)	(0.1107)	(0.1122)	(0.0845)	(0.0974)	(0.1151)	(0.1141)
$dCanadaChair_{it}$	0.0004	0.0965	0.0066	0.0997	-0.0519	0.0156	-0.0176	0.0280	-0.3871	-0.2621
	(0.5038)	(0.4985)	(0.5022)	(0.5031)	(0.5055)	(0.5138)	(0.3794)	(0.5461)	(0.4769)	(0.4905)
Age_{it-1}	0.0207		0.0076		-0.0141		-0.0298*		-0.0169	
	(0.0219)		(0.0252)		(0.0285)		(0.0142)		(0.0250)	
$\ln(AvgFunding)_{it-1}$		-0.0134		-0.0178		-0.0211		-0.0218		-0.0301
		(0.0187)		(0.0188)		(0.0189)		(0.0189)		(0.0204)
Constant	-145.7 ***	-149.50 ***	-7.507***	-7.370***	-10.622***	-10.689 ***	-4.877***	-4.960 ***	-4.8246 ***	-4.8916 ***
	(22.873)	(22.207)	(0.8211)	(0.8505)	(2.2094)	(2.2167)	(0.2901)	(0.3025)	(0.7109)	(0.6635)
$\ln(\alpha)$	2.5107 ***	2.5082 ***	2.4629***	2.4562***	2.4177***	2.4129 ***	2.4031***	2.4064 ***	2.4730 ***	2.4642 ***
	(0.1469)	(0.1485)	(0.1678)	(0.1687)	(0.1817)	(0.1777)	(0.0882)	(0.1680)	(0.1587)	(0.1533)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Wald χ^2	179 ***	199 ***	212 ***	228***	217 ***	231 ***	255 ***	229 ***	237 ***	235 ***
Log likelihood	2.5107	2.5082	2.4629	2.4562	2.4177	2.4129	2.4031	2.4064	2.4730	2.4642

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Table 3 – Impact of collaborations on nanotech papers (*$PaperCit_{it}$*) in Canada - Regression results of nbreg model

Variables	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$ln\ (10^3 \times ClosCent_{t-2})$	38.3010 ***	41.6619 ***								
	(4.2013)	(4.2168)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-3.2240 ***	-3.5068 ***								
	(0.3484)	(0.3490)								
$ln\ (10^4 \times EigenCent_{t-2})$			1.2785***	1.3203***						
			(0.1696)	(0.1630)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			-0.0679***	-0.0702***						
			(0.0188)	(0.0184)						
$ln(10 \times DegCent_{t-2})$					0.9228**	0.9321 **				
					(0.4464)	(0.4337)				
$[ln(10 \times DegCent_{t-2})]^2$					0.0120	0.0094				
					(0.0427)	(0.0415)				
$ln(10^4 \times BetCent_{t-2})$							0.5856***	0.5683 ***		
							(0.0631)	(0.0991)		
$[ln(10^4 \times BetCent_{t-2})]^2$							-0.0037	-0.0055		
							(0.0110)	(0.0149)		
$ln(10^3 \times Cliqness_{t-2})$									2.0288 ***	1.9907 ***
									(0.2420)	(0.2320)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.4843 ***	-0.4739 ***
									(0.0441)	(0.0415)
nbAuthors	0.8532 ***	0.8598 ***	0.8863***	0.8940***	0.9171***	0.9211 ***	0.8121***	0.8198 ***	0.8319 ***	0.8349 ***
	(0.0450)	(0.0441)	(0.0536)	(0.0534)	(0.0532)	(0.0534)	(0.0563)	(0.0461)	(0.0441)	(0.0438)
$dCanadaChair_{it}$	-0.0675	-0.0786	0.0681	-0.0023	-0.0714	-0.1681	-0.1757	-0.2527	-0.3935 *	-0.4589 *
	(0.2149)	(0.2131)	(0.2215)	(0.2200)	(0.1991)	(0.1999)	(0.2227)	(0.2144)	(0.2384)	(0.2385)
Age_{it-1}	0.0490 ***		0.0177*		-0.0087		-0.0199**		-0.0081	
	(0.0110)		(0.0095)		(0.0092)		(0.0093)		(0.0123)	
$ln(AvgFunding)_{it-1}$		0.0336 ***		0.0297***		0.0201 *		0.0078		0.0124
		(0.0107)		(0.0103)		(0.0103)		(0.0113)		(0.0135)
Constant	-110.58 ***	-120.19 ***	-1.8578***	-1.9861***	-2.7933**	-2.9529 ***	0.9346***	0.7881 ***	1.5761 ***	1.4366 ***
	12.49	12.59	(0.3650)	(0.3471)	(1.1366)	(1.0929)	(0.1246)	(0.2354)	(0.4113)	(0.3865)
$ln(\alpha)$	2.2741 ***	2.2785 ***	2.2013***	2.1994***	2.1791***	2.1779 ***	2.2180***	2.2191 ***	2.2521 ***	2.2517 ***
	(0.0379)	(0.0378)	(0.0372)	(0.0370)	(0.0373)	(0.0373)	(0.0238)	(0.0390)	(0.0407)	(0.0407)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Wald χ^2	687 ***	650 ***	968 ***	1012***	909 ***	922 ***	1139 ***	951 ***	882 ***	884 ***
Log likelihood	-16856	-16865	-16720	-16716	-16680	-16677	-16752	-16754	-16812	-16812

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Table 4 – Impact of collaborations on nanotech patents (*$PatentCit_{it}$*) in Canada - Regression results of nbreg model

Variables	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
$\ln(10^3 \times ClosCent_{t-2})$	114.066 ***	111.795 ***								
	36.937	36.452								
$[\ln(10^3 \times ClosCent_{t-2})]^2$	-10.240 ***	-10.049 ***								
	(3.4415)	(3.3852)								
$\ln(10^4 \times EigenCent_{t-2})$			2.4170***	2.3751***						
			(0.5632)	(0.5636)						
$[\ln(10^4 \times EigenCent_{t-2})]^2$			-0.2043***	-0.2006***						
			(0.0673)	(0.0652)						
$\ln(10 \times DegCent_{t-2})$					4.1599***	4.3361 ***				
					(1.1506)	(1.1179)				
$[\ln(10 \times DegCent_{t-2})]^2$					-0.2983***	-0.3177 ***				
					(0.1117)	(0.1055)				
$\ln(10^4 \times BetCent_{t-2})$							1.3556***	1.3684 ***		
							(0.3260)	(0.2516)		
$[\ln(10^4 \times BetCent_{t-2})]^2$							-0.1105**	-0.1190 ***		
							(0.0493)	(0.0390)		
$\ln(10^3 \times Cliqness_{t-2})$									5.4358 ***	5.8701 ***
									(0.8285)	(0.9974)
$[\ln(10^3 \times Cliqness_{t-2})]^2$									-1.1100 ***	-1.1591 ***
									(0.1335)	(0.1580)
nbAuthors	0.0238	0.0719	-0.0022	0.0223	-0.0917	-0.0276	-0.1477	-0.0530	0.0423	0.1712
	(0.2512)	(0.2401)	(0.2562)	(0.2481)	(0.2884)	(0.2786)	(0.2707)	(0.2337)	(0.2448)	(0.2535)
$dCanadaChair_{it}$	-0.2548	-0.0479	-0.2669	-0.1051	-0.2907	-0.0840	-0.0082	0.1918	-0.0136	0.3726
	(0.8605)	(0.9402)	(0.8717)	(0.9473)	(0.8561)	(0.9457)	(1.0764)	(0.8491)	(0.9503)	(0.9974)
Age_{it-1}	0.0255		0.0240		0.0000		-0.0333		-0.0384	
	(0.0369)		(0.0405)		(0.0445)		(0.0356)		(0.0447)	
$\ln(AvgFunding)_{it-1}$		-0.0430		-0.0315		-0.0386		-0.0422		-0.0822 **
		(0.0401)		(0.0382)		(0.0401)		(0.0428)		(0.0415)
Constant	-321.97 ***	-314.78 ***	-11.333***	-10.783***	-18.188***	-18.385 ***	-7.3402***	-7.4863 ***	-9.8168 ***	-10.8071 ***
	99.20	98.24	(1.1830)	(1.2184)	(2.9191)	(2.8942)	(0.8474)	(0.5059)	(1.5120)	(1.5804)
$\ln(\alpha)$	5.0252 ***	5.0201 ***	5.0293***	5.0257***	5.0161***	5.0117 ***	4.9996***	5.0007 ***	4.9520 ***	4.9442 ***
	(0.1377)	(0.1380)	(0.1443)	(0.1452)	(0.1449)	(0.1456)	(0.1000)	(0.1429)	(0.1388)	(0.1390)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Wald χ^2	157 ***	154 ***	262 ***	260***	373 ***	348 ***	75 ***	391 ***	341 ***	309 ***
Log likelihood	-1162	-1162	-1163	-1163	-1162	-1161	-1160	-1160	-1153	-1152

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Since scientists were found to overlap in terms of two different types of links, co-authorship and co-invention,[13] we did not distinguish these links in isolation. Our results reveal that collaboration between scientists has a positive impact not only on publications, but on patents as well.

Similarly to what we have read in the literature so far on the impact of relationships on the number of publications and patents, collaborations show a consistently significant impact on the number of citations to these research outputs. As the results in Tables 1 to 4 indicate, eigenvector centrality, betweenness centrality, degree centrality, closeness centrality and cliquishness all help enhance the quality of publications, as measured by the number of citations in this study. Regarding patents, our results demonstrate that network measures have a convincing impact on the number of citations that patents receive (see Table 4). We can say that the collaborative environment dramatically affects scientific publications and patents, in terms of number as well as quality.

We added the square of network measures to investigate non-linear effects of these variables.[14] All network measures exhibit an inverted-U shape curve in their relationship with the number of papers, suggesting that although a higher centrality or cliquishness has a positive impact on publications, higher values for these network indicators are eventually accompanied by a declining number of papers. Regarding the number of article citations, we observe the same inverted-U shaped impact for closeness centrality and cliquishness. For degree centrality, eigenvector centrality and betweenness centrality, however, we capture only the rising part of the curve up to the start of diminishing returns, which suggests that having more connections and being in an intermediary position contribute to more article citations, but that this increasing effect fades ultimately for eigenvector centrality. Our empirical analysis of the non-linear effect of the network measures on citation numbers and citations to patents shows an inverted-U shaped relationship for closeness centrality, eigenvalue centrality, betweenness centrality (patent citations only) and cliquishness, while degree centrality and betweenness centrality (for

[13] We first started with two distinct networks, but following the suggestion of a referee, we joined them because they were not independent of each other.
[14] The linear effects are all positive and significant. These results are available from the authors upon request.

the citation of patents only) exhibit diminishing returns with increasing values of these network measures (see Fig. 2 and Fig. 3).

Our findings also show that receiving government grants[15] impacts substantially on scientists' publication productivity, and these grants in particular contribute to a higher publication volume and a greater number of citations to the scientist's work.

Although, the nature of interactions among academic scientists and academic inventors differ, and given that their communication activity influences their scientific and technological efficiency, these different links do not operate in isolation in the academic realm and thus affect each other. Our results reveal that collaboration impacts on the scientific and technological performance of our Canadian sample of academic scientists in the same way.

As robustness checks, we report tobit regressions and seemingly unrelated regressions for cross-sections and panel data in which two unrelated outcome variables are predicted. The results are somewhat similar to those presented in Tables 1 to 4, but suffer from the excess number of zeros (and ones) of our dependent variables. The results of the tobit and seemingly unrelated regressions used as robustness checks are presented in Appendix B.

[15] Although they do not appear to be strongly correlated, both Age and AvgFunding interact with each other, since older scientists generally raise more funding, but that relationship is non-linear. Therefore, both variables were introduced in distinct regressions to avoid their interaction. We formally tested various forms of interaction/moderating effects but none were robust enough to be included in the analysis. More research is required in this regard, but that is beyond the scope of this paper.

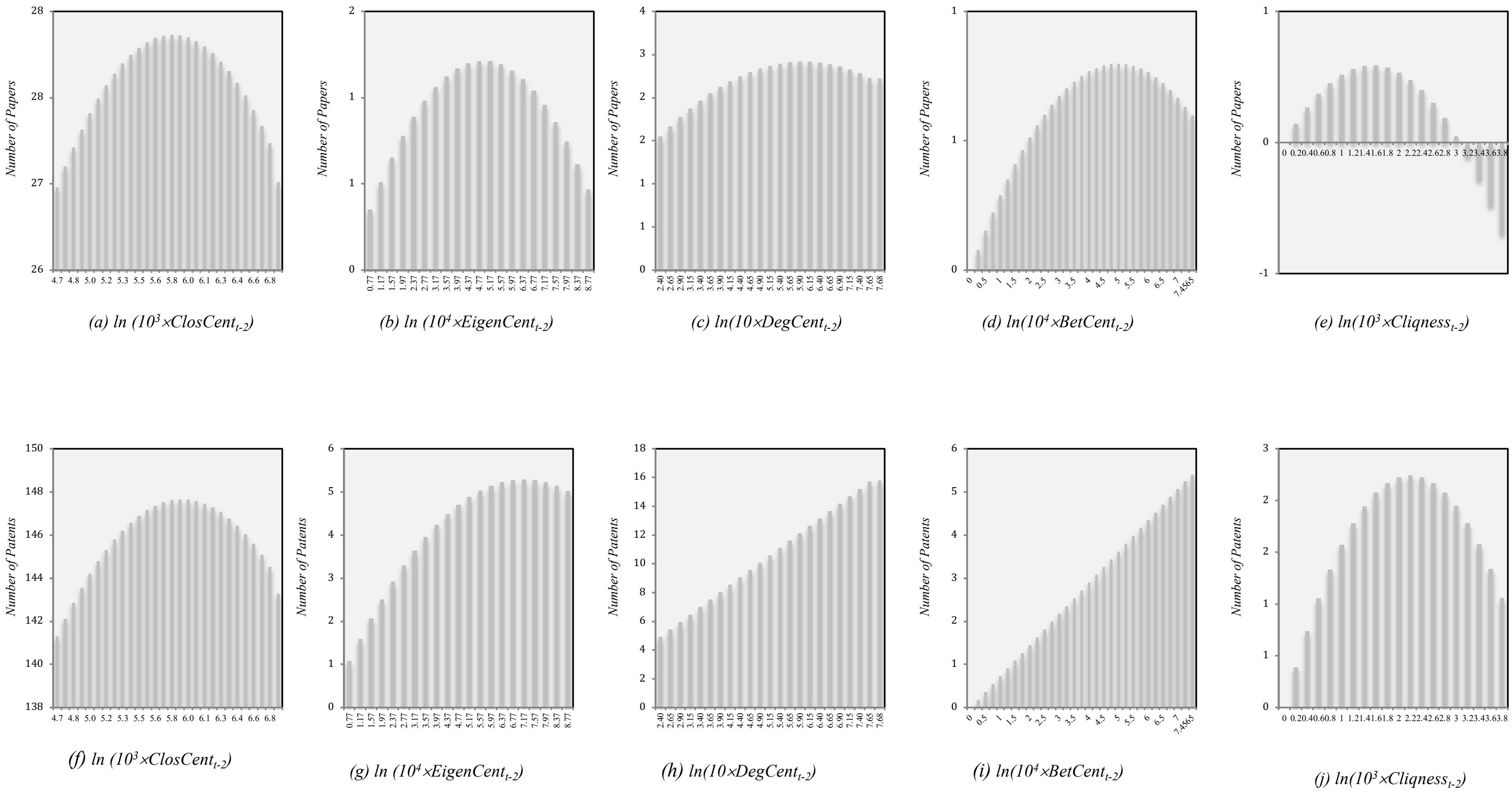
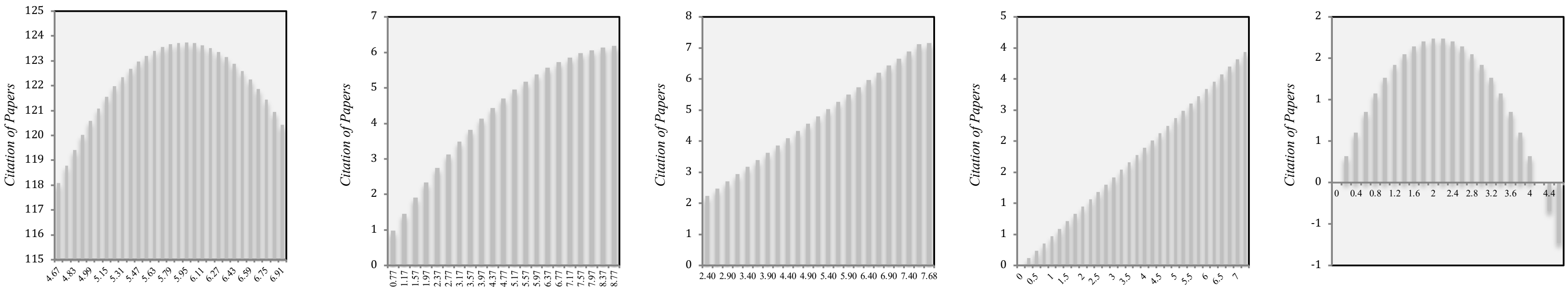
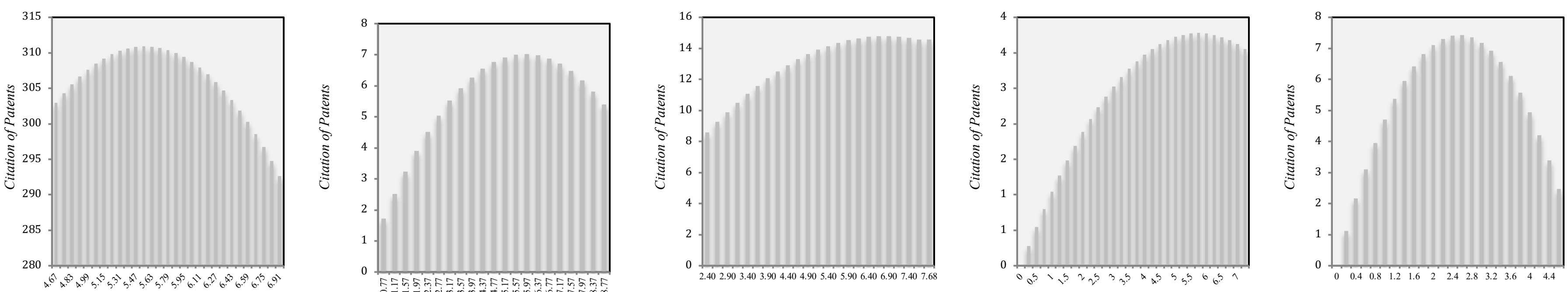


Figure 2 – Non-linear effects of the network measures on the number of papers and patents



(a) ln (10^3×ClosCent$_{t-2}$) *(b) ln (10^4×EigenCent$_{t-2}$)* *(c) ln(10×DegCent$_{t-2}$)* *(d) ln(10^4×BetCent$_{t-2}$)* *(e) ln(10^3×Cliqness$_{t-2}$)*



(f) ln (10^3×ClosCent$_{t-2}$) *(g) ln (10^4×EigenCent$_{t-2}$)* *(h) ln(10×DegCent$_{t-2}$)* *(i) ln(10^4×BetCent$_{t-2}$)* *(j) ln(10^3×Cliqness$_{t-2}$)*

Figure 3 – Non-linear effects of the network measures on the citation of papers and patents

5 Concluding Remarks

The present study aims at investigating how a scientist can better contribute to knowledge creation by building scientific and technological collaborations. The structure and characteristics of academic scientist networks have been areas of interest in recent years. The involvement of scientists in the exploitation of their research results via patenting has been particularly debated. We contribute to the literature by proposing a different network approach to explore the impact of co-activity in academia on the publishing and patenting performance of scientists. Based on our focus on academic research, this study constructed a research network using a combination of co-authorship and co-invention links instead of isolated co-authorship and co-invention networks. By contrast, previous studies mainly focused on the extent to which scientific productivity can be affected by scientists' relationships.

In this article, we used social network theory in an attempt to provide an empirical contribution to knowledge on the role and dynamics of the behavior of individual scientists within their collaboration network. After analyzing the scientific community on the basis of co-authorship and co-invention activities, we found new evidence on the impact of collaborative relationships over time. Our results highlight that these collaborations are important considerations for future research. We found that the position of scientists within collaborative networks has a direct impact on their performance, and that scientists with strong connections generally produce more publications and patents. Regarding network measures, scientists with a higher number of direct connections and those who hold an intermediary position in the network achieve greater research output than those with fewer connections.

More interestingly, this empirical study highlights the importance of collaboration networks on citation impact. Citations are key indicators of academic merit that relate to the dynamics of scientific communication. A scientist's network centrality shows his prominence within the scientific network and strongly affects publication success, measured by number of citations. Further, scientists' centrality in the network is indicative of the visibility of their work (Sarigöl et al. 2014). Scientists with higher centrality in the network at the time their paper or invention is published are the authors/inventors whose papers/patents will be highly cited in future.

We studied correlations between the centrality of authors/academic inventors in collaboration networks and the citation success of their research output and found that these social relations prominently affect the amount of attention and recognition their publications and patents receive. As centrality endeavours to evaluate the importance of scientists within the scientific network, a scientist's scientific excellence could result in that individual becoming more central and receiving more citations.

The correlation between centrality and citation can also be interpreted from another perspective. Though it may be difficult to assess the value of centrality measures in evaluating the impact of an article, the number of citations can indirectly quantify the quality and impact of this and other publications. Hence, centrality incorporates article impact and citation counts (Yan and Ding, 2009).

We found that the impact of prominent positions in research networks on the number of citations to research output, often deemed a proxy for the "quality" of such output, demonstrates that collaborative activities increase opportunities to receive more citations.

There is, however, a limit to increasing one's centrality or cliquishness in the network, given that nearly all of the network measures examined eventually exhibited diminishing returns, if not an outright decline, in a context of increased connectedness. Scientists can therefore eventually become too connected and thus have to spend too much time and effort maintaining the network of collaborators. More research is necessary to understand how scientists strike a healthy balance between the pressures of ever bigger networks, more collaborative research (basic and applied) and greater connectedness, as these factors appear to ultimately be detrimental to scientific and technological production as centrality and cliquishness measures increase.

These preliminary findings regarding research network communities help improve our understanding of the connection between scientists, whether their objective is to publish or to secure a patent. The social innovation links among academic scientists are more likely to be underestimated in universities, where the publish or perish game is still flourishing. Both types of co-author and co-inventor links provide a strong connectedness among scientists that should facilitate the spread of knowledge and thus affect their publishing and patenting productivity. These findings contribute useful information at the policy level to encourage collaboration within academia. We found that receiving grants from government is strongly related to the number and the citation impact of publications. This finding highlights the advantages that funding schemes provide as a tool to incentivize collaborations.

There is clear evidence showing how academic research contributes to economic development (Etzkowitz, 1990; Mansfield, 1991; Bercovitz and Maryann 2006). Universities have a key role to play in economic growth plans, and research innovation activities should be given targeted support such as maintaining an environment in which collaborations are strong and productive enough to drive the knowledge economy forward.

Collaboration gives access to a wider scope of experience, knowledge and expertise and brings advantages for all scientists in that relationship. Science and technology generated through collaborations can enhance the efficiency and productivity of university activities. Collaboration can act as a driving force for innovative academic activities and improve the way that technologies are widely shared among scientists in universities. This relationship encourages scientists to put their goals in a broader context and yields new levels of efficiency. Scientists with different insights, approaches and experiences provide a fertile environment for generating new concepts to spur innovation and improve ideas. But collaboration comes with the cost of maintaining these relationships. More research is required on the administrative burden linked with ever-larger networks of collaborators.

Evolving co-authorship and co-invention networks reveal the dynamic collaboration patterns that occur during different time periods. Considering the high costs of the infrastructure required for nanoscience and nanotechnology research, collaboration is not only encouraged, but it is also necessary to accelerate the development of these fields and to avoid the socially costly duplication of research efforts. Academic collaboration has played a key role in the significant growth of nanotechnology research. The impact of collaborations provides evidence for the need to direct scientific policies to promoting links among scientists as an overall strategy to increase the impact of academic research in the field of nanotechnology. Favouring the establishment of more collaborative links among scientists opens up an effective way to participate in more complex nanotech research areas.

Future economic success will rely on the research and innovation efforts of scientists in academia. Effective support mechanisms provided by future policies on productive partnerships will add even more value to such innovations and to the research system.

Finally, there are a number of limitations to this study. The first lies in the examination of the narrow field of nanotechnology. We used what we thought was an accurate identification of nanotechnology papers and patents but we might have overlooked some nanotechnology related articles and patents. For instance, some new nanotechnology keywords may have been missed in our careful canvassing of the scientific literature. In addition, as we do not have access to the industry or to the financial contribution to the development of academic patents, we very likely underestimated R&D costs by limiting ourselves to academic grants. Further, by considering only nanotechnology papers and patents, we might have passed over important components of the multidisciplinary network.

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Appendix A – Descriptive statistics

Table A1 – Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13
NumPaper	1	1												
NumPatent	2	0.0262	1											
PaperCit5	3	0.5441	0.059	1										
PatentCit5	4	-0.001	0.5743	0.0111	1									
n(10^3×ClosCent)	5	0.0331	0.0026	0.0331	-0.005	1								
ln(10^4×BetCent)	6	0.3032	0.162	0.4424	0.089	-0.068	1							
ln(10^3×Cliqness)	7	-0.235	-0.097	-0.310	-0.049	-0.200	-0.549	1						
ln (10^3×EigenCent)	8	0.3016	0.146	0.4367	0.0802	-0.057	0.81	-0.304	1					
ln(10×DegCent)	9	0.295	0.1613	0.4576	0.0905	-0.075	0.8875	-0.344	0.9387	1				
nbAuthors	10	0.938	0.0308	0.5302	0.0043	0.0326	0.2879	-0.206	0.307	0.294	1			
CanadaChair	11	0.0192	-0.004	0.0206	-0.006	-0.015	0.0096	-0.007	-0.015	0.003	0.01	1		
$Agei_{t-1}$	12	0.1515	0.0346	0.2395	-9E-04	-0.01	0.458	-0.285	0.3294	0.4005	0.1175	0.0836	1	
AvgFunding	13	0.0173	-0.014	0.072	-0.035	0.0074	0.0346	-0.008	-0.006	0.028	0.0004	0.1533	0.2484	1

Table A2 – Descriptive statistics

Variable	**Mean**	**Std.Dev**	**Min**	**Max**
NumPaper	0.304	0.862	0	15
NumPatent	0.100	0.612	0	20
PaperCit5	20.340	66.905	0	1329
PatentCit5	0.260	2.825	0	92
ln (10^3×ClosCent)	5.409	0.372	4.671	6.909
ln(10^4×BetCent)	2.733	1.874	0.000	7.456
ln(10^3×Cliqness)	3.228	0.989	0.000	4.615
ln (10^4×EigenCent)	3.876	1.443	0.775	9.128
ln(10^3×DegCent)	5.028	1.111	2.398	7.6829
nbAuthors	1.081	4.084	0	11
CanadaChair	0.028	0.164	0	1
Age	7.008	4.918	0	22
AvgFunding	11,072	39,358.850	0	2377031

Appendix B1-1 – Impact of collaborations on nanotech papers [*ln*(*NumPaper*$_{it}$)] in Canada - Regression results of tobit model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln $(10^3 \times ClosCent_{t-2})$	0.3333	1.8005								
	(1.0126)	(1.1017)								
$[\ln (10^3 \times ClosCent_{t-2})]^2$	-0.0240	-0.1451								
	(0.0838)	(0.0908)								
ln $(10^4 \times EigenCent_{t-2})$			0.0410	0.2618						
			(0.0596)	(0.3369)						
$[\ln (10^4 \times EigenCent_{t-2})]^2$			-0.0041	-0.0154						
			(0.0069)	(0.0390)						
$\ln(10 \times DegCent_{t-2})$					0.0672	0.0638				
					(0.1335)	(0.1360)				
$[\ln(10 \times DegCent_{t-2})]^2$					-0.0045	-0.0015				
					(0.0128)	(0.0129)				
$\ln(10^4 \times BetCent_{t-2})$							0.0677**	0.0800**		
							(0.0314)	(0.0321)		
$[\ln(10^4 \times BetCent_{t-2})]^2$							-0.0054	-0.0048		
							(0.0047)	(0.0048)		
$\ln(10^3 \times Cliqness_{t-2})$									0.0109	0.0384
									(0.0473)	(0.0410)
$[\ln(10^3 \times Cliqness_{t-2})]^2$									-0.0251 **	-0.0338 ***
									(0.0102)	(0.0087)
nbAuthors	0.4714 ***	0.4689 ***	0.4750***	2.6432***	0.4680***	0.4584 ***	0.4613***	0.4547***	0.4541 ***	0.4545 ***
	(0.0196)	(0.0199)	(0.0194)	(0.1353)	(0.0192)	(0.0189)	(0.0184)	(0.0182)	(0.0191)	(0.0192)
$dCanadaChair_{it}$	0.0392	0.0214	0.0349	0.1539	0.0369	0.0219	0.0332	0.0163	0.0294	0.0091
	(0.0711)	(0.0758)	(0.0713)	(0.4044)	(0.0710)	(0.0745)	(0.0697)	(0.0720)	(0.0697)	(0.0713)
Age_{it-1}	0.0168 ***		0.0172***		0.0159***		0.0125***		0.0079 **	
	(0.0030)		(0.0032)		(0.0033)		(0.0034)		(0.0032)	
$\ln(AvgFunding)_{it-1}$		0.0092 ***		0.0450***		0.0084 ***		0.0074***		0.0067 **
		(0.0027)		(0.0152)		(0.0028)		(0.0027)		(0.0027)
Constant	-1.1550	-5.4269	-0.1595	-4.9960***	-0.2691	-0.2167	-0.1527**	-0.1097	0.2547 ***	0.2943 ***
	(3.0192)	(3.3037)	(0.1331)	(0.7527)	(0.3453)	(0.3549)	(0.0719)	(0.0707)	(0.0697)	(0.0655)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Pseudo R^2	0.7309	0.7195	0.7309	0.4782	0.7313	0.7223	0.7354	0.7310	0.7485	0.7478
Log likelihood	-461	-480	-461	-1353	-460	-475	-453	-460	-431	-432

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B1-2 – Impact of collaborations on nanotech patents [*ln*(*NumPatent*$_{it}$)] in Canada - Regression results of tobit model

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
ln $(10^3 \times ClosCent_{t-2})$	33.6909 ***	34.0618 ***								
	(10.7326)	(10.3349)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-2.9503 ***	-2.9805 ***								
	(0.9626)	(0.9262)								
ln $(10^4 \times EigenCent_{t-2})$			0.6750***	0.6740***						
			(0.2542)	(0.2492)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			-0.0488**	-0.0488**						
			(0.0238)	(0.0236)						
$ln(10 \times DegCent_{t-2})$					0.7950	0.7753				
					(0.5770)	(0.5679)				
$[ln(10 \times DegCent_{t-2})]^2$					-0.0399	-0.0398				
					(0.0492)	(0.0490)				
$ln(10^4 \times BetCent_{t-2})$							0.2828**	0.2589**		
							(0.1122)	(0.1063)		
$[ln(10^4 \times BetCent_{t-2})]^2$							-0.0080	-0.0073		
							(0.0140)	(0.0139)		
$ln(10^3 \times Cliqness_{t-2})$									1.0413 ***	1.0088 ***
									(0.3530)	(0.3627)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.2459 ***	-0.2351 ***
									(0.0649)	(0.0642)
nbAuthors	-0.0272	-0.0263	-0.0289	-0.0289	-0.0534	-0.0525	-0.0626	-0.0613	-0.0211	-0.0208
	(0.0556)	(0.0555)	(0.0539)	(0.0539)	(0.0508)	(0.0512)	(0.0496)	(0.0498)	(0.0529)	(0.0525)
$dCanadaChair_{it}$	0.1596	0.1661	0.1690	0.1702	0.1580	0.1516	0.1604	0.1438	0.0449	0.0524
	(0.3328)	(0.3256)	(0.3276)	(0.3232)	(0.3262)	(0.3255)	(0.3318)	(0.3328)	(0.3250)	(0.3252)
Age_{it-1}	0.0048		-0.0007		-0.0101		-0.0164		-0.0120	
	(0.0122)		(0.0129)		(0.0139)		(0.0144)		(0.0134)	
$ln(AvgFunding)_{it-1}$		0.0008		-0.0007		-0.0031		-0.0033		-0.0057
		(0.0098)		(0.0100)		(0.0102)		(0.0101)		(0.0105)
Constant	-97.5135 ***	-98.5943 ***	-3.5939***	-3.5932***	-4.6342***	-4.6172 ***	-2.3021***	-2.3838***	-2.2699 ***	-2.3699 ***
	(29.9855)	(28.9205)	(0.7163)	(0.7099)	(1.7068)	(1.6962)	(0.3761)	(0.3612)	(0.6404)	(0.6590)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Pseudo R^2	0.0797	0.0794	0.0855	0.0855	0.0927	0.0918	0.0990	0.0965	0.0894	0.0883
Log likelihood	-618	-618	-614	-614	-609	-610	-605	-607	-612	-612

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B1-3 – Impact of collaborations on citation of nanotech papers [$ln(PaperCit_{it})$] in Canada - Regression results of tobit model

Variables	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
$ln\ (10^3 \times ClosCent_{t-2})$	50.9545 ***	2628.66 ***								
	(4.2565)	272.33								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-4.2845 ***	-220.41 ***								
	(0.3561)	22.72								
$ln\ (10^4 \times EigenCent_{t-2})$			1.4936***	1.5821***						
			(0.1621)	(0.1636)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			-0.0896***	-0.0927***						
			(0.0180)	(0.0181)						
$ln(10 \times DegCent_{t-2})$					1.1524***	1.1838 ***				
					(0.3531)	(0.3511)				
$[ln(10 \times DegCent_{t-2})]^2$					-0.0051	-0.0044				
					(0.0335)	(0.0333)				
$ln(10^4 \times BetCent_{t-2})$							0.6145***	0.6217***		
							(0.0763)	(0.0744)		
$[ln(10^4 \times BetCent_{t-2})]^2$							0.0013	0.0018		
							(0.0125)	(0.0124)		
$ln(10^3 \times Cliqness_{t-2})$									2.0858 ***	2.1368 ***
									(0.1470)	(0.1377)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.5455 ***	-0.5590 ***
									(0.0305)	(0.0279)
nbAuthors	1.5232 ***	70.0145 ***	1.4406***	1.4422***	1.3734***	1.3726 ***	1.4097***	1.4104***	1.4724 ***	1.4735 ***
	(0.0516)	(5.8289)	(0.0508)	(0.0516)	(0.0511)	(0.0513)	(0.0485)	(0.0484)	(0.0465)	(0.0465)
$dCanadaChair_{it}$	0.2486	5.0140	0.2413	0.2155	0.1881	0.1428	0.1400	0.0842	-0.0398	-0.0873
	(0.2532)	(11.287)	(0.2341)	(0.2355)	(0.2196)	(0.2188)	(0.2348)	(0.2329)	(0.2555)	(0.2548)
Age_{it-1}	0.0814 ***		0.0534***		0.0228**		0.0105		0.0149	
	(0.0093)		(0.0093)		(0.0093)		(0.0099)		(0.0099)	
$ln(AvgFunding)_{it-1}$		1.9289 ***		0.0357***		0.0235 ***		0.0203**		0.0186 **
		(0.5611)		(0.0091)		(0.0088)		(0.0089)		(0.0093)
Constant	-150.6 ***	-7835.2 ***	-4.8011***	-4.7892***	-5.8073***	-5.8933 ***	-1.7311***	-1.7611***	-0.6902 ***	-0.6596 ***
	12.6	811.8	(0.3600)	(0.3659)	(0.9160)	(0.9149)	(0.1408)	(0.1366)	(0.2206)	(0.2133)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Pseudo R^2	0.1420	0.0627	0.1556	0.1538	0.1643	0.1643	0.1570	0.1573	0.1563	0.1564
Log likelihood	-7560	-16576	-7440	-7456	-7364	-7364	-7427	-7425	-7434	-7433

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B1-4 – Impact of collaborations on citation of nanotech patents [*ln*(*PatentCit$_{it}$*)] in Canada - Regression results of tobit model

Variables	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
ln $(10^3 \times ClosCent_{t-2})$	77.151 ***	77.914 ***								
	29.449	28.050								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-6.7456 ***	-6.8114 ***								
	(2.6008)	(2.4868)								
ln $(10^4 \times EigenCent_{t-2})$			2.2404***	2.2325***						
			(0.7985)	(0.7713)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			-0.1692**	-0.1696**						
			(0.0785)	(0.0784)						
$ln(10 \times DegCent_{t-2})$					2.7833	2.7266				
					(1.7017)	(1.6714)				
$[ln(10 \times DegCent_{t-2})]^2$					-0.1477	-0.1483				
					(0.1476)	(0.1485)				
$ln(10^4 \times BetCent_{t-2})$							0.7944**	0.7388**		
							(0.3091)	(0.2895)		
$[ln(10^4 \times BetCent_{t-2})]^2$							-0.0169	-0.0179		
							(0.0428)	(0.0430)		
$ln(10^3 \times Cliqness_{t-2})$									2.7833 ***	2.7034 ***
									(0.7098)	(0.6816)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.6520 ***	-0.6258 ***
									(0.1373)	(0.1209)
nbAuthors	-0.1399	-0.1330	-0.1955	-0.1921	-0.2993	-0.2933	-0.2949	-0.2816	-0.1603	-0.1587
	(0.2199)	(0.2163)	(0.2113)	(0.2095)	(0.1993)	(0.2006)	(0.2074)	(0.2081)	(0.2152)	(0.2150)
$dCanadaChair_{it}$	-0.0737	0.2312	0.0259	0.2952	0.0245	0.2606	-0.0099	0.1858	-0.3127	-0.0400
	(0.9420)	(0.9521)	(0.9439)	(0.9555)	(0.9408)	(0.9568)	(0.9474)	(0.9637)	(0.9160)	(0.9353)
Age_{it-1}	0.0107		-0.0126		-0.0461		-0.0614		-0.0446	
	(0.0470)		(0.0495)		(0.0541)		(0.0546)		(0.0508)	
$ln(AvgFunding)_{it-1}$		-0.0747 **		-0.0799**		-0.0903 **		-0.0886**		-0.0947 **
		(0.0364)		(0.0362)		(0.0364)		(0.0369)		(0.0368)
Constant	-227.95 ***	-229.67 ***	-14.2878***	-13.9865***	-18.1616***	-17.8920 ***	-9.8447***	-9.8656***	-9.6414 ***	-9.6680 ***
	83.00	79.01	(1.8538)	(1.9537)	(4.6269)	(4.6610)	(0.9788)	(0.9795)	(1.3713)	(1.4165)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252
Pseudo R^2	0.0600	0.0633	0.0714	0.0752	0.0798	0.0833	0.0772	0.0795	0.0668	0.0710
Log likelihood	-740	-737	-731	-728	-724	-722	-726	-725	-735	-731

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B2-1 – Impact of collaborations on nanotech papers and patents in Canada - Regression results of seemingly unrelated regression model for panel data

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$ln(NumPaper_{it})$										
$ln\ (10^3 \times ClosCent_{t-2})$	-0.0043	0.0069								
	(0.0134)	(0.0131)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	0.0006	-0.0006								
	(0.0023)	(0.0022)								
$ln\ (10^4 \times EigenCent_{t-2})$			-0.0041	0.0044						
			(0.0068)	(0.0058)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			0.0008	0.0003						
			(0.0008)	(0.0007)						
$ln(10 \times DegCent_{t-2})$					-0.0068	-0.0037				
					(0.0064)	(0.0061)				
$[ln(10 \times DegCent_{t-2})]^2$					0.0012	0.0016 *				
					(0.0008)	(0.0008)				
$ln(10^4 \times BetCent_{t-2})$							-0.0069	-0.0020		
							(0.0068)	(0.0065)		
$[ln(10^4 \times BetCent_{t-2})]^2$							0.0025***	0.0024**		
							(0.0009)	(0.0009)		
$ln(10^3 \times Cliqness_{t-2})$									0.0097	0.0320 ***
									(0.0135)	(0.0113)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.0034	-0.0080 ***
									(0.0029)	(0.0025)
nbAuthors	0.5092 ***	0.5124 ***	0.5074***	0.5080***	0.5067***	0.5065 ***	0.5036***	0.5036***	0.5066 ***	0.5074 ***
	(0.0050)	(0.0050)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
$dCanadaChair_{it}$	0.0220	0.0230	0.0227	0.0222	0.0224	0.0213	0.0235	0.0220	0.0218	0.0189
	(0.0515)	(0.0517)	(0.0518)	(0.0518)	(0.0519)	(0.0519)	(0.0520)	(0.0522)	(0.0519)	(0.0519)
Age_{it-1}	0.0040 ***		0.0039***		0.0036***		0.0029***		0.0035 ***	
	(0.0010)		(0.0011)		(0.0011)		(0.0011)		(0.0010)	
$ln(AvgFunding)_{it-1}$		0.0018 *		0.0018*		0.0017		0.0018*		0.0020 *
		(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0010)
$ln(NumPatent_{it})$										
$ln\ (10^3 \times ClosCent_{t-2})$	-0.0007	0.0057								
	(0.0139)	(0.0137)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	0.0004	-0.0002								
	(0.0024)	(0.0023)								
$ln\ (10^4 \times EigenCent_{t-2})$			-0.0074	-0.0106*						
			(0.0065)	(0.0058)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			0.0046***	0.0047***						
			(0.0007)	(0.0007)						
$ln(10 \times DegCent_{t-2})$					-0.0336***	-0.0373 ***				
					(0.0059)	(0.0057)				

$[ln(10 \times DegCent_{t-2})]^2$					0.0085***	0.0083 ***				
					(0.0008)	(0.0008)				
$ln(10^4 \times BetCent_{t-2})$							-0.0069	-0.0145**		
							(0.0064)	(0.0063)		
$[ln(10^4 \times BetCent_{t-2})]^2$							0.0069***	0.0073***		
							(0.0009)	(0.0009)		
$ln(10^3 \times Cliqness_{t-2})$									0.0701 ***	0.0629 ***
									(0.0134)	(0.0116)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.0175 ***	-0.0160 ***
									(0.0028)	(0.0025)
nbAuthors	0.0236 ***	0.0247 ***	0.0046	0.0042	-0.0002	-0.0002	-0.0023	-0.0027	0.0147 ***	0.0145 ***
	(0.0053)	(0.0052)	(0.0057)	(0.0056)	(0.0056)	(0.0056)	(0.0055)	(0.0055)	(0.0054)	(0.0054)
$dCanadaChair_{it}$	-0.0222	-0.0175	-0.0193	-0.0183	-0.0164	-0.0170	-0.0123	-0.0152	-0.0282	-0.0262
	(0.0544)	(0.0546)	(0.0548)	(0.0548)	(0.0548)	(0.0547)	(0.0546)	(0.0547)	(0.0545)	(0.0545)
Age_{it-1}	0.0016		-0.0016		-0.0030***		-0.0035***		-0.0013	
	(0.0010)		(0.0010)		(0.0011)		(0.0010)		(0.0010)	
$ln(AvgFunding)_{it-1}$		-0.0008		-0.0009		-0.0009		-0.0011		-0.0010
		(0.0011)		(0.0011)		(0.0011)		(0.0011)		(0.0011)
Constant										
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B2-2 – Impact of collaborations on citations of nanotech papers and patents in Canada - Regression results of seemingly unrelated regression model for panel data

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$ln(PaperCit_{it})$										
$ln\ (10^3 \times ClosCent_{t-2})$	0.0390 ***	0.1826 ***								
	(0.0121)	(0.0118)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	0.0001	-0.0127 ***								
	(0.0020)	(0.0020)								
$ln\ (10^4 \times EigenCent_{t-2})$			-0.0303***	0.0262***						
			(0.0061)	(0.0052)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			0.0399***	0.0370***						
			(0.0007)	(0.0006)						
$ln(10 \times DegCent_{t-2})$					-0.2532***	-0.2592 ***				
					(0.0057)	(0.0054)				
$[ln(10 \times DegCent_{t-2})]^2$					0.0737***	0.0768 ***				
					(0.0007)	(0.0007)				
$ln(10^4 \times BetCent_{t-2})$							0.0231***	0.0386***		
							(0.0060)	(0.0057)		
$[ln(10^4 \times BetCent_{t-2})]^2$							0.0457***	0.0459***		
							(0.0008)	(0.0008)		
$ln(10^3 \times Cliqness_{t-2})$									0.7322 ***	0.9246 ***
									(0.0125)	(0.0103)
$[ln(10^3 \times Cliqness_{t-2})]^2$									-0.1711 ***	-0.2108 ***
									(0.0027)	(0.0022)
nbAuthors	1.2806 ***	1.3278 ***	1.1218***	1.1257***	1.0889***	1.0851 ***	1.0888***	1.0847***	1.2050 ***	1.2135 ***
	(0.0045)	(0.0045)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0047)	(0.0047)	(0.0047)	(0.0046)
$dCanadaChair_{it}$	0.1807 ***	0.1735 ***	0.1716***	0.1241***	0.1688***	0.1162 **	0.1893***	0.1311***	0.0927 **	0.0442
	(0.0462)	(0.0463)	(0.0466)	(0.0466)	(0.0468)	(0.0468)	(0.0467)	(0.0466)	(0.0469)	(0.0466)
Age_{it-1}	0.0579 ***		0.0310***		0.0165***		0.0171***		0.0317 ***	
	(0.0009)		(0.0010)		(0.0010)		(0.0009)		(0.0009)	
$ln(AvgFunding)_{it-1}$		0.0226 ***		0.0227***		0.0206 ***		0.0222***		0.0198 ***
		(0.0010)		(0.0010)		(0.0010)		(0.0010)		(0.0009)
$ln(PatentCit_{it})$										
$ln\ (10^3 \times ClosCent_{t-2})$	0.0112	0.0096								
	(0.1281)	(0.1280)								
$[ln\ (10^3 \times ClosCent_{t-2})]^2$	-0.0017	-0.0013								
	(0.0212)	(0.0216)								
$ln\ (10^4 \times EigenCent_{t-2})$			0.0013	-0.0061						
			(0.0646)	(0.0550)						
$[ln\ (10^4 \times EigenCent_{t-2})]^2$			0.0028	0.0031						
			(0.0073)	(0.0068)						
$ln(10 \times DegCent_{t-2})$					-0.0268	-0.0314				
					(0.0572)	(0.0550)				
$[ln(10 \times DegCent_{t-2})]^2$					0.0071	0.0066				
					(0.0076)	(0.0075)				

ln(10^4 ×BetCent$_{t-2}$)							0.0007	-0.0100		
							(0.0624)	(0.0599)		
[ln(10^4 ×BetCent$_{t-2}$)]^2							0.0044	0.0049		
							(0.0086)	(0.0086)		
ln(10^3 ×Cliqness$_{t-2}$)									0.0614	0.0402
									(0.1331)	(0.1089)
[ln(10^3 ×Cliqness$_{t-2}$)]^2									-0.0149	-0.0104
									(0.0285)	(0.0237)
nbAuthors	0.0268	0.0249	0.0118	0.0110	0.0060	0.0060	0.0072	0.0068	0.0188	0.0175
	(0.0478)	(0.0492)	(0.0492)	(0.0495)	(0.0475)	(0.0475)	(0.0469)	(0.0468)	(0.0474)	(0.0481)
dCanadaChair$_{it}$	0.0033	0.0101	0.0047	0.0072	0.0045	0.0051	0.0060	0.0060	-0.0043	0.0006
	(0.4746)	(0.4917)	(0.4752)	(0.4798)	(0.4620)	(0.4631)	(0.4631)	(0.4648)	(0.4662)	(0.4732)
Age$_{it-1}$	-0.0013		-0.0042		-0.0055		-0.0057		-0.0038	
	(0.0098)		(0.0101)		(0.0101)		(0.0094)		(0.0099)	
ln(AvgFunding)$_{it-1}$		-0.0029		-0.0031		-0.0029		-0.0031		-0.0030
		(0.0104)		(0.0100)		(0.0097)		(0.0096)		(0.0097)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
Nb groups	3252	3252	3252	3252	3252	3252	3252	3252	3252	3252

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels. Standard errors are presented in parentheses.

Appendix B3-1 – Impact of collaborations on nanotech papers and patents in Canada - Regression results of seemingly unrelated regression model

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
ln(NumPaper$_{it}$)										
ln (10^3×ClosCent$_{t-2}$)	0.1409	0.3564 ***								
	(0.0881)	(0.0855)								
[ln (10^3×ClosCent$_{t-2}$)]^2	-0.0116	-0.0297 ***								
	(0.0074)	(0.0072)								
ln (10^4×EigenCent$_{t-2}$)			0.0011	0.0065						
			(0.0047)	(0.0047)						
[ln (10^4×EigenCent$_{t-2}$)]^2			-0.0001	-0.0003						
			(0.0006)	(0.0006)						
ln(10×DegCent$_{t-2}$)					-0.0149	-0.0116				
					(0.0100)	(0.0100)				
[ln(10×DegCent$_{t-2}$)]^2					0.0017*	0.0019 *				
					(0.0010)	(0.0010)				
ln(10^4×BetCent$_{t-2}$)							-0.0013	0.0016		
							(0.0025)	(0.0025)		
[ln(10^4×BetCent$_{t-2}$)]^2							0.0011**	0.0011**		
							(0.0004)	(0.0004)		
ln(10^3×Cliqness$_{t-2}$)									-0.0104 *	-0.0006
									(0.0058)	(0.0055)
[ln(10^3×Cliqness$_{t-2}$)]^2									-0.0006	-0.0030 ***
									(0.0010)	(0.0010)
nbAuthors	0.5098 ***	0.5108 ***	0.5106***	0.5108***	0.5095***	0.5091 ***	0.5070***	0.5065***	0.5071 ***	0.5070 ***
	(0.0023)	(0.0023)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0023)	(0.0023)
dCanadaChair$_{it}$	0.0139	0.0147	0.0135	0.0143	0.0142	0.0145	0.0145	0.0137	0.0135	0.0120
	(0.0096)	(0.0097)	(0.0096)	(0.0097)	(0.0096)	(0.0097)	(0.0096)	(0.0096)	(0.0095)	(0.0096)
Age$_{it-1}$	0.0032 ***		0.0033***		0.0032***		0.0025***		0.0024 ***	
	(0.0003)		(0.0004)		(0.0004)		(0.0004)		(0.0004)	
ln(AvgFunding)$_{it-1}$		0.0016 ***		0.0015***		0.0015 ***		0.0013***		0.0013 ***
		(0.0004)		(0.0004)		(0.0004)		(0.0004)		(0.0004)
Constant	-0.4262 *	-1.0381 ***	-0.0078	-0.0033	0.0273	0.0261	-0.0038	0.0044	0.0460 ***	0.0572 ***
	(0.2591)	(0.2522)	(0.0098)	(0.0099)	(0.0247)	(0.0248)	(0.0053)	(0.0051)	(0.0094)	(0.0092)
ln(NumPatent$_{it}$)										
ln (10^3×ClosCent$_{t-2}$)	1.3449 ***	1.4005 ***								
	(0.1528)	(0.1476)								
[ln (10^3×ClosCent$_{t-2}$)]^2	-0.1127 ***	-0.1174 ***								
	(0.0128)	(0.0124)								
ln (10^4×EigenCent$_{t-2}$)			0.0179**	0.0178**						
			(0.0081)	(0.0080)						
[ln (10^4×EigenCent$_{t-2}$)]^2			0.0008	0.0007						
			(0.0010)	(0.0010)						
ln(10×DegCent$_{t-2}$)					-0.0392**	-0.0403 **				
					(0.0172)	(0.0172)				
[ln(10×DegCent$_{t-2}$)]^2					0.0077***	0.0075 ***				

					(0.0017)	(0.0017)				
ln(10⁴×BetCent_{t-2})							0.0052	0.0028		
							(0.0043)	(0.0042)		
[ln(10⁴×BetCent_{t-2})]²							0.0033***	0.0033***		
							(0.0007)	(0.0007)		
ln(10³×Cliqness_{t-2})									0.0575 ***	0.0535 ***
									(0.0100)	(0.0096)
[ln(10³×Cliqness_{t-2})]²									-0.0147 ***	-0.0137 ***
									(0.0018)	(0.0017)
nbAuthors	0.0018	0.0020	-0.0037	-0.0038	-0.0074*	-0.0073 *	-0.0074*	-0.0070*	0.0003	0.0002
	(0.0040)	(0.0040)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
dCanadaChair_{it}	0.0012	0.0049	0.0034	0.0057	0.0029	0.0044	0.0012	0.0021	-0.0049	-0.0023
	(0.0166)	(0.0167)	(0.0165)	(0.0167)	(0.0165)	(0.0166)	(0.0165)	(0.0166)	(0.0165)	(0.0167)
Age_{it-1}	0.0008		-0.0002		-0.0014**		-0.0021***		-0.0011 *	
	(0.0006)		(0.0006)		(0.0006)		(0.0007)		(0.0007)	
ln(AvgFunding)_{it-1}		-0.0006		-0.0008		-0.0011 *		-0.0012*		-0.0012 *
		(0.0006)		(0.0006)		(0.0006)		(0.0006)		(0.0006)
Constant	-3.9467 ***	-4.1001 ***	-0.0540***	-0.0515***	0.0358	0.0377	-0.0010	-0.0077	0.0178	0.0151
	(0.4492)	(0.4353)	(0.0169)	(0.0170)	(0.0425)	(0.0425)	(0.0091)	(0.0088)	(0.0163)	(0.0159)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
ln(NumPaper)- Wald χ²	53987 ***	53399 ***	53963 ***	53366***	53992***	53485 ***	54176***	53915***	54512 ***	54271 ***
ln(NumPatent)- Wald χ²	169.83 ***	168.67 ***	224.60 ***	225.95***	282.38***	280.52 ***	289.84***	282.60***	203.05 ***	203.60 ***
ln(NumPaper)- R²	0.8818	0.8807	0.8818	0.8806	0.8818	0.8808	0.8822	0.8817	0.8828	0.8824
ln(NumPatent)- R²	0.0229	0.0228	0.0301	0.0303	0.0376	0.0373	0.0385	0.0376	0.0273	0.0274
Breusch-Pagan	1.151	0.751	0.888	0.843	1.306	1.642	2.993	2.653	2.583	2.738

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses

Note : All Breusch-Pagan tests of independence show that there is no correlation between both dependent variables at 10% level in the regression.

Appendix B3-2 – Impact of collaborations on citation of nanotech papers and patents in Canada - Regression results of seemingly unrelated Regression model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(PaperCit$_{it}$)										
ln (10^3×ClosCent$_{t-2}$)	19.0591 ***	21.8667 ***								
	(0.9297)	(0.9045)								
[ln (10^3×ClosCent$_{t-2}$)]^2	-1.5917 ***	-1.8280 ***								
	(0.0779)	(0.0758)								
ln (10^4×EigenCent$_{t-2}$)			0.1996***	0.2412***						
			(0.0484)	(0.0481)						
[ln (10^4×EigenCent$_{t-2}$)]^2			0.0176***	0.0163***						
			(0.0059)	(0.0059)						
ln(10×DegCent$_{t-2}$)					-0.6613***	-0.6546 ***				
					(0.1012)	(0.1011)				
[ln(10×DegCent$_{t-2}$)]^2					0.1184***	0.1195 ***				
					(0.0101)	(0.0101)				
ln(10^4×BetCent$_{t-2}$)							0.0631**	0.0667***		
							(0.0257)	(0.0252)		
[ln(10^4×BetCent$_{t-2}$)]^2							0.0431***	0.0434***		
							(0.0044)	(0.0044)		
ln(10^3×Cliqness$_{t-2}$)									0.6438 ***	0.7015 ***
									(0.0604)	(0.0579)
[ln(10^3×Cliqness$_{t-2}$)]^2									-0.1828 ***	-0.1970 ***
									(0.0110)	(0.0101)
nbAuthors	1.1318 ***	1.1443 ***	1.0507***	1.0527***	1.0023***	1.0026 ***	1.0246***	1.0254***	1.1095 ***	1.1099 ***
	(0.0243)	(0.0244)	(0.0243)	(0.0244)	(0.0239)	(0.0239)	(0.0240)	(0.0240)	(0.0240)	(0.0240)
dCanadaChair$_{it}$	0.0723	0.0810	0.1065	0.0937	0.0971	0.0713	0.0661	0.0334	-0.0118	-0.0318
	(0.1009)	(0.1023)	(0.0989)	(0.0998)	(0.0969)	(0.0975)	(0.0978)	(0.0984)	(0.0997)	(0.1005)
Age$_{it-1}$	0.0421 ***		0.0271***		0.0113***		0.0056		0.0151 ***	
	(0.0036)		(0.0037)		(0.0037)		(0.0039)		(0.0040)	
ln(AvgFunding)$_{it-1}$		0.0205 ***		0.0180***		0.0127 ***		0.0117***		0.0113 ***
		(0.0039)		(0.0038)		(0.0037)		(0.0037)		(0.0038)
Constant	-55.7335 ***	-63.7100 ***	-0.3118***	-0.2987***	1.1369***	1.1104 ***	0.3488***	0.3276 ***	0.8732 ***	0.9301 ***
	(2.7326)	(2.6669)	(0.1011)	(0.1018)	(0.2499)	(0.2501)	(0.0543)	(0.0524)	(0.0981)	(0.0956)
ln(PatentCit$_{it}$)										
ln (10^3×ClosCent$_{t-2}$)	1.1058 ***	1.0957 ***								
	(0.2205)	(0.2129)								
[ln (10^3×ClosCent$_{t-2}$)]^2	-0.0931 ***	-0.0923 ***								
	(0.0185)	(0.0178)								
ln (10^4×EigenCent$_{t-2}$)			0.0222*	0.0210*						
			(0.0117)	(0.0116)						
[ln (10^4×EigenCent$_{t-2}$)]^2			-0.0002	-0.0002						
			(0.0014)	(0.0014)						

ln(10×DegCent$_{t-2}$)					-0.0268	-0.0281				
					(0.0249)	(0.0249)				
[ln(10×DegCent$_{t-2}$)]^2					0.0059**	0.0057 **				
					(0.0025)	(0.0025)				
ln(10^4×BetCent$_{t-2}$)							0.0044	0.0016		
							(0.0063)	(0.0062)		
[ln(10^4×BetCent$_{t-2}$)]^2							0.0028***	0.0028**		
							(0.0011)	(0.0011)		
ln(10^3×Cliqness$_{t-2}$)									0.0544 ***	0.0484 ***
									(0.0145)	(0.0139)
[ln(10^3×Cliqness$_{t-2}$)]^2									-0.0131 ***	-0.0116 ***
									(0.0026)	(0.0024)
nbAuthors	-0.0033	-0.0035	-0.0079	-0.0081	-0.0115*	-0.0115 *	-0.0114*	-0.0111*	-0.0046	-0.0049
	(0.0058)	(0.0057)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0057)	(0.0057)
dCanadaChair$_{it}$	0.0003	0.0069	0.0018	0.0071	0.0017	0.0065	0.0005	0.0049	-0.0048	0.0012
	(0.0239)	(0.0241)	(0.0239)	(0.0241)	(0.0239)	(0.0240)	(0.0239)	(0.0240)	(0.0239)	(0.0241)
Age$_{it-1}$	-0.0001		-0.0011		-0.0021**		-0.0027***		-0.0018 *	
	(0.0009)		(0.0009)		(0.0009)		(0.0010)		(0.0009)	
ln(AvgFunding)$_{it-1}$		-0.0019 **		-0.0021**		-0.0023 **		-0.0024***		-0.0024 ***
		(0.0009)		(0.0009)		(0.0009)		(0.0009)		(0.0009)
Constant	-3.2340 ***	-3.1970 ***	-0.0609**	-0.0557**	0.0113	0.0162	-0.0038	-0.0082	0.0018	-0.0005
	(0.6480)	(0.6276)	(0.0244)	(0.0246)	(0.0616)	(0.0616)	(0.0133)	(0.0128)	(0.0235)	(0.0229)
Nb observations	7235	7235	7235	7235	7235	7235	7235	7235	7235	7235
ln(NumPaper)- Wald χ^2	3929 ***	3767 ***	4406***	4354***	4885***	4889 ***	4659***	4671***	4199 ***	4189 ***
ln(NumPatent)- Wald χ^2	79.23 ***	83.63 ***	99.29***	102.96***	120.05***	121.33 ***	121.27***	120.19***	91.05 ***	94.32 ***
ln(NumPaper)- R^2	0.3519	0.005	0.3785	0.3757	0.4031	0.4033	0.3917	0.3924	0.3672	0.3667
ln(NumPatent)- R^2	0.0108	0.0114	0.0135	0.0140	0.0163	0.0165	0.0165	0.0163	0.0124	0.0129
Breusch-Pagan	0.005	0.001	0.994	0.951	3.808	3.728	3.102	2.934	0.344	3252

Note: ***, **, * indicate significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses

Note : All Breusch-Pagan tests of independence show that there is no correlation between both dependent variables at 10% level in the regression.