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Collaboration or funding: lessons from a study of nanotechnology patenting in Canada and the United States

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Abstract This paper is concerned with how government research funding and collaboration between researchers affect academic technological production in the context of nanotechnology in Canada and in the United States. We use the co-invention and co-authorship networks of scientists to build indicators of collaborative behaviour and investigate whether the nature of the network plays a role in the academic technological productivity and quality. Results suggest that technological output has the potential to offer governments useful guidance concerning the effectiveness of academic grants and collaboration in the United States and in Canada. This paper provides evidence that the position of researchers in both co-invention and co-publication networks does influence technological productivity and quality.

Keywords Research funding · Academic patents · Collaboration · Nanotechnology

JEL Classification O31 · O34

1 Introduction

The rapid increase in academic patenting raises issues regarding the development of new technologies. Universities, as an important source of knowledge, traditionally contribute to solving research problems and publications, but in recent decades, universities have been involved in patenting and supporting industrial innovation (Lawson 2013). Recent development in relationship between university and industry, especially the growth of

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university patenting has attracted considerable attention over past decades. In 1980, the passage of the Bayh–Dole Act in the United States (US) removed patenting restrictions for universities and provided greater flexibility for university licensing agreements, and consequently, the number of academic patents has dramatically increased (Siegel et al. 2003). Bayh–Dole Act resulted in establishing technology transfer offices in universities to identify the potential commercial interest in exploiting and licensing the results of university research. In addition to being a trigger to re-evaluate the role of universities in society towards a multi-faceted and powerful knowledge transfer organization (Grimaldi et al. 2011).

Nanotechnology has been widely considered as one of the leading drivers of future economic development and has been of particular interest for national governments over recent years. Most countries have greatly strengthened their nanotechnology R&D programs and have given nanotechnology research a higher priority in their strategic economic planning (Dang et al. 2010; Pandza and Holt 2007; Shea 2005). Academic research has a strong role to play in the early stages of research program particularly in emerging knowledge-based technologies (Aghion et al. 2008), i.e. when the technology is not yet mature or market-ready.

Because of the large amount of investment in nanotechnology, the question of whether this substantial investment in nanotechnology research enhances technological innovations emanating from universities or only generates scientific output gains is a key issue here. Understanding the impact of funding is critical as it is not trivial that such government expenditure is effective. An efficient allocation of public funding requires identifying the impact of receiving government grant on the subsequent research output. We need more evidence to find out whether such researchers are likely to be more productive. This paper aims to find to what extent government research funding influences academic patenting in the field of nanotechnology in Canada and the US.

Paull et al. (2003) indicated that government investment plays an important role in the development of emerging technologies that are risky and need long-term research. For instance, the US has created the first major investment trend through the funding of the National Nanotechnology Initiative (NNI) to benefit from this new technology. Initiatives such as the NNI have created a new wave of government-funded research and have provided a proper base for nanotechnology development. The cumulative investment in NNI amounted to almost $21 billion over the period 2001–2015 (NNI 2014). Roco (2005) declared that accordingly many countries have followed suit and substantially increased investment in nanotechnology in recent years.

Canada has similarly launched various government-funded programs to support nanotechnology development: examples of federal research funding are provided via organizations such as the Canada Foundation for Innovation (CFI) and the National Research Council (NRC). In addition to the classic grant awarding organisations such as the Natural Sciences and Engineering Research Council (NSERC) and the Canadian Institutes of Health Research (CIHR), the National Institute for Nanotechnology (NINT), established in 2001, operates as a partnership between the NRC and University of Alberta and was jointly founded by the Government of Canada, the Government of Alberta and the University of Alberta. The considerable Canadian federal investments, and the lesser provincial and private sector investments earmarked for nanotechnology helped to spur R&D, attract leading researchers and facilitate the work of local communities of nano researchers in Canada (Hu et al. 2011; Steele 2008).

These nano researchers generally work in well-connected collaborative teams. In the last decades, there is more focus on formation of research collaboration and scientific networks. Academic researchers tend to participate in teams when they receive federal funding and their research would be benefited from new collaborations and may increase the likelihood of good quality and quantity of their research output. Hence, in order to advance knowledge in economics of science, technology and innovation, we need to examine academic research collaborations linking scientists to one another in a scientific environment. This paper explores the impact of a researcher's position in networks on technological activities and investigates whether the nature of the network plays a role in the academic technological productivity and quality. Much attention has been paid to university patenting in recent years and its interaction with university–industry collaborations is of great interest (Geuna and Nesta 2006; Lissoni 2009; Murray 2004). Our paper focuses on this collaborative behaviour of researchers and compares its effect with that of funding on technological output. While this study concentrates on an important field as the technologically advanced world has been considered it to be the future (Besley et al. 2008; El Naschie 2006), it provides direct insight into the scientific and innovative relationships between scientists at the same time, something that has not been considered in previous studies.

A complementary line of study examines this relationship in the US and Canada. The US, being one of Canada's major collaborative partners, there is a high occurrence of co-invention patents between the two countries. A study of 12 foreign patenting countries in the USPTO by Marinova and McAleer (2003) shows that the US ranked first and Canada ranked fifth in terms of the number of nanotechnology patents between 1975 and 2000. Given the breadth of potential applications and significant belief in the potential of nanotechnology to transform economy and society, Canada has followed the US and established nanotechnology initiatives to take advantage of innovation evolution in nanotechnology. Wong et al. (2007) ranked Canada in the 6th position amongst the top 10 inventor countries for nanotechnology patents between 1976 and 2004. In addition, they also found that Canada had the largest improvement in average citations received per patent between 2000 and 2004. In assessing nanotechnology patents, Chen and Roco (2009) demonstrated that Canada continued to rank in the top 10 nanotechnology assignee countries in 2005–2006.

Using patent data from the United States Patent and Trademark Office (USPTO) and other funding databases, this paper makes three useful contributions to prior studies. First, we focus on nanotechnology patents resulting from academic research and investigate whether government funding and collaborations increase the number of patents and enhance university patent quality. Second by focusing on two scientific and innovative networks between academic researchers, we examine the crucial role of these networks in driving technological progress. Third, we supplement our analyses with a comparison between the US and Canada to try to understand the affection of collaboration and funding in academic research. The remainder of the paper is organized as follows: the next section briefly describes the existing literature. We then introduce the data, variables and methodology employed in Sect. 3, and Sect. 4 presents the results. Finally, we conclude with a concise discussion in Sect. 5.

2 Conceptual framework

Academic research is regarded as a key source of new knowledge that contributes to technological change. Since the field of nanotechnology is science-based in nature, universities appear to have an enhanced role to play in terms of innovations and economic development (Etzkowitz et al. 2000). Not so long ago, it was not traditionally a prime concern for universities to bring academic research results to the industry, but it is now increasingly necessary for universities to become significantly involved in economic development, patenting and licensing activities (Van Looy et al. 2004; Perkmann and Walsh 2009; Muscio et al. 2013). Narin et al. (1997) highlighted that rapidly growing linkages exist between scientific publications and patents. Crespi et al. (2011) further showed that academic patenting even could complement publishing. Their findings indeed found an inverted U-shaped relationship between patenting output and publishing, suggesting a positive correlation up to a certain level of patenting. According to Meyer et al. (2010), nanotechnology is perceived to be a highly promising technology.

Wong et al. (2007) found that universities play an increasing role in nanotechnology patenting in Canada and the US. In this regard, governments aggressively support academic research to accelerate its progress via grants to cover the rather high research costs and infrastructure expenses associated with this new technology.

Given the influence of this emerging technology on future scientific and economic development, it is vital to identify the pivotal role of government funding aimed at stimulating nanotechnology. Because of the growth of funding trends in nanotechnology (Bhattacharya 2007; Crawley 2007; Davies 2007; Hullmann 2006; Roco 2005, 2011; Sargent 2008; Seear et al. 2009), it is not surprising that funders, i.e. mainly governments, seek to determine whether such funding increases the return to academic research output. According to Arora et al. (1998), moreover public grants affect both current and future researcher output. A strong correlation between research funding and technological performance has been identified by other scholars, indicating that this R&D funding can lead to the growth of technological production (see Chen et al. 2013; Coupé 2001; Foltz et al. 2000; Geffen and Judd 2004; Huang et al. 2005; Payne and Siow 2003; Piekkola 2007). For instance, the findings of Payne and Siow (2003) show that on average an increase of \$1 million in government research funding results in 0.2 more patents in universities. Furthermore, the statistical analysis of Huang et al. (2005) regarding US nanotechnology demonstrated that the number of citations that each National Science Foundation (NSF)-funded inventor received for patents was 5 times greater than that of other inventors.

In the US, there was an increase in public funding and university patenting in the 1980s due to the Bayh–Dole legislation, which gives intellectual property rights to academic patents derived from publicly funded universities (Argyres and Liebeskind 1998; Mowery and Sampat 2005; Siegel et al. 2003; Zucker and Darby 2005). According to their study of university patenting between 1965 and 1992, Henderson et al. (1998) showed that this act increased the number of patents while the number of inventors remained relatively constant. Mowery et al. (2001) further raised the point that the Bayh–Dole Act was one of the main factors that increased university patenting. In 1999, the Expert Panel on the Commercialization of University Research of the Canadian Prime Minister also suggested that universities should keep ownership of the patents that resulted from publicly funded research (Mowery and Sampat 2005). Grimaldi et al. (2011) reviewed the impact of Bayh–Dole Act and concluded that the ensuring increased research commercialization following its introduction has not decreased the amount of basic research performed in universities.

Thursby and Thursby (2011a, b) examined the research and invention disclosure of universities and their findings did not show any negative effect of this legislation on universities' traditional role in basic research compared to more commercial potential. Quite the contrary, the importance of universities in creating and exploiting knowledge in the aftermath of Bayh–Dole has increased. In addition, university research commercialization stimulated start-up activities, economic efficiency and encouraged entrepreneurship. Aldridge and Audretsch (2011) found that researcher entrepreneurship was prevalent in the Bayh–Dole era.

Academic technological productivity resulting from this increased investment can be assessed by two attributes: quantity and quality. Similarly to a number of science-based domains such as biotechnology or chemistry, nanotechnology heavily relies on patenting to protect intellectual property. A patent is an accessible technology document and patent data are presumed to be indicative of the value of innovations (Ernst 1998). Despite various indicators used to measure the variation of patent quality such as patent renewal data (Deng 2007; Griliches 1990; Harhoff et al. 1999; Hall et al. 2000; Maurseth 2005; Pakes and Schankerman 1984; Pakes 1986; Serrano 2010; Svensson 2011), or family size (Harhoff et al. 1999; Lanjouw and Schankerman 1999; Maurseth 2005; Martinez 2010), citations are more appropriately related to the importance and presence of a patent in other research, indicating the valuable technological content of that patent. While the first indicator is correlated with the value of innovation at the organizational rather than individual level, the second considers the number of countries in which a patent application is submitted.

Higher quality patents are more likely to contain technological advances that can create subsequent innovations (see Breschi and Lissoni 2004; Chen and Roco 2009; Daim et al. 2006; Griliches 1990; Hall et al. 2002; Huang et al. 2003; Huang et al. 2004; Li et al. 2007a, b; Wallin 2005). A number of indicators such as patent renewal, triadic patents, citations, etc. have been used in the literature (Maurseth 2005; Lanjouw and Schankerman 1999; Pakes and Schankerman 1984). According to Meyer et al. (2010), patent citation analysis is a prominent approach to track the strengths of links between science and technology. The citation of patents also indicates the importance of an innovation and can be a signal regarding to potential innovativeness. The signal is more important as the patent is cited more (Mazzucato and Tancioni 2013). Forward citations are the most common indicator used to measure patent "quality" by many scholars (Baron and Delcamp 2010; Breschi and Lissoni 2004; Harhoff et al. 1999; Hall et al. 2000; Lanjouw and Schankerman 1999; Maurseth 2005; Serrano 2010; Weingart 2005).

An alternative to citations as a proxy for patent "quality" is the number of claims. Claims describe the essential novel features of the invention and circumscribe the property rights conferred by a patent. Referring to prior studies, high quality patents contain a large number of claims and can be considered valuable since they indicate the breadth and scope of protection (Baron and Delcamp 2010; Lanjouw and Schankerman 2004; Tong and Frame 1994; Trappey et al. 2012). These measures are appropriate quality proxies given that they are highly correlated with valuable innovations (Trajtenberg 1990; Hall et al. 2000; Harhoff et al. 1999).

One of the questions that driven this research is how academic inventors are affected by government funding and whether dedicated nanotechnology public R&D funding increases the technological production and quality of universities. This assessment is essential for decision-making and R&D planning. However, prior studies that examined the impact of government grants in universities, most commonly focused on scientific output of academic researchers rather than on their technological output. A few studies (see Huang et al.

2005, 2006) specifically consider nanotechnology funding in such an emerging technology field, however, there is a great need to understand how technology development has evolved and been influenced by government funding over this short period of time. We propose *Hypothesis 1* to shed light on this issue:

Hypothesis 1 Academic inventors funded by the government contribute to (a) more nanotechnology patents and (b) higher quality patents than other academic inventors who are less funded by government.

In addition to research funding, numerous studies have investigated factors other than funding that have impacted academic innovation activities. Previous studies (Azoulay et al. 2009; Breschi et al. 2008; Crespi et al. 2008; Thursby and Thursby 2007; Van Looy et al. 2006) have further focused on the link between publications and patents and highlighted a correlation between university patenting and publishing activities. Other scholars have examined social networks and indicated that social relationships do matter for technological innovations, presuming that when researchers work together at least once, they will be able to exchange further information later (Balconi et al. 2004; Breschi and Lissoni 2004; Murray 2002; Newman 2000, 2001; Wasserman and Faust 1994).

In addition to funding, scientists cannot perform the work alone in the realm of increasingly complex technologies. Collaborating with other scientists has become the norm and contributes to improved productivity. Ma and Lee (2008), and Ruegg (2007) further studied technological collaborations and highlighted the role of these collaborative relationships on technological development. Their framework presumes that when inventors apply for a patent together, they will keep in touch afterwards for a period of time to exchange and share knowledge. In this regard, patents can be exploited to map the social relationships between researchers and to measure to what extent collaborative behaviour exists within research communities.

In recent years, these collaborations have attracted much theoretical attention regarding their influence on research productivity given the critical importance of research teams (Cagliano et al. 2000; Frenken et al. 2005; Teichert and Ernst 1999). The structure of networks formed by socially connected researchers influences the extent of knowledge diffusion and consequently the technological performance of inventors within these networks. Patenting activity is generally considered an appropriate proxy to measure technological performance and has been widely used in research studies to examine the impact of collaborative networks, built from co-publication and co-invention data, on research productivity, innovations and knowledge flows (Powell et al. 1999; Ahuja 2000; Breschi and Lissoni 2004, 2009; Lecocq and Van Looy 2009).

Co-invention networks are generally more fragmented than co-publication networks, mainly because there are a smaller number of co-inventors on a patent than there are co-authors on a paper, but academic inventors occupy more prominent and connected positions than non-academic inventors in these technological networks (Balconi et al. 2004; Breschi and Catalini 2008; Murray 2002). Similarly, Breschi and Catalini (2010) compared the patterns of connectivity in co-authorship and co-invention analysis and indicated that single inventor patents are more common than single author publications in scientific output. Furthermore, Breschi and Lissoni (2009) found that connected patents in co-inventor networks are of higher quality than non-connected patents measured by the number of citations they receive.

In this regard, we put forward two propositions on network behaviour from academic inventors in co-invention and co-publication networks to address the influence of social networks on the technological output.

Hypothesis 2 The technological performance of academic inventors who hold a more influential network position in **co-invention** networks is (a) higher and (b) yields better quality patents.

Hypothesis 3 The technological performance of academic inventors who hold a more influential network position in **co-publication** networks is (a) higher and (b) yields better quality patents.

3 Data and methodology

3.1 Data

Our empirical context is associated to the innovative output of academic researchers in nanotechnology. To construct the necessary panel dataset, we drew on various funding, patents and publication databases in Canada and the US. We created two databases of Canadian and American patents in the field of nanotechnology extracted from the United States Patent and Trademark Office (USPTO), using the affiliations of authors to distinguish Canadian-based and US-based inventors.[1] For the American-based inventors we used the Nanobank and StartechZD databanks (which both contain subsets of the USPTO). The justification for using the USPTO instead of the Canadian Intellectual Property Office (CIPO) is that the latter does not systematically contain inventor's addresses, which complicates the disambiguation process. Beaudry and Schiffauerova (2011) suggested that Canadian nanotechnology inventors file their patent applications in the US as well as, or in lieu of, in Canada. Similarly, a country patent analysis by Li et al. (2007b) demonstrated that the number of Canadian patents in the USPTO is much higher than in the European Patent Office (EPO).

To identify nanotechnology-related patents, we performed a lexical extraction on patents which contain nanotechnology related keywords. We used a set of keywords suggested by Porter et al. (2008), Schmoch et al. (2003), Zitt and Bassecoulard (2006), Mogoutov and Kahane (2007) and Zucker et al. (2011). These studies used distinct keywords in their definition of nanotechnology but as there is no agreement on a unified lexical query delineating core nanotechnology keywords, we utilized the keywords which were used in more than one study and considered common keywords of the all keywords used by these different studies. We used this set of common keywords and consulted with nanotechnology experts to validate this choice. This process was very useful and led us to remove some redundant keywords and keywords that would lead to false positive results. Finally we used these keywords in the USPTO database and then extracted only the patents for which at least one inventor had an address in Canada or the US. Using a similar keyword query, we then added nanotechnology-related scientific publications from Elsevier's Scopus.

For the purpose of our analysis, we extracted data between the years 1985–2005. The reason that 2005 is chosen as the end year for the sample is that we aimed to have enough citation years after the end date for the sample (2005) because we examined three periods for citations, 3, 5 and 7 years after grant year for patents. It is not uncommon to find patents that have taken 5 years to be granted and then to count 5 years of citations delays us to 2015. For the analysis that follows the start year of the panel, we chose 1996 for two

[1] Patents with both Canadian and US inventors were counted in both sets.

reasons: first, prior to that date, too few nanotechnology papers and patents are found, second, the Scopus database changed to include many more journals with publication year after 1995.

Patents were employed to build collaborative co-invention networks and articles were used to construct the co-publication networks in 3-, 5- and 7-year intervals starting in 1985. These time intervals are an important consideration in our analysis since we assume that researchers keep in touch to share and exchange their knowledge over time.

Our source of data for funding in both countries is federal funding. Data on federal grants for the US was collected from the Nanobank and StartechZD databases. The government grant data for Canadian researchers was retrieved from two of the three federal agencies: the National Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Institutes of Health Research (CIHR).[2] The data was then precisely and manually cleaned and databases were merged to finally end up with a target panel data for the examination. The data from the Nanobank and the StartechZD databanks were already cleaned. In Canada, the merge between grants, patents and publication databases was performed manually to avoid cases of homonymy and of synonymy. We are confident[3] to have minimised ambiguities by proceeding this way for Canada.

3.2 Dependent variables

To establish the base model, we take into account the number and two proxies for the quality of patents and the complex relationship between funding and collaborative determinants. The first dependent variable, the number of patents (NP_{it}), accounts for the production of technology. Two other variables, the number of citations (NCi_{it}) and the number of claims (NCl_{it}),[4] are proxies for patent quality in the base model (in Eq. 6).

Similarly to the networks, three different time frames were considered in order to count the number of citations: 3-, 5- and 7-year. In the final model, we used the 5-year window for which we found more consistently significant results rather compared to the two other periods.

For each academic inventor the dependent variables are the following:

$$NCi_{it} = \sum_{p=1}^{n} \sum_{j}^{j+5} nCit_{pitj} \tag{1}$$

[2] These two federal agencies invested considerable amounts of funding on nanotechnology and nanomedicine in Canada and they were initiatives in launching research programs in this field. NSERC's funding allocation supports the participation of academic researchers in nanotechnology.

[3] We did a considerable amount of work to clean the data as much as possible to correctly identify inventors and their names. For example to overcome the disambiguation of addresses of individuals, their affiliations were checked manually to clearly identify the inventors from universities, we checked for misspelling of names and eliminated dual entries and identified the researchers with similar names but different affiliations and addresses through time. We assigned unique IDs for individuals to use them as reference point which gave us an excellent base for the merging of different databases. The funding data was provided by the government and had been cleaned and verified. The fact that Scopus links authors with their affiliations was a great help to match with patenting databases and to disambiguate the data.

[4] Because of the gap between patent filing years and patent issue years, we track the impact of funding on the patents based on their filing date for the number of patents and the number of claims, but for citation, the issue year of the patent is considered.

$$NCl_{it} = \sum_{p=1}^{n} nClaim_{pit} \quad (2)$$

where $nCit_{pitj}$ and $nClaim_{pit}$ are respectively the number of forward citations up to j years after the granting year and the number of claims of patent p for inventor i that was filed in year t.

3.3 Independent variables

The average yearly amount of government funding received by an academic-inventor i over the past three years (F) enables us to test our first hypothesis. For the collaboration variables, we make use of the tools developed for social network analysis, i.e. betweenness centrality and the clustering coefficient. Betweenness centrality (BC) measures the importance of intermediary researchers in the network. It is calculated by the number of shortest connecting path (geodesic distance[5]) between two nodes. In our networks the nodes represent individual scientists or inventors. Betweenness centrality was first suggested by Freeman (1977) as an indicator of the level of control of a specific researcher on communication and knowledge sharing within an interrelated community. According to some scholars (see Balconi et al. 2004; Salmenkaita 2004; Izquierdo and Hanneman 2006), betweenness centrality in co-invention networks is positively correlated with the productivity of scientists. If a researcher with a high level of betweenness centrality leaves the network, the network may break into smaller subnetworks. For a researcher k, this indicator is calculated by (Leydesdorff 2007):

$$BC(k) = \sum_{i} \sum_{j} \frac{g_{ij}(k)}{g_{ij}}, \quad \forall i \neq j \neq k \quad (3)$$

where g_{ij} indicates the number of geodesic paths between i and j and $g_{ij}(k)$ is defined as the number of these paths that include researcher k. From this equation, we derive two variables: PBC measures betweenness centrality in the co-invention network (the prefix P stands for patents) and ABC measures betweenness centrality in the co-publication network (the prefix A hence stands for articles).

The clustering coefficient (CC) is defined as the likelihood that two researchers are related when they both have a mutual relationship with a third researcher in the network. This measure represents the tendency of researchers to cluster. Networks with a high clustering coefficient enhance the innovative output and performance of individuals. Clustering offers connectivity between researchers and increases the speed with which, and the probability that, partners access knowledge (Schilling and Phelps 2007). The clustering coefficient is calculated by Eq. 4:

$$CC_i = \frac{2E_i}{k_i(k_i - 1)} \quad (4)$$

where k_i is the number of neighbours of i and E_i denotes the number of direct links that connects the k_i nearest neighbours of researcher i (Watts and Strogatz 1998). For this equation, we also derive two variables: PCC measures the clustering coefficient in the co-

[5] The geodesic distance is the shortest distance between two nodes indicated the number of relationships in the shortest path connecting one researcher to another.

invention network (the prefix P stands for patents) and ACC measures the clustering coefficient in the co-publication network (the prefix A stands for articles).

We employ software package Pajek to calculate these network determinants for our two co-publication and co-invention networks. The two network characteristics of the co-invention network (PBC and PCC) and of the co-publication network (ABC and ACC) are used to evaluate hypothesis 2 and hypothesis 3.

3.4 Model

An important consideration in this study is the potential influence of the time delay between our explanatory variables and research output. The patenting of innovations or the publication of results is more likely to occur at the end of a funding period or within a few years of setting up a scientific or technological network. Given this time delay, we assume a 1-year lag[6] for funding and a 2-year[7] lag for the network determinants before publication/ application of research output. Our model can therefore be expressed as:

$$\left\{ \begin{matrix} NP_{it} \\ C(NCi_{it}) \\ NCl_{it} \end{matrix} \right\} = f\begin{pmatrix} \ln(F_{it-1}), NPP_{it-1}, PBB_{it-2} \\ PCC_{it-2}, ABC_{it-2}, ACC_{it-2}, D_t \end{pmatrix} \tag{5}$$

where D_t represent time dummy variables.

To analyze the data, we estimate Poisson and Negative Binomial regression models, which are both appropriate for count measures (numbers of patents and claims). The former provides a means to deal with skewness and the latter allows us to account for significant over-dispersion. In the presence of over-dispersion which was observed in our data, the negative binomial model is more appropriate. Because nanotechnology-related patents received fewer citations and are not in sufficient numbers to be examined as a count variable, we hence created an ordered categorical variable for the number of forward citations. We define a categorical variable ($C(NCi_{it})$) based on the number of citations received over 5 years. This variable takes the value 0 if NCi_{it} is 0, the value 1 if NCi_{it} is between 1 and 5, and the value 2 if the number of citations over 5 years is more than 5 (Eq. 6). Ordered probit regressions are appropriate for modeling with such a categorical dependent variable. This model distinguishes unequal differences between ordinal categories of dependent variable (Greene 2003).

$$C(NCi_{it}) = \begin{cases} 0 & if \quad NCi_{it} = 0 \\ 1 & if \quad 1 \le NCi_{it} \le 5 \\ 2 & if \quad NCi_{it} > 5 \end{cases} \tag{6}$$

The inclusion of funding and research output in this equation raises concerns regarding potential endogeneity. The decision to assign grants to scientists and their prior and subsequent research output are intrinsically linked, in addition to which we may have some omitted variables that affect the opportunity to receive grants. Researchers with a higher performance receive more funding from governments, and the amount of future grants raised may be related to previous productivity of researchers.

[6] This study has considered various time lags, 1-, 2- and 3-year lag, for funding and 1-year lag was found to be more appropriate yielding the most consistently significant results which was similar to the time lag that Beaudry and Allaoui (2012) used in their study of the impact of funding on publications.

[7] Different time lags were tested and we found 2-year lag produced the most consistent results.

To specifically address this concern and control for potential endogeneity, we employ the Two-Stage-Residual-Inclusion used by Bíró (2009). We therefore estimate a variant of the model using a set of instruments for the estimation of our funding variable (Eq. 7), the endogenous variable. We include the career age of a scientist since the first publication or the first grant or the first patent in the field of nanotechnology, Age, as a proxy for real age. The quadratic form of this variable (Age^2) helps account for potential non-linearity. The number of past articles of researchers over 3 years (NA) is included to explain the fact that funding is generally given to academic researchers with a high publication rate (Van Raan 2004).

$$\ln(F_{it-1}) = g\begin{pmatrix} Age_{it-1}, NA_{it-2} \\ NPP_{it-1}, PBC_{it-2}, PCC_{it-2} \\ ABC_{it-2}, ACC_{it-2}, D_t \end{pmatrix} \tag{7}$$

Endogeneity tests using the Durbin–Wu–Hausman test showed that our funding regressor is in fact endogenous. We then performed tests for overidentifying restrictions[8] where the null hypothesis is that the instruments are valid instruments. This tests that the instruments are not correlated with the error term and the excluded instruments are correctly excluded from the model. The results showed that our instruments are valid instruments.

The residuals of this first-stage equation are then added to the regressors of the second stage equation given by Eq. (5) prior to its estimation. Because of a small number of years of observations per academic-inventor, our estimations provide clustered robust standard errors rather than what would be obtained from panel regressions.

Moreover, the network positions occupied by individuals may be a result of high quality publication and inventive activity, which once again raises the issue of possible endogeneity problem related to these variables as well. Prior studies show that knowledge diffusion is more efficient in clustered networks since collaboration among such network facilitates the sharing of new knowledge (Cowan and Jonard 2004; Cowan 2005). Well-connected scientists because of their higher involvement with other researchers in these higher clustered networks are presumed to possess a greater ability to produce output. This also becomes more important when members have high knowledge levels in a clustered group and are known as the source of knowledge and innovation in that cliquish group (Cowan and Jonard 2004). A researcher with a more cliquish position is more likely to attract other researchers to his/her "clique" as additional co-inventors by virtue of his/her reputation among other researchers. These concepts are closely intertwined and can be a cause of potential endogeneity due to a simultaneity problem. We therefore suspect that our network variables are likely to be endogenous.

To address this endogeneity concern regarding our second and third hypotheses, we estimated instrumental variables regressions and Durbin–Wu–Hausman tests to determine whether endogenous regressors in the model are in fact exogenous variables. Tests regarding potential endogeneity of the network variables all failed to reject endogeneity in our study. Similar results were obtained for the co-publication and co-invention networks.

[8] This includes Sargan statistic, Basmann test and Sargan and Basmann pseudo-F test.

Table 1 Impact of funding and collaborations on nanotechnology patents in Canada and in the United States

NP_{it}	Canada			United States					
	(1)	(2)	(3)	(4)		(5)		(6)	
	1-1 (NO End.)	2-1 (NO End.)	3-1 (NO End.)	4-1 (NO End.)	4-2 (2SRI)	5-1 (NO End.)	5-2 (2SRI)	6-1 (NO End.)	6-2 (2SRI)
$ln(F_{it-1})$	−0.0603	−0.0726	−0.0896	0.0218	0.2236***	0.0173	0.2216***	0.0110	0.1608***
	(0.1283)	(0.1275)	(0.1301)	(0.0287)	(0.0391)	(0.0285)	(0.0388)	(0.0259)	(0.0372)
$[ln(F_{it-1})]^2$	0.0065	0.0077	0.0092	−0.0010	−0.0027	−0.0006	−0.0024	−0.0002	−0.0016
	(0.0128)	(0.0127)	(0.0130)	(0.0025)	(0.0026)	(0.0025)	(0.0026)	(0.0022)	(0.0023)
NPP_{it-1}	0.4129***	0.4344***	0.4046***	0.1691***	0.1540***	0.1735***	0.1588***	0.3097***	0.2871***
	(0.0443)	(0.0487)	(0.0525)	(0.0072)	(0.0074)	(0.0074)	(0.0076)	(0.0299)	(0.0287)
$[NPP_{it-1}]^2$	−0.0100***	−0.0101***	−0.0091***					−0.0086***	−0.0077***
	(0.0032)	(0.0031)	(0.0035)					(0.0021)	(0.0020)
$ln(10^4 \times PBC_{it-2})$	0.3962***			0.1223	0.1202	0.4884***	0.5455***	0.0983	0.1341
	(0.1522)			(0.0935)	(0.1081)	(0.1325)	(0.1362)	(0.0956)	(0.1119)
$ln(10^4 \times ABC_{it-2})$	0.0815			0.0321	−0.0514	0.0820	−0.0138	0.0845	−0.0087
	(0.0704)			(0.1688)	(0.1980)	(0.1641)	(0.1876)	(0.1690)	(0.1943)
$ln(10^3 \times PCC_{it-2})$		−0.0384	0.5446***	0.0056	0.0066	0.0036	0.0044	−0.0641	−0.1570*
		(0.0235)	(0.2048)	(0.0073)	(0.0072)	(0.0074)	(0.0073)	(0.0882)	(0.0909)
$[ln(10^3 \times PCC_{it-2})]^2$			−0.0868***					0.0081	0.0221
			(0.0304)					(0.0131)	(0.0135)
$ln(10^3 \times ACC_{it-2})$		0.0546**	0.3432**	−0.0227**	−0.0492***	−0.0216**	−0.0487***	0.0552	0.0957
		(0.0218)	(0.1727)	(0.0093)	(0.0097)	(0.0092)	(0.0096)	(0.1270)	(0.1315)
$[ln(10^3 \times ACC_{it-2})]^2$			−0.0449*					−0.0101	−0.0191
			(0.0267)					(0.0189)	(0.0196)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$						−0.0444***	−0.0536***		
						(0.0104)	(0.0132)		

Table 1 continued

NP_{it}	Canada			United States					
	(1)	(2)	(3)	(4)		(5)		(6)	
	1-1 (NO End.)	2-1 (NO End.)	3-1 (NO End.)	4-1 (NO End.)	4-2 (2SRI)	5-1 (NO End.)	5-2 (2SRI)	6-1 (NO End.)	6-2 (2SRI)
Residual($ln(F_{it-1})$)					−0.1877***		−0.1892***		−0.1377***
					(0.0270)		(0.0250)		(0.0270)
Constant	−2.7334***	−2.6812***	−2.7198***	−1.1075***	−1.8673***	−1.1135***	−1.8787***	−1.2488***	−1.7978***
	(0.2443)	(0.2623)	(0.2599)	(0.0680)	(0.1368)	(0.0678)	(0.1292)	(0.0818)	(0.1336)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(*alpha*)	−0.0064	−0.0675	0.0060	−0.3165***	−0.3795***	−0.3274***	−0.3982***	−0.6455***	−0.6679***
	(0.2544)	(0.2649)	(0.2479)	(0.0871)	(0.0861)	(0.0874)	(0.0867)	(0.1175)	(0.1136)
Nb observations	1329	1329	1329	9157	9157	9157	9157	9157	9157
Nb groups	532	532	532	5381	5381	5381	5381	5381	5381
Loglikelihood	−656.496	−655.736	−651.37	−6828	−6786.6	−6820	−6777.4	−6689	−6666
χ^2	226.57***	234.44***	204.41***	1618***	1649.4***	1696.2***	1742.7***	3135.3***	2923.2***

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

Table 2 Impact of funding and collaborations on the citations received by nanotechnology patents in Canada and in the United States

$C(NCi_{it})$	Canada				United States			
	(1)		(2)		(3)		(4)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End.)	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)	4-1 (NO End.)	4-2 (2SRI)
$ln(F_{it-1})$	−0.0142	0.1047	−0.0058	0.1019	−0.0569	−0.2364	−0.0656	−0.2556
	(0.1194)	(0.1805)	(0.1203)	(0.1821)	(0.1722)	(0.1896)	(0.1745)	(0.1942)
$[ln(F_{it-1})]^2$	0.0000	−0.0005	−0.0009	−0.0014	0.0024	0.0028	0.0033	0.0039
	(0.0115)	(0.0117)	(0.0117)	(0.0119)	(0.0152)	(0.0154)	(0.0154)	(0.0156)
NPP_{it-1}	0.3963***	0.4337***	0.3842***	0.4199***	0.1286***	0.1557***	0.1308***	0.1582***
	(0.0855)	(0.0851)	(0.0868)	(0.0888)	(0.0234)	(0.0311)	(0.0234)	(0.0331)
$[NPP_{it-1}]^2$	−0.0162**	−0.0170***	−0.0159**	−0.0167***	−0.0020***	−0.0027***	−0.0019***	−0.0028**
	(0.0067)	(0.0064)	(0.0065)	(0.0063)	(0.0005)	(0.0010)	(0.0005)	(0.0011)
$ln(10^4 \times PBC_{it-2})$	0.1489	0.2033	0.0110	0.0777	−0.0814	−0.0418	0.0214	0.0060
	(0.1695)	(0.1733)	(0.2217)	(0.2367)	(0.1765)	(0.1837)	(0.1910)	(0.1982)
$ln(10^3 \times PCC_{it-2})$	0.1308***	0.1061**	0.4228	0.3614	0.0017	−0.0018	−0.2370	−0.1073
	(0.0422)	(0.0514)	(0.3185)	(0.3379)	(0.0268)	(0.0271)	(0.2287)	(0.2435)
$[ln(10^3 \times PCC_{it-2})]^2$			−0.0435	−0.0377			0.0359	0.0160
			(0.0465)	(0.0481)			(0.0345)	(0.0365)
$ln(10^3 \times ACC_{it-2})$	0.0048	−0.0025	0.0022	−0.0043	0.0104	0.0118	0.0084	0.0087
	(0.0338)	(0.0325)	(0.0339)	(0.0326)	(0.0272)	(0.0279)	(0.0269)	(0.0277)
$Residual(ln(F_{it-1}))$		−0.1168		−0.1063		0.1799**		0.1872**
		(0.1193)		(0.1215)		(0.0717)		(0.0733)
Constantcut1	2.1299***	2.9056***	2.0894***	2.7969***	2.7530***	2.0324***	2.7646***	2.0160***
	(0.4731)	(0.8975)	(0.4733)	(0.9261)	(0.4623)	(0.5839)	(0.4684)	(0.5893)
Constantcut2	2.9937***	3.7714***	2.9591***	3.6681***	3.8086***	3.1169***	3.8240***	3.1062***
	(0.5182)	(0.9087)	(0.5134)	(0.9339)	(0.6248)	(0.7400)	(0.6310)	(0.7466)
Nb observations	201	201	201	201	2531	2531	2531	2531

Table 2 continued

$C(NCi_{it})$	Canada				United States			
	(1)		(2)		(3)		(4)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End.)	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)	4-1 (NO End.)	4-2 (2SRI)
Nb groups	155	155	155	155	1966	1966	1966	1966
χ^2	62.80***	65.43***	77.79***	82.00***	2060.7***	1950.9***	1950.5***	1827.5***
Pseudo R^2	0.2700	0.2723	0.2745	0.2738	0.3003	0.3119	0.3140	0.3087

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

4 Empirical Results

The estimation results for models mentioned in the previous section are shown in Tables 1, 2 and 3 and include the results of Ordered probit regressions (Table 2), Negative Binomial regressions (Table 1, 3) of Eq. 6 (second stage) and OLS regression of Eq. 6 (no endogeneity) using the clustering method appropriate to repeated observations for the same individual over a number of years. In each table, we consider 6 models estimated both with and without controlling for potential endogeneity (2SRI and No end.). The results of first stage regressions (Eq. 7) are presented in "Appendix 2". Our analyses have considered various sets of variables in a hierarchical progression including non-linear effects.

When we consider the number of generated patents, the results in Table 1 show no impact of funding (F) on technological productivity in Canada: even when we re-estimated the results to correct for potential endogeneity, we cannot capture the endogeneity. In the US, in contrast, there is a positive impact of lagged federal funding (1-year lag) on the number of patents when we account for endogeneity. The results are robust to the introduction of a quadratic effect of network measures (Models 3 and 6). In terms of instrument variables, they are all strongly significant and appropriate for the US, and in Canada only the number of articles over the past 3 years (NA_{it}) does not seem to be a consistently good instrument, but the age variable (Age) which we used as a proxy for career age of researchers is significant. These significant results show that these variables affect the amount of funding received by researchers and can be appropriate instruments to correct the potential endogeneity. While, we successfully account for endogeneity in the US, the results cannot capture the endogeneity in Canada. In terms of capturing the endogeneity, we also need our instrumental variables to be validated and verified by examining their correlation with other exogenous variables, with dependent variables and with our endogenous variable. This condition was also respected in models that we captured endogeneity problem and we found these instrumental variables significant in the first stage of 2SRI models, which suggests that these are appropriate instruments to correct the potential endogeneity in our models.

Our findings in the US are generally in line with that of other scholars (Chen et al. 2013; Huang et al. 2005; Payne and Siow 2003) who found a correlation between funding and technological productivity. In addition, past experience in patenting activity (NPP_{it}) is associated with new patents in both Canada and the US. Examining the quadratic effect of a researcher's industrial interests in the past 3 years shows that this positive impact has a limit: the maximum threshold of the resulting inverted-U relationship corresponds to roughly 20 patents for Canada and 18 patents for the US. Contributing to more patents beyond these points is associated with a decreasing trend (Fig. 1).

In terms of the role that collaboration in co-invention research networks plays in patenting activity, our results find a positive impact of betweenness centrality (PBC) on the number of patents. The results are consistently significant in Canada. In the US we are only able to find this positive impact in Model 5 when we include the interactive variable. Turning to the betweenness centrality of co-authorship networks, we cannot find any impact on the technological productivity of researchers. These results confirm that in terms of technological productivity, a more central position in a co-invention network is more important than in a co-authorship network.

When we account for the nonlinear form of the clustering coefficient measure of these two networks (PCC, ACC) variables in the model, we observe a positive linear impact and a negative quadratic impact in both of these networks in Canada, indicating an inverted-U

Table 3 Impact of funding and collaborations on the number of claims of nanotech patents in Canada and the United States

NCL_{it}	Canada						United States					
	(1)		(2)		(3)		(4)		(5)		(6)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End.)	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)	4-1 (NO End.)	4-2 (2SRI)	5-1 (NO End.)	5-2 (2SRI)	6-1 (NO End.)	6-2 (2SRI)
$ln(F_{it-1})$	−0.1080	−0.3745*	−0.0878	−0.2952	−0.1774	−0.5926**	0.2397***	0.4352***	0.2346***	0.4275***	0.2379***	0.4161***
	(0.1646)	(0.2080)	(0.1639)	(0.2060)	(0.1709)	(0.2332)	(0.0576)	(0.0705)	(0.0576)	(0.0705)	(0.0591)	(0.0713)
$[ln(F_{it-1})]^2$	0.0113	0.0093	0.0097	0.0087	0.0174	0.0168	−0.0188***	−0.0193***	−0.0184***	−0.0189***	−0.0188***	−0.0196***
	(0.0164)	(0.0162)	(0.0164)	(0.0162)	(0.0171)	(0.0174)	(0.0049)	(0.0050)	(0.0049)	(0.0050)	(0.0050)	(0.0051)
NPP_{it-1}	0.3764***	0.4588***	0.3982***	0.4251***	0.4488***	0.5167***	0.2393***	0.2115***	0.2468***	0.2192***	0.3066***	0.2740***
	(0.0725)	(0.0819)	(0.0938)	(0.0967)	(0.0975)	(0.1000)	(0.0136)	(0.0130)	(0.0141)	(0.0134)	(0.0156)	(0.0150)
$[NPP_{it-1}]^2$	−0.0074	−0.0150**	−0.0081	−0.0116*	−0.0128**	−0.0206***					−0.0055***	−0.0047***
	(0.0053)	(0.0061)	(0.0061)	(0.0065)	(0.0059)	(0.0065)					(0.0004)	(0.0004)
$ln(10^4 \times PBC_{it-2})$	0.4549**	0.5926**					0.0887	0.1149	0.4065**	0.4350***	−0.0776	−0.0036
	(0.2013)	(0.2316)					(0.1166)	(0.1192)	(0.1653)	(0.1640)	(0.1522)	(0.1554)
$ln(10^4 \times ABC_{it-2})$	0.1411	0.2218**					−0.1119	−0.0605	−0.0709	−0.0449	−0.0497	−0.0099
	(0.0961)	(0.1045)					(0.2413)	(0.2530)	(0.2387)	(0.2513)	(0.2495)	(0.2609)
$ln(10^3 \times PCC_{it-2})$			−0.0284	−0.0092	0.9810***	1.1145***	−0.0019	−0.0009	−0.0036	−0.0026	0.3728	0.2629
			(0.0380)	(0.0382)	(0.2815)	(0.2883)	(0.0147)	(0.0147)	(0.0149)	(0.0148)	(0.2308)	(0.2312)
$[ln(10^3 \times PCC_{it-2})]^2$					−0.1545***	−0.1707***					−0.0566*	−0.0401
					(0.0424)	(0.0433)					(0.0337)	(0.0337)
$ln(10^3 \times ACC_{it-2})$			0.0392	0.0538*	0.7921***	1.2389***	−0.0207	−0.0522***	−0.0206	−0.0516***	0.5505*	0.7240**
			(0.0315)	(0.0309)	(0.2466)	(0.3008)	(0.0162)	(0.0171)	(0.0162)	(0.0171)	(0.2996)	(0.3184)
$[ln(10^3 \times ACC_{it-2})]^2$					−0.1191***	−0.1851***					−0.0842*	−0.1140**
					(0.0372)	(0.0454)					(0.0438)	(0.0466)

Table 3 continued

NCL_{it}	Canada						United States					
	(1)		(2)		(3)		(4)		(5)		(6)	
	1-1 (NO End.)	1-2 (2SRI)	2-1 (NO End.)	2-2 (2SRI)	3-1 (NO End.)	3-2 (2SRI)	4-1 (NO End.)	4-2 (2SRI)	5-1 (NO End.)	5-2 (2SRI)	6-1 (NO End.)	6-2 (2SRI)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$									−0.0552***	−0.0554***		
									(0.0134)	(0.0133)		
$Residual(ln(F_{it-1}))$		0.3056**		0.2329*		0.4467***		−0.1950***		−0.1919***		−0.1749***
		(0.1446)		(0.1309)		(0.1579)		(0.0317)		(0.0314)		(0.0315)
Constant	0.3409	2.0425**	0.4906	1.7625**	0.4563	2.9577***	1.8040***	1.1190***	1.7953***	1.1222***	1.7564***	1.1478***
	(0.3256)	(0.8731)	(0.3122)	(0.8184)	(0.3249)	(0.9522)	(0.0957)	(0.1602)	(0.0961)	(0.1593)	(0.0982)	(0.1602)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ln(alpha)	3.2671***	3.2599***	3.2730***	3.2685***	3.2515***	3.2386***	2.3505***	2.3432***	2.3497***	2.3425***	2.3380***	2.3322***
	(0.0837)	(0.0833)	(0.0835)	(0.0833)	(0.0838)	(0.0836)	(0.0272)	(0.0272)	(0.0272)	(0.0273)	(0.0272)	(0.0273)
Nb observations	1329	1329	1329	1329	1329	1329	9157	9157	9157	9157	9157	9157
Nb groups	532	532	532	532	532	532	5381	5381	5381	5381	5381	5381
Loglikelihood	−1535.46	−1534.34	−1536.38	−1535.67	−1533.05	−1531.06	−17,890.2	−17,876	−17,888.6	−17,875.2	−17,865.9	−17,855
χ^2	219.38***	251.22***	238.50***	245.62***	146.26***	143.0889***	1825.5***	1836.9***	1872.4***	1890.6***	2263.6***	2281.4***

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

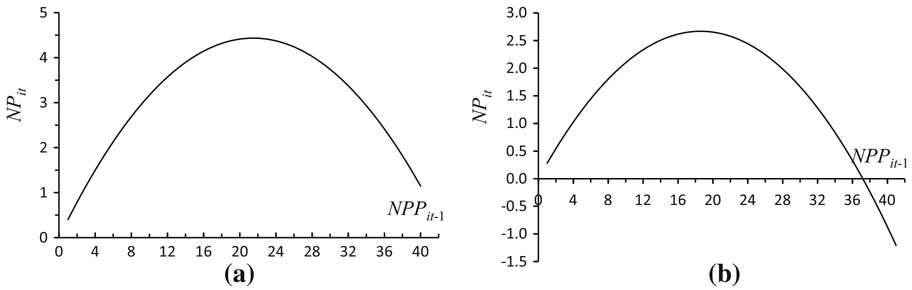


Fig. 1 Non-linear impact of the number of patents in past 3 years (*NPP*) on the number of patents in **a** Canada and **b** in the United States

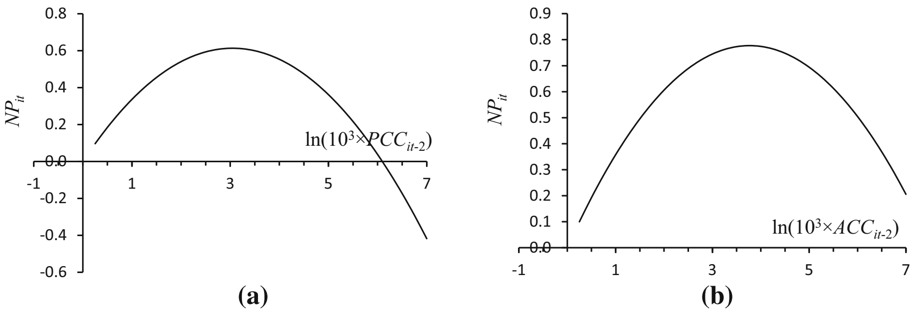


Fig. 2 Non-linear impact of the clustering coefficient in **a** the co-invention network (*PCC*) and **b** the co-publication network (*ACC*), on the number of patents in Canada (Model 3-1)

shape relationship. This implies that when researchers tend to cluster, they are more likely to produce more patents, but a higher clustering coefficient value exhibits decreasing returns (see Fig. 2). Those networks that become too closely clustered may start suffering from Not-Invented-Here effects. In contrast, we cannot observe a significant influence of innovative collaborations for the US. Hence, our results for Canada are generally in line with previous studies (Balconi et al. 2004; Breschi and Catalini 2008; Murray 2002; Schilling and Phelps 2007), highlighting the importance of research collaboration.

The results as presented in Table 2 show a positive impact of the number of patenting activities in the past 3 years (*NPP*) on categorical variable of citations ($C(NCi_{it})$). The results show a positive linear impact of clustering (*PCC*) on patent citations in the first model only for Canada (Model 1-1). However, patenting activity is positively associated with patent citation and the results are strongly significant for both Canada and the US. We also observe a negative nonlinear impact implying that there is a limit for this positive effect and once we reach that limit, the probability of receiving more citations starts to decrease.

The other patent quality determinant considered is the number of claims (NCL_{it}) declared in patent documents. Table 3 displays the results of the Negative Binomial model with clustered robust standard errors. As expected, the results are positive and highly significant in the US: accessing greater amounts of government funding is associated with a higher number of claims. In the US the results indicate that beyond a specific amount of funding, patent quality diminishes (Fig. 3a). Surprisingly, when we conducted this analysis for Canada, we found a negative impact of funding on the number of claims in our studied

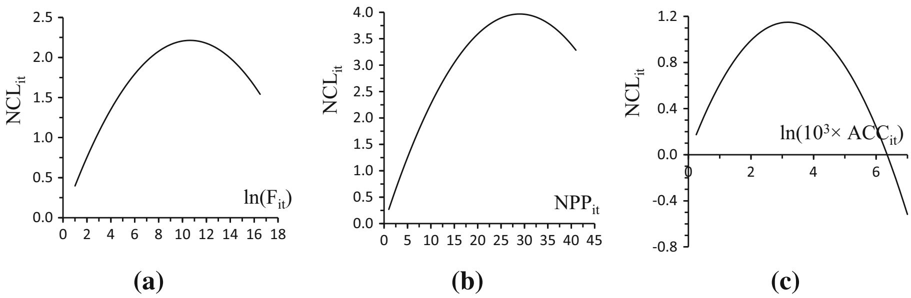


Fig. 3 Non-linear impact of **a** funding (*F*), **b** the number of patents in past 3 years (*NPP*) and **c** the clustering coefficient in co-publication networks (*ACC*) on the number of claims in the United States (Model 6-2)

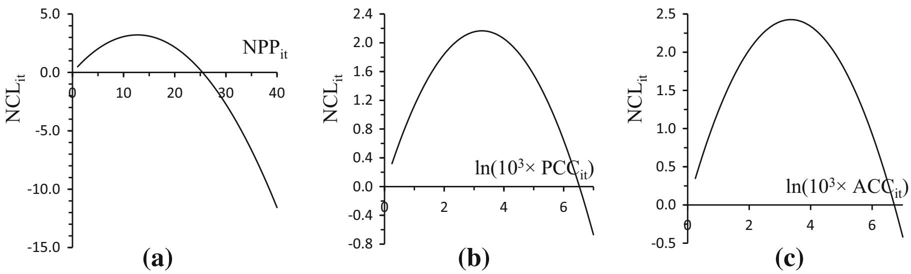


Fig. 4 Non-linear impact of **a** the number of patents in past 3 years (*NPP*), **b** the clustering coefficient in co-invention networks (*PCC*), and **c** the clustering coefficient in co-publication networks (*ACC*) on the number of claims in Canada (Model 3-2)

period. Past experience measured by the number of patents in the past 3 years in both Canada and the US positively influences the number of claims but only up to a point. Beyond this threshold (13 patents in Canada and 29 patents in the US), one more patent reduces the number of claims (Figs. 3b, 4a).

With respect to the influence of betweenness centrality in innovative and scientific networks, we only observed a positive impact in Canada, but once we add the interactive effect of betweenness with the number of previous patents, we observed the positive impact in the US as well. In the US, our results illustrate that only the co-publication networks enhance patent quality (see Fig. 3c), while in Canada, both co-invention and co-publication networks boost patent quality (see Figs. 4b, c).

As observed above, that a higher clustering coefficient eventually yields fewer patents, after an increase in the relationship, further along the inverted U-shaped curve we notice that more integrated clusters also lead to lower number of claims. These findings tend to suggest that although collaboration in integrated groups tends to result in higher quality patents, slightly more integrated networks eventually decrease the patent quality.

In particular, comparing the effects of funding and network measures in Canada and the US provides further evidence that having previously patented has a stronger positive effect on increasing the number of patents in Canada compared to the US[9] (Fig. 5a). The

[9] For the purpose of comparing the effects of funding and network measures in Canada and the US, we defined a dummy variable for Canada (dCA) and estimated a model where dCA interacts with other

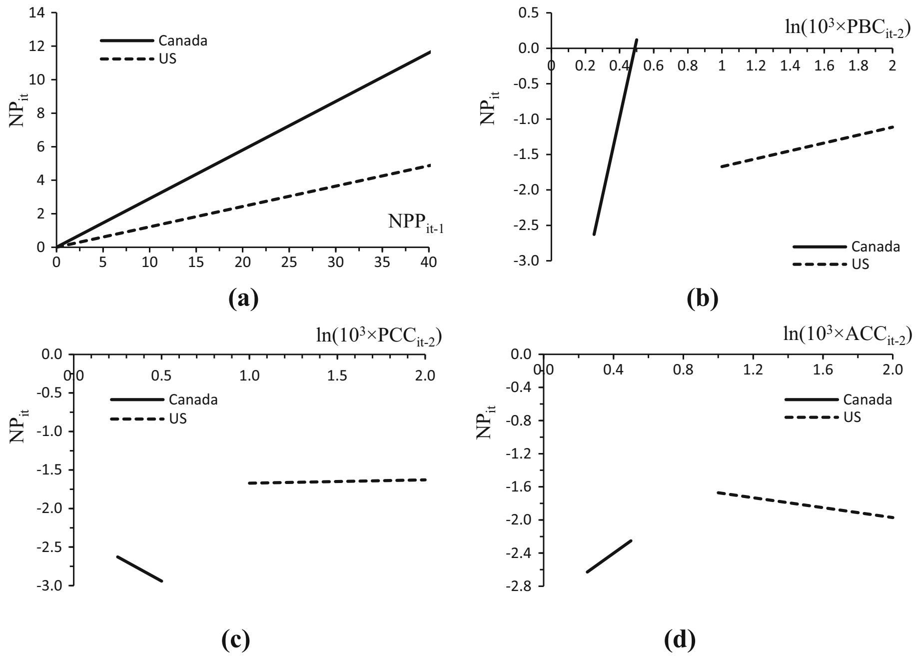


Fig. 5 Comparison of the impact of **a** the number of patents in past 3 years (*NPP*), **b** betweenness centrality in the co-invention network (*PBC*), **c** the clustering coefficient in co-invention networks (*PCC*), and **d** the clustering coefficient in co-publication networks (*ACC*) on the number of nanotechnology patents in Canada and in the United States

intermediary position of researchers in co-invention networks seems to have more influence in Canada than in the US (Fig. 5b). Although both Canada and the US have a positive slope, one unit increase in betweenness centrality will have a stronger impact on the number of patents in Canada. In regards to assessing the impact of the clustering coefficient in co-invention networks, Fig. 5c shows that the number of patents is associated with a slight increase in the US while we have a negative slope in Canada, i.e. increasing the co-invention clustering coefficient will decrease the number of patents in Canada. The results are the opposite for the co-invention clustering coefficient: a positive slope for Canada and a negative slope for the US (Fig. 5d).[10]

Turning now to the patent citation, we find once more that past patenting experience has a positive impact on patent citations in Canada, i.e. the probability of higher quality patents increases in accordance with the number of patents generated in previous years (Fig. 6a).

Footnote 9 continued
variables. Due to the difference in the number of observations between Canada and the US, we created 5 random samples without replacement from the US data that have approximately the same number of observations as the Canadian sample. Table C-3 in Appendix C compares the Canadian and US samples for all the variables of interest. We ran *t* test to investigate whether there is a statistically significant difference in the means of variables in our two datasets ([Canada vs US-s1], [Canada vs US-s2], …, [Canada vs US-s5]).

[10] We investigated whether the co-invention and co-publication clustering coefficients could have a moderating effect on one another by interacting the two variables, but this added interaction term was never significant.

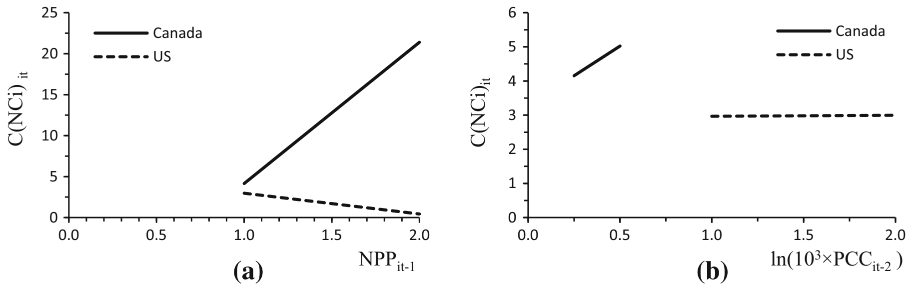


Fig. 6 Comparison of the impact of **a** the number of patents in past 3 years (*NPP*), **b** the clustering coefficient in co-invention networks (*PCC*) on the number of citations in Canada and in the United States

Additionally, the clustering coefficient in co-publication networks has a higher impact in Canada compared to the US, where the relationship is relatively flat (Fig. 6b).

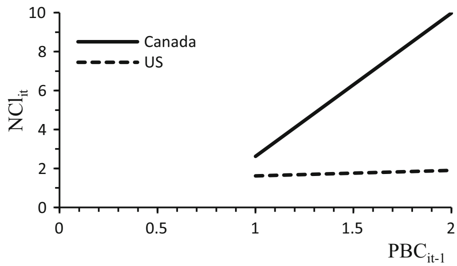
According to the comparison analysis of our second indicator of patent quality (the number of claims), a better intermediary position in an innovative network has more impact in Canada than in the US and increasing the betweenness centrality will result in higher quality patents (see Fig. 7). Neither the Negative Binomial nor the Ordered Probit regressions could provide significant results to compare the importance of dynamic effects of funding in the US and Canada.

5 Conclusions and implications

This paper presents an empirical analysis of the impact of public funding and of collaboration between academic researchers on university technological outputs in the emerging science and technology domain, nanotechnology, on a sample of Canadian and American academic patents. A limited number of studies have explored in details the influence of funding and collaboration together on academic innovative activity. More importantly, the large body of literature generally focuses on the influence of funding on scientific productivity. This paper expands the focus of research on patenting by examining whether funding and collaboration in both the scientific and the technological networks is an issue when scientists address industrial interests. To our knowledge this is the first study where technological performance is examined to provide insight on the impact of funding and compare between the networks of science and of technology in the field of nanotechnology in Canada and in the US. Three hypotheses were proposed at the start of the paper, which we discuss in the following paragraphs.

We focus here on two relatively similar, yet very distinct countries and the results are a rather different. We find empirical evidence that government funding enhances technological productivity in the US, but we are unable to find such a relationship in Canada. We hence accept *Hypothesis 1a* for the US, but reject this hypothesis for Canada. For the second part of the first hypothesis on quality, we confirm the impact of public funding on patent quality but only in the US, and thus accept *Hypothesis 1b* for the US. In this regard, the number of claims yields significant results while the number of citations, regardless of the form of the indicator, does not, even when we include 7-year forward citations following the patent grant year. While more government funds in the US undoubtedly lead to more academic patents that are associated with higher quality patents, we find there is a

Fig. 7 Comparison of the impact of betweenness centrality in the co-invention network (*PBC*) on the number of claims in Canada and in the United States



limit to the increase in patent quality. This suggests that beyond a specific amount of funding (nearly 42,000 $), patent quality begins to decrease. The policy implication of these results could be that governments allocate various smaller grants to researchers in order to enhance the research output.

In parallel, the amount of public funds at the disposal of researchers in Canada does not yield a positive impact on patent quality; hence we reject *Hypothesis 1b* for Canada. Although, government plays a central role as a source of research financing in universities, across the different domains of scientific research close to commercial applications, Canadian nanotechnology-related patents appear to be independent from research financing. Nanotechnology is however in its infancy and technology development is slightly slower in Canada than in the US. With respect to the fact that the patents considered in this paper are the technological output of academic researchers, because scientists aim first and foremost to publish rather than patent, it is possible that more collaboration and funding from industry are necessary to incite patenting activities in Canada.

This analysis further sheds light on our understanding of the influence that collaboration, within the network of science and of technology, has on enhancing commercial interests of academic researchers. We characterised two technological and scientific networks based on co-invention and co-publication links between individual researchers. In Canada we find that collaborations in both networks have a significant influence on patenting productivity and quality, but in the US, collaborations are more effective in terms of patent quality and we are not able to capture a consistently significant impact on the number of patents. These findings suggest that the position of a researcher and the structure of collaborative teams do matter and are effective in enabling academic researchers to enhance their technological output. Therefore following previous studies (Agrawal et al. 2006; Baba et al. 2009; Balconi et al. 2004; Breschi and Catalini 2008; Breschi and Lissoni 2009; Murray 2002; Schilling and Phelps 2007; Teichert and Ernst 1999) that generally studied the relationship between collaboration and research productivity, we contribute to the literature in terms of a detailed analysis of the effect of collaborations on technological productivity. We accept *Hypothesis 3a* and *Hypothesis 3b* only for Canada and *Hypothesis 2a* and *Hypothesis 2b* for both Canada and partly for the US as we have seen only betweenness centrality in co-invention network has a positive influence on patent quality in the US. It is worth noting that although our findings confirm that the structure of clusters in networks of researchers can be beneficial, the collaboration of various disciplines is required and the maximum clustering coefficient cannot yield fruitful results. As we see in this study, if researchers do not attempt to establish relationships beyond their circles and maintain some level of fragmentation, maximum clustering leads to a reduction in research productivity and quality.

Moreover, we extended our models to further our understanding of the role that patenting experience plays on future patents. Our results, which are consistently significant in both Canada and the US, display a reinforcing direct impact on the technological productivity and quality of academic inventors. There is however a limit as we observe a threshold: no positive influence is observed beyond a specific number of patents (in terms of the number of patents, our threshold are 21 patents for Canada and 18 patents for the US, and in terms of the patent quality, the thresholds are 13 patents in Canada and 29 patents in the US).

We can also formulate some concluding remarks to contribute to the comparison of the US and Canada. Moreover, in Canada, if an academic inventor already holds a better intermediary position than other researchers and has a well-integrated clique around him/herself (with some level of fragmentation), he/she contributes to more and higher quality technological output. These findings suggest that collaborations in Canada are effective in enhancing academic technological output.

From this analysis, we realize that both funding and collaborations contribute to enhancing patenting activities in the academic world. The findings highlight the importance and potential of both types of network connections. The study of co-authorship collaborations shows that the establishment of even these relationships becomes effective in the future academic patenting. Nevertheless, it is also necessary to consider that although our analysis tracks different performance in terms of funding and collaboration in nanotechnology area in these two countries, attempting to follow nanotechnology development requires the investment of governments not only in the young field of nanotechnology, but also in the forming the relationships between nanotechnology researchers. Thus, increasing attention to both research financing and knowledge exchange and collaboration could have the effect of raising the commercial applications in academic area. As Foray (2009) stressed in smart specialisation strategies, there is a role for government policies to supply incentives for researchers who are involved in the discovery of the right specialisations and support the investments which are complementary to these specialisations; for example investing in the co-invention of applications and connecting researchers with the centers that invent and produce in right specialisations. Since the growth of nanotechnology relates to technologies from various fields, it is of great importance for governments to encourage scientists to work in teams. Researchers need to widen their connections within these domains in order to stimulate growth in this emerging high technology.

As in all research, there are limitations associated with this study. We focused specifically on the field of nanotechnology (a multidisciplinary field), and different keywords were used to determine whether a patent is related to nanotechnology. Fields evolve and we may miss some of the patents that use emerging keywords to describe the technology. Furthermore, we may have used keywords that may be too general and have cast too wide a net. In addition, nanotechnology is an emerging field: not only has the number of patents and publications been rapidly growing, but funding has also been increasing to develop this new technology. Hence the collaborative structures of scientists have been rapidly changing over time. Our database does not cover extensively the multidisciplinarity of research and technological collaborations, which should bias the results towards more monodisciplinary teams (their position in the network would appear stronger than multidisiciplinary teams). Furthermore, in order to measure the applied knowledge in terms of innovations, we suggest that the intervention of industrial funding and industry collaboration be considered in future research.

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Appendix 1: Variable description

See Table 4.

Table 4 Variable description

Variable	Description
Dependent variables	
NP_{it}	Number of patents of an academic inventor i in a given year t
NCi_{it}	Number of citations received by the patent(s) of an academic-inventor i over the following 5 years
$C(NCi_{it})$	An ordered categorical variable for the number of citations that takes the value 0 if NCi_{it} is 0, the value 1 if NCi_{it} is between 1 and 5, and takes the value 2 if the number of citations over 5 years is more than 5
NCl_{it}	Number of claims contained in the patent(s) of an academic-inventor i applied for in year t
Independent variables	
F_{it-1}	Average yearly amount of government funding received by an academic-inventor i over the past 3 years ($t-3$ to $t-1$)
NPP_{it-1}	Number of applied patents of an academic-inventor i over past 3 years ($t-3$ to $t-1$)
PBC_{it-2}	Betweenness centrality of an academic-inventor i in the 3-year **co-invention** subnetwork lagged 2 years
PCC_{it-2}	Clustering coefficient of an academic-inventor i in the 3-year **co-invention** subnetwork lagged 2 years
ABC_{it-2}	Betweenness centrality of an academic-inventor i in the 3-year **co-publication** subnetwork lagged 2 years
ACC_{it-2}	Clustering coefficient of an academic-inventor i in the 3-year **co-publication** subnetwork lagged 2 years
D_t	Dummy variables for different years ($t = 1985, \ldots, 2005$)
Instrumental variables	
Age_t	Career age of a scientist since the first publication or the first grant or the first patent in the field of nanotechnology
NA_{it}	Number of past articles published by academic inventor i over 3 years

Appendix 2

See Tables 5, 6 and 7.

Table 5 First-stage regression results—number of patents—Canada and the United States

	NP_{it}		
	US (4)	US (5)	US (6)
NPP_{it-1}	−0.0090	−0.0118	0.0073
	(0.0243)	(0.0254)	(0.0353)
$[NPP_{it-1}]^2$			−0.0012
			(0.0009)
$ln(10^4 \times PBC_{it-2})$	−0.0562	−0.2338	−0.3689
	(0.2250)	(0.3500)	(0.2327)
$ln(10^4 \times ABC_{it-2})$	0.1183	0.1119	0.1799
	(0.5653)	(0.5656)	(0.5636)
$ln(10^3 \times PCC_{it-2})$	0.0023	0.0033	0.6898**
	(0.0205)	(0.0206)	(0.3131)
$[ln(10^3 \times PCC_{it-2})]^2$			−0.1022**
			(0.0462)
$ln(10^3 \times ACC_{it-2})$	0.0781***	0.0778***	−0.7427
	(0.0281)	(0.0281)	(0.4646)
$[ln(10^3 \times ACC_{it-2})]^2$			0.1209*
			(0.0684)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$		0.0261	
		(0.0370)	
Age_{it}	0.3847***	0.3849***	0.3805***
	(0.0389)	(0.0389)	(0.0391)
$[Age_{it}]^2$	−0.0119***	−0.0119***	−0.0118***
	(0.0021)	(0.0021)	(0.0021)
NA_{it}	0.2650***	0.2641***	0.2627***
	(0.0329)	(0.0330)	(0.0330)
Constant	2.0645***	2.0652***	2.0798***
	(0.2445)	(0.2445)	(0.2453)
Years	Yes	Yes	Yes
Nb observations	9157	9157	9157
Nb groups	5381	5381	5381
F	27.66***	26.38***	24.27***
R^2	0.0432	0.0432	0.0443

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

Table 6 First-stage regression results—number of claims—Canada and the United States

NCL_{it}	Canada (1)	US (4)	Canada (2)	US (5)	Canada (3)	US (6)
NPP_{it-1}	0.0484	−0.0090	0.0125	−0.0118	0.0057	0.0073
	(0.1613)	(0.0243)	(0.1711)	(0.0254)	(0.1721)	(0.0353)
$[NPP_{it-1}]^2$	−0.0115		−0.0091		−0.0097	−0.0012
	(0.0128)		(0.0131)		(0.0134)	(0.0009)
$ln(10^4 \times PBC_{it-2})$	0.3876	−0.0562		−0.2338		−0.3689
	(0.3208)	(0.2250)		(0.3500)		(0.2327)
$ln(10^4 \times ABC_{it-2})$	−0.0529	0.1183		0.1119		0.1799
	(0.2043)	(0.5653)		(0.5656)		(0.5636)
$ln(10^3 \times PCC_{it-2})$		0.0023	0.0376	0.0033	0.2600	0.6898**
		(0.0205)	(0.0433)	(0.0206)	(0.5425)	(0.3131)
$[ln(10^3 \times PCC_{it-2})]^2$					−0.0331	−0.1022**
					(0.0796)	(0.0462)
$ln(10^3 \times ACC_{it-2})$		0.0781***	−0.0302	0.0778***	0.5958	−0.7427
		(0.0281)	(0.0456)	(0.0281)	(0.4646)	(0.4646)
$[ln(10^3 \times ACC_{it-2})]^2$					−0.0938	0.1209*
					(0.0698)	(0.0684)
$ln(10^4 \times PBC_{it-2}) \times NPP_{it-1}$				0.0261		
				(0.0370)		
Age_{it}	0.3106***	0.3847***	0.3176***	0.3849***	0.3084***	0.3805***
	(0.0822)	(0.0389)	(0.0852)	(0.0389)	(0.0850)	(0.0391)
$[Age_{it}]^2$	−0.0111**	−0.0119***	−0.0113**	−0.0119***	−0.0111**	−0.0118***
	(0.0047)	(0.0021)	(0.0049)	(0.0021)	(0.0049)	(0.0021)
NA_{it}	0.0814	0.2650***	0.0811*	0.2641***	0.0211	0.2627***
	(0.0583)	(0.0329)	(0.0480)	(0.0330)	(0.0541)	(0.0330)

Table 6 continued

NCL_{it}	Canada (1)	US (4)	Canada (2)	US (5)	Canada (3)	US (6)
Constant	5.4600***	2.0645***	5.4188***	2.0652***	5.4709***	2.0798***
	(0.5009)	(0.2445)	(0.5064)	(0.2445)	(0.5054)	(0.2453)
Years	Yes	Yes	Yes	Yes	Yes	Yes
Nb observations	1329	9157	1329	9157	1329	9157
Nb groups	532	5381	532	5381	532	5381
F	87.71***	27.66***	82.06***	26.38***	73.81***	24.27***
R^2	0.2242	0.0432	0.2245	0.0432	0.2257	0.0443

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

Table 7 First-stage regression results—number of citations—Canada and the United States

$C(NCi_{it})$	Canada		United States	
	1	2	3	4
NPP_{it-1}	−0.4716	−0.4766	0.0447	0.0335
	(0.3053)	(0.3076)	(0.0458)	(0.0458)
$[NPP_{it-1}]^2$	0.0148	0.0149	−0.0011	−0.0011
	(0.0195)	(0.0196)	(0.0014)	(0.0014)
$ln(10^4 \times PBC_{it-2})$	−0.6760	−0.7409	0.2715	−0.1477
	(0.4815)	(0.6679)	(0.3729)	(0.4124)
$ln(10^3 \times PCC_{it-2})$	0.2132*	0.3668	−0.0107	0.9696**
	(0.1132)	(1.1178)	(0.0386)	(0.4922)
$[ln(10^3 \times PCC_{it-2})]^2$		−0.0230		−0.1463**
		(0.1667)		(0.0732)
$ln(10^3 \times ACC_{it-2})$	0.0361	0.0351	−0.0202	−0.0230
	(0.1124)	(0.1123)	(0.0548)	(0.0547)
Age_{it}	0.4888**	0.4910**	0.2982***	0.3011***
	(0.2327)	(0.2341)	(0.0911)	(0.0909)
$[Age_{it}]^2$	−0.0190	−0.0192	−0.0031	−0.0033
	(0.0130)	(0.0131)	(0.0052)	(0.0052)
NA_{it}	−0.0346	−0.0336	0.1274**	0.1282**
	(0.0878)	(0.0880)	(0.0535)	(0.0527)
Constant	−2.4917**	−2.5083**	2.3235***	2.3367***
	(0.9860)	(1.0067)	(0.4848)	(0.4854)
Nb observations	201	201	201	201
Nb groups	155	155	155	155
F	21.88***	20.74***	9.52***	9.13***
R^2	0.2948	0.2948	0.0522	0.0539

***,**,* Significance at the 1, 5 and 10% levels. Standard errors are presented at parentheses

Appendix 3: Descriptive statistics

See Tables 8, 9 and 10.

Table 8 Correlation matrix—Canada

Variable	Obs	Mean	SD	Min	Max		1	2	3	4	5	6	7	8	9	10	11
NP_t	1329	0.2242	(0.9023)	0.00	25.00	1	1										
NCi_t	1329	0.4605	(3.0835)	0.00	48.00	2	0.2828	1									
NCL_t	1329	4.9360	(18.5001)	0.00	265.00	3	0.7944	0.3346	1								
F_t	1329	9.9168	(0.9354)	6.06	13.03	4	−0.0225	−0.0161	0.0104	1							
NPP_t	1329	0.7186	(1.8360)	0.00	40.00	5	0.8290	0.3767	0.7017	−0.0075	1						
PBC_t	1329	0.0403	(0.2842)	0.00	4.89	6	0.0670	0.0248	0.1119	0.0341	0.0836	1					
ABC_t	1329	0.3593	(0.9247)	0.00	4.97	7	0.0173	−0.0107	0.012	0.0235	0.0357	0.1711	1				
PCC_t	1329	2.3144	(3.1827)	0.00	6.91	8	0.2581	0.1707	0.2815	0.0514	0.3997	0.1435	0.1338	1			
ACC_t	1329	2.7350	(3.1575)	0.00	6.91	9	0.0193	0.0447	0.0147	−0.0338	0.0688	0.0607	0.3513	0.1304	1		
Age_t	1329	5.6110	(4.0906)	1.00	20.00	10	0.0002	0.0734	−0.0045	0.1048	0.0736	0.0146	0.0553	−0.0235	0.0459	1	
NA_t	1329	1.0191	(2.6056)	0.00	37.00	11	0.0154	0.0053	0.0258	0.0265	0.0451	0.0446	0.6708	0.1098	0.325	0.0516	1

Table 9 Correlation matrix—United States

Variable	Obs	Mean	SD	Min	Max		1	2	3	4	5	6	7	8	9	10	11
NP_t	9157	0.4667	(1.0853)	0.00	25.00	1	1										
NCi_t	9157	0.0282	(1.1145)	0.00	74.00	2	0.1012	1									
NCL_t	9157	12.7836	(34.3505)	0.00	1115.00	3	0.8609	0.0938	1								
F_t	9157	11.4381	(1.1189)	5.95	16.59	4	0.0362	−0.0104	0.0366								
NPP_t	9157	1.6626	(2.7040)	0.00	41.00	5	0.7531	0.0726	0.6166	0.0493	1						
PBC_t	9157	0.0273	(0.2231)	0.00	4.55	6	0.1748	0.0085	0.1641	0.0324	0.2477	1					
ABC_t	9157	0.0170	(0.1276)	0.00	2.75	7	−0.0095	−0.0034	−0.0091	0.0043	−0.0134	0.019	1				
PCC_t	9157	1.8951	(3.0034)	0.00	6.91	8	0.2201	0.0268	0.1965	0.0194	0.2857	0.1519	0.0098	1			
ACC_t	9157	1.3979	(2.7425)	0.00	6.91	9	−0.0457	0.0366	−0.0444	0.0717	−0.0511	−0.0007	0.1777	−0.0059	1		
Age_t	9157	10.3610	(5.2142)	1.00	21.00	10	0.0323	−0.0067	0.0400	0.1257	0.1157	0.028	−0.0179	−0.0992	0.0552	1	
NA_t	9157	1.5193	(2.4994)	0.00	40.33	11	0.095	0.0082	0.083	0.1358	0.143	0.0925	0.0284	0.0355	0.2256	0.1774	1

Table 10 Mean comparison between Canada and five similarly-sized random subsamples for the United States

Variable	Canada N = 1329	US N = 9157	US-s1 N = 1367	US-s2 N = 1382	US-s3 N = 1335	US-s4 N = 1398	US-s5 N = 1308	Two-sided p values					
								Canada versus US	Canada versus US-s1	Canada versus US-s2	Canada versus US-s3	Canada versus US-s4	Canada versus US-s5
NP_t	0.2242	0.4667	0.4601	0.5014	0.4029	0.4828	0.5045	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9023)	(1.0853)	(1.0194)	(1.2235)	(0.9769)	(1.0698)	(1.0644)						
NCi_t	0.4605	0.0282	0.0651	0.0086	0.0044	0.0085	0.0114	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	(3.0835)	(1.1145)	(2.0115)	(0.1741)	(0.1160)	(0.1511)	(0.1972)						
NCL_t	4.9360	12.7836	13.1843	14.3914	10.5790	12.8283	14.3019	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(18.5001)	(34.3505)	(34.8538)	(42.9191)	(28.2920)	(31.4050)	(36.3335)						
F_t	9.9168	11.4381	11.412	11.4151	11.4500	11.4517	11.402	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9354)	(1.1189)	(1.0896)	(1.1463)	(1.0684)	(1.0835)	(1.1319)						
NPP_t	0.7186	1.6626	1.6247	1.6548	1.5048	1.7238	1.6766	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.8360)	(2.7040)	(2.6154)	(2.5636)	(2.5277)	(2.6842)	(2.6372)						
PBC_t	0.0403	0.0273	0.0284	0.0222	0.0436	0.0382	0.0288	0.2340	0.2439	0.0546	0.7737	0.8449	0.2501
	(0.2842)	(0.2231)	(0.2423)	(0.1925)	(0.3162)	(0.2629)	(0.2240)						
ABC_t	0.3593	0.0170	0.0192	0.0151	0.0172	0.0133	0.0144	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9247)	(0.1276)	(0.1268)	(0.1140)	(0.1411)	(0.0989)	(0.1152)						
PCC_t	2.3144	1.8951	1.8522	1.8548	1.7419	1.9728	1.9154	0.0000	0.0001	0.0001	0.0000	0.0042	0.0010
	(3.1827)	(3.0034)	(2.9817)	(2.9858)	(2.9247)	(3.0357)	(3.0166)						
ACC_t	2.7350	1.3979	0.4224	1.3435	1.5473	1.4064	1.2378	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(3.1575)	(2.7425)	(2.7590)	(2.7006)	(2.8433)	(2.7428)	(2.6165)						
NA_t	1.0191	1.5193	1.5794	1.5537	1.5003	1.6268	1.3409	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
	(2.6056)	(2.4994)	(2.8198)	(2.3780)	(2.9054)	(2.7673)	(2.2317)						

Standard deviation in parentheses

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